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Developing national complementary indicators of SDG15 that consider forest quality: Applications in Colombia, Ecuador, and Peru

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A R T I C L E I N F O

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A B S T R A C T

The UN 2030 Agenda for Sustainable Development Goal 15, termed Life on Land, is monitored by indicators and sub-indicators that largely deal with forest extent. In countries with structurally complex and species-rich forests, indicators and sub-indicators of forest quality are also needed to effectively monitor and sustain ecological integrity. The goal of the paper is to demonstrate the use of complementary sub-indicators of forest quality for SDG15 reporting and conservation planning. Our objective is to apply these sub-indicators within Colombia, Ecuador, and Peru and evaluate spatial patterns and trends over time as a basis for revealing how the results complement the official indicators of forest extent and forest extent in protected areas in informing conservation. The sub-indicators of forest quality quantify naturalness, riparian forest, forest structure and integrity, forest fragmentation, and forest connectivity. We quantified change during 2000–2021 in these metrics and highlighted insights gained from the complementary sub-indicators of forest quality relative to the official sub-indicators based on forest extent,

Forests covered about 60–70% of the forested ecoregions in each country in 2000 and this proportion declined in all three countries by approximately 4% by 2021. Only a subset of the forested area was of high forest quality. Natural forests represented about 40% of forests in Colombian and Ecuador in 2000 and 50% in Peru. Those proportions declined: by 6.3% in Colombia, 6.5% in Ecuador, and 3.4% in Peru. Even less of the forested area was Core Forest in 2013; less than 28% among countries. During 2013–2021, the proportion of forest that was Core decreased by 2.3% in Colombia, 4.5% in Ecuador, and 6.7% in Peru. Connected Forests were about 17–22% of forests among the countries in 2013 and declined 10.4% in Colombia, 1.6% in Ecuador, and 3.8% in Peru by

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2021. Forests high in forest structure were 10–18% of forests in 2012 among the countries and increased by 1.1–2% by 2021. Forests of high integrity were 7–13% of forests in 2012 and increased by1.4–2% by 2021. Riparian forests represented less than about 7–9% among the countries and declined by 0.6–1.3% by 2021. Thus, the area of highly quality forest across the countries was substantially less than full forest extent and high-quality forest declined at a higher rate than forest extent during 2000–2021. Forest structure and integrity did increase slightly over this time period.

Our results for trends in forest naturalness, riparian association, within stand structure, fragmentation, and connectivity demonstrate how consideration of forest quality provides a much stronger basis for evaluating success in meeting SDG15 targets than consideration of forest extent alone.

1. Introduction

Nature conservation is essential to sustainable development. However, we are in a global emergency of biodiversity loss, climate change, infectious diseases, and inequality (IPBES, 2019) which threaten nature and human sustainability. This reality motivated the 2030 Agenda for Sustainable Development, which was adopted by all member states of the United Nations (UN) in 2015.[1] This agenda was designed to provide a "shared plan for peace and prosperity for people and the planet, now and in the future".[2] The program's 17 Sustainable Development Goals (SDGs) deal with human health, equity, and economic status as well as with nature and climate. The UN has identified for each of the SDGs specific targets for the year 2030 and indicators (and sub-indicators) that should be used to monitor progress towards these targets. Implementation of the SDGs is to be done by member countries. Therefore, the indicators should be effective for monitoring progress towards the international SDG targets but also meaningful to the national SDG targets and feasible for implementation within countries. In this paper we introduce indicators of forest quality that are nationally relevant to the countries of Colombia, Ecuador, and Peru and present methods for monitoring them and trends in the indicators during 2000–2021.

The UN General Assembly tasked the UN Statistical Commission, represented by Member States' National Statistical Offices, to create the Inter-Agency and Expert Group on Sustainable Development Goals Indicators (IAEG-SDGs).[3] This group then developed a Global Indicators Framework for the SDGs and targets. The framework specifies the metrics that are to be used to monitor progress on reaching each target. These metrics are organized hierarchically, with indicators being the broader level metrics and sub-indicators being more narrow metrics within indicators.

In recognition of geographical variation in ecosystems and human communities, the 2030 Agenda encouraged the development of regional and national indicators and sub-indicators to complement the global ones where needed and in alignment with national priorities. These complementary national indicators and sub-indicators are to be developed by member states as appropriate to meeting the SDGs (United Nations, 2017). Thus, countries are encouraged to develop complementary indicators and sub-indicators for SDG targets that are most relevant to their individual sustainable development situation.

Among the SDGs is SDG15, termed Life on Land, which aims to "Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss". The 12 targets of this goal are oriented to conserve and restore terrestrial and freshwater ecosystems, end deforestation, restore degraded forests, and protect biodiversity and natural habitats.[4] Given that ecological systems vary geographically with climate, topography, species pools, and other factors, the specific indicators and means of achieving these targets are likely to vary among countries and regions.

Countries in the moist tropical forest biome have unique challenges for sustaining nature and people. This biome is dominated by dense rainforests that are unique globally in high levels of biodiversity, carbon storage, climate mitigation, and unique genetic resources (Dinerstein et al., 2017). Local communities are often highly dependent on the ecological services provided by these forests. Yet the forests are especially vulnerable to human pressure (Betts et al., 2017, Pillay et al. 2022a). Thus, achieving the SDG15 targets in this region will require indicators that consider the unique ecological characteristics of these ecosystems. Colombia, Ecuador, and Peru, for example, include a variety of moist and dry tropical forest types. These forests are the most biodiverse in the world, contain the largest tracts of the Earth's remaining natural forests, and store vast quantities of carbon but also include areas of intense land use and rapid climate change (Hansen et al., 2020, Pillay et al. 2020b). Indicators and sub-indicators are needed that are most relevant to these globally important ecosystems.

The indicators designed by the IAEG-SDGs for SDG15 largely deal with forest extent and protected area coverage. For example, indicator 15.1.1 is forest area as a proportion of total land area and indicator 15.1.2 is the proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type. While the amount of forest remaining and forest protection status are clearly important, they do not take into account the key attributes that most influence the ecological value of these forests. In addition to forest extent as specified by the IAEG-SDGs[4], there is a need for indicators and sub-indicators of forest quality.

Forests differ in their contributions to biodiversity and ecosystem services (Watson et al., 2018, Betts et al., 2022, Hua et al., 2022). Locations classified as forest may include primary forests and old-growth forests with large tracts of tall, complex canopies of diverse native species that function naturally and yield high benefits to biodiversity and ecosystem services (Lindenmayer et al., 2014). In contrast, in many countries, industrial tree plantations are also classified as forest (Chiarucci and Piovesan, 2020). Many plantations are designed to maximize wood production but are often low in biodiversity and lack resilience to global change (Rozendaal et al., 2019, Betts et al., 2022, Hua et al., 2022). Forests fragmented and degraded by logging, fire, livestock grazing, or other human activities also tend to have reduced native species richness, impaired ecological function and do not support levels of connectivity for species to respond to climate change (Gibson et al., 2011). Thus, in the context of SDG15, monitoring of not only the extent of forest, but the quality of that forest is critical to developing effective conservation plans (Watson et al., 2018, Chiarucci and Piovesan, 2020).

The ecological value of forests can be quantified based on the

[1] A/RES/70/1 (21 October 2015). Transforming our world. The Agenda for Sustainable Development. Resolution adopted by the United Nations General Assembly on 25 September 2015. Available for consultation at: https://sdgs.un.org/es/2030agenda.

[2] https://sdgs.un.org/es/goals.

[3] https://unstats.un.org/sdgs/iaeg-sdgs/.

[4] See the global indicator framework for the SDGs and targets of the 2030 Agenda for Sustainable Development at: https://unstats.un.org/sdgs/indicators/indicators-list/.

concept of ecological integrity (Hansen et al., 2021, Elsen et al., 2023). This term refers to the composition, structure and function of an ecosystem in relation to the system's natural or historical range of variation. Human pressures can alter these ecosystem properties and reduce ecological integrity. Thus, the evaluation of elements of forest composition, structure, and function relative to reference conditions allows objective assessment of the extent to which forests may support the biodiversity and ecosystem services characteristic of a region (Chiarucci et al. 2020). Consequently, international policy increasingly calls for sustaining and restoring natural forest, intact forest, old-growth forest, and forest with high ecological integrity (CBD 2022, European Commission, 2020). Some elements of ecological integrity can now be monitored through remote sensing and spatial analysis, particularly if validated with *in-situ* data.

We provide in this paper complementary sub-indicators of forest quality relating to naturalness, canopy structure, and landscape pattern. They were chosen based on relevance to forest ecological integrity, experience of our team in monitoring forest condition, and interest to ministries in each country charged with reporting on SDG15 targets.

The goal of the paper is to demonstrate the use of complementary sub-indicators of forest quality for SDG15 reporting and conservation planning. Our objective is to apply these sub-indicators within Colombia, Ecuador, and Peru and evaluate spatial patterns and trends over time as a basis for revealing how the results complement the official indicators of forest extent and forest extent in protected areas in informing conservation.

2. Methods

2.1. Study area

The 1,472,259 km^2 study area of Colombia, Ecuador, and Peru ranges from the Pacific and Caribbean coasts of South America, over the Andes Mountains, and into the Amazon Basin (Fig. 1A). The pronounced topographic and climatic gradients result in 8 biome types and 42 ecoregions (Dinerstein et al., 2017). This area has the highest terrestrial biodiversity in the world and includes two of the five top global biodiversity hotspots that are most endangered (Myers et al., 2000). Over 100 million people live in the Tropical Andes or in regions that depend directly on these natural resources (Buytaert et al., 2011). Agriculture and urban areas dominate the slopes of the Andes and the Caribbean dry forest. Extensive wildlands cover the coastal forests and much of the Amazon Basin but are increasingly infringed by deforestation fronts (Armenteras et al., 2017).

We focus here on forested ecoregions within two biomes, Tropical & Subtropical Moist Broadleaf Forests and Tropical & Subtropical Dry Broadleaf Forests as defined by the World Wildlife Fund Resolve 2017 classification (Dinerstein et al., 2017). The forested ecoregions within these biomes in the study area are depicted in Fig. 1B and described in Table SM1. Protected area boundaries were derived from the World Database on Protected Areas (WDPA, 2019) and included IUCN categories I–IV, which represent allocations where conservation of biodiversity is a primary objective. While WDPA is the global standard for protected area mapping, there can be lag-time in updates and the global dataset may not include the most recently created protected areas within countries.

All maps shown in this paper use the Equal Earth projection, an

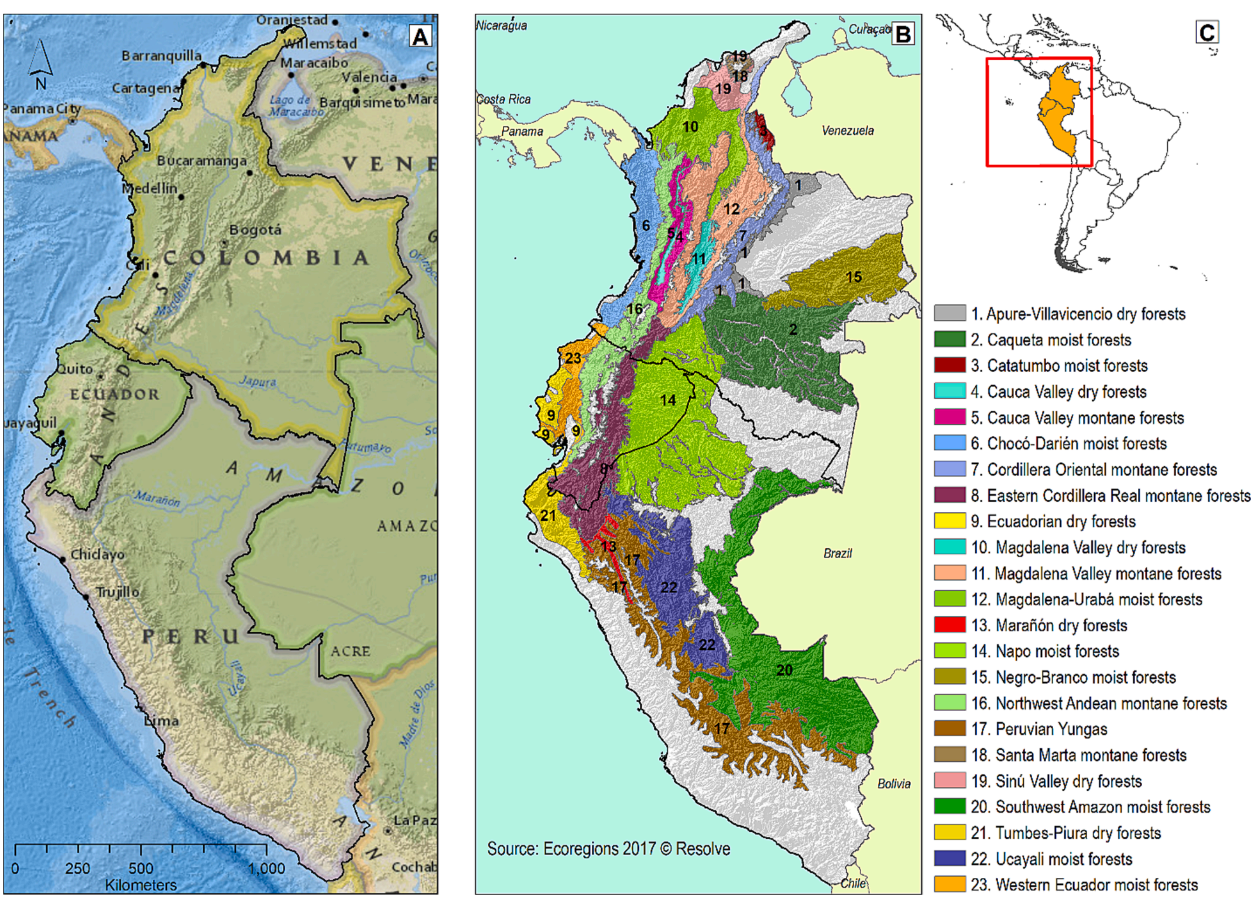

Fig. 1. Map of the study area showing shaded relief, national boundaries, and major cities (A). Map of World Wildlife Fund ecoregions (B). Location of the study area in South America (C).

equal-area pseudo cylindrical projection for world maps.

2.2. Development of the complementary sub-indicators

We developed the sub-indicators of forest quality identified in Table 1 across the three countries. Among these metrics is a measure of human pressure (Human Footprint) used to quantify the naturalness of forests. The three-dimensional forest stand structure is represented by the Forest Structural Condition Index-Ecoregional Potential (FSCI-ERP) and the intersection of this index with human pressure is the Forest Structural Integrity Index-ERP (FSII-ERP). These metrics have been shown to be associated with reduced endangerment status of forest vertebrates and carbon storage (Pillay et al. 2022a). We include three measures of landscape pattern. Extent of Riparian Forest is an indicator of potential of buffering aquatic systems from the effects of deforestation. Core Forest is area of moderate to high FSII-ERP that is not exposed to negative forests/non-forest edge effects, which can emerge from forest fragmentation. Connected Forest is where a landscape connectivity index indicates high potential for movement of forest-dependent animals among patches of moderate to high integrity forest. These complementary sub-indicators are directly relevant to SDG15 targets and indicators. They allow forest extent (Indicator 15.1.1) and protection status (Indicator 15.1.2) to be expressed by naturalness, forest structure, and landscape pattern (Table 2).

We used widely available global data sets to derive these metrics where possible to demonstrate an approach that could be used elsewhere in the world for this paper. We also worked in parallel with Colombia, Ecuador, and Peru to produce national versions using nationally validated data. For metrics that can be quantified over time, we plotted values annually during approximately 2001–2021, depending on metric. We did similar analyses for the official sub-indicators of forest extent for SDG-15 identified by the UN IAEG-SDGs. This allowed comparison of the insights gained from our complementary sub-indicators of forest quality with the official sub-indicators based on forest extent. Methods and details for each complementary sub-indicator are described below and in Table SM2. The analyses used in this paper are then described. All codes and files are available through the Github repository: https://github.com/gonzalezivan90/SDG15_indicators.

2.3. Forest Extent

We used the forest cover layer of Hansen (2013) that defined forest as land cover with tree canopy height $\geq$ 5 m and with a canopy cover > 25 % in 2000, including natural and planted trees, not having undergone defined as a stand-replacement disturbance since 2001. 'Forest Cover Loss' is defined as a stand-replacement disturbance, or a change from a forest to non-forest state, during the period 2000–2021.

2.4. Human Footprint and Natural Habitat

Natural habitats are defined as areas that maintain ecological integrity with "the ability of the system to maintain ecosystem structure and functions using processes and elements characteristic of its ecoregion" (Hansen et al., 2021). We proposed two complementary sub-indicators of natural forest: proportion of forest that is natural forest and proportion of natural forest that is protected. Because the national ministries were also interested in non-forested ecosystems, we also quantified proportion of land area that is natural.

These metrics were generated based on the Human Footprint (HF) of Williams et al. (2020), which is a spatial index of cumulative human pressures on ecosystems. HF has been used to assess intact terrestrial ecosystems and wilderness areas (Riggio et al., 2020; Watson et al., 2016; Williams et al., 2020), the risk of species extinction (Di Marco et al., 2018; Pillay et al., 2022), global effectiveness of the protected areas (Jones et al., 2018), reductions in terrestrial mammalian movements (Tucker et al., 2018). Areas absent of pressures or with a low HF

Table 1
Metrics used to develop complementary sub-indicators of forest quality quantified in this analysis. Acronyms are: FSCI-ERP - Forest Structural Condition Index Ecoregional Potential; and FSII-ERP - Forest Structural Integrity Index Ecoregional Potential.

	Metric	Description	Relevance to conservation	Reference
Human pressure	Human Footprint	Index of human pressure based on nine measures of human population, infrastructure, and land use.	Human pressure can reduce native species abundance and richness, favor invasive species, and degrade ecosystem processes.	Venter et al., 2016a
	Natural Forest	Forest with low Human Footprint (HF < 4),	Forest with low human pressure is likely to have high ecosystem integrity,	Venter et al., 2016b
Canopy structure	FSCI-ERP	Vegetation structure within forest stands. Inputs include canopy cover, canopy height, and time since disturbance. ERP denotes ecoregional potential and is scaled to natural stands within ecoregions,	High levels of the index denote tall, multilayered, older forests that are known to support high levels of biodiversity, carbon storage, and ecosystem services,	Hansen et al., 2019,2020
	FSII-ERP	This index integrates the FSCI-ERP with human pressure.	Forests with high structural condition and low human pressure are of high ecological value because of the ecological benefits of well-developed forest structure and lack of alteration by human activities.	Hansen et al., 2019,2020
Landscape pattern	Riparian Forest	Proportion of forests within 100 m of streams and rivers,	Riparian forests can buffer aquatic systems from negative effects of deforestation and other intense land uses,	Gonzalez et al., 2024
	Core Forest	This metric quantifies fragmentation of moderate and high FSII-ERP forests based on the percentage of core forest relative to total forest.	Landscape pattern, especially the creation of edges and the resulting core forest that is free from edge effects has direct impacts on a number of ecological processes.	Vogt et al., 2007
	Connected Forest	This metric maps least cost pathways from points within forests of	Reductions in tree cover lead to reductions in movement for a large number of	Compton et al., 2007, Kaszta et al., 2020

(continued on next page)

Table 1 (*continued*)

Metric	Description	Relevance to conservation	Reference
	moderate and high FSII-ERP to all surrounding points using forest integrity in the intervening matrix and assumptions about animal movements.	forest animals especially arboreal species and those adapted to interior forest conditions.	

value have been used to represent ecosystems likely in natural or closer to natural states (Sanderson et al., 2002; Venter et al., 2016).

HF is derived by summing the influence of eight pressures: built environments, crop lands, pasture lands, population density, nighttime lights, and accessibility via roads, railways, and navigable waterways. The maps were validated through comparison against a similar but independent measure of cumulative pressures from the visual interpretation of high-resolution imagery, finding strong agreement between them. We used the global HF maps from 2000, 2005, 2010 and 2013 (Williams et al., 2020). Natural habitats were designated as areas with low HF (HF < 4). This value approximates the threshold at which the landscape becomes human-dominated (Di Marco et al., 2018; Watson et al., 2016).

2.5. Forest Structural Condition Index – Ecoregional Potential

Forest structure refers to the three-dimensional distribution of vegetation within a forest. In tropical forest ecosystems, undisturbed forests (often referred to as primary forests) tend to have tall, multistory canopies and high variation in plant size, often including large emergent trees. We refer to such forests as having high structural condition. The positive influence of forests of high structural condition on biodiversity, ecological function and ecosystem services is increasingly well understood (Hansen et al., 2020, Pillay et al., 2022). We previously drew on remote sensing products to develop the Forest Structural Condition Index (FSCI) by integrating canopy cover, canopy height, and time since disturbance across the Humid Tropical Forest Biome (Hansen et al., 2019).

For our application to SDG15 indicators, we use a modified version of this index called FSCI-ERP (ecoregional potential). This metric is scaled to the structural conditions typical of natural forests within the ecoregion. We developed the FSCI-ERP for both the Humid and Dry Tropical Forest Biomes within Colombia, Ecuador, and Peru. See Supplementary Materials for further details on methods.

We focused here on high-FSCI-ERP forest, defined as index ≥ 14. This level was selected to represent high-structure forests based on map accuracy and representing levels of structure typical of undisturbed natural forests in the biome. An accuracy assessment found that the FSCI adequately distinguished forest structure levels up to FSCI $= 14$ but the relationship saturated above that level (Hansen et al., 2019).

2.6. Forest Structural Integrity Index – Ecoregional Potential

The original FSII was derived from overlaying the HF of human pressure (see above) on the FSCI. Human activities can influence forests in several ways in addition to altering forest structure. Hunting and poaching alter wildlife populations without direct effects on habitat (Harrison, 2011, Harrison et al., 2016). Human settlements, roads, and deforested areas create edge effects that can extend hundreds of meters into adjacent forests (Haddad et al., 2015). These edge effects include invasive species, livestock and pet effects, altered ecological processes, noise and light (Betts et al., 2017). The effects of anthropogenic disturbance on biodiversity may exceed that of deforestation (Barlow et al., 2016). Integrating human pressure with forest structural condition reveals forests that may be of the highest value for biodiversity and various ecosystem services. Methods used to derive FSII and FSII-ERP are described in Supplementary Materials.

We analyzed change over 2012–2022 for the two metrics of forest structure in terms of loss rates of high FSCI-ERP and high FSII-ERP forests, mean values of FSCI-ERP and FSII-ERP in remaining forests,

Table 2
Indicators and sub-indicators for SDG15 Targets identified by the UN Statistics Division Inter-Agency and Expert Group on Sustainable Development Goals Indicators (denoted by IAEG-SDGs) and complementary sub-indicators of forest quality developed in this project (denoted as Complementary). All sub-indicators are summarized at national and ecoregional extents. Acronyms are as defined in Table 1.

Target	Indicator	Sub-indicators	Type of Sub-indicator
TARGET 15.1: By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements	INDICATOR 15.1.1: Forest area as a proportion of total land area	Percentage of forest area of the total land area of a country	IAEG-SDGs
		Proportion of forest area that is natural forest	Complementary
		Proportion of forest area that is riparian forest	Complementary
		Proportion of forest area in high FSCI-ERP	Complementary
		Proportion of forest area in high FSII-ERP	Complementary
		Proportion of forest area in moderate to high FSII-ERP that is Core Forest	Complementary
		Proportion of forest area in moderate to high FSII-ERP that is Connected Forest.	Complementary
	INDICATOR 15.1.2: Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type	Proportion of forest area within protected areas	IAEG-SDGs
		Proportion of natural forest that is in protected areas	Complementary
		Proportion of riparian forest in protected areas.	Complementary
		Proportion of high FSCI-ERP areas in protected areas	Complementary
		Proportion of high FSII-ERP areas in protected areas	Complementary
		Proportion of moderate to high FSII-ERP Core Forest covered by protected areas	Complementary
		Proportion of moderate to high FSII-ERP Connected Forest covered by protected areas	Complementary

https://unstats.un.org/sdgs/metadata/.

and representation of high FSCI-ERP and high FSII-ERP in protected areas. We summarized the proportional representation of forest, high-FSCI-ERP forest and high-FSII-ERP forest within and outside of protected areas at the national level.

2.7. Riparian Forest

Two complementary sub-indicators related to the water-forest nexus: proportion of forest area that is riparian forest; and proportion of riparian forest in protected areas. The role of riparian vegetation includes the protection of water where it mediates sediment and pollutant transport. Additionally, riparian vegetation can provide habitat for species, function as landscape corridors, and regulate physical conditions in aquatic ecosystems, where changes in temperature or light can trigger degradation of biological communities (Brauman et al., 2007). The presence of natural vegetation has been found as a main determinant for aquatic ecosystem quality and represents a structural indicator for ecosystem function since it is related to biota in multiple forms (King et al., 2005). Given these considerations, the presence of forests in riparian areas becomes an appropriate and viable surrogate to analyze the interrelationships between aquatic and terrestrial ecosystems (Macfarlane et al., 2017, Yirigui et al., 2019).

Riparian zones were identified using buffers adjacent to water bodies, encompassing the critical interface between water bodies and vegetation. The riparian areas in this study were identified by extracting river and stream features from official national hydrographic layers (lines and polygons at 1:100.000 scale) and buffering them by 100 m. This width is a relevant value in the context of the three countries' legislation regarding water policy. We used polygon features to remove permanent water bodies from the resulting buffer. In the riparian areas, we identify the presence of forest using the forest extent layer described in section 2.3. We estimated the percentage of riparian forest relative to total forest yearly from 2000 to 2021 and aggregated those values nationally and with protected areas.

2.8. Core Forest

We characterized fragmentation of moderate to high-FSII-ERP forest (>= 10, MHFSII-ERP) using morphological spatial pattern analysis (MSPA, Vogt et al., 2007) to derive Core Forest. Core Forest represents an ecologically relevant baseline condition for assessing fragmentation because most tropical moist forest naturally forms large patches in which most forest has minimal exposure to edge effects. MSPA uses information on whether MHFSII-ERP forest is within a user-specified distance from an edge where edges are defined as shared cell boundaries between MHFSII-ERP forest and non-MHFSII-ERP forest. We set MSPA parameters such that MHFSII-ERP forest greater than 1 km from an edge was classified as core and edges formed by water, study area boundaries, and small gaps (<= 1 ha) within MHFSII-ERP forest were ignored.

We quantified the extent of Core Forest annually from 2012 to 2021 and calculated the percentage of core forest relative to the total available forest per year.

2.9. Connected Forest

As with fragmentation, we assessed connectivity for MHFSII-ERP forest annually from 2012 to 2021. We used the cumulative resistant kernel (CRK) approach (Compton et al., 2007, Cushman et al., 2013, Diniz et al., 2020) to calculate the probability of moving through the landscape from a target pixel to all other surrounding pixels within a user-defined neighborhood. The probability surfaces generated around each target pixel are then summed on a pixel-wise basis to provide a map of the magnitude of connectivity between target pixels, allowing the connectivity contribution of both target pixels and areas between target pixels to be assessed. To reduce computation time, FSII-ERP values at 30 m resolution were resampled to 1000 m cells.

We defined the neighborhood around each MHFSII-ERP pixel based on allometric dispersal distance scaling for a theoretical species of 100 kg with median and maximum dispersal distances of 50 km and 150 km, respectively (Sutherland et al., 2000).

We assumed that forest integrity is negatively related to resistance to movement through the landscape and transformed FSII-ERP values accordingly (Keeley et al., 2016). Finally, to convert resistance to a probability of dispersal, we parameterized a negative exponential dispersal kernel such that the median dispersal distance was 50 km. Thus, in undisturbed forest landscapes, the theoretical forest species would be expected to move 50 km with a probability of 0.5.

To build the indicator, we calculated the 75th percentile CRK value in 2012 and used it as the threshold that defines well-connected forest pixels, generating a binary layer yearly. The resulting "Connected Forest" indicator relates the percentage of well-connected pixels area to the total forest area by each year.

3. Results

3.1. Forest Extent

Forests covered about 70 % of the forest biome land area in Colombian and Ecuador and about 60 % in Peru in 2000 (Fig. 2, Table 3). The proportion of land area in forests declined in all three countries by approximately 4 % by 2021. Forest cover and rates of loss varied among ecoregions (Fig. 3 left). In Colombia, for example, Magdalena-Urabá moist forests and Negro-Branco moist forests underwent little change, while Magdalena Valley montane forests and Solimoes-Japur moist forests declined substantially in area.

Protected areas represented 10 % of the land area in Colombia, 4 % in Peru, and 0 % in Ecuador in 2001 (Table 3). These proportions increased in all three countries by 2021: by 26 % in Colombia, 108 % in Peru, and changed from 0 to 3 % of land area in Ecuador. An increase in protected areas occurred across most of the ecoregions (Fig. 3 right). While not yet recorded in the World Protected Areas Database used for this analysis, the protected area coverage increased to 20.65 % of land area across the three countries by March 2023.

3.2. Natural Habitat

At the national level, we found that the proportion of land area that was natural habitat decreased at a similar rate in each country between 2000 and 2013 (~-2.5 %). The percentages of remaining natural habitat in 2013 were notably different among countries, with Ecuador and Colombia having only 34.94 % and 38.16 % natural habitat remaining and Peru having 66.72 %. The variation between ecoregions was also high, with 17 out of 23 losing more than 0.1 % (Table SM4, Fig. 4). The ecoregions that lost less than 0.1 %, or didn't lose or gained natural habitat had little natural habitat left in 2013 (under 0.12 %). The most considerable losses were found in the Chocó-Darién moist forests (14.49 %). Other ecoregions had a substantial loss of ~ 3.5 % and had relatively little natural habitat remaining in 2013 (i.e., under 15 %): Western Ecuador moist forests, Northwest Andean montane forests, Marañón dry forests, Cordillera Oriental montane forests).

The proportion of forest that was natural in 2000 was 41 % in Colombia, 37 % in Ecuador and 49 % in Peru (Table 4). This proportion declined by 3.5–6.5 % by 2013. The proportion of natural forest in protected areas in 2000 ranged from 15 to 33 % among countries and this increased from 0.8 to 2.7 % by 2013.

3.3. Forest Structure

Forests high in FSCI-ERP respectively represented 9.7 %, 16.7 %, and 12.3 % of the forested area of Colombia, Ecuador and Peru in 2012 (Table 5). The proportion of forest that was high in FSCI-ERP, however,

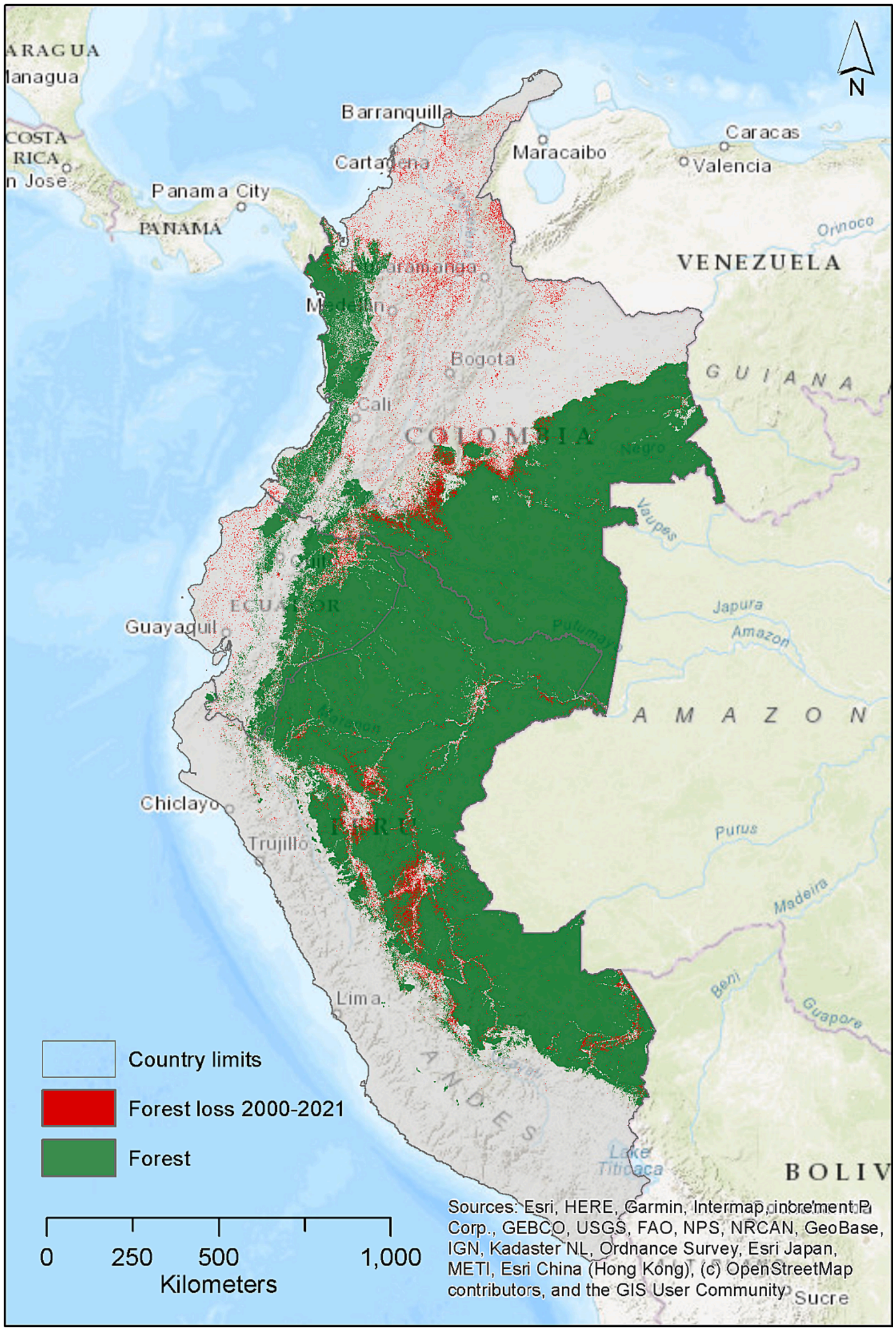

Fig. 2. Distribution of forests within forested ecoregions of the study area in 2021 and areas of forest loss 2001–2021.

Table 3
Proportion of land area in forest or protected in 2000 and 2021 and rate of change 2000–2021.

Country	% of land area in forest 2000	% of land area in forest 2021	% change in land area in forest 2000–2021	% of land area protected in 2000	% of land area protected in 2021	% change in land area protected 2000–2021
Colombia	69.2	66.2	−4.3	10.6	13.4	26.2
Ecuador[1]	71.4	68.7	−3.9	0.00	3.00	NA
Peru	60.3	58.1	−3.7	4.0	8,4	108.7

[1] While not yet recorded in the World Protected Areas Database used for this analysis, the protected area coverage increased to 20.65 of land area by March 2023.

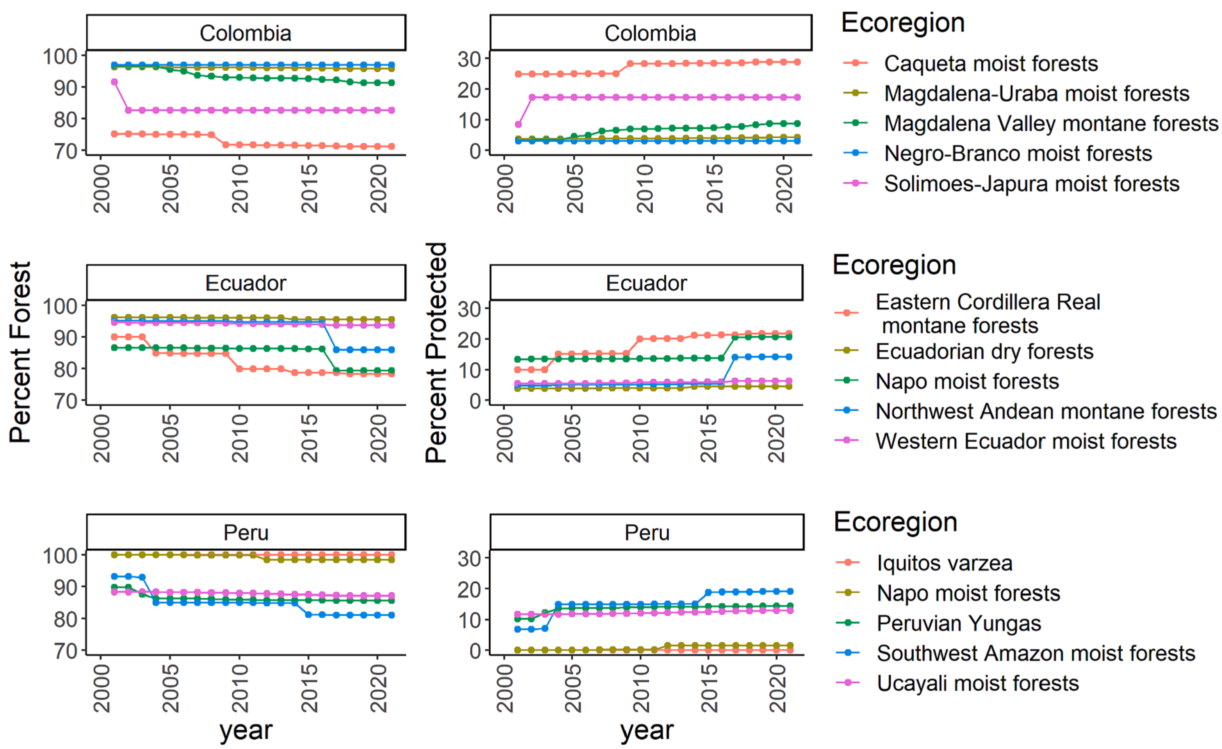

Fig. 3. Proportion of land area occupied by forest (left) and in protected areas (right) during 2000–2021 by ecoregions within countries.

increased in all three countries to 2021, by 1.8 % in Colombia, 1.1 % in Peru, and 1.3 % in Ecuador. The proportion of areas high in FSCI-ERP that were within protected areas in 2012 was 0 % in Ecuador and about 14–15 % in Colombia and Peru. The level of protection increased substantially in Ecuador (from 0 to 4.3 %) and Peru (by 22 %), but less so in Colombia.

The proportion of forest high in FSII-ERP in 2012 was less than for forest structural condition, 7 %-13 % among the countries, and rates of gain were somewhat higher, 1.4 %-1.9 % (Table 6). Forests in the Amazon Basin were relatively high in forest structure and integrity, while forests in the Pacific Coast and Andes Mountains were substantially lower (Fig. 5). The level of protection of forest high in FSII-ERP increased substantially in Ecuador and Peru, but less so in Colombia.

3.4. Riparian Forest

The proportion of forest area that was riparian forest in the year 2000 was about 7.4 %-9.4 % across the countries (Table 7). This proportion increased by about 1 % by 2021 in Colombia and Ecuador, and decreased by 0.6 % in Peru. Some 12.2 % – 17.2 % of the riparian forests were in protected areas across the countries. The proportion increased by 3.1 %-3.4 % by 2021.

3.5. Landscape Pattern

The core area of the MHFSII was sensitive to the gaps identified by FSII-ERP values under 10, in addition to the gaps caused by all kinds of forest loss. This resulted in a percentage of Core Forest relative to the total forest of 28 % in Colombia, 17 % in Ecuador, and 23 % in Peru in 2013 (Table 8). In 2021 these percentages decreased by 2.3 % in Colombia, 4.5 % in Ecuador, and 3.4 % in Peru. This indicated that the Core Forest was lost faster than the total forest in Peru. The resulting core areas were located mainly inside the Amazon basin. Protected areas contained 30 % of Colombia's Core Forest and 15 % in Ecuador and Peru by 2012, but in 2021 they had an increase of 5 % in Colombia and Ecuador, and a 6 % decrease in Peru.

Connected Forest represented about 22 % of total forest in Colombia in 2013, 15 % in Ecuador, and 21 % in Peru, with decreases of 10.4 % in Colombia, 1.6 % in Ecuador, and 3.8 % in Peru by 2021 (Table 9). Similarly, the protected area estate contained 17 % of well-connected forests in Colombia, 31 % in Ecuador, and 9 % in Peru in 2012. During the 2012–2021 period, the losses in protected areas were 36 % in Colombia and 17 % in Ecuador, with a gain of 3 % in Peru. As for the Core Forest analysis, most of the Connected Forest was located in the Amazon basin (Fig. 6). The changes in forest connectivity were influenced not only by the total amount of forest lost but also by the spatial patterns of these events.

4. Discussion

Countries within the Tropical & Subtropical Moist Broadleaf Forests biome benefit from the high levels of biodiversity and ecosystem services present in the region. Consequently, these countries require SDG15 indicators that consider not only forest extent as is currently specified by the official SDG indicators. They also need indicators of the quality of the forests with regards to supporting biodiversity and ecosystem services. Indicators of forest quality include measures of human pressure and forest structure, function, and composition. In this paper we developed sub-indicators of forest quality that are nationally relevant in Colombia, Ecuador, and Peru.

In total, our results illustrate how the complementary sub-indicators of forest quality complement the official indicators developed by the IAEG-SDGs that deal with forest extent. Forests covered about 70 % of the forest biome land area in Colombian and Ecuador and about 60 % in Peru in 2000. The proportion of land area in forests declined in all three countries by approximately 4 % by 2021. However, only a subset of the forested area was of high forest quality (Fig. 7).

Natural forests represented about 40 % of forests in Colombian and Ecuador in 2000 and 50 % in Peru. Those proportions declined: by 6.3 % in Colombia, 6.5 % in Ecuador, and 3.4 % in Peru by 2021. Even less of the forested area was Core Forest in 2013: less than 28 % among countries. During 2013–2021, the proportion of forest that was Core

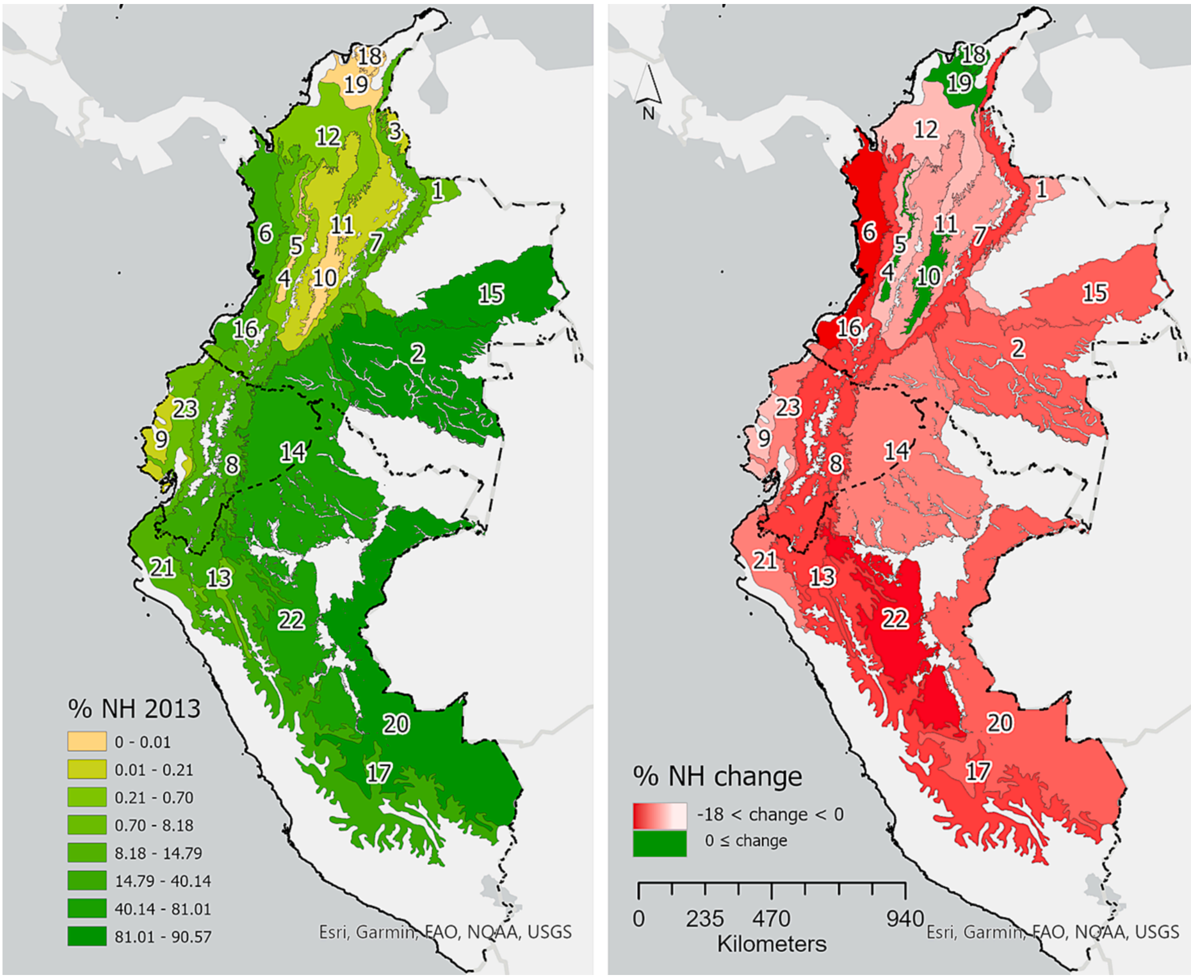

Fig. 4. Map of natural habitat (NH) remaining in 2013 and NH change in Peru, Ecuador, and Colombia by ecoregion. The number of ecoregions comes from Table SM2.

Table 4
Proportion of forest area that is natural forest and proportion of natural forest in protected areas in 2000 and 2013 an rates of change in each 2000–2013.

Country	% of forest that is natural 2000	% of forest that is natural 2013	% change in proportion of forest that is natural 2000–2013	% of natural forest protected in 2000	% of natural forest protected in 2013	% change in natural forest protected 2000–2013
Colombia	40.7	38.2	−6.3	19.5	19.8	1.7
Ecuador	37.4	34.9	−6.5	32.7	32.9	0.8
Peru	49.1	46.7	−4.85	15.1	5.5	2.7

Table 5
Proportion of forest area high Forest Structural Condition Index (FSCI-ERP) in 2012 and 2021 and percent change to 2012–2021. Identical metrics for proportion of high FSCI-ERP forest in protected areas.

Country	% of forests that are high in FSCI-ERP in 2012	% of forests that are high in FCII-ERP in 2021	Change in % of forests high in FSCI-ERP in 2012–2021	% of high FSCI-ERP forests protected in 2012	% of high FSCI-ERP forests protected in 2021	Change in % of high FSCI-ERP forests protected in 2012–2021
Colombia	9.7	9.9	1.8	13.6	13.7	0.4
Ecuador	16.7	18.9	1.1	0.0	4.3	NA
Peru	12.3	12.4	1.3	15.4	18.5	22.1

Forest decreased by 2.3 % in Colombia, 4.5 % in Ecuador, and 6.7 % in Peru. Connected Forests were about 17 %–22 % of forests among the countries in 2013 and declined 10.4 % in Colombia, 1.6 % in Ecuador, and 3.8 % in Peru by 2021. Forests high in forest structure were 10 %-18 % of forests in 2012 among the countries and increased by 1.1 % 2 % by 2021. Forests of high integrity were 7–13 % of forests in 2012 and increased by1.4 % 2 % by 2021. Riparian forests represented less than about 7 %-9% among the countries and declined by 0.6 %-1.3 % by 2021. Thus, the area of highly quality forest across the countries was substantially less than full forest extent and high-quality forest declined at a higher rate than forest extent during 2000–2021. Forest structure and integrity did increase slightly over this time period.

Colombia, Ecuador, and Peru made substantial progress in expanding protected area coverage during 2001–2019. Consequently, the

Table 6
Proportion of forest area high Forest Structural Integrity Index (FSII-ERP) in 2012 and 2021 and percent change to 2012–2021. Identical metrics for proportion of high FSII-ERP forest in protected areas.

Country	% of forests that are high in FSII-ERP in 2012	% of forests that are high in FSII-ERP in 2021	Change in % of forests high in FSII-ERP in 2012–2021	% of high FSII-ERP forests protected in 2012	% of high FSII-ERP forests protected in 2021	Change in % of high FSII-ERP forests protected in 2012–2021
Colombia	7.0	7.1	1.9	19.0	19.0	0.3
Ecuador	13.3	13.4	1.4	0.0	5.3	NA
Peru	11.3	11.4	1.42	16.5	19.7	19.9

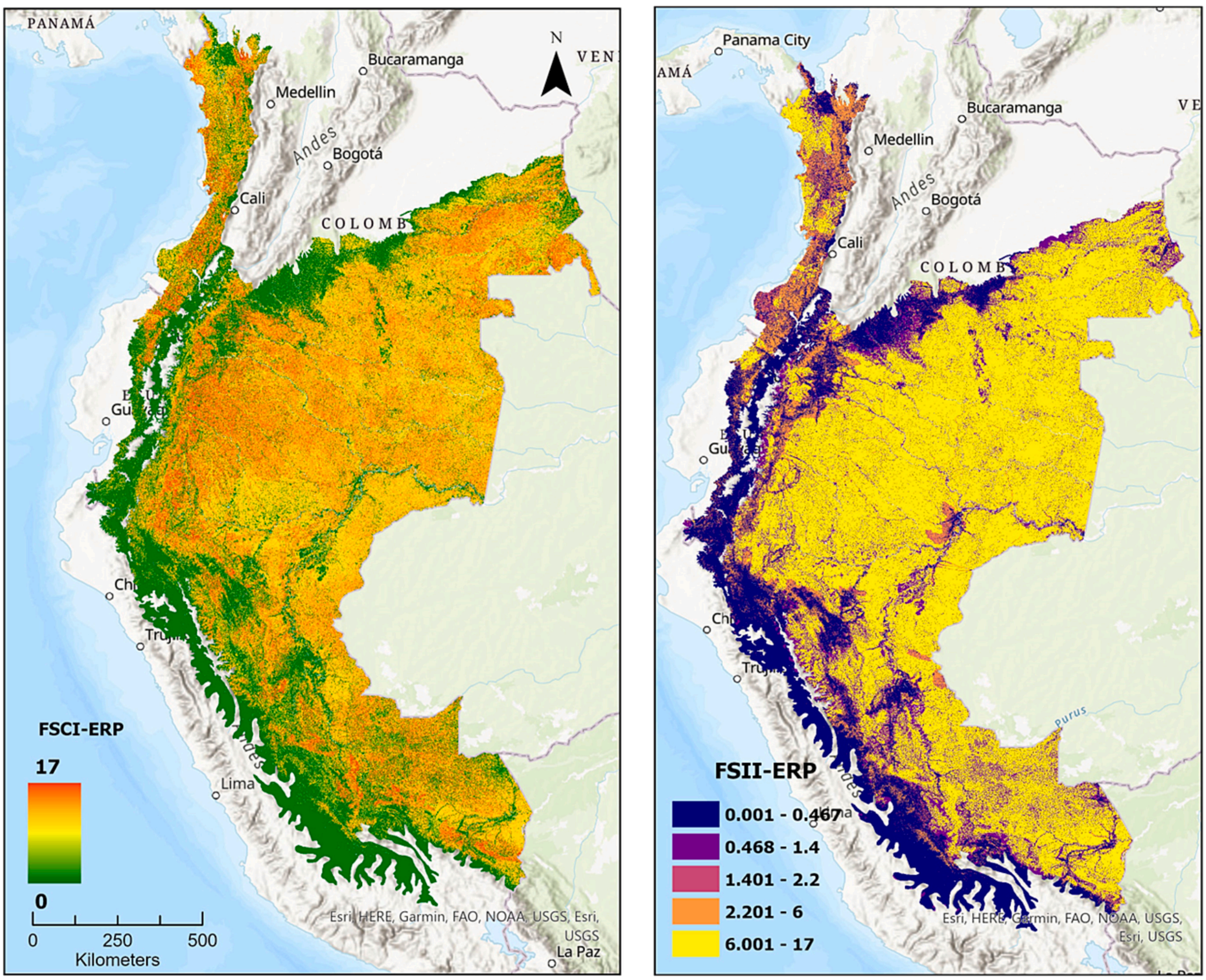

Fig. 5. Distribution of FSCI-ERP and FSII-ERP across the study area in 2021.

Table 7
Proportion of forest area that is riparian forest and proportion of riparian forest in protected areas in 2000 and 2021 and rates of change in each 2000–2021.

Country	% of forest that is riparian 2000	% of forest that is riparian 2021	Change in % of forest that is riparian 2000–2021	% of riparian forest protected in 2000	% of riparian forest protected in 2021	Change in riparian forest protected 2000–2021
Colombia	7.5	7.5	1.3	12.6	13.1	3.4
Ecuador	9.3	9.3	1.0	12.3	12.6	3.2
Peru	7.4	7.4	−0.6	16.5	17.2	4.7

proportion of high-quality forest that were protected increased for riparian forests, high structure and integrity forests, core forests, and highly connected forests.

Users of these metrics of forest quality will be interested in the reliability, sensitivity, and operational applicability for SDG15 applications. The global HF used in this analysis was validated against a dataset of visually interpreted high resolution imagery, and found to have high agreement with a rootmean-square error of 0.116 and a Kappa statistic of 0.806 ($P < 0.01$) (Williams et al., 2020). The metric is based on several inputs on human pressure such as population density and land use and is likely sensitive to forest changes of interest to the SDG15 targets. A limitation of our analyses was that we used data for the

Table 8
Proportion of forest area in moderate to high Forest Structural Integrity Index (MHFSII-ERP) that is Core Forest in 2012 and percent change to 2021 and proportion of moderate to high Forest Structural Integrity Index (MHFSII-ERP) Core Forest covered by protected areas in 2021 and change to 2021.

Country	% of forests that are MHFSII-ERP core forest in 2013	% of forests that are MHFSII-ERP core forest in 2021	Change in % MHFSII-ERP core forests 2013–2021	% of MHFSII-ERP core forests protected in 2013	% of MHFSII-ERP core forests protected in 2021	Change in % of MHFSII-ERP core forests protected in 2013–2021
Colombia	27.8	27.1	−2.3	29.1	30.4	4.6
Ecuador	14.5	13.9	−4.5	14.9	15.6	4.7
Peru	22.1	21.3	−3.4	15.6	14.7	−5.8

Table 9
Proportion of forest area in high Forest Structural Integrity Index (FSII-ERP) that is Connected Forest in 2012 and percent change to 2021 and proportion of high Forest Structural Integrity Index (FSII-ERP) Connected Forest covered by protected areas in 2021 and change to 2021.

Country	% of forests that are high FSII-ERP connectivity forest in 2013	Change in % high FSII-ERP connectivity forests 2013–2021	% of high FSII-ERP connectivity forests protected in 2013	Change in % of high FSII-ERP connectivity forests protected in 2013–2021
Colombia	22.3	20.0	−2.3	−36.7
Ecuador	14.5	13.9	−4.5	−17.3
Peru	21.16	20.4	−3.8	3.7

2000–2013 period because the more recent versions of the data set were developed with different methods and were not suitable for change analyses (Williams et al., 2020). While we used this global version of the HF, many countries require that only officially government sanctioned data be used for national reporting. Thus, for operational applications countries may choose to develop a HF dataset using national data for inputs. For example, Columbia has completed a HF layer (Correa and Ayram 2020) and Ecuador and Peru are in the process of doing so (Personal Communication). In each case, the data products were developed to allow change analysis for 2000–2020.

The FSCI metric of forest structure was validated against airborne lidar data using samples which were available in Brazil (Hansen et al., 2019). Accuracy was 93 %. The ERP version, which indexes the metric to the structure found in natural forests in each ecoregion has not yet been validated and countries may wish to do so for SDG15 reporting. The

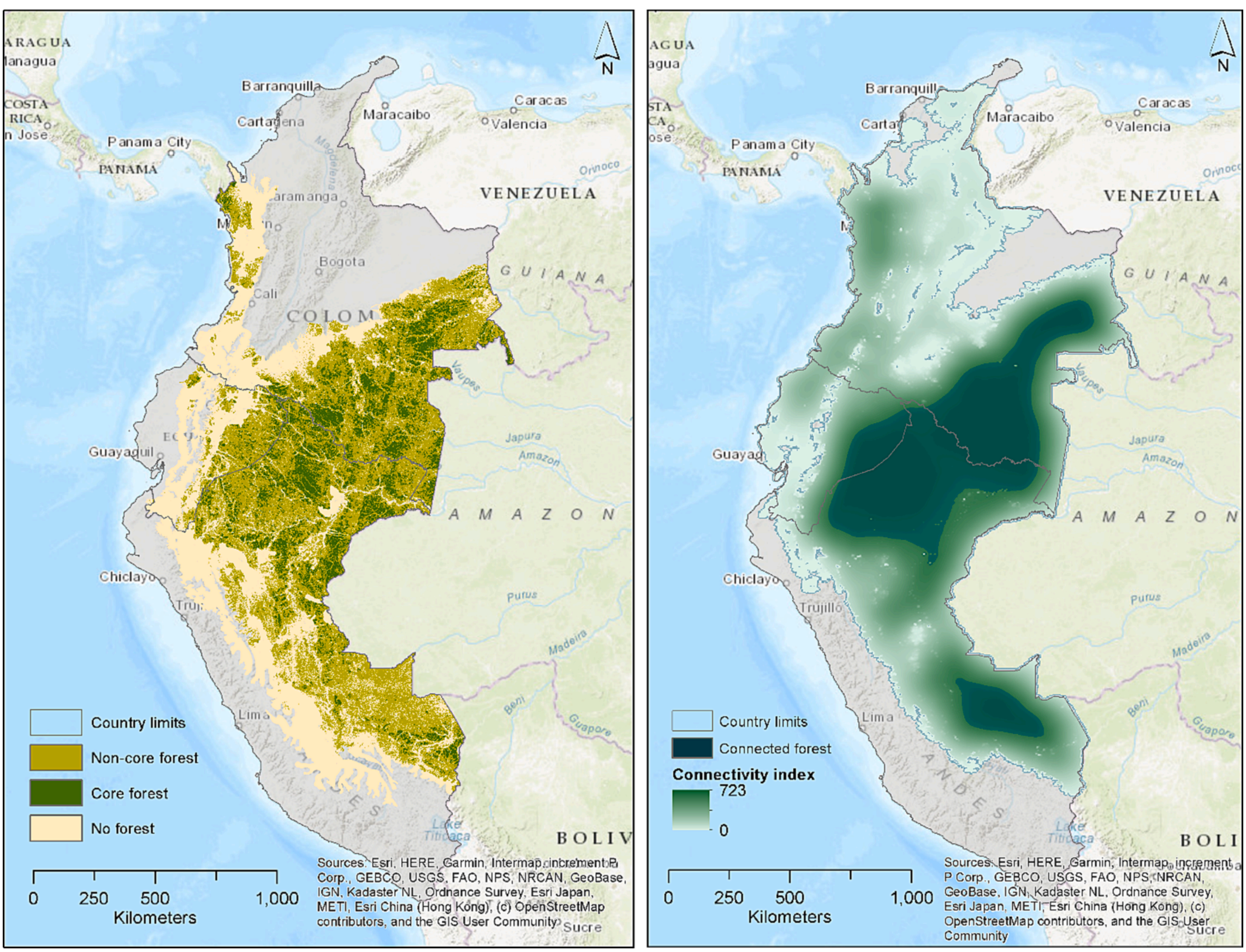

Fig. 6. Maps of Core Forest (A) and Connected Forest (B) in the study area for 2018.

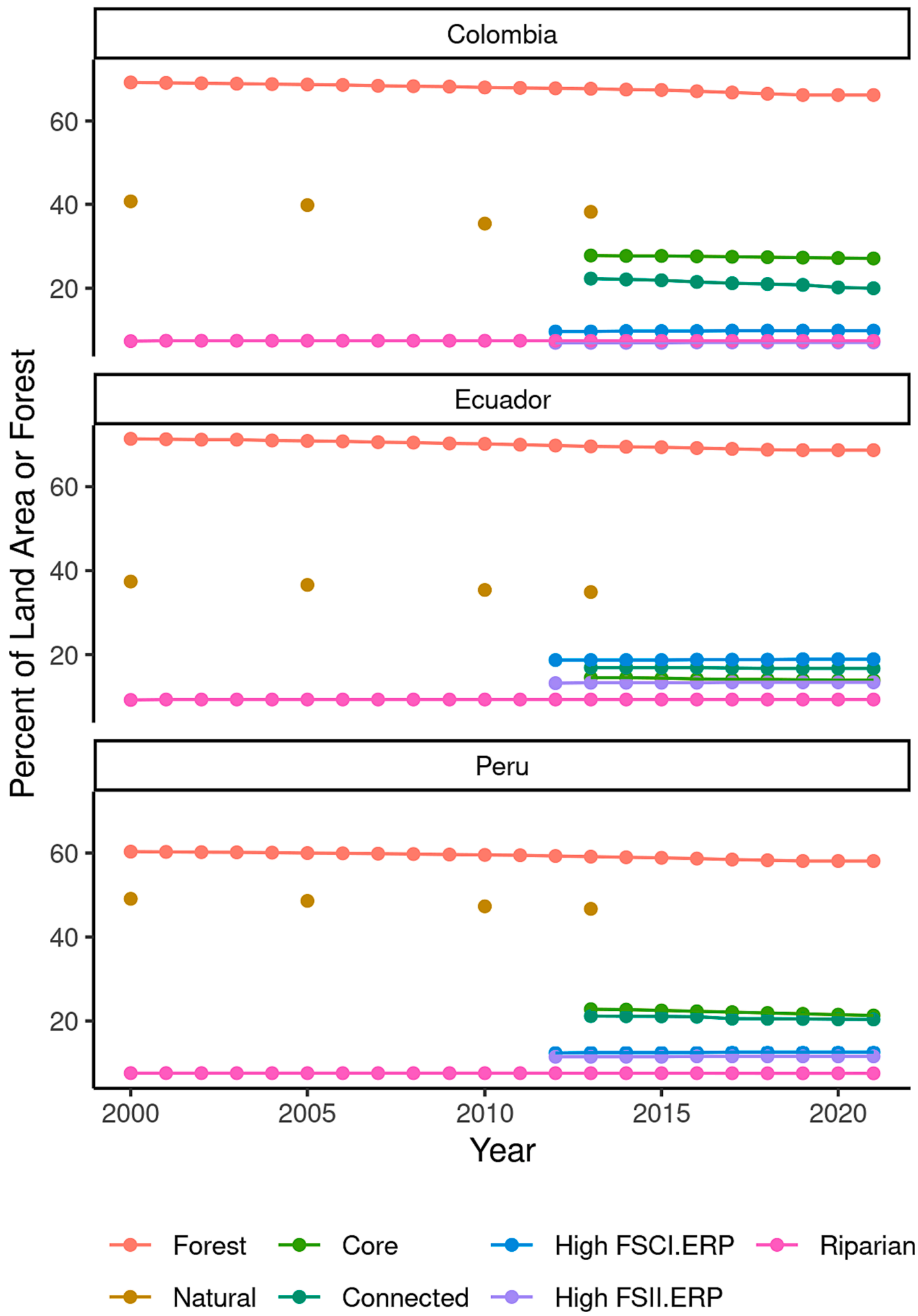

Fig. 7. Summary of trends for forest extent as a percentage of land area and measures of forest quality as a percentage of forest area during the study period for each of the three countries.

three input metrics (canopy height, canopy cover, and time since disturbance) have been found to be sensitive to human modification of forests (Hansen et al., 2020). As with HF, Ecuador and Peru are in the process of developing nationally sanctioned versions of FSCI-ERP thus allowing use for SDG15 reporting (Personal Communication).

Riparian Forest is derived from the global forest maps of Hansen et al. (2013) and official national hydrographic layers. Each of the three countries are in the process of using national data on forest cover and hydrography for use in national reporting.

The other metrics of forest quality used here (FSII-ERP, Core Forest, and Connected Forest) and derived from the HF and/or the FSCI-ERP layers. Their reliability, sensitivity, and operational feasibility are similar to those layers.

Conceptual and empirical support for the Core Forest and Connected Forest indicators have been well established in numerous publications assessing the importance of core area and connectivity for a broad range of species and ecosystems (Laurance and Jensen 1991, Vogt et al., 2007, Compton et al., 2007, Asensio et al., 2012, Zeller et al., 2018, Grantham et al., 2020, Kaszta et al., 2020). Both indicators decrease with forest quality loss, increase with forest quality gain, and are spatially comprehensive, registering change if forest quality loss or gain occurs anywhere in the study area. They are sensitive to where forest quality change occurs and to parameterization. The Connected Forest indicator is more sensitive to forest loss that disconnects remaining forest. Both indicators are more sensitive to forest loss that occurs in core forest compared to peripheral or already fragmented forest. Connected Forest results for a given dispersal scale and resistance surface parameterization will be different than those for another. This is by design and users can set the scale of dispersal and resistance surface parameterization to appropriate values based on their monitoring and assessment goals.

Similarly, a given value for the edge influence parameter will provide different Core Forest results, with higher edge influence values resulting in lower core forest areas. The calculation of both indicators is straightforward, although computationally demanding for large geographic domains, and can be conducted in publicly available software packages or using common scripting languages (e.g., Python or R).

The implication of our findings for conservation is that during the initial period that countries have strived towards SDG15 targets, fundamental attributes of forests have eroded at rates even faster than loss of forest extent. This is concerning because of the high biodiversity and ecological value of high-quality forests. Landscape naturalness, for example, is seen as critical for species adaptation under anthropogenic climate change as it facilitates individuals and populations to track their preferred microclimates (Watson et al., 2016). Beyond species-specific benefits, intact landscapes allow for increased ecosystem function and resilience by ensuring that nutrient cycling can continue unabated, as well as other important abiotic conditions such as radiation, wind, light regimes, humidity, and key hydrological regimes (Haddad et al., 2015). It is well known that land uses such as farming, urbanization, and unsustainable forestry disrupt the intactness of landscapes to various degrees (Potapov et al., 2000). We note however, that the forest product we used in this analysis does not distinguish between natural agents of forest loss and anthropogenic ones and that the global data can be complemented with national data for a finer understanding of forest dynamics.

Similarly, forests of high structural condition are important ecologically because they tend to be high in biodiversity, productivity, carbon storage, and water provisioning. Such forests provide high microclimate and habitat niche diversity and thus support high species diversity (Rozendaal et al., 2019, Cortés-Gómez et al., 2013). For example, biodiversity value is 41 % lower in degraded forests (including selectively logged forests, secondary forests and forests converted into various forms of agriculture) than in primary forest across the humid tropics (Gibson et al., 2011). More recently, Pillay (2020) found that high FSCI and FSII forests are associated with considerably lower risk of humid tropical vertebrate species extinctions and population declines, when directly compared with forest cover. Forests of high structural condition are also relatively high in productivity and carbon storage (Poorter et al., 2015). Primary forests in Brazil, the Democratic Republic of the Congo, and Indonesia were found to be 38 %–59 % taller in canopy height, have 100 %–183 % greater aboveground biomass and store 279 %–866 % more carbon than other dense tree cover (Turubanova et al., 2018). Tall multistoried forests also influence water provisioning, providing higher levels of evapotranspiration that enhance regional precipitation and maintain the conditions for dense humid forests to persist (Bonan et al. 2018).

Pillay et al. (2022a) have argued that the single most important policy action nations can take to prevent catastrophic biodiversity loss in tropical rainforests is to commit to a target of "net gain in area, connectivity, and integrity" of these high-quality forest ecosystems. Just as important is the development of proactive indicators that provide a comprehensive picture of progress towards these targets on forest integrity. Thus, monitoring and reporting trends in forest quality should be a high priority in the context of SDG15.

Our work adds to a growing body of studies developing complementary sub-indicators for SDG reporting. Rotllan-Puig et al. (2021), for example, provided methods for calculating a land productivity sub-indicator that is relevant to quantifying land degradation. Similarly, Keys et al. (2021) used machine-learning to develop a sub-indicator of human pressure for application to SDG reporting.

While monitoring forests based on forest quality has not yet been officially recommended by the IAEG-SDGs, some countries such as the United States., Australia, and the European Union have specified the importance of conserving older and natural forest because of the perceived benefits such forests have for maintaining biodiversity and ecosystem function and providing ecological services (Barnett et al., 2023, Lindenmayer and Taylor, 2020, O'Brien et al., 2021). Old-growth forest is late seral stage forest that typically has a range of tree sizes including large trees and high variation in canopy layers. Primary forest is that which has never harvested by people. Our sub-indicators of naturalness, FSCI-ERP and FSII-ERP draw on global satellite and ancillary data sets to allow mapping of components of forest structure, age, and human pressure that are relevant to forest quality and could be used to support these efforts to map old growth and primary forest.

The approaches used here are likewise highly relevant for countries party to the Convention on Biological Diversity, which recently adopted the landmark Kunming-Montreal Global Biodiversity Framework (GBF), including 4 goals, 23 targets, and a mission to "put nature on a path to recovery for the benefit of people and planet" by 2030 (CBD 2022a). The associated Monitoring Framework of the GBF (CBD 2022b) recognizes the value of nationally relevant indicators for biodiversity monitoring, including around forest and ecosystem integrity. As countries work to develop their monitoring plans in accordance of the Monitoring Framework by October 2024, the sub-indicators and approaches presented here may be useful to support the development of monitoring plans that include measures of forest quality, particularly for Goal A and Targets 1–3.

5. Conclusion

We recommend adding to the SDG15 indicators of forest extent developed by the IAEG-SDGs complementary sub-indicators of forest quality for national monitoring and reporting. Our results for trends in forest naturalness, riparian association, within stand structure, fragmentation, and connectivity demonstrate how consideration of forest quality provides a much stronger basis for evaluating success in meeting SDG15 targets than consideration of forest extent alone. The utility of the approach was demonstrated with application to Colombia, Ecuador, and Peru, which are proceeding to officially adopt some of these sub-indicators (Aragon et al. in prep). Further, we showed how the official SDG15 indicators can be extended and complemented using a few extra open datasets, appropriate questions, assumptions, and open-source methods.The provided spatial calculation can be summarized in UN stats format, but with geographical representation (explicit maps) for other national and regional usages. Using the forest extent as a baseline, it is possible to provide a viable spatiotemporal baseline to build upon, as shown in the new set of indicators. Thus, our approach is highly generalizable for applications in other countries.

CRediT authorship contribution statement

Andrew J. Hansen: Writing – original draft, Funding acquisition, Conceptualization. **Jose Aragon-Osejo:** Writing – review & editing. **Iván González:** Writing – review & editing, Formal analysis. **Jaris Veneros:** Writing – review & editing, Visualization. **Anne Lucy Stilger Virnig:** Writing – review & editing, Supervision, Conceptualization. **Patrick Jantz:** Writing – review & editing. **Oscar Venter:** Writing – review & editing, Supervision, Conceptualization. **Scott Goetz:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **James E.M. Watson:** Conceptualization. **Natalia Cordoba:** Writing – review & editing. **Susana Rodriguez:** Writing – review & editing. **Luisa Monroy:** Writing – review & editing. **Juan Iglesias:** Writing – review & editing. **Lenin Beltrán:** Writing – review & editing. **Daniel Borja:** Writing – review & editing. **Diego Ureta:** . **Jossie Tingo:** . **Carlos Oñate:** Writing – review & editing. **Freddy Valencia:** Writing – review & editing. **Holger Zambrano:** Writing – review & editing. **Tatiana Pequeño:** Writing – review & editing. **William Llactayo:** Writing – review & editing. **Walter Huamani:** Writing – review & editing. **Patricia Duran:** Writing – review & editing. **Alexs Arana:** Writing – review & editing. **Marco Arenas:** Writing – review & editing. **Claudia Pasquel:** Writing – review & editing. **Antonio Tovar:** Writing – review & editing. **Patricia Huerta:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.111654.

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