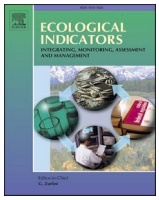
Ecological Indicators 190 (2026) 115314



Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind





The ecosystem integrity index: a component indicator in the Kunming-Montreal global biodiversity framework reveals the integrity of terrestrial ecosystems globally

S.L.L. Hill *, M.L.K. Harrison, C. Maney, J. Bedford, M. Harris, T.H.E. Mason, N. Ash, J. Hughes, M. Jones

UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), 219 Huntington Road, Cambridge, UK

ARTICLE INFO

Keywords:
Ecosystems
Condition
Global biodiversity framework
Indicator
Terrestrial

ABSTRACT

The Ecosystem Integrity Index (EII), developed by UNEP-WCMC and adopted as a Component Indicator for the Kunming-Montreal Global Biodiversity Framework (KM-GBF), provides a simple and robust framework to assess terrestrial ecosystem integrity globally, for use by governments as well as businesses and financial institutions. Being able to flexibly deploy our EII framework will help global to local users to both assess integrity, but also to measure changes due to conservation interventions by government, business and civil society. It is formed of three components (structural, compositional and functional integrity) and provides a continuous measure of ecosystem integrity from fully degraded to fully pristine. Applying the EII framework, we provide trends in ecosystem integrity globally from 2000 to 2020. This analysis shows that approximately one fifth of all terrestrial ecosystems have lost at least half of their ecosystem integrity. The greatest losses are seen in regions of the world where human population is dense or where development has been intense, whereas least developed regions have more intact scores. The loss of ecosystem integrity at this scale, and ongoing changes in other regions, is likely to have significant consequences for humanity and all life on Earth.

1. Introduction

While the importance of ecosystem integrity has long been recognised (Leopold, 1949), and there have been many calls for the application of the concept within global conservation efforts (e.g., Díaz et al., 2020; Hansen et al., 2021; Rogers et al., 2022), conservation science has tended to focus on species and their habitats, avoiding the complexities of working at the ecosystem level. This relative lack of attention is due to the challenges of working with ecosystems as they are highly dynamic, defined along continuous levels of variation by both living and non-living components as well as their interactions (CBD, 1992), and altered by a variety of direct and indirect pressures which may be historic or spatially distant, making the concept less useful for direct management of large systems.

Ecosystem integrity, an analogous concept to ecological integrity, is the extent to which the structural, compositional and functional components of an ecosystem, along with their interactions, are similar to their 'natural' state (Carter et al., 2019). Although the concept of a 'natural' state has both definitional and philosophical challenges leading to barriers in quantification (e.g., Siipi, 2004), it is used repeatedly in international policies (e.g., the Kunming-Montreal Global Biodiversity Framework (KM-GBF) (CBD, 2022), the International Finance Corporation's Performance Standard 6 (IFC (International Finance Corporation), 2012) and the European Union Habitats Directive (European Commission, 2007/2012)) and is embedded within conservation research and practice.

The degradation of ecosystem integrity contributes to human poverty, disease risk, and a loss of cultural and spiritual connection with nature (Kohler et al., 2018; Potts et al., 2018; Morand, 2020). In contrast, areas containing higher integrity have greater potential to provide a broader range of ecosystem services (Martin and Watson, 2016; Le Provost et al., 2023) such as carbon sequestration (Lewis et al., 2009), maintenance of water quality (Mello et al., 2018), climate regulation (Rogers et al., 2022), pest control (Bianchi et al., 2006), and pollination (Carvalheiro et al., 2010), as well as supporting higher levels of biodiversity (Barlow et al., 2016).

* Corresponding author.
E-mail address: Samantha.Hill@unep-wcmc.org (S.L.L. Hill).

https://doi.org/10.1016/j.ecolind.2026.115314
Received 10 March 2026; Received in revised form 26 June 2026; Accepted 2 August 2026
Available online 31 August 2026
1470-160X/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

The importance of ecosystems with high integrity is recognised in the three Rio Conventions: the Convention on Biological Diversity (CBD), the UN Framework Convention on Climate Change and the UN Convention to Combat Desertification. Ecosystem integrity is explicitly included within the global ambitions of Goal A and Targets 1, 2 and 12 of the KM-GBF, negotiated under the CBD (CBD (Convention on Biological Diversity), 2022). Meeting the global goals and targets of the KM-GBF requires a whole of society approach, including not only governments, but also businesses, financial institutions, and Indigenous Peoples and local communities, among others. This societal need to measure ecosystem integrity requires a pragmatic approach, using the best available data, to facilitate action that reverses ecological degradation.

1.1. Conceptualisation of ecosystem integrity

The notion of ecosystem, or ecological, integrity first emerged in the work of Leopold (1949), who used the term to encompass the basic criteria necessary for biotic communities to remain stable. It was further developed in the context of conservation of freshwater ecosystems in the United States in the latter part of the 20th century (Noss, 1990a). Terrestrial ecosystem integrity was often conceptualised using three components: structure, composition and function (e.g., Franklin et al., 1981; Noss, 1990b). Parrish et al. (2003) elaborated upon the concept, proposing that 'an ecological system has integrity when its dominant ecological characteristics (e.g., elements of structure, composition, function, and ecological processes) occur within their natural ranges of variation'. This definition was simplified by Carter et al. (2019) to include three components – structure, composition and function – measured against a natural baseline (Box 1). Although structure, composition and function are listed as separate components, all definitions emphasise the importance of the interactions between components and their co-dependence. The System of Environmental Economic Accounting (SEEA) has a similar definition of ecosystem integrity as 'the ecosystem's capacity to maintain it characteristic composition, structure, functioning and self-organization over time within a natural range of variability' (United Nations Committee of Experts on Environmental-Economic Accounting, 2021).

A variety of indicators and spatial datasets have been developed which capture impacts on ecosystem integrity; however, they are commonly used as proxies for ecosystem integrity as a whole. For example, 'Mean Species Abundance' (Alkemade et al., 2009) is a metric that is commonly applied in approaches for estimating the biodiversity 'footprint' of businesses, but measures one aspect of compositional integrity only, and does not cover structural or functional integrity. The Ecological Integrity Index (Sun et al., 2026) quantifies potential productivity removal through human modification but does not cover compositional or structural integrity.

Similarly, other metrics have focused on integrity of specific biomes or land use types. For example, Dias et al. (2023) and Grantham et al. (2020) produced indices of forest integrity, whilst Hansen et al. (2019) designed an index of forest structure specifically for humid tropical forests. Blumetto et al. (2019) concentrated their metric on agricultural systems at the farm level. Region-specific metrics have also been formulated. Zelený et al. (2021) generated a metric focusing on functional integrity for two areas in Europe and McGarigal et al. (2018) produced a metric focusing on relative levels of disturbance for the northeastern USA.

We build on these frameworks, developing a methodological framework that advances the measurement of ecosystem integrity more holistically. Our metric was developed to meet three core criteria:

1) Assess ecosystem integrity comprehensively across the three components of structure, composition and function holistically.
2) Allow for assessment of integrity with global coverage, and rapid comparison between regions, meeting the decision-making needs of governments, businesses and financial institutions.
3) Be adaptable to the incorporation of data at different scales (e.g. company data, national data, habitat specific data) to allow flexibility for the end user.

Here, we present the Ecosystem Integrity Index (EII) – we outline the framework to calculate the EII, discuss the insights the EII provides on the state of the terrestrial biosphere, and provide the envisioned applications of the EII for applied decision making.

2. Methods

The Ecosystem Integrity Index follows the concept of integrity as defined by Carter et al. (2019) namely assessing structural integrity, functional integrity, and compositional integrity, against pristine baselines (Fig. 1). Our methodology uses publicly available datasets to produce novel models for each of the components and provides trends in EII over time, having based our framework upon indicators which are regularly updated. However, our methodological framework is flexible and can be adapted to incorporate datasets at varying scales, for instance, national datasets for countries wishing to track progress against KM-GBF goals or targets, or site level datasets for businesses or local planning.

2.1. Structural integrity

2.1.1. Review of existing approaches to measuring structural integrity

Ecosystem structure has been defined in different ways. Some consider it to be the three-dimensional physical structure of ecosystems, whilst others define it as the structure of the wider landscape (Staudhammer and LeMay, 2001). The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) defines ecosystem structure as the distribution of biomes: 'the terrestrial realm can be demarcated according to a pattern of ecosystem structure (Units of Analysis) where different dominant species cause the ecosystems to differ in structural complexity (e.g., tropical rainforest vs tundra or deserts) and the natural resources they can provide to people' (Ichii et al., 2019).

Traditionally, metrics focusing on the diversity of structural elements have been produced using on-the-ground data (McElhinny et al., 2006).

Box 1
The three components of ecosystem integrity as defined by Carter et al. (2019).

Structural integrity comprises physical aspects of ecosystems – the variability in biotic and abiotic elements that form the heterogeneous matrix supporting the other elements.

Compositional integrity refers to the biotic constitution of ecosystems – the pattern of the makeup of species communities encompassing elements of both alpha and beta diversity.

Functional integrity describes the ecological processes and interactions provided by the ecosystem.

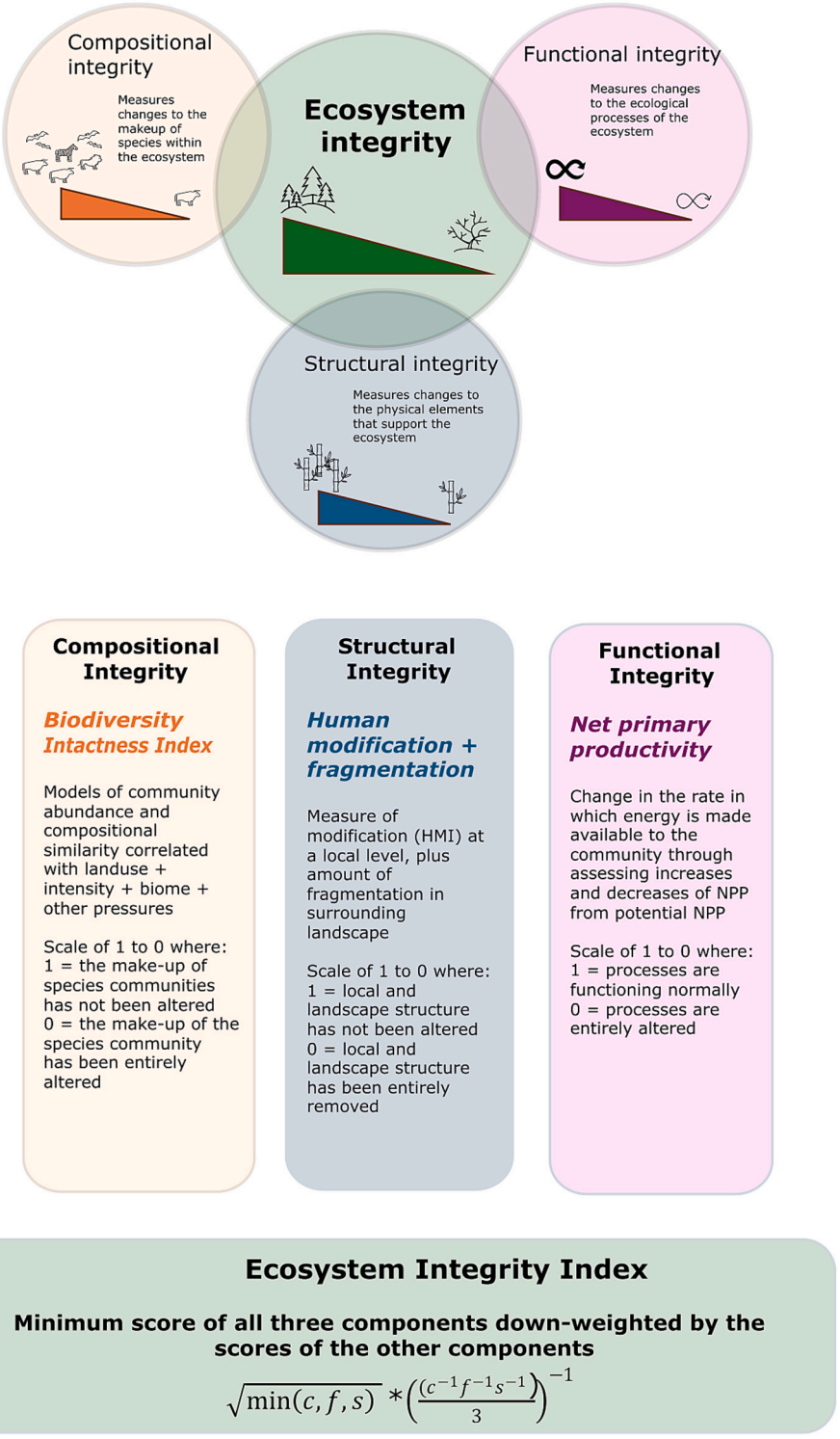


Fig. 1. Schematic of the methodological framework of the Ecosystem Integrity Index.

For instance, using information such as the heights of different canopy levels and the spacing of trees' (Franklin et al., 1981). A focus on specific structural characteristics such as vegetation height is unsuitable for measuring ecosystem structural integrity at the global scale. This is because the variability in how 'natural' the state of ecosystem structure within any local area depends on biotic variables as well as the climatic and geophysical characteristics of the site, and features of the wider landscape (e.g., Tierney et al., 2009). Furthermore, ground-based assessments of structural complexity can be costly in terms of time and effort, particularly if undertaking repeated samples (Zenner and Hibbs, 2000; Gibbons and Freudenberger, 2006). With the advancement of remote-sensing technologies, monitoring structural complexity at larger scales has become possible. LiDAR data is useful to identify and measure structural attributes beyond the local scale; however, researchers have concluded that there is a lack of sufficient LiDAR data for many ecosystems and there have been calls to gather more data for more ecosystems (Moudrý et al., 2023; Kissling and Shi, 2023).

At a broader scale, landscape configuration, including patch size,

connectivity and fragmentation are often used to describe ecosystem structure (e.g., Keeley et al., 2021). Many of these metrics also focus on forested biomes, such as the forest structure index developed by Hansen et al. (2019) specifically for humid tropical forests.

An ideal measurement of structural integrity should capture both complexity and the multi-dimensionality of an ecosystem. This should include a measure of how intact the vertical or internal structure of a given location is, as well as the intactness of such features in the surrounding landscape (Carter et al., 2019; Grantham et al., 2020).

2.1.2. Construction of the structural integrity layer

We focus the structural integrity component on capturing the landscape level intactness through a knowledge of where human pressures have cumulatively degraded structural integrity (e.g., Kennedy et al., 2019; Venter et al., 2016), combined with an adaptation of the methods established by Beyer et al. (2020) to produce a layer that is sensitive to patch size and fragmentation. We adopt this approach because the correlation between human pressure and ecosystem structure has been shown in multiple studies across different biomes (for instance, in grasslands: Listopad et al., 2018, in forests: De Marzo et al., 2023, and in savannas: Ouédraogo et al., 2015). This method essentially captures the vertical structural integrity at sites and the horizontal structure characterised by the surrounding landscape (see Fig. 2).

Thus, to measure structural integrity across all terrestrial ecosystems, we used the Human Modification Index (HMI) (Kennedy et al., 2019). This provides a spatially explicit layer based upon the following pressure layers: croplands, pasturelands, rangelands, plantations, built-up areas, human population density, roads, rails, quarries and mining, wind turbines, electrical infrastructure and powerlines. We used the same pressure intensities described in Kennedy et al. (2019). Second, we inverted the human modification layer to transform it to an equivalent of the quality and extent layer in Beyer et al. (2020). Finally, we applied the Beyer et al. (2020) method to incorporate landscape quality and fragmentation through the use of a moving window that compares the quality of a grid cell with that of cells in their neighbourhood, which we defined as cells within a 27 km distance (i.e., grid cells in a 55 km × 55 km box were used to estimate the structural integrity of the target cell at the centre of the box). This distance was selected based on findings by Beyer et al. (2020) that 99.5% of the exponential distribution was captured. Beyond this radius the contribution of cells to the metric value becomes negligibly small, due to the influence of the distance-weighting parameter. For further detail, see Beyer et al. (2020). We applied this methodology to HMI data from 2000, 2005, 2010, 2015 and 2020, to produce our time series of structural integrity. All spatial processing was done in Google Earth Engine with a resolution of 1km^2.

Our approach differs from the one produced in the Beyer et al. (2020) paper due to the source of the 'quality' layer. Where Beyer et al. (2020) use the Human Footprint Index (HFI) (Venter et al., 2016), rescaled with an exponential function, we use the HMI as described by Kennedy et al. (2019) for our layer. This approach has the benefit of meaningful interpretation: an area with a value of 0.5 has twice the 'intactness' of an area with a value of 0.25. It also avoids the double use of neighbourhood functions. For example, the HFI takes roads and applies a buffer to estimate the area of their impact; when the landscape-level effects are calculated this area is then further expanded, which may overestimate the spatial extent of these threats to ecosystem structure. In contrast, the HMI uses the physical footprint of these threats, preventing this issue when comparing at the landscape scale.

2.2. Compositional integrity

2.2.1. Review of existing approaches to measuring compositional integrity

To represent compositional integrity, we needed to use a metric that measures change in community assemblages as compared to a natural reference state. We reviewed several of the most widely used metrics that fit these criteria. One of the most widely used metrics for measuring biotic composition, particularly by businesses and financial institutions, is Mean Species Abundance (MSA) (Alkemade et al., 2009). MSA is the abundance of individual species in a habitat under human influence, compared to their abundance in a natural, undisturbed reference state. Other well-known state metrics that measure biotic intactness include Potentially Disappeared Fraction of Species (PDF) (Goedkoop and Spriensma, 2001) and the Living Planet Index (LPI) (Loh et al., 2005). The PDF predicts the disappearance of species as a function of environmental pressures, over a certain period and within a specified area. There is an assumption that once a pressure is mitigated, disappeared species will return. It is popular metric of choice for life-cycle assessments. The Living Planet Index (LPI) provides the average rate of change in animal populations, with the primary goal of assessing levels of extinction risk. The metric focusses on declines in population density within single species, averaged across many species.

We selected the Biodiversity Intactness Index (BII) (Newbold et al., 2016) as it was the only globally consistent index that incorporates both species' abundance and community composition, thereby following

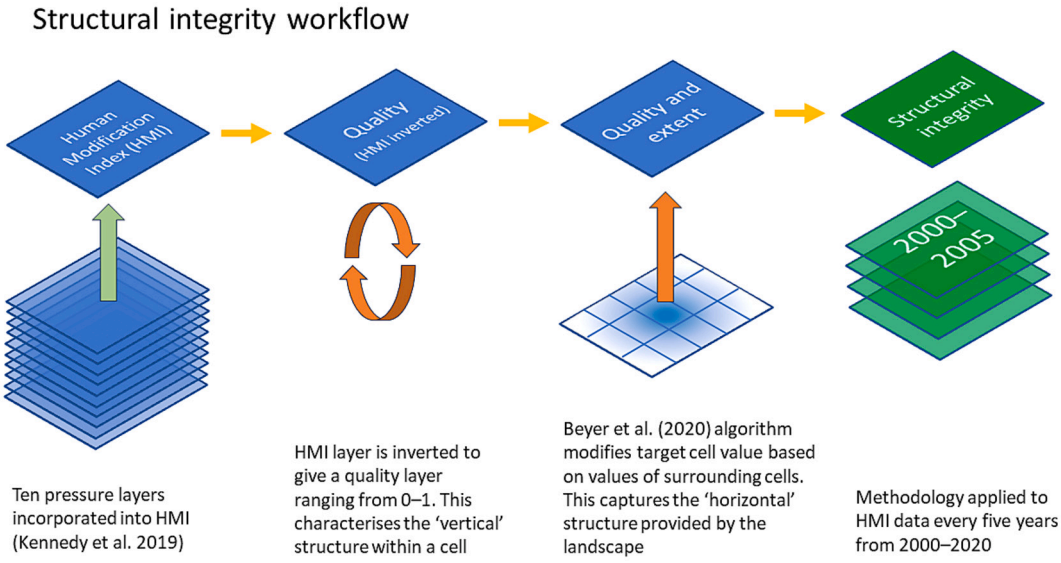


Fig. 2. Workflow for the structural integrity component.

the definitions of compositional integrity as proposed by Haase et al. (2018) and Carter et al. (2019). BII is also flexible in that new pressure data can be easily included within the modelling framework, for instance novel or updated land use data, and the PREDICTS database can be easily subset to a region of interest, for instance at a country level. It has been selected as a Component Indicator for the Kunming-Montreal Global Biodiversity Framework and has been suggested as a suitable metric to track global planetary boundaries due to its relevance to ecosystem health and functioning (Steffen et al., 2015).

The production of the compositional integrity layer involves the production of models as well as the projection of the models onto spatial layers. The workflow to produce the compositional integrity layer is shown in Fig. 3 and we provide detailed methodologies for each stage below.

2.2.2. *Development of a new BII*

The framework to calculate the BII using the PREDICTS database was first published by Newbold et al. (2016). We have adapted this framework to 1) include temporal land use and other input data (thus allowing for trend data as well as updates), 2) incorporate land use and other input data that allows unrestricted commercial use, and 3) quantify biodiversity responses specific to biogeographic classes rather than assuming the same dose-response applies globally.

Our novel BII was calculated using two types of models, abundance and compositional similarity models, fitted to data from the PREDICTS database (Hudson et al., 2017). The PREDICTS database is a large taxonomically and geographically representative dataset of primary biodiversity observations. The dataset is taken from published literature where community data (i.e., all members of a taxonomic grouping) were sampled in two or more sites with varying levels of anthropogenic disturbance. The data we used included 3.85 million rows and information on approximately 31,000 taxa from 32,000 sites and 767 studies, globally. The PREDICTS database is geographically representative with the number of sites included approximately proportionate to the area of biomes and is taxonomically representative with the number of taxa approximately proportionate to the proportion of taxa within vertebrates, invertebrates, fungi and plants (Hudson et al., 2017).

The biodiversity models are constructed using hierarchical, mixed effect modelling frameworks which can partition variability between effects of interest (anthropogenic pressures) and artifacts of sampling. The modelling framework applies a 'space for time' assumption in that it equates the difference between current day pristine and degraded sites to the results of degradation to a pristine site over time. Sites providing the pristine, or baseline, level in our models were therefore those containing primary vegetation and no human populations present in the current day.

Following the Newbold et al. (2016) methodology, we calculated the total species abundance as the summed number of individuals of all species for each site, and composition similarity using the asymmetric Jaccard index (Chao et al., 2005).

Land use and land use intensity categories were registered in the PREDICTS database and were originally assigned using information from the original source publications. The following land use/land use intensity classes were used: primary vegetation, mature secondary vegetation, intermediate secondary vegetation, young secondary vegetation, plantation forest, cropland with intense use, cropland with light use, cropland with minimal use, rangeland (see Hill et al. (2018) for description of categorisation of PREDICTS sites into rangeland category), pasture with light use, pasture with intense use, and urban.

Human population density was extracted for each PREDICTS site from the WorldPop dataset (date accessed: 29/01/2023; Lloyd et al., 2019; Center for International Earth Science Information Network, 2011). Road density for each PREDICTS site was extracted from the Global Roads Inventory Project (GRIP) database (data accessed 9/11/2023; Meijer et al., 2018). Exploratory abundance models were run against road density based upon all categories of roads in the GRIP database as well as against only the major road categories (Types 1 and 2). As road density values based upon all roads was a stronger predictor of abundance than only the major roads, road density values of all roads were used in the full model selection process. Abundance of species and compositional similarity of species assemblage models were built using a mixed-effects modelling framework with the R package lme4 (Bates et al., 2015).

For modelling abundance, the PREDICTS database was first

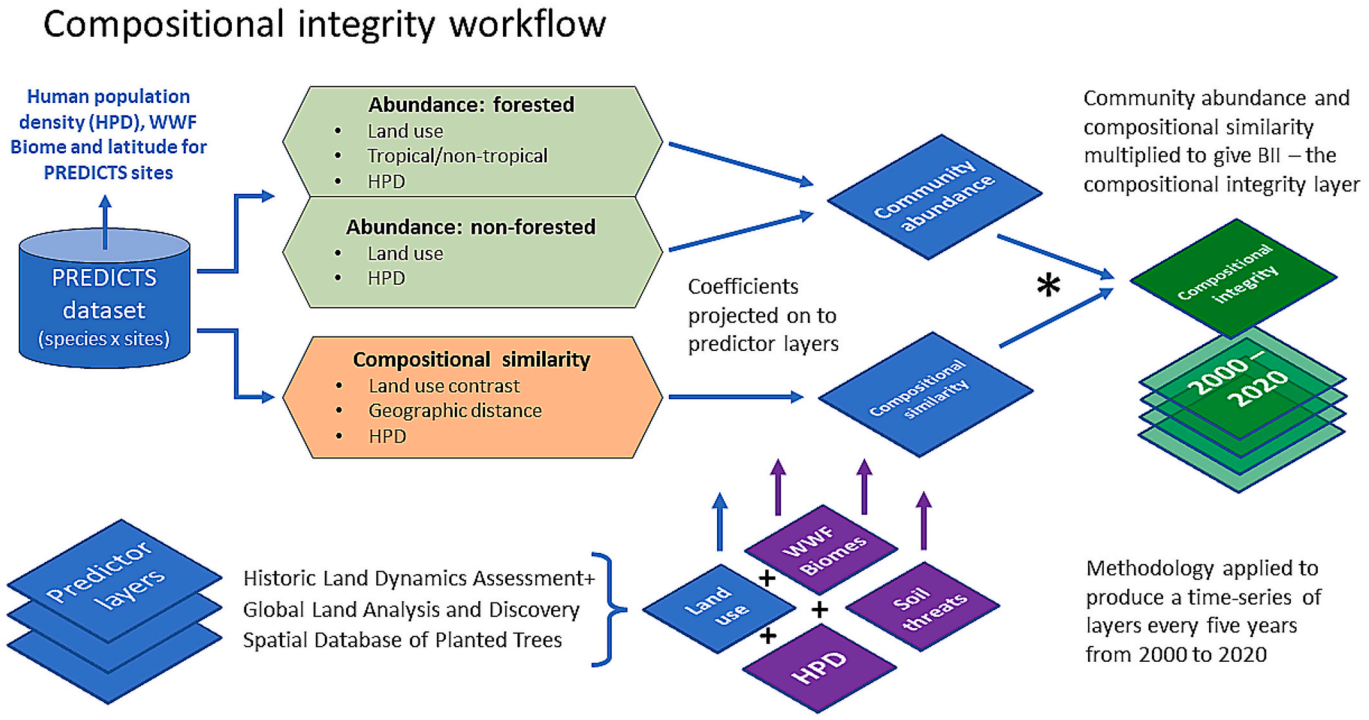


Fig. 3. Workflow for the compositional integrity component.

disaggregated based upon whether sampling sites would naturally be forested or not according to biome classifications. Sites were considered to be naturally forested if they were located in the following biomes (as recorded in the PREDICTS database based upon the WWF typology): 'Tropical & Subtropical Coniferous Forests', 'Tropical & Subtropical Dry Broadleaf Forests', 'Tropical & Subtropical Moist Broadleaf Forests', 'Mangroves', 'Temperate Broadleaf & Mixed Forests', 'Mediterranean Forests, Woodlands & Scrub', 'Temperate Conifer Forests', and 'Boreal Forests/Taiga'. All other sites were classified as naturally non-forested. An identical model selection process was then undertaken on each subset of the dataset separately.

Along with allowing responses to vary within forested/non-forested categories, we also introduced a tropical/non-tropical classification into the model selection process to account for differences in responses between climatic zones. Sites bounded by the Tropic of Cancer (23.4^{o}) and the Tropic of Capricorn (-23.4^{o}) were considered tropical, and all others were non-tropical.

Abundance was square root transformed. For all models, site information relative to source, study and block information were used as random intercepts, as selected using Akaike's Information Criterion (AIC) (Zuur et al., 2009). We considered the following fixed effects in the abundance models: human population density (log-transformed), road density (log-transformed), land use/land use intensity, tropical/non-tropical, and interactions between land use/land use intensity and all other variables. We selected the most parsimonious set of fixed effects using backwards stepwise selection based on AIC values (Zuur et al., 2009).

After model selection, the final model structures were:

for non-forested land

$$abundance \sim land\ use^{*}\log(population\ density) + (1|Source/Block)$$

for forested land

$$abundance \sim land\ use^{*}\log(population\ density) + tropical : nontropical + (1|Source/Block)$$

Compositional similarity models were built upon pairwise comparisons within studies using all studies that contained at least one site with primary vegetation (the baseline reference condition). Predictor variables of pairwise comparisons included in the model selection process were land use, Jaccard's asymmetric compositional similarity (logit transformed), geographic distance (log transformed), environmental distance (cube root transformed), road density of the comparison site (log transformed), human population density of the comparison site (log transformed), difference in road density, and difference in human population density (log transformed). Along with the variables listed, the interaction between land use and human population density and the interaction between land use and road density was also included in the model selection process.

The final model structure was:

$$Compositional\ similarity \sim \log(geographic\ distance) + landuse\ contrast^{*}\log(population\ density) + \log(population\ density\ of\ site\ 1 - population\ density\ of\ site\ 2) + (1|Source/Study)$$

2.2.3. Projection of model coefficients to form a global layer

Coefficients (see Appendix A, Tables A3, A4 and A5, for tables of coefficients) for each of the models were projected onto raster data for predictor datasets at $1km^2$ resolution. To project land use/land use intensity responses we aggregated several published layers to produce a novel layer that: 1) matched well with the PREDICTS land use/land use intensity categories, 2) was regularly updated, and 3) was available for unrestricted commercial use. Our primary input layer is the Historic Land Dynamics Assessment+ (HILDA+, Winkler et al., 2021) dataset; however, this layer aggregates managed pasture with rangeland. Therefore, we incorporated a layer that maps pasture but explicitly excludes rangeland areas: the Global Land Analysis and Discovery (GLAD, Potapov et al., 2022) dataset. This was overlaid with HILDA+ to identify areas that were categorised as agriculture in GLAD and pasture in HILDA+. Areas within this intersection were categorised in the new land use layer as 'Pasture' and those areas of pasture in HILDA+ that fell outside of this intersection were classified as 'Rangeland'. Data from the Spatial Database of Planted Trees (Harris et al., 2019) were used to identify plantations. Where there was any difference in resolution, we resampled the data to harmonise with the HILDA+ layer. We used the time series data within HILDA+ to track transitions from various land uses back to natural states to classify our secondary vegetation land uses with thresholds of 50 years, 30 years and 15 years to designate mature, intermediate and young secondary vegetation. Use intensity within agricultural land use categories was assigned based on threat level from the Potential Threats to Soil Biodiversity from the Global Soil Biodiversity Atlas (Orgiazzi et al., 2016).

We projected each model onto the corresponding datasets to produce community abundance layers for forested as well as non-forested regions, as well as a compositional similarity layer, all at a resolution of $1km^2$. The BII is formed from the compound of community abundance and compositional similarity with values taken from the forested abundance layer for forested regions and the non-forested abundance layer for non-forested regions. Finally, to produce a historical time series for compositional integrity, we used HILDA+ data from 2000, 2005, 2010, 2015 and 2020, applying the methodology described above for each layer.

2.3. Functional integrity

2.3.1. Review of existing approaches to measuring functional integrity

In a review of the most commonly used definitions, Pettorelli et al. (2018) suggest that ecosystem function should be defined as 'attributes related to the performance of an ecosystem that are the consequence of one or more multiple ecosystem processes', where ecosystem processes are described as 'transfer of energy, material, or organisms among pools in an ecosystem'. *IPBES* (2023) have adopted a different definition to Pettorelli et al. (2018), describing ecosystem function as 'the flow of energy and materials through the biotic and abiotic components of an ecosystem. It includes many processes such as biomass production, trophic transfer through plants and animals, nutrient cycling, water dynamics and heat transfer'. In contrast, others view functional integrity as the capacity of an ecosystem to provide Natures Contributions to People (NCP) and contribute to biosphere processes (Mohamed et al., 2024). Attempts at mapping ecosystem functioning have explored changes in the values of specific ecosystem function variables. Vyvlečka and Pechanec (2023) provide a review of remoted sensed variables which can be used to estimate ecosystem functions. One example comes from the framework assessing Human Appropriation of Net Primary Productivity (HANPP), which explores departures from potential net primary production (NPP) values to investigate where human production systems have modified ecosystem functioning and the extent of this change (Mayer et al., 2021). Other authors have taken a very different approach to functioning through mapping patterns in the diversity of functional traits. For instance, Faurby and Svenning (2015) estimated changes to the richness of mammalian functional traits. However, no single metric has yet been developed that is considered to represent all aspects of ecosystem functioning. This lack of consensus on how to define ecosystem functioning has hindered progress on the development of widely accepted and suitable metrics for monitoring ecosystem function.

In the absence of any existing method that encompasses all aspects of ecosystem functioning, we opted to focus on one key ecosystem function, NPP, because of its well-documented association with ecosystem functioning (Malhi et al., 2011; Mayer et al., 2021; Vyvlečka and Pechanec, 2023). Using NPP also has advantages in terms of spatial

resolution (layers are available in raster format at 1km^2 resolution or higher) and update frequency (e.g., MODIS releases a global new NPP layer annually). Indeed, within the planetary boundaries' framework, HANPP, as a fraction of Holocene levels of NPP, is the metric of choice for functional biosphere integrity (Richardson et al., 2023). NPP is also closely associated with the provision of key ecosystem services such as mass flow regulation and atmospheric regulation, pest control and water purification (Harrison et al., 2014). Pragmatically, data on NPP is easily accessible, regularly updated, available globally and is produced at suitable spatial resolutions.

We developed a global layer of potential NPP used as a 'natural' reference and compared it with observed NPP derived from remote sensing to map alterations in NPP and therefore ecosystem functioning. The workflow to create the functional integrity layer is shown in Fig. 4.

2.3.2. Creating a baseline layer of potential NPP

A layer of potential NPP was constructed using spatial projections of two novel models of potential NPP, along with two previously published potential NPP layers (Brun et al., 2022; Haberl et al., 2007). Novel models were constructed through the use of two approaches to construct novel layers of potential NPP: 1) we trained models using mean NPP measured within strictly managed protected areas (IUCN categories I and II) between 2001 and 2021 (UNEP-WCMC and IUCN, 2022) and 2) we trained models using 500,000 data points sampled randomly across all terrestrial areas (repeated 30 times and results were averaged). Variables included in the model selection process were: Latitude, bioclimatic variables (Brun et al., 2022); mean, min and max solar radiation (Fick and Hijmans, 2017); aridity (global aridity index, Zomer et al., 2022); total nitrogen, cation exchange capacity, predicted sand concentration, pH of water in soil (Pogio et al., 2021); continuous heat-insolation load index (CHILI, Theobald et al., 2015); roughness of terrain, slope, topographic position index, terrain ruggedness index (Amatulli et al., 2018); and landforms (Amatulli et al., 2018). For method 2) we included land use (identical to that used in the production of the composition layer) in models to account for variability in NPP due to land use, then removed this variable in the final projection process. Spatial projections of the two methods were used as inputs to the NPP calculation, along with two previously published potential NPP layers (Brun et al., 2022; Haberl et al., 2007). Final model structure was determined using stepwise selection based on AIC values. Both models used a generalised linear model framework, with a gamma distribution for the response variable and a log-link. Final model structures are provided below and coefficients are provided in Appendix A (tables A1 and A2).

$$NPP \sim poly(bio1, 2)*biome + poly(\log(bio12), 2) + nitrogen \quad (1)$$

$$NPP \sim poly(bio1, 2) + poly(sqrt(bio12, 2) + poly(bio4, 2) + pol(bio5, 2) + bio7 + bio10 + latitude + landuse \quad (2)$$

The calculation of potential NPP for our baseline improves on previous methods in that it includes a range of potential values at the 1km^2 grid cell level based on the variability of NPP observed throughout a 20-year period. We considered two types of uncertainty in our calculations: model uncertainty and natural variation (Regan et al., 2002). Firstly, for each grid cell, we calculated the model uncertainty using the lowest value and highest value observed across the four models of potential NPP. Secondly, we accounted for natural inter-annual variation by modelling the standard deviation of annual measures between 2001 and 2021. This allowed us to adjust our estimates to account for some areas experiencing much greater natural variability year to year than others. The model uncertainty plus the amount of natural inter-annual variability added together provided our estimate of the natural range of NPP values within a given grid cell.

2.3.3. Calculating change in NPP

Alterations in NPP were calculated by comparing the natural range in NPP calculated per 1km^2 grid cell compared to observed NPP taken from MODIS (Running and Zhao, 2019) in 2000, 2005, 2010, 2015 and 2020. All measures were calculated as deviations from the natural range (i.e.,

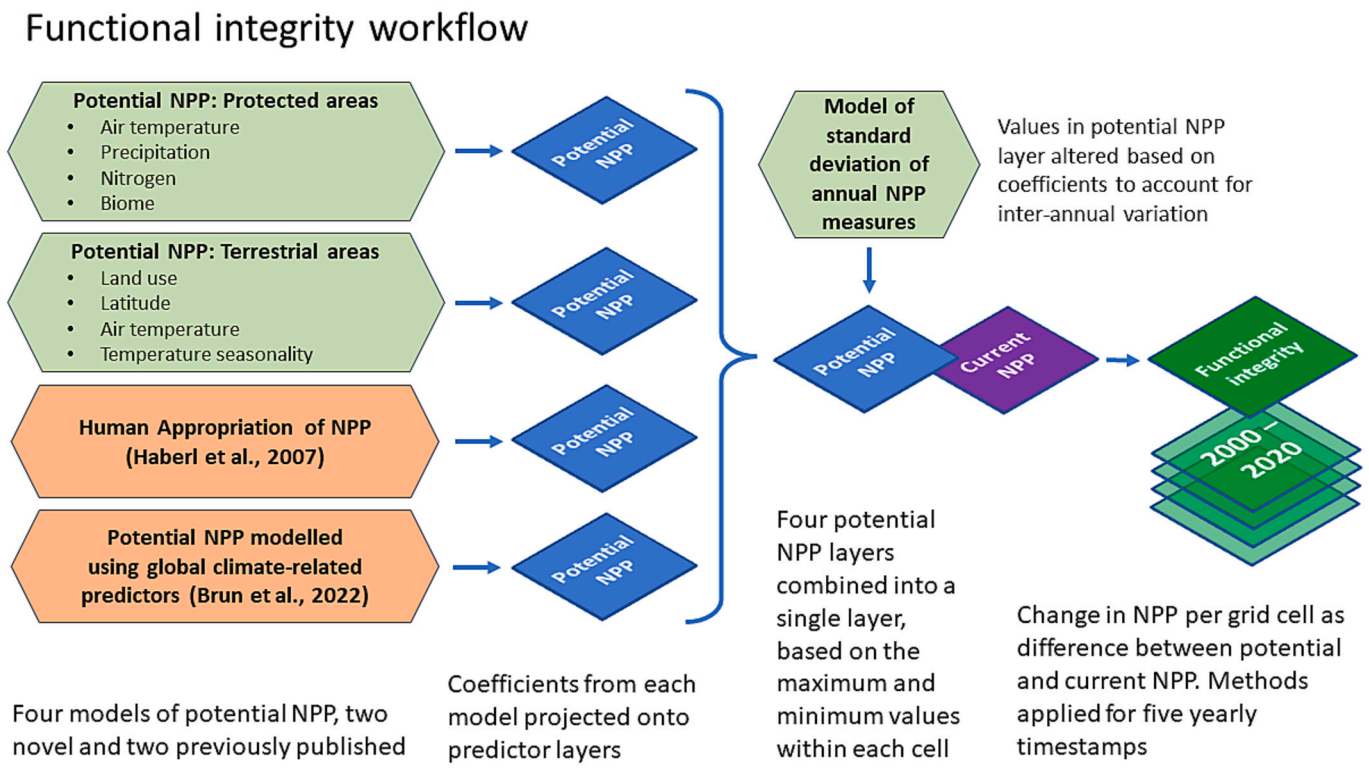


Fig. 4. Workflow for the functional integrity component.

where NPP was estimated to be lost, the value was compared to the lowest potential value, and where NPP was estimated to be gained, the value was compared to the highest potential value).

Ecosystem functioning occurs on different scales. To assess changes to ecosystem functioning on a broader scale the absolute loss or gain of NPP per grid cell was calculated; however, to account for changes to ecosystem functioning on a local scale the proportion of NPP measured versus potential per grid cell was calculated. Values of absolute losses were categorised into equal-interval bins so that the greatest loss of NPP recorded globally was scored as 0.1, ranging to no loss of NPP as 1.0. This process was repeated for absolute gains. The mean of the proportional change and the binned value of the absolute change provided the final functional integrity score.

2.4. EII aggregation approach

We use the data from each of the above three layers to derive the final EII scores across the terrestrial realm. We first extracted the lowest scoring of the three ecosystem components within every grid cell (see Appendix A for an analysis of correlations between components (Fig. A3)). To account for the influence of all three components, we adjusted the EII value by multiplying the square root of the minimum value by the harmonic mean of all three components. This approach prevents the final score from exceeding the score of the minimum component value emphasizing the importance of integrity in each of the three components, as well as adjusting the score according to the scores of all components, thus emphasizing the integration of all components.

Mean EII scores for all 1km^2 grid cells mapped to the terrestrial realm, were calculated at the level of ecosystems (Sayre et al., 2020) and biomes (Dinerstein et al., 2017). The biome level analyses are equivalent to the IUCN ecosystem typology 'biome – level 2', and the ecosystems data is at similar spatial scale to 'global ecosystem types – level 5' (Keith et al., 2020).

3. Results

3.1. Component results

Structural integrity estimates show that wide expanses of high-latitude regions have retained high levels of structural integrity (Fig. 5A). The same is true for the desert and dryland regions of Africa, Eurasia, and Australia. Although the Amazon Forest is another region with large areas of high structural integrity, degradation on the edges of the Forest is most observable in the structural integrity layer. Notable regions of the world with degraded structural integrity include India and China, Europe, eastern USA and Canada and sub-Saharan Africa.

Degradation to functional integrity (Fig. 5B) is less widespread than degradation to structural (Fig. 5A) or compositional integrity (Fig. 5C). Highly degraded areas are often found where agriculture has replaced savanna, grasslands or scrub, for instance, those in the central agricultural regions of South America and Europe, in the Sahelian and Guinea Savanna region of Africa, Central Asia, and the Midwest United States. Other areas of notable degradation to functional integrity are in northern tundra regions of Canada and Eurasia and the southern tip of South America. It is likely that the functional integrity of these regions has been impacted by climate change.

Compositional integrity shows many of the same patterns as structural integrity with highly degraded areas in India and China, and widespread degradation throughout the densely populated and/or agricultural regions of the world (Fig. 5C). However, there are notable differences. For instance, across grassland plains of Central Eurasia and Australia compositional integrity is estimated to have experienced low levels of widespread degradation, likely due to anthropogenic pressures such as harvesting or low-intensity grazing.

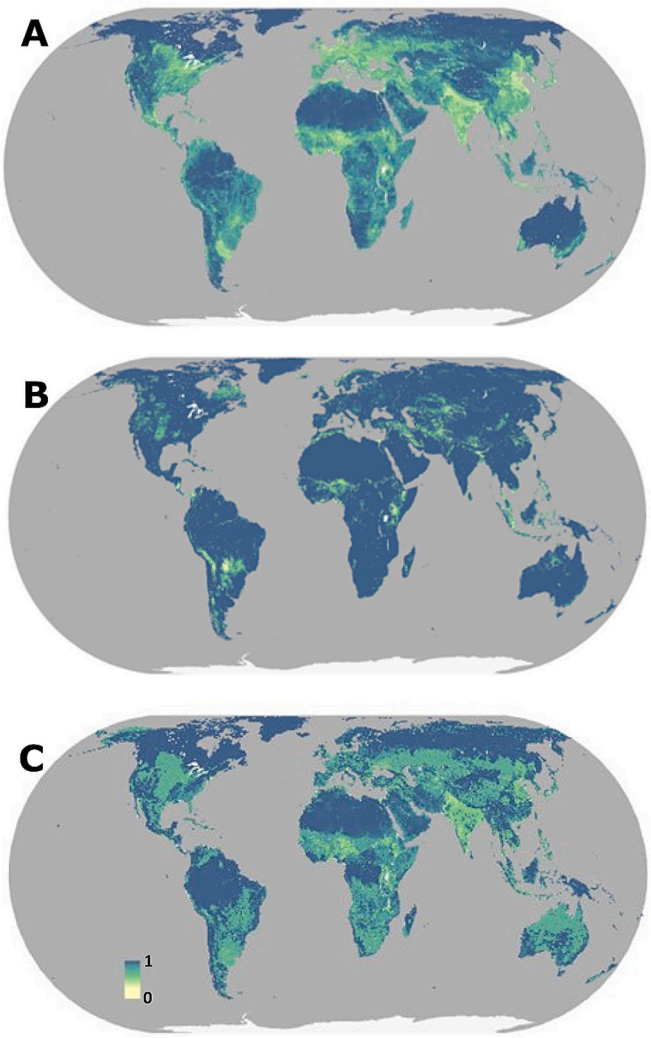
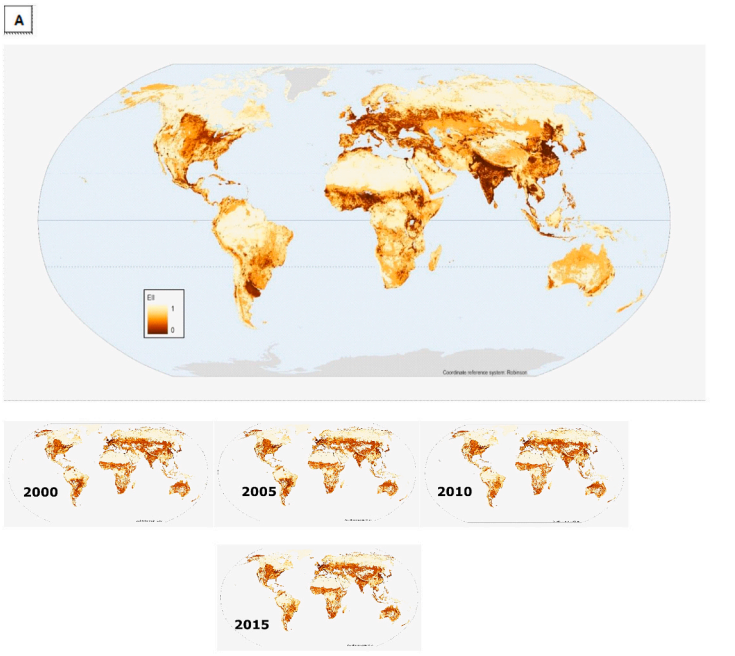


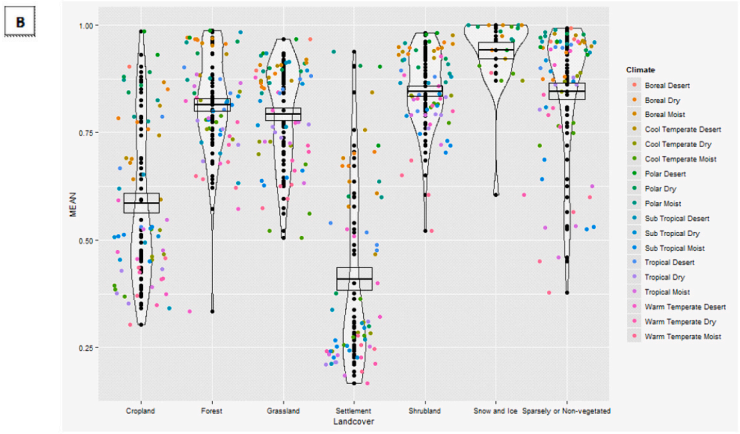
Fig. 5. The components of EII A) structural integrity, B) functional integrity, C) compositional integrity. Highest integrity areas are shown in dark blue, lowest integrity in yellow. Note: the boundaries and names shown and the designations used on these maps do not imply official endorsement or acceptance by the United Nations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

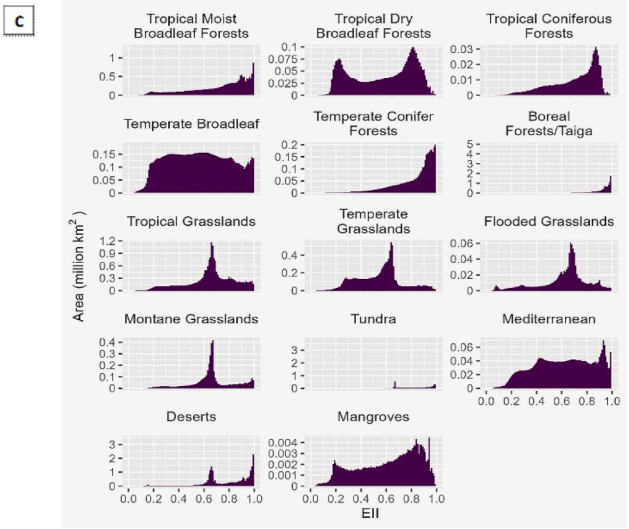
3.2. EII results

Ecosystem integrity is highly degraded across much of the world (Fig. 6A). Only remote areas at higher latitudes (note that Antarctica was excluded from the analysis), remote areas of rainforest across the tropics, and hyper-arid areas across the planet are estimated to have extensive areas where ecosystem integrity has been retained. Widespread severe degradation is found in areas where high human population density intersects with significant land conversion, for instance, in much of India, Nepal and northern Europe along with areas of depletion in North America, Central America, Argentina and Uruguay, Niger, Nigeria and Chad, northeastern China (Fig. 6A).

Mean ecosystem integrity scores, averaged from 1km^2 grids into the ecosystem classification of Sayre et al. (2020), was 0.68 (±0.14). Of 422 ecosystems, 87 have on average have seen a reduction of at least 50% in EII and 25 ecosystems have at least a 75% reduction in EII. Ecosystems within human settlement areas in warm temperate, tropical or subtropical regions have the lowest levels of ecosystem integrity, followed by ecosystems within cropland areas (Fig. 6B). Ecosystems within grasslands, forests, shrubland and sparsely or non-vegetated areas had similar ranges with a trend towards tropical, subtropical and warm







(caption on next page)

Fig. 6. Global ecosystem integrity. A) The global Ecosystem Integrity Index for terrestrial areas mapped on a 1km^2 grid from 2000 to 2020. Areas with high levels of ecosystem integrity are shown in pale yellow, whereas those with highly degraded ecosystem integrity are shown in dark red. Note: the boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations. B) Mean ecosystem integrity per ecosystem, grouped by landcover types (ecosystems and landcover types as defined by Sayre et al., 2020). Colours indicate climate regions. C) Frequency of ecosystem integrity index values within terrestrial biomes, as originally defined by Olsen et al. (2001) and updated by Dinerstein et al. (2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

ecosystems being more degraded than cooler ecosystems in all land covers apart from grasslands, where the lowest values were found in cool temperate ecosystems (Fig. 6B). This pattern may be explained by low intensity grazing occurring in these areas. Polar and boreal ecosystems tended to be the least degraded ecosystems in all landcovers, with a greater range of values observed in settlement and cropland land uses (Fig. 6B).

At the broader biome scale, dry tropical broadleaf forests have lost more ecosystem integrity than moist tropical broadleaf forests (Fig. 6C). High levels of loss are also seen in temperate grasslands, temperate broadleaf forest and Mediterranean forests, woodlands and scrub biomes (Fig. 6C).

4. Discussion

Our index shows that ecosystem integrity has been highly reduced across the terrestrial world with a mean EII value across ecosystems of 0.68 (SD: 0.14) and nearly one fifth of all ecosystems having lost, on average, over half of their ecosystem integrity. Only remote areas of rainforest, desert and areas in higher latitudes have extensive areas where ecosystem integrity has been retained. Such levels of degradation are likely to have significantly reduced the ecological resilience of ecosystems (Brand, 2009) and their ability to provide and sustain ecosystem services (Lewis et al., 2009; Mello et al., 2018; Bianchi et al., 2006; Carvalheiro et al., 2010). For example, higher integrity in tropical forests is associated with greater levels of carbon storage (Lewis et al., 2009), higher water quality (Mello et al., 2018) and positive climate buffering effects (Bonan, 2008).

Landscape level spatial distribution of ecosystem integrity is also likely to be important for maintenance of ecosystem resilience and provision of ecosystem services. For instance, in temperate biomes, mosaic landscapes that have patches of high integrity habitat provide important pest control and pollination services (Bianchi et al., 2006; Carvalheiro et al., 2010). Future research is needed to explore how local, regional, and global levels of ecosystem integrity correlate with provision of ecosystem services. This information would enable policymakers to evaluate the synergies and trade-offs among actions taken to restore degraded ecosystems (e.g., Target 2 of the KM-GBF) and to enhance service provision (e.g., Target 11 of the KM-GBF), as well as identifying integrated pathways towards achievement of Goals A and B of the KM-GBF. Research in this area may also reveal how close we are to critical tipping points, at a variety of scales, at which small reductions in ecosystem integrity could lead to the loss of key ecosystem services. Such information could be used to identify future global ambitions that define ‘safe operating spaces’ for humanity (Rockström et al., 2023).

Although we have carefully chosen appropriate data layers as inputs for the global scale (see Appendix A for complete list of datasets utilised (Table A6) and validation of EII and its components against other indicators (Section A2)), users at regional, national or local scale could select data inputs that are tailored to their local circumstances and derive versions of the EII specific to their needs. The methodological framework we have developed has been designed to be flexible, allowing 1) regular updates including where datasets improve or new datasets are produced, 2) substitution of global datasets with national or even site level data as appropriate to produce the EII at a scale suitable for user needs.

4.1. Target users and applications of the EII

We developed the EII for two main use cases, whilst acknowledging that there are many potential applications and users. The first is for countries seeking ways to monitor progress against their national goals and targets within the context of the Kunming-Montreal Global Biodiversity Framework (KM-GBF) (Table 1). Ecosystem integrity is explicitly included within the global ambitions of Goal A and Targets 1, 2 and 12 of the KM-GBF, negotiated under the CBD (2022), and the EII has been recognised in the monitoring framework for the KM-GBF as a Component Indicator for Goal A (https://www.cbd.int/doc/decisions/cop-16/cop-16-dec-31-en.pdf).

We provide an illustration of the use of EII by national governments in tracking progress towards KM-GBF Target 3 (Table 1) in Appendix A (section A4). Here we use o polygons delineating protected areas to interrogate the time series of EII to quantify temporal trends in the integrity, and thereby effectiveness, of individual protected areas. These can be aggregated to give average scores at the country level, allowing countries to gauge national performance against the Target. With annual updates to the EII layer planned, this will allow continued monitoring of protected areas to highlight degradation and track recovery. The EII can also be used to monitor emerging threats to protected areas within their surrounding landscapes. More detail on this use case is provided in Appendix A (section A4 and in Box 2). This use case demonstrates the versatility of EII in providing information at multiple scales, including local sites, at the landscape level, as well as at broader regional, national and global scales.

Our second use case is for the businesses and financial institutions, which are increasingly integrating biodiversity into strategy design and external reporting. This includes using biodiversity measurement for screening value chains, comparing options, tracking potential changes in impacts/dependencies and observing biodiversity outcomes (IPBES 2026). There is an urgent need for simple and rapidly applicable methods for screening complex value chains, setting targets and measuring progress that facilitate businesses to move towards positive outcomes for biodiversity (Diaz et al., 2020). For example, the Taskforce on Nature-Related Financial Disclosures (TNFD) requires under ‘Strategy Disclosure D' (TNFD, 2023) that the location of assets or activities are disclosed for ‘priority locations', defined as, inter alia, those which have ‘high ecosystem integrity’ and those with ‘rapid decline in ecosystem integrity’. The EII has been designed to help with this task providing a repeatable, fine scale and globally consistent measure of ecosystem integrity. The global coverage of EII makes it particularly useful for screening and comparing options at higher levels of decision making, and it can be complemented with on the ground measurement tracking site level outcomes (IPBES 2026). The EII is also proposed as an indicator for which targets can be set in Step 3 of the Science Based Targets for Nature (SBTN) guidance. The EII can also be used to estimate pressures within supply chains where there may be varying levels of traceability through linking with a tool such as TRASE (2019), or, by modelling how integrity might respond to changes in management practice, the EII can guide stakeholders towards actions that will have the greatest benefits for nature, whether that be at a jurisdictional level (for policymakers) or an asset/portfolio level (for the businesses and financial institutions). For example, our EII framework has been adopted by the Landbanking Group to provide companies with information suitable for screening and monitoring the progress of conservation interventions (https://www.thelandbankinggroup.com/science/indi

Table 1
Mapping the uses of the Ecosystem Integrity Index onto the needs of countries to monitor components of the KM-GBF.

GBF Goal or Target	Description	EII use case
Goal A: Protect and Restore	The integrity, connectivity and resilience of all ecosystems are maintained, enhanced, or restored, substantially increasing the area of natural ecosystems by 2050; Human induced extinction of known threatened species is halted, and, by 2050, the extinction rate and risk of all species are reduced tenfold, and the abundance of native wild species is increased to healthy and resilient levels; The genetic diversity within populations of wild and domesticated species, is maintained, safeguarding their adaptive potential.	Recognised by the CBD as a Component Indicator, EII can be used to assess and monitor the integrity of ecosystems.
Target 1: Plan and Manage all Areas to Reduce Biodiversity Loss	Ensure that all areas are under participatory, integrated and biodiversity inclusive spatial planning and/or effective management processes addressing land- and sea-use change, to bring the loss of areas of high biodiversity importance, including ecosystems of high ecological integrity, close to zero by 2030, while respecting the rights of indigenous peoples and local communities.	Recognised by the CBD as a Complementary Indicator, EII can be used to aid spatial planning by identifying priority areas for conservation action and to track change in the integrity of these areas
Target 2: Restore 30% of all Degraded Ecosystems	Ensure that by 2030 at least 30% of areas of degraded terrestrial, inland water, and marine and coastal ecosystems are under effective restoration, in order to enhance biodiversity and ecosystem functions and services, ecological integrity and connectivity	EII can identify potential priority areas for restoration and can monitor the effectiveness of restoration actions
Target 3: Conserve 30% of Land, Waters and Seas	Ensure and enable that by 2030 at least 30% of terrestrial and inland water areas, and of marine and coastal areas, especially areas of particular importance for biodiversity and ecosystem functions and services, are effectively conserved and managed through ecologically representative, well-connected and equitably governed systems of protected areas and other effective area-based conservation measures, recognizing indigenous and traditional territories, where applicable, and integrated into wider landscapes, seascapes and the ocean, while ensuring that any sustainable use, where appropriate in such areas, is fully consistent with conservation outcomes, recognizing and respecting the rights of indigenous peoples and local communities, including over their traditional territories.	EII can be used to assess condition within protected areas as a measure of their effectiveness (see Box 2 for example use case)
Target 10: Enhance Biodiversity and Sustainability in Agriculture, Aquaculture, Fisheries, and Forestry	Ensure that areas under agriculture, aquaculture, fisheries and forestry are managed sustainably, in particular through the sustainable use of biodiversity, including through a substantial increase of the application of biodiversity friendly practices, such as sustainable intensification, agroecological and other innovative approaches, contributing to the resilience and long-term efficiency and productivity of these production systems, and to food security, conserving and restoring biodiversity and maintaining nature's contributions to people, including ecosystem functions and services.	EII can assess the sustainability of management practices, guide actions and track responses to sustainable practices. Furthermore, the functional integrity component of EII allows monitoring of impacts to ecosystem functions.
Target 15: Businesses Assess, Disclose and Reduce Biodiversity-Related Risks and Negative Impacts	Take legal, administrative or policy measures to encourage and enable business, and in particular to ensure that large and transnational companies and financial institutions: (a) Regularly monitor, assess, and transparently disclose their risks, dependencies and impacts on biodiversity, including with requirements for all large as well as transnational companies and financial institutions along their operations, supply and value chains, and portfolios; (b) Provide information needed to consumers to promote sustainable consumption patterns; (c) Report on compliance with access and benefit-sharing regulations and	EII can be used to monitor, assess and disclose biodiversity risks and positive or negative impacts. EII can further be used to guide management decisions, and for biodiversity footprinting.

(*continued on next page*)

Table 1 (*continued*)

GBF Goal or Target	Description	EII use case
	measures, as applicable; in order to progressively reduce negative impacts on biodiversity, increase positive impacts, reduce biodiversity-related risks to business and financial institutions, and promote actions to ensure sustainable patterns of production.	
Target 16: Enable Sustainable Consumption Choices to Reduce Waste and Overconsumption	Ensure that people are encouraged and enabled to make sustainable consumption choices, including by establishing supportive policy, legislative or regulatory frameworks, improving education and access to relevant and accurate information and alternatives, and by 2030, reduce the global footprint of consumption in an equitable manner, including through halving global food waste, significantly reducing overconsumption and substantially reducing waste generation, in order for all people to live well in harmony with Mother Earth.	EII can be used to aid assessment of the biodiversity footprint of organisations, supply chains or trading patterns. EII could be used as a simple communication tool for educational purposes.

cators/ecosystem-integrity). The case study in section A3 of Appendix A, shows how EII can be used to model company actions, providing guidance to businesses on which intervention will produce the greatest gains in ecosystem integrity. Here we took data on cotton farms within the USA, and we modelled how a shift to organic practices would have gains for ecosystem integrity. We disaggregated EII into each of its components, modifying each layer to reflect how a shift towards organic practices would change integrity values within the farming polygons. We then aggregated across all sourcing sites, deriving a mean integrity for organic farming and compared this to the mean for conventional cotton farming. The resulting increase in EII was approximately 13% across the country. For more detail on this case study see Appendix A (section A3).

The EII can be disaggregated into its components, which may be informative when determining underlying causes of and/or trends towards low ecosystem integrity. However, we encourage its use as an aggregated holistic index, with actions focussed on improving overall integrity, rather than a single component. Although many actions will be beneficial for all three components of integrity, it should be recognised that components may respond at different rates in terms of recovery towards higher integrity.

In the case of both state and non-state users, the EII should be seen as complementary to, and ideally used in conjunction with, measures of other components of biodiversity. Examples of complementary measures include the Species Threat Abatement and Restoration (STAR) (Mair et al., 2021), or range rarity metrics such as those presented in Hill et al. (2019). The Red List of Ecosystems (RLE) provides a framework for assessment and prioritisation of ecosystems (Rodríguez et al., 2015) which can be informed or complemented by the EII's spatially explicit data.

4.2. Limitations and future developments

EII provides data on the trend in ecosystem integrity over time and datasets have been selected to allow regular updates. As a flexible framework approach, it can also incorporate new datasets to continually increase the accuracy and precision of the overall index as they become available. As a tool for forecasting, the EII has the flexibility to allow exploration of different management practices at a local level and over short timeframes to guide business practice, or pathways to sustainability with the alignment of the EII framework to national or global scenarios over longer timeframes, and future work will target these key areas.

There is a need to be able to distinguish between 'natural' and 'non-natural' states as this terminology is used frequently in international policies and target-setting exercises; for instance, Goal A of the KM-GBF requires knowledge of what constitutes a 'natural ecosystem'. This distinction is compounded by some ecosystems that are considered to be 'natural' but have experienced significant human modification or have been created by human-environment interactions (Innes and Blackford, 2023). It is also important to recognise the vital role that Indigenous people can have in maintaining ecosystem integrity (e.g. Garnett et al., 2018*)*. To support this, the EII can identify areas with high integrity, and monitor changes to their state.

The components of ecosystem integrity within the EII have been designed to detect anthropogenic degradation and they each have their strengths and limitations in being able to do so. For instance, the models used to assess compositional integrity make a 'space for time' assumption, meaning that the baseline level is taken from sites that field researchers consider to be undisturbed (comprised of primary vegetation with minimal ongoing disturbance). In contrast, the models used to assess functional integrity are based on levels of NPP observed in the last few decades, thus they will not pick up on natural disturbances that occurred prior to satellite data being made available.

The EII has limitations in that only the functioning layer directly quantifies degradation to ecosystem integrity caused by climate change and it cannot account for changes that occurred prior to 2000. We note that some of the high latitude areas that appear unimpacted in this analysis may be at particular risk from climate change (Beaumont et al., 2011). We also do not directly account for other pressures such as pollution or exploitation. Further work will target these limitations to examine the sensitivity of the components to these assumptions and make any further adjustments to the data or models used.

Current ongoing work with EII is assessing protected area condition and management effectiveness, producing national and regional versions of EII, exploring links between EII and tipping points to predict areas at risk of crossing boundaries, and improving the linkages between EII and dynamic earth observation products to produce near real time updates to EII. These advances will enhance use by governments, businesses and the financial sector. For instance, linking EII to those remote sensed products that are provided at very fine scales and/or at regular intervals be advantageous when considering decision making at very fine scales and understanding the relationship between levels of EII and safe operating spaces will aid companies and other decision makers to target restoration actions. There is great potential for building bottom-up versions of EII through linking EII to local data for use cases that do not require global comparability, as this would ensure that local land uses, knowledge or areas of interest are explicit in the calculations. Such bottom-up versions of EII are likely to be of interest to both governments and businesses as well as other end users. Future work to provide this capacity within a dedicated EII tool would be advantageous, allowing flexibility, transparency and traceability at local to national scales.

In conclusion, our results show that ecosystem integrity has been severely degraded across the world with only a limited number of remote areas retaining most of their ecosystem integrity. Such dramatic losses of ecosystem integrity will have already had severe consequences for species persistence, and for the provision of ecosystem services on

Box 2
A case study to demonstrate the use of EII in monitoring protected area effectiveness.

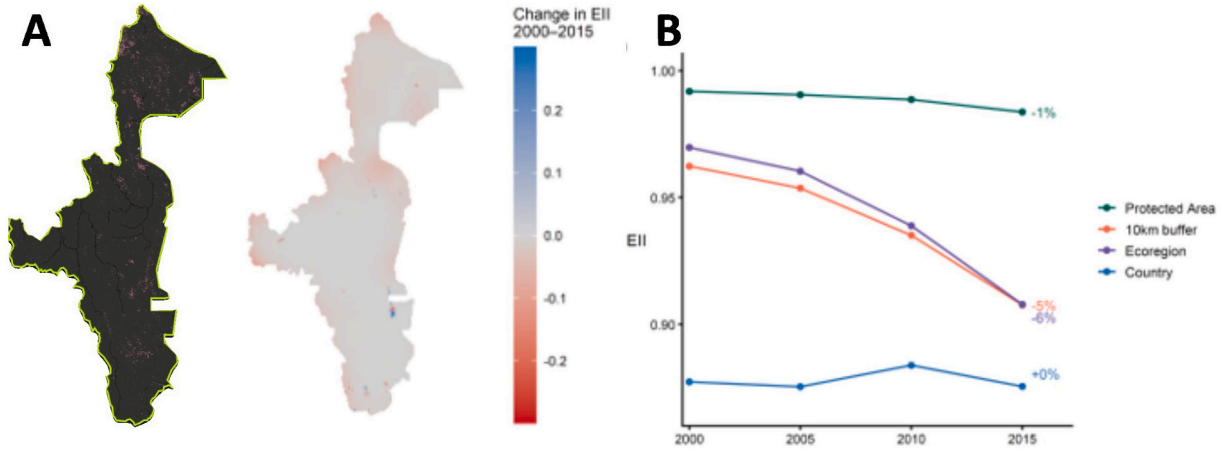


Figure I. *Panel A) shows a comparison of the forest loss (indicated by dark pink area) experienced in the Parque Nacional Cordillera Azul, Peru, between 2000 and 2015 (map on left) and the changes in the Ecosystem Integrity Index over the same time period (map on right). Panel B) displays temporal trends in the mean Ecosystem Integrity Index within park boundaries (green line), a 10 km buffer surrounding the area (red line), within the Ucayali moist forest ecoregion (purple line) and within Peru (blue line). Forest loss data collected from www.globalforestwatch.org. Ecoregion boundary taken from Dinerstein et al. (2017) An Ecoregion-Based Approach to Protecting Half the Terrestrial Realm.*

By exploring spatial variation in how ecosystem integrity has changed, we can determine where within the protected area degradation may be occurring. This spatial information could help protected area managers to target actions in specific areas to improve condition. In Fig. I, we overlay the EII with a polygon from the World Database on Protected and Conserved Areas for a protected area in Peru, the *Parque Nacional Cordillera Azul*. In Cordillera Azul, there are noticeable areas of degradation in ecosystem integrity around the edges of the site (Fig. IA, map on right), particularly where logging and other pressures have been intense (data not shown), indicating that some threats may be spilling over the park boundaries. A comparison of the ecosystem integrity map with forest loss (Fig. IA, map on left), reveals a similar pattern of degradation over the same period, indicating that at least part of the change in EII was due to loss of forest cover.

The mean value of EII within the protected area can be used to explore changes in the integrity of the protected area over time (Fig. IB). By comparing trends in the ecosystem integrity of the protected area to those of unprotected 'reference' areas we can quantify the effectiveness of protection in maintaining or improving integrity relative to surrounding or similar areas. In this example, we present three types of reference area: a 10 km buffer around the site; the Ucayali moist forest ecoregion within which the Cordillera Azul is found; and for the whole of Peru (Fig. IB). The trend data shows that ecosystem integrity has remained relatively stable within Cordillera Azul, decreasing by only 1%, as opposed to the steep declines in integrity that are observed in the surrounding landscape and across the ecoregion (Fig. IB).

which humanity depends at local and global scales. However, there is greater global ambition to conserve and restore biodiversity than ever before with the adoption of the KM-GBF and a huge growth in momentum in businesses to adopt more sustainable practices and to ensure greater transparency on impacts to nature. The EII provides a responsive, flexible and comparable tool for both governments and businesses to understand how and where ecosystem integrity has been degraded and to guide actions that will protect and restore ecosystem integrity, safeguarding ecosystems and the benefits they provide on which we all depend.

CRediT authorship contribution statement

S.L.L. Hill: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **M.L.K. Harrison:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **C. Maney:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **J. Bedford:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **M. Harris:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **T.H.E. Mason:** Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization. **N. Ash:** Writing – review & editing, Supervision. **J. Hughes:** Writing – review & editing, Supervision. **M. Jones:** Writing – review & editing, Writing – original draft, Supervision.

Funding

UK Research and Innovation's Global Challenges Research Fund under the Trade, Development and the Environment Hub project (project number ES/S008160/1). Funding was also received from the Science Based Targets Network (SBTN).

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.

Acknowledgments

We would like to thank Javier Fajardo, Neil Burgess, Daniella Guaras, Mike Harfoot, Fiona Danks, Sharon Brooks, Andrew Skowno,

Sebastian Bekker, Maria Julia Oliva, Tom Evans, Malcolm Starkey, Craig Beatty, Marco Daldos Pirri, Varsha Vijay and Pamela Collins for their comments and review of the EII methodology.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.115314.

Data availability

Data is available at https://wcmc.io/ecosystem-integrity-index.

References

Alkemade, R., van Oorschot, M., Miles, L., et al., 2009. GLOBIO3: a framework to investigate options for reducing global terrestrial biodiversity loss. Ecosystems 12 (3), 374–390. https://doi.org/10.1007/s10021-009-9229-5.

Amatulli, G., Domisch, S., Tuanmu, M.-N., et al., 2018. A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. Sci. Data 5 (1), 180040. https://doi.org/10.1038/sdata.2018.40.

Barlow, J., Lennox, G.D., Ferreira, J., et al., 2016. Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation. Nature 535 (7610), 144–147.

Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67 (1), 1–48. https://doi.org/10.18637/jss.v067.i01.

Beaumont, L.J., Pitman, A., Perkins, S., et al., 2011. Impacts of climate change on the world's most exceptional ecoregions. Proc. Natl. Acad. Sci. 108 (6), 2306–2311.

Beyer, H.L., Venter, O., Grantham, H.S., Watson, J.E., 2020. Substantial losses in ecoregion intactness highlight urgency of globally coordinated action. Conserv. Lett. 13 (2), e12692. https://doi.org/10.1111/conl.12692.

Bianchi, F.J., Booij, C.J.H., Tscharntke, T., 2006. Sustainable pest regulation in agricultural landscapes: a review on landscape composition, biodiversity and natural pest control. Proc. R. Soc. B Biol. Sci. 273 (1595), 1715–1727.

Blumetto, O., Castagna, A., Cardozo, G., et al., 2019. Ecosystem integrity index, an innovative environmental evaluation tool for agricultural production systems. Ecol. Indic. 101, 725–733.

Bonan, G.B., 2008. Forests and climate change: forcings, feedbacks, and the climate benefits of forests. Science 320, 1444–1449.

Brand, F., 2009. Critical natural capital revisited: ecological resilience and sustainable development. Ecol. Econ. 68 (3), 605–612.

Brun, P., Zimmermann, N.E., Hari, C., Pellissier, L., Karger, D.N., 2022. Global climate-related predictors at kilometer resolution for the past and future. Earth Syst. Sci. Data 14 (12), 5573–5603.

Carter, S.K., Fleishman, E., Leinwand, I.I., et al., 2019. Quantifying ecological integrity of terrestrial systems to inform management of multiple-use public lands in the United States. Environ. Manag. 64 (1), 1–19. https://doi.org/10.1007/s00267-019-01163-w.

Carvalheiro, L.G., Seymour, C.L., Veldtman, R., Nicolson, S.W., 2010. Pollination services decline with distance from natural habitat even in biodiversity-rich areas. J. Appl. Ecol. 47 (4), 810–820.

CBD (Convention on Biological Diversity), 1992. Convention on Biological Diversity: text and annexes. https://www.cbd.int/convention/text/.

CBD (Convention on Biological Diversity), 2022. Decision 15/4 Kunming-Montreal global biodiversity framework. In: Fifteenth Meeting of the Conference of the Parties to the Convention on Biological Diversity, Montreal.

Center for International Earth Science Information Network, 2011. Global Rural-Urban Mapping Project (GRUMP) v1.

Chao, A., Chazdon, R.L., Colwell, R.K., Shen, T.-J., 2005. A new statistical approach for assessing similarity of species composition with incidence and abundance data. Ecol. Lett. 8 (2), 148–159. https://doi.org/10.1111/j.1461-0248.2004.00707.x.

De Marzo, T., Pratzer, M., Baumann, M., Gasparri, N.I., Pötzschner, F., Kuemmerle, T., 2023. Linking disturbance history to current forest structure to assess the impact of disturbances in tropical dry forests. For. Ecol. Manag. 539, 120989.

Dias, A., Van Houdt, S., Meschin, K., et al., 2023. Using essential biodiversity variables to assess forest ecosystem integrity. Front. For Glob. Change 6. https://doi.org/10.3389/ffgc.2023.1098901.

Díaz, S., Zafra-Calvo, N., Purvis, A., et al., 2020. Set ambitious goals for biodiversity and sustainability. Science 370 (6515), 411–413.

Dinerstein, E., Olson, D., Joshi, A., Vynne, C., Burgess, N.D., Wikramanayake, E., Hahn, N., Palminteri, S., Hedao, P., Noss, R., Hansen, M., 2017. An ecoregion-based approach to protecting half the terrestrial realm. BioScience 67 (6), 534–545.

Faurby, S., Svenning, J.C., 2015. Historic and prehistoric human-driven extinctions have reshaped global mammal diversity patterns. Divers. Distrib. 21 (10), 1155–1166.

Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37 (12), 4302–4315. https://doi.org/10.1002/joc.5086.

Franklin, J.F., Cromack, K., Denison, K., McKee, A., Maser, C., Sedell, J., Swanson, F., Juday, G., 1981. Ecological Characteristics of Old-Growth Douglas-Fir Forests. General Technical Report PNW-118. USDA Forest Service, Portland, OR.

Garnett, S.T., Burgess, N.D., Fa, J.E., et al., 2018. A spatial overview of the global importance of indigenous lands for conservation. Nat. Sustainability 1 (7), 369–374. https://doi.org/10.1038/s41893-018-0100-6.

Gibbons, P., Freudenberger, D., 2006. An overview of methods used to assess vegetation condition at the scale of the site. Ecol. Manag. Restor. 7 (s1), S10–S17. https://doi.org/10.1111/j.1442-8903.2006.00286.x.

Goedkoop, M., Spriensma, R., 2001. The eco-Indicator'99. A damage oriented method for life cycle impact assessment, methodology report, 3rd edition. PRé consultants, Amersfoort.

Grantham, H.S., Duncan, A., Evans, T.D., et al., 2020. Anthropogenic modification of forests means only 40% of remaining forests have high ecosystem integrity. Nat. Commun. 11 (1), 1–10.

Haase, P., Tonkin, J.D., Stoll, S., et al., 2018. The next generation of site-based long-term ecological monitoring: linking essential biodiversity variables and ecosystem integrity. Sci. Total Environ. 613, 1376–1384.

Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., et al., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proc. Natl. Acad. Sci. 104 (31), 12942–12947. https://doi.org/10.1073/pnas.0704243104.

Hansen, A., Barnett, K., Jantz, P., et al., 2019. Global humid tropics forest structural condition and forest structural integrity maps. Sci. Data 6 (1), 232.

Hansen, A.J., Noble, B.P., Veneros, J., et al., 2021. Toward monitoring forest ecosystem integrity within the post-2020 global biodiversity framework. Conserv. Lett. 14 (4), e12822.

Harris, N., Goldman, E.D., Gibbes, S., 2019. Spatial database of planted trees (SDPT version 1.0).

Harrison, P.A., Berry, P.M., Simpson, G., et al., 2014. Linkages between biodiversity attributes and ecosystem services: a systematic review. Ecosyst. Serv. 9, 191–203.

Hill, S.L.L., Gonzalez, R., Sanchez-Ortiz, K., et al., 2018. Worldwide impacts of past and projected future land-use change on local species richness and the biodiversity intactness index. BioRxiv. https://doi.org/10.1101/311787.

Hill, S.L., Arnell, A., Maney, C., et al., 2019. Measuring forest biodiversity status and changes globally. Front. For. Glob. Change 2, 70. https://doi.org/10.3389/ffgc.2019.00070.

Hudson, L.N., Newbold, T., Contu, S., et al., 2017. The database of the PREDICTS (projecting responses of ecological diversity in changing terrestrial systems) project. Ecol. Evol. 7 (1), 145–188.

Ichii, K., Molnar, Z., Obura, D., et al., 2019. IPBES Global Assessment Report on Biodiversity and Ecosystem Services, Chapter 2.2 Status and Trends – Nature. In: IPBES Global Assessment Report. IPBES.

IFC (International Finance Corporation), 2012. Performance Standard 6: Biodiversity Conservation and Sustainable Management of Living Natural Resources.

Innes, J.B., Blackford, J.J., 2023. Disturbance and succession in early to mid-Holocene northern English forests: palaeoecological evidence for disturbance of woodland ecosystems by Mesolithic hunter-gatherers. Forests 14 (4), 719. https://doi.org/10.3390/f14040719.

IPBES glossary, 2023. Accessed June 2023. https://www.ipbes.net/glossary.

Keeley, A.T.H., Beier, P., Jenness, J.S., 2021. Connectivity metrics for conservation planning and monitoring. Biol. Conserv. 255, 109008. https://doi.org/10.1016/j.biocon.2021.109008.

Keith, D.A., Ferrer-Paris, J.R., Nicholson, E., Kingsford, R., 2020. IUCN Global Ecosystem Typology 2.0. IUCN, Swizerland.

Kennedy, C.M., Oakleaf, J.R., Theobald, D.M., Baruch-Mordo, S., Kiesecker, J., 2019. Managing the middle: a shift in conservation priorities based on the global human modification gradient. Glob. Chang. Biol. 25 (3), 811–826. https://doi.org/10.1111/gcb.14549.

Kissling, W.D., Shi, Y., 2023. Which metrics derived from airborne laser scanning are essential to measure the vertical profile of ecosystems? Divers. Distrib. 29 (10), 1315–1320. https://doi.org/10.1111/ddi.13760.

Kohler, F., Kotiaho, J., Navarro, L., Desrousseaux, M., Wegner, G., Bhagwat, S., Reid, R., Wang, T., 2018. Chapter 2: concepts and perceptions of land degradation and restoration. In: Montanarella, L., Scholes, R., Brainich, A. (Eds.), IPBES assessment report on land degradation and restoration. Secretariat of the intergovernmental science-policy platform on biodiversity and ecosystem services, Bonn, Germany, pp. 53–134.

Le Provost, G., Schenk, N.V., Penone, C., et al., 2023. The supply of multiple ecosystem services requires biodiversity across spatial scales. Nat. Ecol. Evol. 7 (2), 236–249. https://doi.org/10.1038/s41559-022-01918-5.

Leopold, A., 1949. A Sand County Almanac. Oxford University Press, USA, Oxford and New York.

Lewis, S.L., Lopez-Gonzalez, G., Sonké, B., Affum-Baffoe, K., Baker, T.R., Ojo, L.O., Phillips, O.L., Reitsma, J.M., White, L., Comiskey, J.A., Ewango, C.E., 2009. Increasing carbon storage in intact African tropical forests. Nature 457 (7232), 1003–1006.

Listopad, C.M., Köbel, M., Príncipe, A., Gonçalves, P., Branquinho, C., 2018. The effect of grazing exclusion over time on structure, biodiversity, and regeneration of high nature value farmland ecosystems in Europe. Sci. Total Environ. 610, 926–936.

Lloyd, C.T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F.R., Tatem, A. J., 2019. Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. Big Earth Data 3 (2), 108–139. https://doi.org/10.1080/20964471.2019.1625151.

Loh, J., Green, R.E., Ricketts, T., Lamoreux, J., Jenkins, M., Kapos, V., Randers, J., 2005. The Living Planet Index: using species population time series to track trends in biodiversity. Phil. Trans. R. Soc. B 360 (1454), 289–295. https://doi.org/10.1098/rstb.2004.1584.

Mair, L., Bennun, L.A., Brooks, T.M., et al., 2021. A metric for spatially explicit contributions to science-based species targets. Nat. Ecol. Evol. 5 (6), 836–844.

Malhi, Y., Doughty, C., Galbraith, D., 2011. The allocation of ecosystem net primary productivity in tropical forests. Philos. Trans. R. Soc. B 366, 3225–3245.

Martin, T.G., Watson, J.E.M., 2016. Intact ecosystems provide best defence against climate change. Nat. Clim. Chang. 6 (2), 122–124. https://doi.org/10.1038/nclimate2918.
Mayer, A., Kaufmann, L., Kalt, G., et al., 2021. Applying the human appropriation of net primary production framework to map provisioning ecosystem services and their relation to ecosystem functioning across the European Union. Ecosyst. Serv. 51, 101344.
McElhinny, C., Gibbons, P., Brack, C., 2006. An objective and quantitative methodology for constructing an index of stand structural complexity. For. Ecol. Manag. 235 (1), 54–71. https://doi.org/10.1016/j.foreco.2006.07.024.
McGarigal, K., Compton, B.W., Plunkett, E.B., DeLuca, W.V., Grand, J., Ene, E., Jackson, S.D., 2018. A landscape index of ecological integrity to inform landscape conservation. Landsc. Ecol. 33 (7), 1029–1048.
Meijer, J.R., Huijbregts, M.A., Schotten, K.C., Schipper, A.M., 2018. Global patterns of current and future road infrastructure. Environ. Res. Lett. 13 (6), 064006.
Mello, K.D., Valente, R.A., Randhir, T.O., Vettorazzi, C.A., 2018. Impacts of tropical forest cover on water quality in agricultural watersheds in southeastern Brazil. Ecol. Indic. 93, 1293–1301.
Mohamed, A., DeClerck, F., Verburg, P.H., et al., 2024. Securing nature's contributions to people requires at least 20%–25% (semi-)natural habitat in human-modified landscapes. One Earth 7 (1), 59–71. https://doi.org/10.1016/j.oneear.2023.12.008.
Morand, S., 2020. Emerging diseases, livestock expansion and biodiversity loss are positively related at global scale. Biol. Conserv. 248. https://doi.org/10.1016/j.biocon.2020.108707.
Moudrý, V., Cord, A.F., Gábor, L., et al., 2023. Vegetation structure derived from airborne laser scanning to assess species distribution and habitat suitability: the way forward. Divers. Distrib. 29 (1), 39–50. https://doi.org/10.1111/ddi.13644.
Newbold, T., Hudson, L.N., Arnell, A.P., et al., 2016. Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. Science 353 (6296), 288–291. https://doi.org/10.1126/science.aaf2201.
Noss, R.F., 1990a. Can we maintain biological and ecological integrity? Conserv. Biol. 4 (3), 241–243.
Noss, R.F., 1990b. Indicators for monitoring biodiversity: a hierarchical approach. Conserv. Biol. 4, 355–364.
Orgiazzi, A., Bardgett, R.D., Barrios, E., et al. (Eds.), 2016. Global Soil Biodiversity Atlas. Publications Office of the European Union, Luxembourg, European Commission, p. 176.
Ouédraogo, O., Bondé, L., Boussim, J.I., Linstädter, A., 2015. Caught in a human disturbance trap: responses of tropical savanna trees to increasing land-use pressure. For. Ecol. Manag. 354, 68–76.
Parrish, J.D., Braun, D.P., Unnasch, R.S., 2003. Are we conserving what we say we are? Measuring ecological integrity within protected areas. Bioscience 53, 851–860.
Pettorelli, N., Schulte to Bühne, H, Tulloch, A., et al., 2018. Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sens. Ecol. Conserv. 4 (2), 71–93. https://doi.org/10.1002/rse2.59.
Potapov, P., Hansen, M.C., Pickens, A., et al., 2022. The global 2000-2020 land cover and land use change dataset derived from the Landsat archive: first results. Front. Remote Sensing. https://doi.org/10.3389/frsen.2022.856903.
Potts, M.D., Holland, T., Erasmus, B.F.N., Et al., S., 2018. Chapter 5: land degradation and restoration associated with changes in ecosystem services and functions, and human well-being and good quality of life. In: Montanarella, L., Scholes, R., Brainich, A. (Eds.), IPBES assessment report on land degradation and restoration. Secretariat of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, Bonn, Germany, pp. 341–432.
Regan, H.M., Colyvan, M., Burgman, M.A., 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecol. Appl. 12 (2), 618–628.
Richardson, K., Steffen, W., Lucht, W., et al., 2023. Earth beyond six of nine planetary boundaries. Sci. Adv. 9 (37), eadh2458.
Rockström, J., Gupta, J., Qin, D., Lade, S.J., Abrams, J.F., Andersen, L.S., Armstrong McKay, D.I., Bai, X., Bala, G., Bunn, S.E., Ciobanu, D., 2023. Safe and just earth system boundaries. Nature 619 (7968), 102–111.
Rodríguez, J.P., Keith, D.A., Rodríguez-Clark, K.M., et al., 2015. A practical guide to the application of the IUCN red list of ecosystems criteria. Philos. Trans. R. Soc. B Biol. Sci. 370 (1662), 20140003.\z+.
Rogers, B.M., Mackey, B., Shestakova, T.A., et al., 2022. Using ecosystem integrity to maximize climate mitigation and minimize risk in international Forest policy. Front. Forests Global Change 5. https://doi.org/10.3389/ffgc.2022.929281.
Running, S.W., Zhao, M., 2019. Daily GPP and annual NPP (MOD17A2H/A3H) and year-end gap- filled (MOD17A2HGF/A3HGF) products NASA earth observing system MODIS land algorithm (for collection 6). MODIS Land Team, Version 4 (2), 35.
Sayre, R., Karagulle, D., Frye, C., Boucher, T., Wolff, N.H., Breyer, S., Wright, D., Martin, M., Butler, K., Van Graafeiland, K., Touval, J., 2020. An assessment of the representation of ecosystems in global protected areas using new maps of world climate regions and world ecosystems. Global Ecology Conservation 21, e00860.
Siipi, H., 2004. Naturalness in Biological conservation. J. Agric. Environ. Ethics 17 (6), 457–477. https://doi.org/10.1007/s10806-004-1466-1.
Staudhammer, C.L., LeMay, V.M., 2001. Introduction and evaluation of possible indices of stand structural diversity. Can. J. For. Res. 31 (7), 1105–1115. https://doi.org/10.1139/x01-033.
Steffen, W., Richardson, K., Rockström, J., et al., 2015. Planetary boundaries: guiding human development on a changing planet. Science 347 (6223), 1259855.
Sun, T., Hughes, A.C., He, K., et al., 2026. Ecological integrity index, timely annual tracking of biodiversity change. Sci. Data 13, 174. https://doi.org/10.1038/s41597-025-06485-5.
Theobald, D.M., Harrison-Atlas, D., Monahan, W.B., Albano, C.M., 2015. Ecologically-relevant maps of landforms and physiographic Diversity for climate adaptation planning. PLoS One 10 (12), e0143619. https://doi.org/10.1371/journal.pone.014361.
Tierney, G.L., Faber-Langendoen, D., Mitchell, B.R., Shriver, W.G., Gibbs, J.P., 2009. Monitoring and evaluating the ecological integrity of forest ecosystems. Front. Ecol. Environ. 7 (6), 308–316.
TNFD, 2023. Task force on nature-related financial disclosures. Guidance on the identification and assessment of nature-related issues: the LEAP approach.
Trase, 2019. Transparent supply chains for sustainable economies (Trase). Available at: www.trase.earth.
UNEP-WCMC, IUCN, 2022. Protected Planet: The World Database on Protected Areas (WDPA) June 2022. UNEP-WCMC and IUCN, Cambridge, UK. Available at: www.protectedplanet.net.
United Nations Committee of Experts on Environmental-Economic Accounting, 2021. System of Environmental-Economic Accounting - Ecosystem Accounting, Background Document Submitted to United Nations Statistical Commission, February 2021. United Nations, New York.
Venter, O., Sanderson, E.W., Magrach, A., et al., 2016. Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. Nat. Commun. 7 (1), 1–11.
Vyvlečka, P., Pechanec, V., 2023. Optical Remote Sensing in Provisioning of Ecosystem-Functions Analysis—Review. Sensors 23 (10), 4937. https://doi.org/10.3390/s23104937.
Winkler, K., Fuchs, R., Rounsevell, M., Herold, M., 2021. Global land use changes are four times greater than previously estimated. Nature communications 12 (1), 2501.
Zelený, J., Mercado-Bettín, D., Müller, F., 2021. Towards the evaluation of regional ecosystem integrity using NDVI, brightness temperature and surface heterogeneity. Sci. Total Environ. 796, 148994.
Zenner, E.K., Hibbs, D.E., 2000. A new method for modeling the heterogeneity of forest structure. For. Ecol. Manag. 129 (1), 75–87. https://doi.org/10.1016/S0378-1127(99)00140-1.
Zomer, R.J., Xu, J., Trabucco, A., 2022. Version 3 of the Global Aridity Index and Potential Evapotranspiration Database. Scientific Data 9 (1), 409. https://doi.org/10.1038/s41597-022-01493-1.
Zuur, A.F., Ieno, E.N., Saveliev, A.A., 2009. Mixed Effects Models and Extensions in Ecology with R. Springer, New York.