Only 40% of the world's forests are in good health

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Abstract: Many global environmental agendas, including halting biodiversity loss, reversing land degradation, and limiting climate change, depend upon retaining forests with high ecological integrity, yet the scale and degree of forest modification remains poorly quantified and mapped.

By integrating data on direct and indirect forest pressures and lost forest connectivity, we generate the first globally-consistent, continuous index of forest condition as determined by degree of anthropogenic modification, which we term 'forest health'. Globally, only 17.4 million km^2 of forest (40.5%) can be considered in high health (mostly found in Canada, Russia, the Amazon, Central Africa and New Guinea) and only 27% of this area is found in nationally-designated protected areas. Of all the world's forests found within protected areas, only 56% can be considered in high health. Ambitious policies that prioritize the retention of forest health are now urgently needed alongside current efforts aimed at restoring the health of forests globally.

MAIN TEXT

Introduction

Deforestation is a major environmental issue (*1*), but far less attention has been given to the degree of anthropogenic modification of remaining forests, which diminishes many of the benefits that these forests provide (*2, 3*). This is worrying since modification is potentially as significant as outright forest loss in determining overall environmental outcomes (*4*). There is increasing recognition of this issue, for forests and other ecosystems, in synthesis reports by global science bodies (e.g. *5*), and it is now essential that the scientific community develop improved tools and data to facilitate the consideration of the degree of forest modification in decision-making. Mapping and monitoring this globally will provide essential information for coordinated global, national and local policy-making, planning and action, to help nations and other stakeholders achieve the Sustainable Development Goals (SDGs) and implement other shared commitments such as the United Nations Convention on Biological Diversity (CBD), Convention to Combat Desertification (UNCCD), and Framework Convention on Climate Change (UNFCCC).

Ecosystem integrity is foundational to all three of the Rio Conventions (UNFCCC, UNCCD, CBD). As defined by Parrish *et al.* (*6*), it is essentially the degree to which a system is free from anthropogenic modification of its structure, composition and function. Such modification causes the degradation of many ecosystem benefits, and is often also a precursor to outright deforestation (*7, 8*). Forests largely free of significant forest modification (i.e. forests having high ecosystem integrity), typically provide higher levels of many forest benefits than modified forests of the same type (*9*), including; carbon sequestration and storage (*10*), healthy watersheds (*11*), traditional homelands for imperiled cultures (*12*), contribution to local and regional climate processes (*13*), and forest-dependent biodiversity (*14-17*). Industrial-scale logging, fragmentation by infrastructure, farming (including cropping and ranching) and urbanization, as well as less visible forms of modification such as over-hunting, wood fuel extraction and changed fire or hydrological regimes (*18, 19*), all degrade the degree to which forests still support these benefits, as well as their long-term resilience to climate change (*9*). There can be trade-offs however, between the benefits provided by less-modified forests (e.g., carbon sequestration) and those production services that require some modification (e.g., timber production). These trade-offs can, at times, result in disagreement among stakeholders as to which forest benefits are, or should be, prioritized (*20*).

In recent years, easily accessible satellite imagery and new analytical approaches have dramatically improved our ability to map and monitor forest extent globally (*21-23*). However, while progress has been made in developing tools for assessment of global forest losses and gains, consistent monitoring of the degree of forest modification has proved elusive (*24, 25*). Technical challenges include the detection of low intensity and unevenly distributed forest change, the wide diversity of changes that comprise forest modification, and the fact that many changes are concealed by the forest canopy (*24*). New approaches are emerging on relevant forest indicators, such as canopy height, canopy cover and fragmentation, and maps of different human pressures, which are used as proxies for impacts on forests (e.g., *26, 27, 28*). Some binary measures of forest modification, such as Intact Forest Landscapes (*29*) and wilderness areas (*30*), have also been mapped at the global scale and used to inform policy, but do not resolve the degree of modification within remaining forests, which we aimed to do with this assessment.

Human activities influence the degree of forest modification at multiple spatial scales, including intense, localized modifications such as road-building and canopy loss, more diffuse forms of change that are often spatially associated with these localized pressures (e.g. increased accessibility for hunting and selective logging), and changes in spatial configuration that alter landscape-level connectivity. Previous studies have quantified several of these aspects individually (e.g. *26, 27, 28*), but there is a need to integrate them to measure and map the overall degree of modification. Here, we integrate data on highly localized ('direct') human pressures, the associated but more diffuse 'indirect' human pressures, and alterations in forest connectivity, to create an index that we refer to as the "Forest Health Index" (FHI), that describes the degree of forest modification for 2019. The result is the first globally applicable, continuous-measure map of forest health, which offers a timely indicator of the status and management needs of Earth's remaining forests, as well as a flexible methodological framework (Fig. 1) for measuring changes in forest health that can be adapted for more detailed analysis at national or subnational scales.

Results

Forest modification caused by human activity is both highly pervasive and highly variable across the globe (Fig. 2). We found 31.2% of forests worldwide are experiencing some form of direct human pressure. Our models also identified indirect pressures and the impacts of lost connectivity in almost every other forest location (91.2% of forests), albeit sometimes at very low levels. Diverse, recognizable patterns of forest health can be observed in maps at a range of scales, depending on the principal forms and general intensity of human activity in an area. Broad regional trends can be readily observed, for example the overall gradient of decreasing human impact moving northwards through eastern North America (Fig. 2), and finer patterns of impact are also clearly evident, down to the scale of individual protected areas, forest concessions, settlements and roads (Fig. S2).

FHI scores range from 0 (lowest health) to 10 (highest). We discretized this range to define three broad illustrative categories: low (≤6.0); medium (>6.0 and <9.6); and high health (≥9.6) (see Methods). Only 40.5% (17.4 million km^2) of forest was classified as having high health (Fig. 3; Table 1). Moreover, even in this category of high health 36% still showed at least a small degree of human modification. The remaining 59% (25.6 million km^2) of forest was classified as having low or medium health, including 25.6% (11 million km^2) with low health (Fig. 3; Table 1). When we analyzed across biogeographical realms (defined by *31*) not a single biogeographical realm of the world had more than half of its forests in the high category (Fig. 3; Table 1).

The biogeographical realms with the largest area of forest in high health are in the Paleartic, particularly northern Russia, and the Neartic, in northern Canada, and Alaska. There are also large areas of forest in high health in the Neotropics, concentrated in the Amazon region, including within the Guianas (Fig. 3, Table 1). The Afrotropic realm has significant areas in high health, particularly within the humid forests of central Africa (e.g., in Republic of Congo and Gabon) and in some of the surrounding drier woodland belts (e.g., in South Sudan, Angola and Mozambique) (Fig. 3). In tropical Asia, the largest tracts of forest in high health are in New Guinea. Smaller but still very significant tracts of forest in high health are also scattered elsewhere in each of the main forested regions, including parts of Sumatra, Borneo, Myanmar and other parts of the greater Mekong subregion, Madagascar, West Africa, Mesoamerica, the Atlantic forests of Brazil, southern Chile, the Rocky Mountains, northern Assam, the Pacific forests of Colombia, the Caucasus, and the Russian Far East (Fig. 3).

Concentrations of forest in low health are found in many regions including west and central Europe, the south-eastern USA, island and mainland South-East Asia west of New Guinea, the Andes, much of China and India, the Albertine Rift, West Africa, Mesoamerica and the Atlantic Forests of Brazil (Fig. 3). The overall extent of forests in low health is greatest in the Paleartic realm, followed by the Neotropics, which are also those biogeographic realms with the largest forest cover (Table 1). The Indo-Malayan realm has the highest percentage in low health, followed by the Afrotropics (Fig. 3; Table 1).

These patterns result in variation in forest health scores at a resolution relevant for policy and management planning, such as at national and sub-national scales. The global average FHI score for all countries is 5.48 representing generally low forest health, and a quarter of forested countries have a national average score < 4. National mean scores vary widely, ranging from >9 in Guyana, French Guiana, Gabon, Sudan and South Sudan to <3 in Sierra Leone and many west European countries (see Fig 4. And Table S5 for full list of countries). Provinces and other sub-national units vary even more widely, in ways that allow objective comparisons to be made between locations (see Fig. S2 and Table S6)

Over one-quarter (26.1%) of all forests in high health fall within protected areas, compared to just 13.1% of low and 18.51% of medium health forests, respectively. For all forests that are found within nationally designated protected areas (around 20% of all forests globally), we found the proportions of low, medium and high health forests were 16.8%, 30.3%, and 52.8% respectively (Table 2). Within the different protected area categories, we typically found that there was more area within the high health category versus the medium and low except for Category V (protected landscape/seascape) (Table 2). However, with 47.1% of forests within protected areas having low to medium health overall, it is clear that forest considered 'protected' are already often fairly modified (Table 2).

Discussion

By providing a transparent and defensible methodological framework, and taking advantage of global data on forest extent, changes in forest connectivity, and human drivers of forest modification, our analysis paints a new, sobering picture of the extent of human impacts on the world's forests. This analysis enables the changes that degrade many forest values *(8)* to be visualized in a new and compelling way and for policy makers and decision makers to see where Earth's remaining forests that are in good condition are. By integrating data on multiple pressures that are known to modify forests, our analysis is the first to move global quantification beyond the use of simple categories to a more nuanced depiction of this issue as a continuum, recognising that not all existing forests are in the same condition. Our analysis reveals that severe and extensive forest modification has occurred across all biogeographic regions of the world. Consequently, indices only using forest extent may inadequately capture the true impact of human activities on forests, and are insensitive to many drivers of forest modification and the resulting losses of forest benefits.

A plan is clearly needed to put in place retention strategies for the remaining forests in high health, tailored towards the context in each country or jurisdiction and its different forest types (*32, 33*), because such areas are known to hold exceptional value. Avoiding modification is a better strategy than aiming to restore forest condition after it is lost, because restoration is more costly, risky, and unlikely to lead to full recovery of benefits (*5*). For the least-modified forests to be retained they should ideally be mapped using nationally appropriate criteria by the countries that hold them, formally recognized, prioritized in spatial plans, and placed under effective management (e.g. protected areas and other effective conservation areas, lands under Indigenous control etc.). These forests must be protected from industrial development impacts that degrade them, and sensible public and private sector policy that is effective at relevant scales is needed (*12, 34*). Our global assessment reveals where these places are found, and can be refined at more local scales where better data are available.

Around a third of global forests had already been cleared by 2000 (*35*), and we show that at least 59% of what remains is in low to medium health, with > 50% falling in these two broad categories in every biogeographical realm. These levels of human modification result partly from the large areas affected by diffuse, anthropogenic edge effects and lost connectivity. We also map a surprising level of more localized direct effects, such as infrastructure and recent forest loss, which are observed in nearly a third of forests worldwide.

Conservation strategies in these human-dominated forests should focus on securing any remaining fragments of forests in good condition, proactively protecting those partially modified forests most vulnerable to further modification (*7*) and planning where restoration efforts might be most effective (*36-38*). In addition, effective management of production forests is needed to sustain yields without further worsening their ecological integrity (*39*). More research is required on how to prioritize, manage, and restore forests in low to medium health (*38, 40*), and the FHI presented here might prove useful for this, for example, by helping prioritize where the best return on investments are, in combination with other sources of data (*41*).

Loss of forest health severely compromises many benefits of forests that are central to achieving many of the Sustainable Development Goals and other societal targets (*42, 43*). Therefore, nations must adopt policies and strategies to retain and restore the ecological health of their forests, whilst ensuring that the solutions are also economically viable, socially equitable, and politically acceptable within complex and highly diverse local contexts. This is an enormous challenge and our efforts to map the degree of forest modification are designed both to raise awareness of the importance of the issue, and to support implementation through target setting, evidence-based planning, and enhanced monitoring efforts.

Whilst policy targets for halting deforestation are generally precise and ambitious, only vague targets are typically stipulated around reducing levels of forest modification (*9, 44*). We urgently need SMART (specific, measurable, achievable, realistic, and time-bound) goals and targets for maintaining and restoring forest health that directly feed into higher-level biodiversity, climate, land degradation, and sustainable development goals (*45*). These types of targets should be included within an over-arching target on ecosystems within the post-2020 Global Biodiversity Framework, which is currently being negotiated among Parties to the CBD (*46*). This target should be outcome-focused and address both the extent and the integrity of ecosystems (e.g. using FHI for forests), in a way that enables quantitative, measurable goals to be set but allows flexibility for implementation between Parties.

In addition to broader goals in global frameworks, the retention and restoration of forest health should also be addressed in nationally-defined goals embodied in, and aligned between, Nationally Determined Contributions under the UNFCCC, efforts to stop land degradation and achieve land degradation neutrality under the UNCCD, and National Biodiversity Strategy and Action Plans under the CBD. Since no single metric can capture all aspects of a nation's environmental values, efforts to conserve high levels of forest health should be complemented by consideration of areas support important values according to other measures (e.g. Key Biodiversity Areas (*47*) and notable socio-cultural landscapes).

The overall level and pervasiveness of impacts on Earth's remaining forests is likely even more severe than our findings suggest, because some input data layers, despite being the most comprehensive available, are still incomplete as there are lags between increases in human pressures and our ability to capture them in spatial datasets (e.g., infrastructure, *48, 49, see also Fig. S1 and text S5*). For example, roads and seismic lines used for natural resource exploration and extraction in British Columbia, Canada, are not yet fully reflected in global geospatial datasets (Fig. S1; see also *50*). Furthermore, because natural fires are such an important part of the ecology of many forest systems (e.g. boreal forests) and because we cannot consistently identify anthropogenic fires from natural fires at a global scales (*51*) we have taken a strongly conservative approach to fire in our calculations, treating all tree cover loss in 10 km pixels where fire was the dominant driver *(23)* as temporary, and not treating such canopy loss as evidence of direct human pressure. Varying these assumptions where human activity is shown to be causing permanent tree cover losses, increasing fire return frequencies, or causing fire in previously fire-free systems would result in lower forest extent and/or lower forest health scores in some regions than we report.

We map forest health based on quantifiable processes over the recent past (since 2000). In some areas, modification that occurred prior to this is not detectable by our methods yet, and may have influenced the present-day modification of the forest and, in such cases, we may overestimate forest health (e.g. historical logging). This is another reason why our index should be considered as conservative, and we therefore recommend that the index be used alongside other lines of evidence to determine the absolute level of ecological integrity of a given area. Moreover, the definition of forest in this study is all woody vegetation taller than 5 m, following (*22*) and hence includes not only naturally regenerated forests but also tree crops, planted forests, wooded agroforests and urban tree cover in some cases. Users should be mindful of this when interpreting the results, especially when observing areas with low health scores. Inspection of the results for selected countries with reliable plantation maps (*52*) shows that the great majority of planted forests have low health scores, because they are invariably associated with dense infrastructure, frequent canopy replacement and patches of farmland.

We note our measure of forest health does not address past, current and future climate change. As climate change affects forest condition both directly and indirectly, this is a clear shortfall and needs research attention. The same is true for invasive species, as there is no globally coherent data on the range of those invasive species that degrade forest ecosystems, although this issue is indirectly addressed since the presence of many invasive species which are spatially correlated with the human pressures that we use as drivers in our model (*53*). If global data became available it would also be valuable to incorporate governance effectiveness into our model, because there are potentially contexts (e.g. well-managed protected areas and community lands, production forests under ‘sustainable forest management’) where the impacts associated with the human pressures we base our map on are at least partially ameliorated (*39*), and enhanced governance is also likely to be a significant component of some future strategies to maintain and enhance forest health.

The framework we present has great potential to be tailored for use at smaller scales, ranging from regional to national and sub-national scales, and even to individual management units. Forest definitions and the relative weights of the global parameters we use can be adjusted to fit local contexts and, in many cases, better local data could be substituted, or additional variables incorporated. This would increase the precision of the index in representing local realities, and increase the degree of ownership amongst national and local stakeholders whose decisions are so important in determining forest management trajectories.

Materials and Methods

To produce our global Forest Health Index (FHI), we combined four sets of spatially explicit datasets representing: (i) forest extent (*22*); (ii) direct pressure from high impact, localized human activities, specifically: infrastructure, agriculture, and recent deforestation (*53*); (iii) indirect pressure associated with edge effects (*54*), and other diffuse processes, (e.g. activities such as hunting and selective logging) (*55*) modelled using proximity to direct pressures; and iv) anthropogenic changes in forest connectivity due to forest loss (*56 see Table S1 for data sources*). These datasets were combined to produce an index score for each forest pixel (300m), with the highest scores reflecting the highest forest health (Fig 1), and applied to forest extent for the start of 2019. We use globally consistent parameters for all elements (i.e. parameters do not vary geographically). All calculations were conducted in Google Earth Engine (GEE) (*57*).

Forest extent

We derived a global forest extent map for 2019 by subtracting from the Global Tree Cover product for 2000 (*22*) annual Tree Cover Loss 2001-2018, except for losses categorized by Curtis and colleagues (*23*) as those likely to be temporary in nature (i.e. those due to fire, shifting cultivation and rotational forestry). We applied a canopy threshold of 20% (based on related studies e.g. *29, 58*) and resampled to 300m resolution and used this resolution as the basis for the rest of the analysis (see text S1 for further mapping methods).

Direct human pressures

We quantify direct human pressures (P) within a pixel as the weighted sum of impact of infrastructure (I; representing the combined effect of 41 types of infrastructure weighted by their estimated general relative impact on forests (Table S3), agriculture (A) weighted by crop intensity (indicated by irrigation levels), and recent deforestation over the past 18 years (H; excluding deforestation from fire, see Discussion). Specifically, for pixel i:

$$P_i = \exp(-\beta_1 I_i) + \exp(-\beta_2 A_i) + \exp(-\beta_3 H_i)$$

whereby the values of β were selected so that the median of the non-zero values for each component was 0.75. This use of exponents is a way of scaling variables with non-commensurate units so that they can be combined numerically, while also ensuring that the measure of direct pressure is sensitive to change (increase or decrease) in the magnitude of any of the three components, even at large values of I, A or H. This is an adaptation of the 'Human Footprint' methodology (*53*). See text S3 for further details.

Proximity (indirect) pressures

Indirect pressures are the diffuse, non-localized effects of a set of processes that includes microclimate and species interactions relating to the creation of forest edges (*59*) and a variety of intermittent or transient anthropogenic pressures such as: selective logging, fuelwood collection, hunting; spread of fires and invasive species, pollution, and livestock grazing (*55, 60, 61*). We modelled the collective, cumulative impacts of these proximity effects through their spatial association with direct human pressure in nearby pixels, including a decline in effect intensity according to distance, and a partitioning into stronger short-range and weaker long-range effects. The indirect pressure (P') on pixel *i* from source pixel *j* is:

$$P'_{i,j} = P_j \, (w_{i,j} + v_{i,j})$$

where $w_{i,j}$ is the weighting given to the modification arising from short-range pressure, as a function of distance from the source pixel, and $v_{i,j}$ is the weighting given to the modification arising from long-range pressures.

Short-range effects include most of the processes listed above, which together potentially affect most biophysical features of a forest, and predominate over shorter distances. In our model they decline exponentially, approach zero at 3 km, and are truncated to zero at 5 km (see text S4).

$$w_{i,j} = \alpha \exp(-\lambda \times d_{i,j}) \qquad [\text{for } d_{i,j} \leq 5 \text{ km}]$$

$$w_{i,j} = 0 \qquad [\text{for } d_{i,j} > 5 \text{ km}]$$

where α is a constant set to ensure that the sum of the weights across all pixels in range is 1.85 (see below), λ is a decay constant set to a value of 1 (see (*62*) and other references in text S4) and $d_{i,j}$ is the Euclidean distance between the centres of pixels *i* and *j* expressed in units of km.

Long-range effects include over-harvest of high socio-economic value animals and plants, changes to migration and ranging patterns, and scattered fire and pollution events. We modelled long-range effects at a uniform level at all distances below 6 km and they then decline linearly with distance, conservatively reaching zero at a radius of 12 km (*55, 63 and other references in text S4*):

$$v_{i,j} = \gamma \qquad [\text{for } d_{i,j} \leq 6 \text{ km}]$$

$$v_{i,j} = \gamma \times (12 - d_{i,j})/6 \qquad [\text{for } 6 \text{ km} < d_{i,j} \leq 12 \text{ km}]$$

$$v_{i,j} = 0 \qquad [\text{for } d_{i,j} > 12 \text{ km}]$$

Where γ is a constant set to ensure that the sum of the weights across all pixels in range is 0.15 and $d_{i,j}$ is the Euclidean distance between the centres of pixels *i* and *j*, expressed in kilometres.

The form of the weighting functions for short- and long-range effects and the sum of the weights (α+γ) were specified based on a hypothetical reference scenario where a straight forest edge is adjacent to a large area with uniform human pressure, and ensuring that in this case total indirect pressure immediately inside the forest edge is equal to the pressure immediately outside, before declining with distance. γ is set to 0.15 to ensure that the long-range effects conservatively contribute no more than 5% to the final index in the same scenario, based on expert opinion and supported e.g. Berzaghi *et al.* (*64*) regarding the approximate level of impact on values that would be affected by severe defaunation and other long-range effects.

The aggregate effect from indirect pressures (P') on pixel i from all n pixels within range ($j=1$ to $j=n$) is then the sum of these individual, normalized, distance-weighted pressures, i.e.

$$P'_i = \Sigma_{[j=1 \ldots n]} P'_{i,j}$$

Loss of forest connectivity

Average connectivity of forest extent around a pixel was quantified using a method adapted from Beyer *et al.* (*56*). The connectivity Ci around pixel i surrounded by n other pixels within the maximum radius (numbered j=1, 2…n) is given by:

$$C_i = \Sigma_{[j=1 \ldots n]} (F_j G_{i,j})$$

where Fj is the forest extent is a binary variable indicating if forested (1) or not (0) and Gi,j is the weight assigned to the distance between pixels i and j. Gi,j uses a normalized Gaussian curve, with $\sigma = 20$km and distribution truncated to zero at 4σ for computational conveniences (see text S3). The large value of σ captures landscape connectivity patterns operating at a broader scale than processes captured by other data layers. C_i ranges from 0 to 1 ($C_i \in [0,1]$).

Current Configuration (CC_i) of forest extent in pixel i was calculated using the final forest extent map and compared to the Potential Configuration (PC) of forest extent without extensive human modification, so that areas with naturally low connectivity, e.g. coasts, are not penalized. PC was calculated from a modified version of the map of Laestadius *et al.* (*35*) and resampled to 300 m resolution (see text S2 for details). Using these two measures, we calculated Lost Forest Configuration (LFC) for every pixel as:

$$LFC_i = 1 - (CC_i/PC_i)$$

Values of CC_i/PC_i >1 are assigned a value of 1 to ensure that LFC is not sensitive to apparent increases in forest connectivity due to inaccuracy in estimated potential forest extent – low values represent least loss, high values greatest loss ($LFC_i \in [0,1]$).

Calculating the Forest Health Index

The three constituent metrics, LFC, P and P', all represent increasingly modified conditions the larger their values become. To calculate a health index in which larger values represent less degraded conditions we therefore subtract the sum of those components from a fixed large value (here, 3). Three was selected as our assessment indicates that values of LFC + P + P' of 3 or more indicate the most severely degraded areas with losses in many forest benefits. The metric is also rescaled to a convenient scale (0-10) by multiplying by an arbitrary constant (10/3). The forest health index for forest pixel *i* is thus calculated as:

$$FHI_i = [10/3] * (3 - \min(3, [P_i + P'_i + LFC_i]))$$

where FHI_i ranges from 0 - 10, areas with no modification detectable using our methods scoring 10 and those with the most (that remain classified as forest) scoring 0.

Illustrative forest health classes

Whilst a key strength of the index is its continuous nature, the results can also be categorized for a range of purposes. In this paper three illustrative classes were defined, mapped and summarized to give an overview of broad patterns of modification in the world's forests. The three categories were defined as follows.

High Forest Health (scores ≥9.6) Interiors and natural edges of more or less unmodified naturally-regenerated forest ecosystems, comprised entirely or almost entirely of native species, occurring over large areas either as continuous blocks or natural mosaics with non-forest vegetation; typically little human use other than low intensity recreation or spiritual uses and/or low intensity extraction of plant and animal products and/or very sparse presence of infrastructure; key ecosystem functions such as carbon storage, biodiversity and watershed protection and resilience expected to be very close to natural levels (excluding any effects from climate change) although some declines possible in the most sensitive elements (e.g. some high value hunted species).

Medium Forest Health (scores >6.0 but <9.6) Interiors and natural edges of naturally-regenerated forest ecosystems in blocks smaller than their natural extent but large enough to have some core areas free from strong anthropogenic edge effects (e.g. set asides within forestry areas, fragmented protected areas), dominated by native species but substantially modified by humans through a diversity of processes that could include fragmentation, creation of edges and proximity to infrastructure, moderate or high levels of extraction of plant and animal products, significant timber removals, scattered stand-replacement events such as swidden and/or moderate changes to fire and hydrological regimes; key ecosystem functions such as carbon storage, biodiversity, watershed protection and resilience expected to be somewhat below natural levels (excluding any effects from climate change).

Low Forest Health (score ≤6.0): Diverse range of heavily modified and often internally fragmented ecosystems dominated by trees, including (i) naturally regenerated forests, either in the interior of blocks or at edges, that have experienced multiple strong human pressures, which may include frequent stand-replacing events, sufficient to greatly simplify the structure and species composition and possibly result in significant presence of non-native species, (ii) tree plantations and, (iii) agroforests; in all cases key ecosystem functions such as carbon storage, biodiversity, watershed protection and resilience expected to be well below natural levels (excluding any effects from climate change).

The numerical category boundaries were derived by inspecting FHI scores for a wide selection of example locations whose health according to the category definitions was known to the authors, see text S6 and Table S4.

Protected areas analysis

Data on protected area location, boundary, and year of inscription were obtained from the February 2018 World Database on Protected Areas (*65*). Following similar global studies (e.g. *66*), we extracted protected areas from the WDPA database by selecting those areas that have a status of "designated", "inscribed", or "established", and were not designated as UNESCO Man and Biosphere Reserves. We included only protected areas with detailed geographic information in the database, excluding those represented as a point only. To assess health of protected forest, we extracted all 300m forest pixels that were at least 50% covered by a formal protected area and measured the average FHI score.

H2: Supplementary Materials

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Author contributions: Conceived and design the study: HG, TE and JEW, collected data and developed the model: AD, HG, TE, HB, RS, analyzed and interpreted the results: AD, HG, TE, HB, RS, KJ, JEW, wrote draft manuscript: HG, TE and JEW, contributed to the writing of the manuscript: all co-authors.

Competing interests: There are no competing interests

Data and materials availability: Data will be available for download when published.

Figures and Tables

Table 1. A summary of the Forest Health Index scores for each biogeographic realm globally, measuring the mean score, in addition to the area and proportion of realm for each category of health. Scores are divided into three categories of health: high, medium and low.

Table 2. A summary of the Forest Health Index scores for each type of protected area designation based on the IUCN Protected Areas categories measuring mean score, in addition to the area and proportion of realm for each category of health. Scores are divided into three categories of health: high, medium and low.

Figure 1. The Forest Health Index was constructed based on three main data inputs: 1) direct pressures (infrastructure, agriculture, tree cover loss), 2) indirect forest pressure (based on proximity to the direct pressures), and change in forest connectivity.

Figure 2. A global map of Forest Health for 2019. Three regions are highlighted including A) USA, B) Equatorial Guinea C) Myanmar. For a) shows the edge of Smoky Mountains National Park in Tennessee b) shows a logging truck passing through some partially degraded forest along a newly constructed highway in Shan State, c) An intact mangrove forest within Reserva Natural del Estuario del Muni, near the border of Gabon. The star indicates approximately where the photos were taken (A2, B2 and C2).

Figure 3. The Forest Health Index for 2019 categorized into three broad, illustrative classes and mapped for across each biogeographic realm (A – G). The size of the pie charts indicates the relative size of the forests within each realm (A - G), and H shows all the world's forest combined.

Figure 4. The Forest Health Index for 2019 categorized into three broad, illustrative classes for each major forested country in the world. (A) countries with a forest extent larger than 1 million km^2, and (B) countries with forest extent between 1 million km^2 and 100,000 km^2 of forest. The size of the bar represents the area of a country's forests.

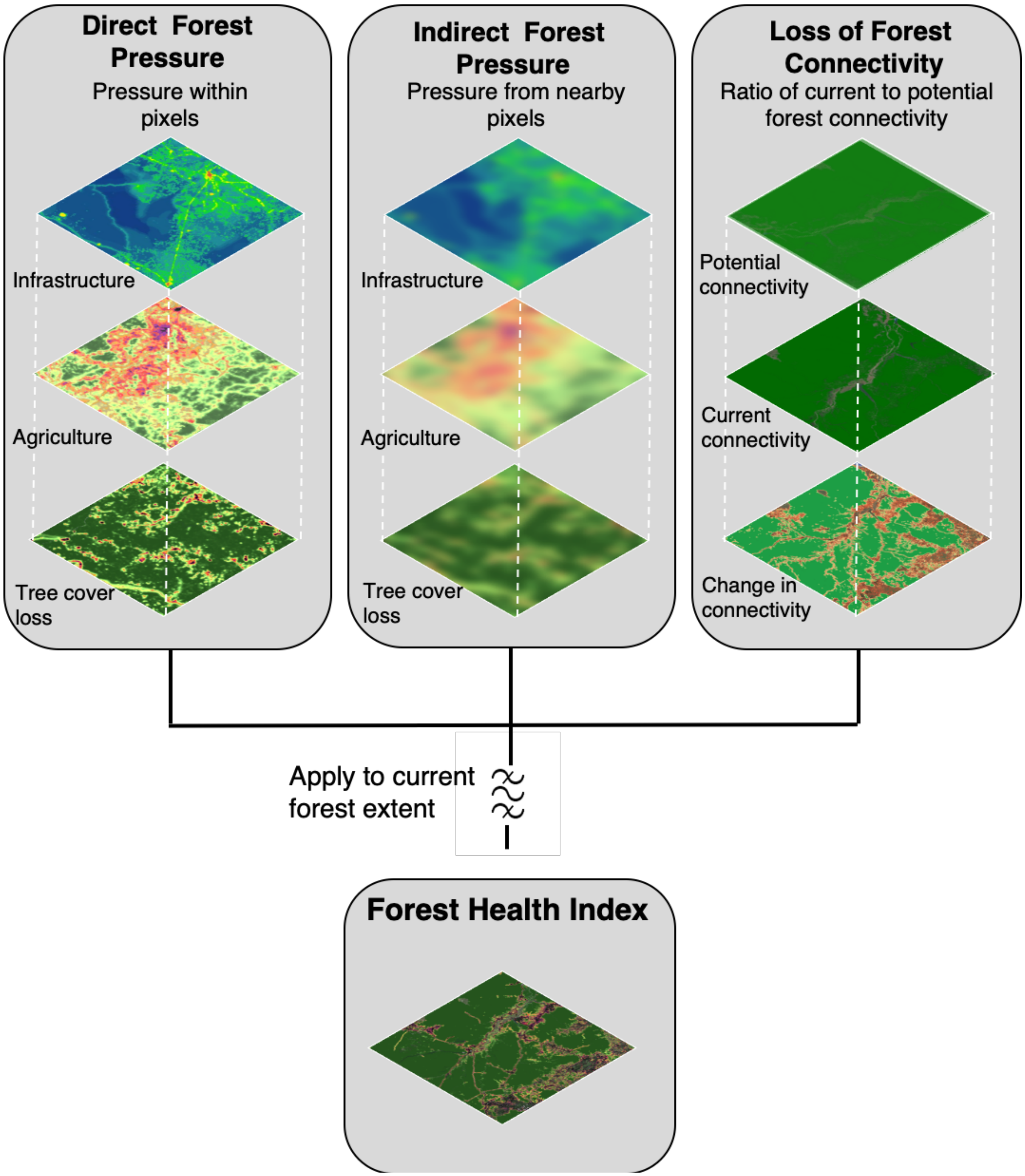
Table 1

Biogeographic Realm	**Total forest**	**FHI**	**High (9.6 - 10)**		**Medium (6 – 9.6)**		**Low (0 - 6)**	
	Km²	*Mean*	*Km²*	*% of realm*	*Km²*	*% of realm*	*Km²*	*% of realm*
Afrotropic	7,362,740	7.34	2,450,953	33.3	2,903,483	39.4	2,008,304	27.3
Australasia	1,711,684	8.05	656,701	38.4	753,188	44.0	301,796	17.6
Indo-malayan	3,596,249	5.9	420,977	11.7	1,599,049	44.5	1,576,223	43.8
Neotropic	10,271,519	7.81	4,579,406	44.6	3,122,706	30.4	2,569,407	25.0
Oceania	23,389	7.66	5,279	22.6	14,331	61.3	3,780	16.2
Palearctic	12,172,668	8	5,571,997	45.8	3,910,629	32.1	2,690,042	22.1
Nearctic	7,794,117	7.84	3,716,855	47.7	2,257,518	29.0	1,819,744	23.3
Total	42,932,367	7.76	17,402,170		14,560,903		10,969,294	

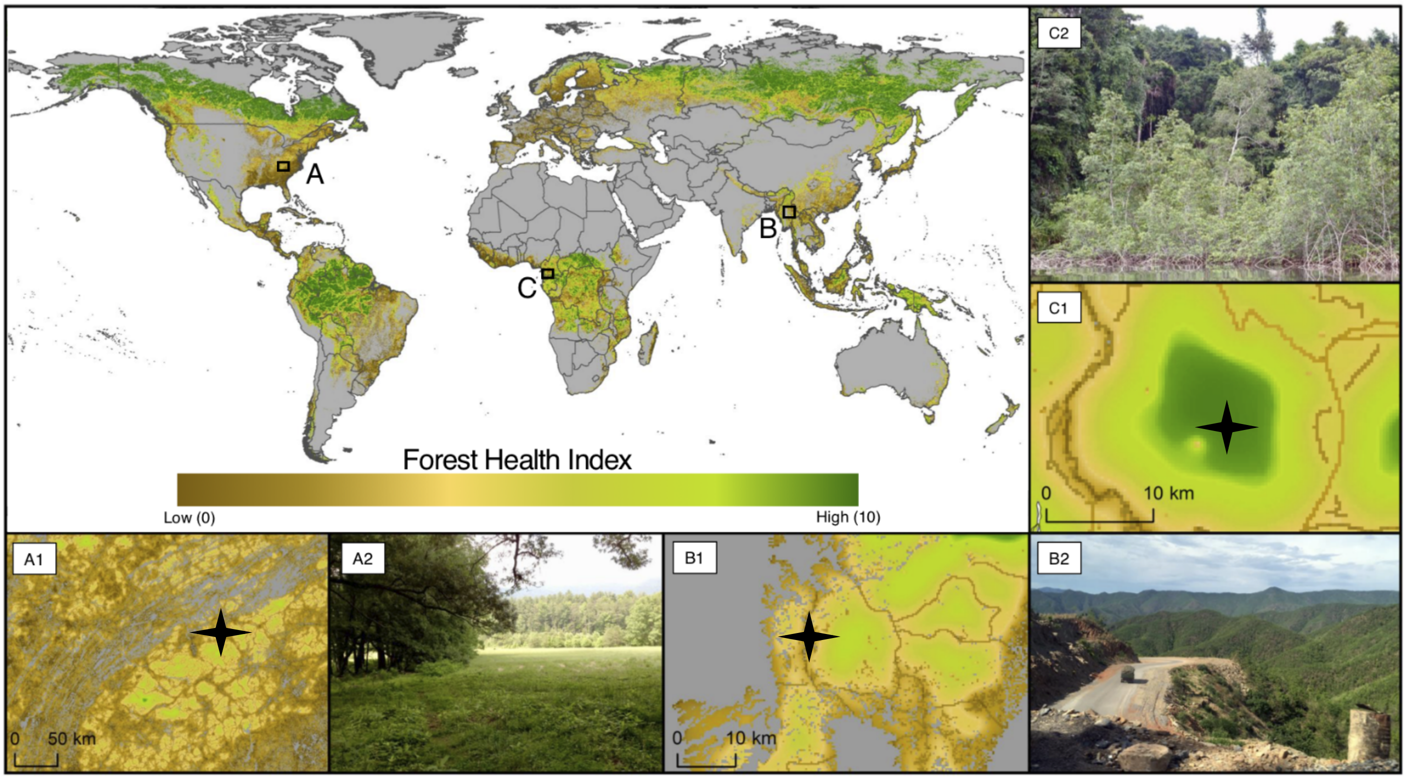
Table 2.

Protected Area Category	Total forest	FHI	High (score 9.6 - 10)		Medium (score 6 – 9.6)		Low (score 0 - 6)	
	Km^2	*Mean*	*Km^2*	*% of protected area*	*Km^2*	*% of protected area*	*Km^2*	*% of protected area*
Ia (strict nature reserve)	439,082	9.27	304,329	69.31	106,703	24.3	28,049	6.39
Ib (wilderness area)	367,330	9.22	240,453	65.46	102,096	27.79	24,780	6.75
II (national park)	1,900	9.14	1,223,138	64.38	540,805	28.46	136,056	7.16
III (natural monument or feature)	113,805	8.49	54,476	47.87	40,021	35.17	19,308	16.97
IV (habitat/species management area)	838,707	8.69	432,828	51.61	268,027	31.96	137,850	16.44
V (protected landscape/seascape)	840,919	6.4	224,491	26.7	295,769	35.17	320,658	38.13
VI (Protected area with sustainable use of natural resources)	1,472,278	9.21	1,026,169	69.7	344,617	23.41	101,491	6.89
Not Applicable / Not Assigned / Not Reported	2,613,541	8.29	1,030,430	39.42	906,745	34.69	676,365	25.88
All Protected Areas	8,585,661	8.55	4,536,314	52.83	2,694,784	30.34	1,444,562	16.82

50 Fig 1


Direct Forest Pressure
Pressure within pixels
Infrastructure
Agriculture
Tree cover loss
Indirect Forest Pressure
Pressure from nearby pixels
Infrastructure
Agriculture
Tree cover loss
Loss of Forest Connectivity
Ratio of current to potential forest connectivity
Potential connectivity
Current connectivity
Change in connectivity
Apply to current forest extent
Forest Health Index

54 Fig 2


Forest Health Index
Low (0)
High (10)
A
B
C
C2
C1
0
10 km
A1
0
50 km
A2
B1
0
10 km
B2

55
56

57 Fig 3

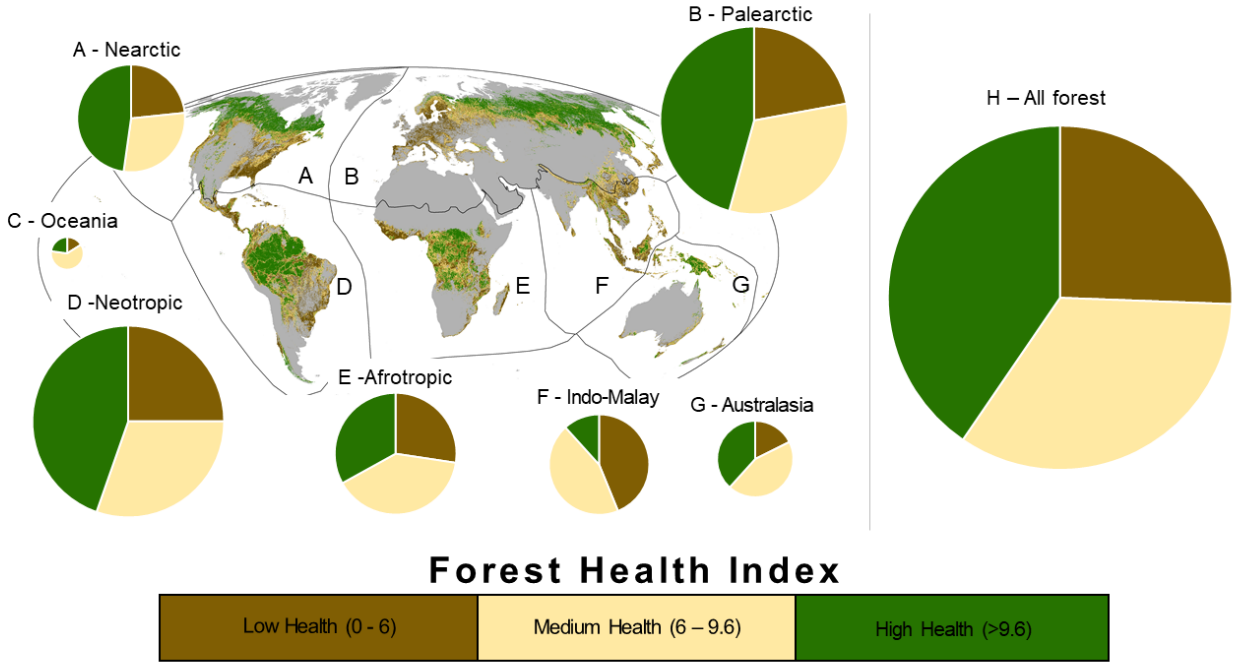
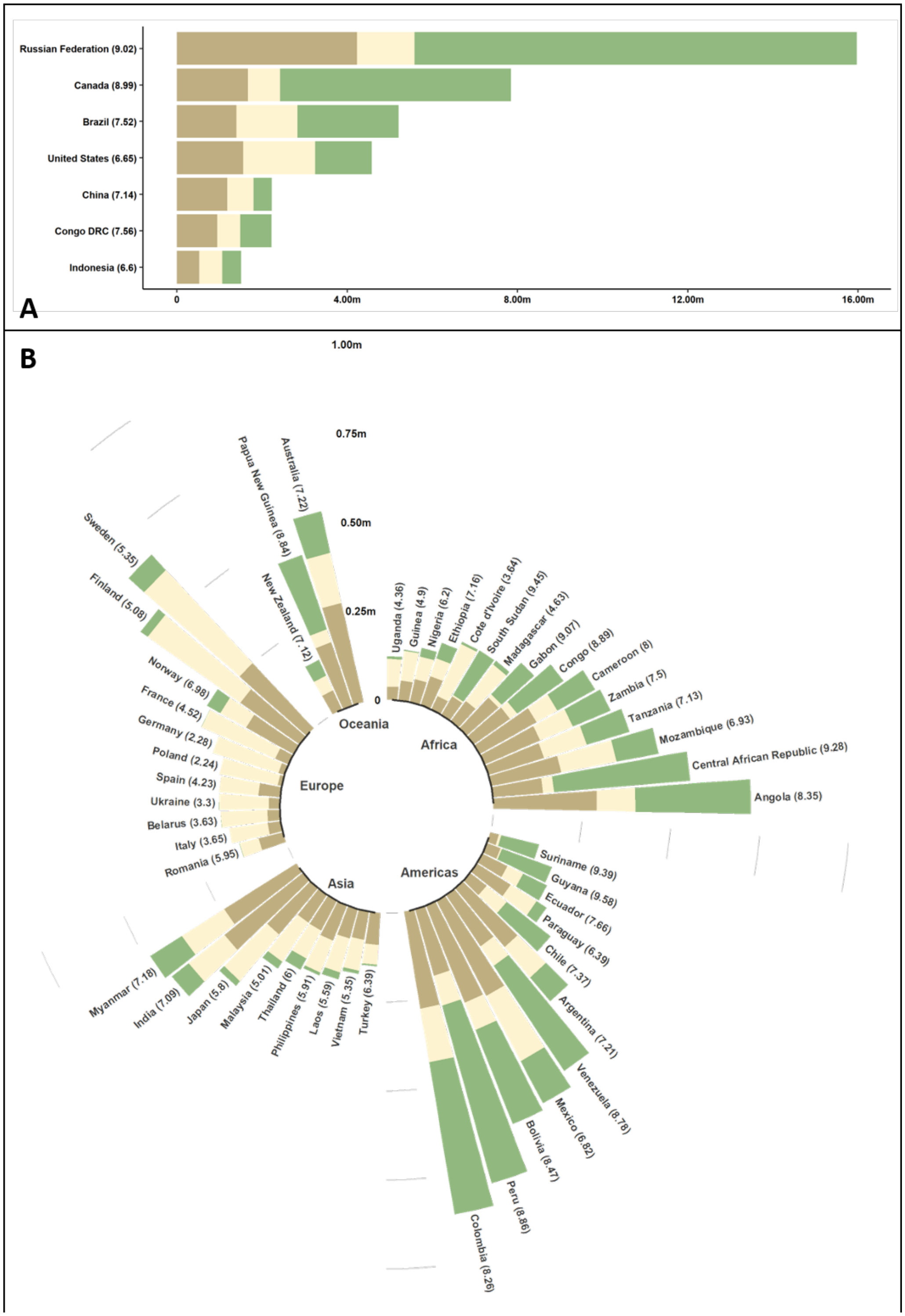

A - Nearctic
B - Palearctic
C - Oceania
D -Neotropic
E -Afrotropic
F - Indo-Malay
G - Australasia
H – All forest
A
B
D
E
F
G
Forest Health Index
Low Health (0 - 6)
Medium Health (6 – 9.6)
High Health (>9.6)

Fig 4.


A
Russian Federation (9.02)
Canada (8.99)
Brazil (7.52)
United States (6.65)
China (7.14)
Congo DRC (7.56)
Indonesia (6.6)
0
4.00m
8.00m
12.00m
16.00m
B
1.00m
0.75m
0.50m
0.25m
0
Oceania
Africa
Europe
Asia
Americas
Papua New Guinea (8.84)
Australia (7.22)
New Zealand (7.12)
Sweden (5.35)
Finland (5.08)
Norway (6.98)
France (4.52)
Germany (2.28)
Poland (2.24)
Spain (4.23)
Ukraine (3.3)
Belarus (3.63)
Italy (3.65)
Romania (5.95)
Uganda (4.36)
Guinea (4.9)
Nigeria (6.2)
Ethiopia (7.16)
Cote d'Ivoire (3.64)
South Sudan (9.45)
Madagascar (4.63)
Gabon (9.07)
Congo (8.89)
Cameroon (8)
Zambia (7.5)
Tanzania (7.13)
Mozambique (6.93)
Central African Republic (9.28)
Angola (8.35)
Suriname (9.39)
Guyana (9.58)
Ecuador (7.66)
Paraguay (6.39)
Chile (7.37)
Argentina (7.21)
Venezuela (8.78)
Mexico (6.82)
Bolivia (8.47)
Peru (8.86)
Colombia (8.26)
Myanmar (7.18)
India (7.09)
Japan (5.8)
Malaysia (5.01)
Thailand (6)
Philippines (5.91)
Laos (5.59)
Vietnam (5.35)
Turkey (6.39)

Supplementary Materials

Text S1. Mapping forest extent

We generated a preliminary base map of global forest extent for the start of 2019 at 30 m resolution by subtracting annual Tree Cover Loss 2001-2018 (with exceptions noted in the next paragraph) from the Global Tree Cover 2000 product (*22*) using a canopy cover threshold of 20%. This is one of the most widely used tree cover datasets globally, so it has been widely tested in many settings and its strengths and constraints are well understood. It has many advantages, including its high resolution, high accuracy, global coverage, annual time series and good prospects of sustainability in the coming years. The definition of forest in the source dataset is all woody vegetation taller than 5 m and hence includes naturally regenerated forests as well as tree crops, planted forests, wooded agroforests and urban tree cover. No globally consistent dataset was available that allowed natural and planted tree cover to be consistently distinguished in this study. Therefore, be mindful of the many differences between planted and natural tree cover (e.g. (*67*)).

More than 70% of the tree cover loss shown by the Hansen *et al.* (*22*) products has been found to be in 10 km pixels where the dominant loss driver is temporary and so tree cover is expected to return above the forest definition threshold within a short period (*23*). It is important to take account of this issue as treating all such areas as permanent loss would severely under-estimate current forest cover in many regions. However, no global map of forest cover gain exists for the study period other than the 2000-2012 gain product from Hansen *et al.* (*22*), so we developed an alternative approach. When removing annual loss shown by the Global Tree Cover Loss product cited above we elected not to remove any loss that was in a 10 km pixel categorized by Curtis *et al.* (*23*) as dominated by temporary loss under the categories of fire, shifting cultivation or rotational forestry. This resulted in the adjusted preliminary forest base map. The balance of evidence is that the great majority of such areas would have begun to regenerate and hence qualify as forest by our definition again by 2019 or soon after (*23*). The anthropogenically disturbed nature of many of these areas of temporary tree cover loss and recovery is reflected in scoring within the index, because temporary tree cover loss in the categories of shifting cultivation or rotational forestry is treated as an indicator of direct pressure. We do not treat tree cover loss through fire as an indicator of direct human pressure, because fires are often part of natural processes, especially in the boreal zone. This makes our global index conservative as a measure of degradation in these zones, because in some locations fires are anthropogenic in nature.

The adjusted preliminary base map was then resampled to a final base map for 2019 at 300m resolution using a pyramid-by-mode decision rule, with the resulting pixels simply classified as forest or non-forest based on a majority rule. The FHI was calculated for every forest pixel but not for non-forest pixels. GEE performs calculations in WGS84. Supplementary analyses outside GEE were applied using a Mollweide equal-area projection.

Text S2. Mapping potential forest configuration

Potential connectivity (PC) is calculated from an estimate of the potential extent of the forest zone taken from Laestadius *et al.* (*35*), treating areas below 25% crown cover (this was the nearest class to the tree cover data of 20%) as non-forest and resampling to 300 m resolution. To minimize false instances of lost connectivity and ensure measures of forest modification are conservative we masked from this data layer areas which we believe to include a significant proportion of naturally unforested land using selected land-cover categories in ESA ((*68*); see Table S1). Because these natural non-forest patches are shown in the Hansen *et al.* (*22*) dataset but not Laestadius *et al.* (*35*), not excluding such classes would result in an inflated estimate of the loss of connectivity and hence the level of degradation. We have elected to remain conservative in our estimate of modification.

Text S3. Mapping direct human pressure

Several recent analyses have developed composite, multi-criteria indices of human pressure to provide assessments of ecosystem condition for the USA (*69*) or globally (*26, 70, 71*). Thompson *et al.* (*72*) set out a framework specific to forest ecosystems that could indicate modification through a balanced mix of available pressure and state variables. We adapted the methodology of Venter et al. (*26*), informed by the other studies cited, to generate measures of (i) the modification of forest associated with direct human pressure from infrastructure, agriculture and deforestation and (ii) the more diffuse modification effects (e.g. edge effects) resulting from proximity to these focal areas of human activity ('indirect pressure'). Edge effects resulting entirely from natural processes are excluded, because they do not represent modification by our definition, although, like many other natural factors, they do also have a role in determining ecosystem benefits.

Infrastructure

We generated the infrastructure (I') data layer by rasterizing the OpenStreetMap data (*73*) from Feb 2018, using weights for each type of infrastructure as noted in Table S3. The weights were derived from authors' expert opinion and experimentation with weights according to their relative impact on forest condition.

Agriculture

For agriculture (A') we made a global binary composite of the croplands datasets produced by the USGS (Table 1) at 30 m resolution, and weighted each cropped pixel at this resolution by the likely intensity of cropping using the global irrigation dataset at 1km resolution (Teluguntla et al, (*74*)), with values of Irrigation Major = 2, Irrigation Minor = 1.5, Rainfed = 1. The average cropping intensity (including uncropped areas, which score zero) was then calculated across the whole of each 300 m pixel of our final basemap.

Deforestation

For deforestation (H') we made a binary composite of tree cover loss 2001-2018 at 30 m resolution (*22*), masked out 30 m pixels already classified as agriculture in the preceding step to avoid double-counting, and excluded loss predicted by Curtis *et al*. (*23*) to be most likely caused by fires, to give a conservative data layer of recent permanent and temporary tree cover loss indicative of human activity in the immediate vicinity. We excluded small clusters of 6 or fewer pixels (0.54 ha) because they may have been natural tree cover loss (e.g. small windthrows) or classification errors. Each 30 m pixel was then weighted by its year of loss, giving higher weight to the most recent loss (2001 = 1, 2002 = 2, etc.). The average 'recentness' of deforestation (including areas not deforested, which score zero) was then calculated across the whole of each 300 m pixel of our base map.

Transformations

The exponential transformations described in the main text were used to convert I', A' and H' to the variables I, A and H respectively.

Text S4. Modelling indirect human pressure

Each cell also experiences modification as a result of pressures originating from nearby cells that have signs of direct human pressure, largely through the family of processes known as 'edge effects' (*54*). Edge effects are partly a result of the changes relating to biophysical factors (such as humidity, wind, temperature and the increased presence of non-forest species) that accompany the creation of new edges in formerly continuous forest (as exemplified by the carefully controlled studies in tropical forests summarized by Laurance *et al.* (*59*)). They also result in part from the increased pressure associated with human activities within tropical forest near to edges such as logging (*61*), anthropogenic fire (*60*), hunting (*55*), livestock grazing, pollution, visual and auditory disturbances, etc. These multiple factors are synergistic and so we model them together, notwithstanding regional and local variations in the relative intensity of each one.

We model the proximity effect caused by each nearby source cell as a function of (a) the direct human pressure observed in that source cell and (b) a decline in the intensity of edge effects with distance from the source cell, based on a review of the literature. We then determine the total proximity effect on a given cell by summing the individual effects from all source cells within a certain range.

Two complementary types of proximity effect are modelled and added together. One relates to the diverse, strong, relatively short-range edge effects which decay to near zero over a few kilometers and have the potential to affect most biophysical features of a forest to a greater or lesser extent. The other relates to weaker, longer-range effects such as over-hunting of high-value animals that affect fewer biophysical features of a forest (and so have a much smaller maximum effect on overall integrity) but can nonetheless have detectable effects in locations more than 10 km from the nearest permanent human presence.

The literature on the spatial influence of short-term effects uses a variety of mathematical descriptors, in two broad categories – continuous variables and distance belts. As we wish to model edge effects as a continuous variable we concentrated on studies that have taken a similar approach, and used distance-belt studies as ancillary data.

Chaplin-Kramer *et al.* (*62*) is a good example of a continuous variable approach, estimating detailed biomass loss curves near tropical forest edges. Because they analyze a key forest condition variable with a very large pantropical dataset we hypothesize that the exponential declines in degradation with distance that they find are likely to be a common pattern and so we use a similar framework for our more general model of degradation. We consider that a model of exponential decay is also a sufficient approximation to the evidence presented by some authors as graphs without an associated mathematical model (e.g., (*60, 75*)) or analyzed using logistic regression (e.g., (*76*)). In our model we set the exponential decay constant to be broadly consistent with these four studies, resulting in degradation at 1 km inside a forest that is approximately 37% of that at the forest edge, declining to 14% at 2 km and near zero at 3 km. We truncate the distribution at 5 km to minimize computational demands.

Distance-belt studies define the width of a belt within which edge effects are considered to occur, and beyond which forests are considered to be free of edge effect. Belts of 1 km are commonly used (e.g., (*54*)) but smaller distances may be used for specific parameters (e.g. 300 m for biomass reduction near edges in DRC's primary forests; (*27*)). Our continuous variable approach is broadly consistent with these studies, with the majority of our modelled degradation within a 1 km belt and little extending beyond 2 km. While most individual edge effects reported in the literature penetrate less than 100-300 m (e.g., (*59, 77*)) most of the effects reported on in these studies relate to the changed natural factors mentioned in an earlier paragraph, and are likely to be dwarfed in both intensity and extent by edge effects relating to spillovers of human activity, so our model emphasizes the spatial distribution of the latter (e.g., (*60*)). We consider our model to be conservative.

For the weaker, more widespread long-range effects we use recent large-scale studies of defaunation, which is one of the key long-range pressures and also acts as a proxy for other threats including harvest of high value plants (such as eaglewood *Aquilaria* spp. in tropical Asia), occasional remote fires, pollution associated with artisanal mining, etc. We adopt a simplified version of the distribution used by Peres *et al.* (*55*) to model hunting around settlements in the Amazon, which sets 2σ=12 km; this is likely conservative compared to evidence for hunting-related declines in forest elephants in central Africa up to 60 km from roads (*63*) and the extensive declines in large-bodied quarry species in remote areas in many regions modelled by Benitez-Lopez *et al.* (*78*).

Text S5. Limitations in data: example with infrastructure data in British Columbia, Canada

OpenStreetMap (OSM) represents the most detailed publicly available global dataset but is nonetheless noted to be incomplete, even for one of the most heavily used categories of infrastructure, paved roads (*48*). No global assessment is available for the completeness of other categories in the dataset. One of the key categories for forest health, unpaved roads used for resource extraction, has been shown to be incomplete over much of insular South-east Asia (*49*). In Canada, for example, roads and other linear corridors used to explore, access and extract natural resources (e.g., logging, oil and gas, and minerals) are sometimes missing. Government data for the province of British Columbia (available at https://catalogue.data.gov.bc.ca/dataset/digital-road-atlas-dra-master-partially-attributed-roads) demonstrates, for example, the larger extent and density of regional roads as compared to OSM (Fig S1).

Text S6. Classification of Forest Health Index scores

In this paper, three illustrative classes were defined, mapped and summarized to give an overview of broad patterns of degradation in the world's forests. Three categories were defined as set out in the Materials and Methods. To determine the approximate levels of the Forest Health Index associated with these three categories, example locations were selected in sites that could unambiguously be assigned to one of the categories using the authors' personal knowledge. At each site a single example pixel was selected within a part of the area with relatively uniform scores. The sample points are summarized in Table S4; they are widely spread across the world to ensure that the results are not only applicable to a limited region. The scores at these points suggest the following category boundaries:

- High FHI – 9.6-10

- Medium FHI – 6-9.6
- Low FHI – 0-6

Table S1. The datasets used to develop the Forest Health Index. The factor column indicates the component of the index the dataset was used in.

Dataset	Factor	Sources
Tree cover and tree cover loss	Forest extent, connectivity, direct and indirect pressure	Global Forest Cover datasets; Hansen *et al.* (*22*); updates to 2018 available on-line from: http://earthenginepartners.appspot.com/science-2013-global-forest.
Major tree cover loss driver	Forest extent, direct and indirect pressure, connectivity	Curtis *et al.* (*23*)
Landover and ocean extent	Forest extent	Lamarche *et al.* (*79*)
Potential forest cover	Connectivity	Laestadius *et al.* (*35*)
Natural non-forest areas within extent of potential forest	Connectivity	ESA-CCI Land Cover dataset; ESA (*68*)
Infrastructure	Direct and indirect pressure	Open Street Map (selected elements) as of 2018; OpenStreetMap contributors (*73*)
Cropland	Direct and indirect pressure	GFSAD 2015 Cropland Extent; Gumma *et al.* (*80*), Massey *et al.* (*81*), Oliphant *et al. (82)*, Phalke *et al.* (*83*), Teluguntla *et al.* (*84*), Xiong *et al. (85)* and Zhong *et al. (86)*
Cropping intensity (irrigation)	Direct and indirect pressure	GFSAD 2010 Cropland Mask; Teluguntla *et al.* (*74*)
Water surface	Direct and indirect pressure	JRC Global Surface Water Occurrence (all classes with >75% occurrence); Pekel *et al.* (*87*)

Table S2. Classes in ESA-CCI dataset excluded from our potential forest cover layer because they overlap extensively with potential forest cover mapped by Laestadius *et al.* (*35*) but contain significant areas of natural non forest

Legend code	Class name
60	Treecover, broadleaved, deciduous, closed to open, >15%
100	Mosaic tree and shrub (>50%]/ Herbaceous cover (<50%)
120	Shrubland
121	Evergreen shrubland
122	Deciduous shrubland
130	Grassland
140	Lichens and mosses
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
152	Sparse shrub (<15%)
180	Shrub or herbaceous cover, flooded, fresh/saline/brackish water
200	Bare areas
201	Consolidated bare areas
202	Unconsolidated bare areas
220	Permanent snow and ice

Table S3. Weightings used for Open Street Map (OSM) to combine into the Infrastructure data layer.

OSM Category	OSM Subcategory	Weighting applied for FPI
Aeroway	Apron / Helipad / Runway / Taxiway	8
	Hangar / Terminal	4
	Aerodrome / Heliport / Spaceport	3
Amenity / Landuse / Man-made object	Fuel station / Gasometer / Petroleum well / Pipeline / Adit / Mineshaft / Quarry / Landfill / Sanitary dump station / Wastewater plant	15
	Chimney	10
	Industrial	8
	Basin / Covered Reservoir / Pumping station / Water tower / Water well / Water works / Watermill	7
	Silo / Storage tank / Works	6
	Aerialway / Beacon / Lighthouse / Breakwater / Dyke / Embankment / Groyne / Pier / Communications tower / Mast / Observatory / Tower / Telescope	5
	Salt pond	4
	Alpine hut / Beach resort / Camp site / Cemetery / Golf course / Marina / Pitch / Village green / Wilderness hut	3
Barrier	City wall / Retaining wall / Wall	5
	Ditch / Snow fence / Snow net	3
	Hedge	2
Road	Motorway / Motorway link / Raceway	15
	Trunk / Trunk link	11
	Primary / Primary link	9
	Secondary / Secondary link	7
	Tertiary / Tertiary link	6
	Bus guideway / Service	5
	Living street / Mini roundabout / Residential / Turning circle / Unclassified / Unknown/ Elevator / Rest area	4
	Escape / Track	3
	Bridleway / Cycleway/ Footway / Path / Pedestrian / Steps	2
Military	Nuclear explosion site	30
	Danger area / Range / Trench	15
	Ammunition / Barracks / Bunker / Checkpoint	7
	Airfield / Military-owned land / Naval base / Training area	3
Power	Plant/generator - coal	20
	Plant/generator - oil	15
	Plant/generator – gas/ Plant/generator - bio / waste	10
	Plant/generator – hydro; nuclear; other / Line, Substation	7
	Plant/generator - solar / Heliostat / wind / Windmill	5
	Cable	3
Railway	Funicular / Preserved / Rail / Monorail / Subway	10
	Light rail / Miniature / Narrow gauge/ Tram	7
	Station	5
	Halt / Platform	4
	Abandoned / Disused	2
Waterway	Dam / Lock gate	20
	Canal	13
	Ditch/ Drain / Weir	3

Table S4. Points assessed to determine category boundaries for classifying the FHI into high, medium and low classes.

Category	Code	Point description	Country	Point Score
High	103	Interior of Lopé National Park	Gabon	10.000
High	106	Interior of Taï National Park	Cote d'Ivoire	10.000
High	108	Interior of Pacaya-Samiria National Reserve	Peru	10.000
High	109	Interior of Central Suriname Nature Reserve	Suriname	10.000
High	116	Interior of Liard River area	Canada	10.000
High	101	Interior of Okapi Faunal Reserve	DRC	9.997
High	104	Interior of Nyungwe National Park	Rwanda	9.992
High	111	Interior of Rio Platano Biosphere Reserve	Honduras	9.990
High	102	Interior of Odzala National Park	RoC	9.974
High	117	Interior of Wells Gray Provincial Park	Canada	9.972
High	119	Interior of Øvre Pasvik National Park	Norway	9.944
High	115	Interior of Tasmania Wilderness World Heritage Area	Australia	9.918
High	107	Interior of Marojejy National Park	Madagascar	9.910
High	112	Interior of Khao Yai National Park	Thailand	9.908
High	105	Interior of Niassa Special Reserve	Mozambiuque	9.819
High	110	Interior of Maya Biosphere Reserve	Guatemala	9.798
High	114	Interior of Batang Ai National Park	Malaysia	9.756
High	118	Interior of Quetico Provincial Park	Canada	9.750
High	113	Interior of Sundarbans National Park	Bangladesh	9.606
Medium	215	Interior of Bialowieża National Park	Poland	9.086
Medium	208	Interior of Mabira Central Forest Reserve	Uganda	9.067
Medium	211	Area of selective logging	Gabon	8.840
Medium	219	Near main tourism corridor, Mt Myohyang National Park	DPR Korea	8.762
Medium	203	Interior of Phnom Kulen Wildlife Sanctuary	Cambodia	8.710
Medium	210	Area of selective logging	Guyana	8.364
Medium	202	Interior of Dong Hua Sao National Protected Area	Lao PDR	8.078
Medium	212	Area of selective logging	DRC	7.981
Medium	206	Interior of Manga Forest Reserve	Tanzania	7.960
Medium	207	Near margin of Nyungwe National Park	Rwanda	7.938
Medium	204	South part of Nagarahole National Park	India	7.759
Medium	213	Area of selective logging	Cameroon	7.379
Medium	201	Tat Leuk, Phou Khaokhoay National Protected Area	Lao PDR	7.251
Medium	216	Interior of Loch Garten Nature Reserve	UK	7.146
Medium	209	Area of selective logging	Congo	6.734
Medium	217	Tourism area, Lamington National Park	Australia	6.729
Medium	214	Lowlands of Guanacaste National Park	Costa Rica	6.719
Medium	218	Near margin of Sepilok Forest Reserve	Malaysia	6.353
Medium	205	Interior of Similajau National Park	Malaysia	6.130
Low	305	Dong Nathat	Lao PDR	5.638
Low	317	Foothills of Mt Makiling	Philippines	5.395
Low	310	Suburban woodlot, Dobbs Ferry	USA	4.710
Low	309	Jozani Forest Reserve	Tanzania	4.680
Low	316	Foothills of Mt Canlaon	Philippines	4.597
Low	320	Forest fragment near Paramaribo	Suriname	4.566
Low	302	Central Park, New York	USA	3.575
Low	301	Bagley Wood, Oxford	UK	3.525
Low	307	Boeng Yeak Lom Protected Area	Cambodia	3.323
Low	304	Angkor Thom	Cambodia	3.122
Low	315	Forest in rural complex, Mambasa area	DRC	2.689
Low	312	Woodland in Beaumont area	USA	2.581
Low	318	Swidden near Andoung Kraloeng village	Cambodia	2.304
Low	319	Forest mosaic near Kaev Seima village	Cambodia	2.187

Low	303	Thetford Forest	UK	2.082
Low	313	Woodland in Augusta area	USA	0.686
Low	314	Woodland in Emporia area	USA	0.589
Low	311	River Park, Chicago	USA	0.566
Low	306	Houei Nhang Forest Reserve	Lao PDR	0.000
Low	308	Pugu Forest Reserve	Tanzania	0.000

Table S5. Mean Forest Health Index scores and areas for forest health categories by country.

Country	Mean FHI	Low health (km²)	Medium health (km²)	High health (km²)	Total forest area (km²)
Afghanistan	8.85	90	1,475	977	2,542
Albania	6.77	2,426	5,256	122	7,805
Algeria	5.22	7,418	6,044	81	13,543
Andorra	4.45	170	49	0	219
Angola	8.35	105,487	284,054	315,895	705,436
Antigua and Barbuda	4.72	114	92	0	206
Argentina	7.21	98,249	189,966	72,557	360,772
Armenia	5.46	1,894	1,681	3	3,577
Australia	7.22	117,672	239,624	103,852	461,148
Austria	3.55	36,666	12,422	21	49,109
Azerbaijan	6.55	4,820	7,189	1,534	13,543
Bahamas	7.35	741	1,935	399	3,075
Bangladesh	5.45	10,013	7,251	1,947	19,211
Belarus	3.63	77,870	20,847	91	98,808
Belgium	1.36	8,803	297	0	9,099
Belize	6.15	7,004	7,957	2,744	17,705
Benin	5.86	4,724	3,698	1,769	10,191
Bhutan	8.85	1,620	16,769	10,140	28,529
Bolivia	8.47	78,745	280,532	272,007	631,284
Bosnia and Herzegovina	5.99	13,387	17,031	574	30,993
Botswana	9.13	13	187	372	572
Brazil	7.52	1,374,902	1,354,961	2,338,101	5,067,963
Brunei Darussalam	7.71	1,102	2,842	1,498	5,442
Bulgaria	6.09	18,884	26,325	847	46,057
Burundi	4.5	6,882	3,841	46	10,769
Cabo Verde	6.37	27	38	0	65
Cambodia	6.31	30,143	31,939	16,349	78,431
Cameroon	8	66,191	181,336	119,263	366,789
Canada	8.99	480,206	1,027,386	2,968,268	4,475,860
Central African Republic	9.28	30,161	139,350	379,097	548,608
Chad	6.18	5,261	6,016	1,910	13,187
Chile	7.37	56,849	41,971	93,537	192,357
China	7.14	533,800	974,431	301,051	1,809,282
Colombia	8.26	150,737	272,442	428,320	851,499
Comoros	7.69	284	1,149	82	1,515
Congo	8.89	24,512	124,215	158,184	306,911
Congo DRC	7.56	533,118	935,508	727,983	2,196,608
Costa Rica	4.65	27,164	12,838	4,164	44,167

Cote d'Ivoire	3.64	158,010	41,005	7,288	206,303
Croatia	4.92	15,732	10,522	379	26,633
Cuba	5.4	22,605	18,460	1,632	42,697
Cyprus	7.06	388	1,026	18	1,432
Czechia	1.71	32,161	1,611	0	33,772
Denmark	0.5	5,756	31	0	5,787
Dominica	1.06	531	2	0	533
Dominican Republic	4.19	19,890	9,364	518	29,772
Ecuador	7.66	48,822	77,585	73,492	199,900
Egypt	0.56	4,772	218	69	5,059
El Salvador	4.05	8,837	2,947	0	11,784
Equatorial Guinea	7.99	3,982	17,595	5,007	26,585
Estonia	3.05	24,473	4,832	52	29,358
Ethiopia	7.16	52,652	84,430	44,397	181,479
Fiji	8.35	1,753	10,802	3,594	16,148
Finland	5.08	144,310	83,572	9,294	237,176
France	4.52	161,987	49,496	74,121	285,604
Gabon	9.07	11,780	118,348	120,852	250,979
Gambia	4.56	181	85	0	266
Georgia	7.79	6,982	17,803	9,784	34,570
Germany	2.28	122,168	11,307	0	133,475
Ghana	4.53	57,519	28,901	2,160	88,580
Greece	6.6	14,548	27,833	1,078	43,459
Grenada	4.22	221	86	0	308
Guatemala	3.85	58,572	18,764	5,592	82,928
Guinea	4.9	81,702	54,877	2,895	139,475
Guinea-Bissau	5.7	9,274	8,702	855	18,831
Guyana	9.58	4,162	40,817	147,413	192,391
Haiti	4.01	7,116	2,831	12	9,959
Honduras	4.48	57,899	23,802	3,692	85,392
Hungary	2.25	18,729	2,047	0	20,776
India	7.09	117,992	254,792	54,428	427,211
Indonesia	6.6	535,370	509,018	431,973	1,476,361
Iran	7.67	3,361	12,930	2,162	18,453
Iraq	3.59	104	9	0	113
Ireland	0.92	5,283	96	0	5,378
Israel	4.14	170	85	0	255
Italy	3.65	79,403	26,858	25	106,286
Jamaica	5.01	5,362	3,249	158	8,770
Japan	5.8	135,783	133,480	16,005	285,268
Jordan	2.79	12	0	0	12
Kazakhstan	8.23	6,068	18,926	15,294	40,288
Kenya	4.2	28,427	13,558	4,702	46,686

Kosovo	5.19	2,628	1,775	47	4,450
Kyrgyzstan	8.86	329	2,819	2,761	5,909
Laos	5.59	92,986	80,564	19,252	192,801
Latvia	2.09	38,164	2,137	0	40,301
Lebanon	3.76	541	115	0	656
Lesotho	7.4	1	4	0	5
Liberia	4.79	51,975	31,162	11,025	94,163
Libya	4.85	15	2	0	17
Liechtenstein	4.5	59	42	0	101
Lithuania	1.62	24,554	930	0	25,484
Luxembourg	1.12	1,170	0	0	1,170
Macedonia	7.42	2,034	7,090	459	9,583
Madagascar	4.63	120,340	66,584	11,922	198,846
Malawi	5.74	12,514	12,167	2,396	27,078
Malaysia	5.01	130,825	91,957	21,499	244,281
Mali	7.16	451	996	140	1,586
Mauritius	5.46	567	478	0	1,045
Mexico	6.82	193,908	280,445	121,842	596,195
Micronesia	7.55	8	35	0	43
Moldova	2.2	3,113	202	0	3,315
Mongolia	9.36	520	11,915	27,407	39,841
Montenegro	6.41	2,949	4,778	82	7,809
Morocco	6.74	2,260	4,076	451	6,787
Mozambique	6.93	150,665	189,362	115,379	455,406
Myanmar	7.18	129,745	220,188	96,924	446,857
Namibia	8.43	5	13	17	36
Nepal	7.23	13,785	41,992	3,760	59,538
Netherlands	0.6	5,250	72	0	5,322
New Zealand	7.12	34,503	44,155	35,334	113,992
Nicaragua	3.63	65,356	17,646	4,858	87,860
Nigeria	6.2	64,621	65,355	24,307	154,283
North Korea	8.02	8,374	40,156	8,410	56,939
Norway	6.98	39,343	67,383	16,627	123,352
Pakistan	7.42	2,090	7,859	1,139	11,088
Palau	8.09	45	333	9	387
Panama	6.37	25,420	21,310	14,605	61,336
Papua New Guinea	8.84	37,294	183,415	216,355	437,064
Paraguay	6.39	78,538	102,626	29,877	211,041
Peru	8.86	85,793	190,547	509,720	786,061
Philippines	5.91	91,820	100,831	8,393	201,044
Poland	2.24	101,886	7,103	0	108,989
Portugal	8.82	25,966	553	0	26,519
Romania	5.95	38,395	48,394	607	87,395

Russian Federation	9.02	739,484	2,245,281	5,137,079	8,121,843
Rwanda	3.85	5,665	2,170	619	8,454
Saint Kitts and Nevis	4.55	95	50	0	145
Saint Lucia	6.17	235	316	0	551
Saint Vincent and the Grenadines	6.95	91	221	0	312
San Marino	0.01	7	0	0	7
Sao Tome and Principe	6.64	31	140	0	171
Senegal	7.11	847	2,456	162	3,465
Serbia	5.29	17,513	14,112	516	32,141
Seychelles	10	0	0	68	68
Sierra Leone	2.76	52,512	11,858	640	65,010
Singapore	1.11	170	2	0	172
Slovakia	4.34	17,615	8,165	0	25,781
Slovenia	3.78	11,065	3,791	0	14,856
Solomon Islands	7.19	6,871	15,310	3,149	25,329
Somalia	7.16	347	1,384	46	1,777
South Africa	4.94	45,489	34,968	3,196	83,653
South Korea	6.02	25,060	32,009	888	57,956
South Sudan	9.45	5,083	59,389	146,218	210,691
Spain	4.23	82,770	46,013	133	128,916
Sri Lanka	5.83	20,541	22,390	1,613	44,544
Sudan	9.8	1	72	495	569
Suriname	9.39	6,796	25,031	107,954	139,781
Swaziland	4.21	5,054	2,501	14	7,569
Sweden	5.35	174,415	109,779	23,494	307,687
Switzerland	3.53	13,636	4,412	10	18,058
Syria	3.64	841	282	0	1,123
Taiwan	6.38	8,786	14,547	1,453	24,786
Tajikistan	8.65	34	137	130	301
Tanzania	7.13	123,997	159,712	122,812	406,521
Thailand	6	86,276	89,326	33,612	209,214
Timor-Leste	7.11	1,783	7,008	47	8,838
Togo	5.88	5,064	4,522	1,076	10,662
Trinidad and Tobago	6.62	1,478	2,176	418	4,072
Tunisia	5.14	1,354	987	0	2,340
Turkey	6.39	43,043	68,243	3,516	114,801
Turkmenistan	6.31	5	33	0	37
Uganda	4.36	77,303	36,381	7,507	121,190
Ukraine	3.3	89,540	20,183	176	109,900
United Kingdom	1.65	29,149	2,917	35	32,101
United States	6.65	1,328,079	1,144,693	658,645	3,131,417
Uruguay	3.61	11,793	3,998	0	15,791

Uzbekistan	6.77	214	227	199	640
Vanuatu	8.82	734	5,322	4,448	10,504
Venezuela	8.78	64,650	170,792	351,112	586,554
Vietnam	5.35	82,551	75,353	9,588	167,492
Zambia	7.5	96,969	164,376	110,822	372,167
Zimbabwe	6.31	9,450	14,417	1,644	25,511

Table S6. Mean Forest Health Index scores for provinces of Democratic Republic of Congo (DRC), Indonesia and Canada.

DRC		**Indonesia**		**Canada**	
Province	**Mean FHI**	**Province**	**Mean FHI**	**Province**	**Mean FHI**
Lualaba	8.57	**Papua**	9.34	**Northwest Territories**	9.90
Tshuapa	8.55	**West Papua**	9.00	**Yukon**	9.86
Tshopo	8.39	**Kalimantan Utara**	8.52	**Newfoundland and Labrador**	9.66
Bas-Uélé	8.38	**Maluku**	8.03	**Nunavut**	9.65
Équateur	8.37	**Maluku Utara**	7.41	**Manitoba**	9.58
Haut-Lomami	8.29	**Nusa Tenggara Barat**	6.86	**Saskatchewan**	9.40
Tanganyika	8.24	**Aceh**	6.83	**Ontario**	8.94
Nord-Ubangi	8.19	**Nusa Tenggara Timur**	6.80	**Québec**	8.80
Haut-Katanga	8.05	**Gorontalo**	6.60	**Alberta**	8.46
Kwango	7.83	**Sulawesi Utara**	6.58	**British Columbia**	8.22
Maï-Ndombe	7.58	**Sulawesi Tengah**	6.54	**Nova Scotia**	6.07
Haut-Uélé	7.46	**Kalimantan Timur**	6.42	**New Brunswick**	5.15
Maniema	7.44	**Sulawesi Barat**	6.31	**Prince Edward Island**	2.74
Sankuru	7.34	**Sumatera Barat**	6.20		
Lomami	7.20	**Sulawesi Tenggara**	5.99		
Kasaï	7.11	**Kalimantan Tengah**	5.84		
Ituri	6.70	**Sulawesi Selatan**	5.63		
Mongala	6.23	**Banten**	4.97		
Nord-Kivu	6.22	**Bengkulu**	4.94		
Sud-Kivu	6.20	**Sumatera Utara**	4.89		

Kasaï-Central	5.95	**Kalimantan Barat**	4.87
Sud-Ubangi	5.93	**Kepulauan Riau**	4.86
Kwilu	5.65	**Jawa Barat**	4.76
Kinshasa	4.75	**Lampung**	4.73
Kasaï-Oriental	4.13	**Jawa Tengah**	4.59
Kongo-Central	3.95	**Bali**	4.43
		Jawa Timur	4.40
		Jambi	4.01
		Riau	3.92
		Kalimantan Selatan	3.24
		Sumatera Selatan	2.86
		Yogyakarta	2.83

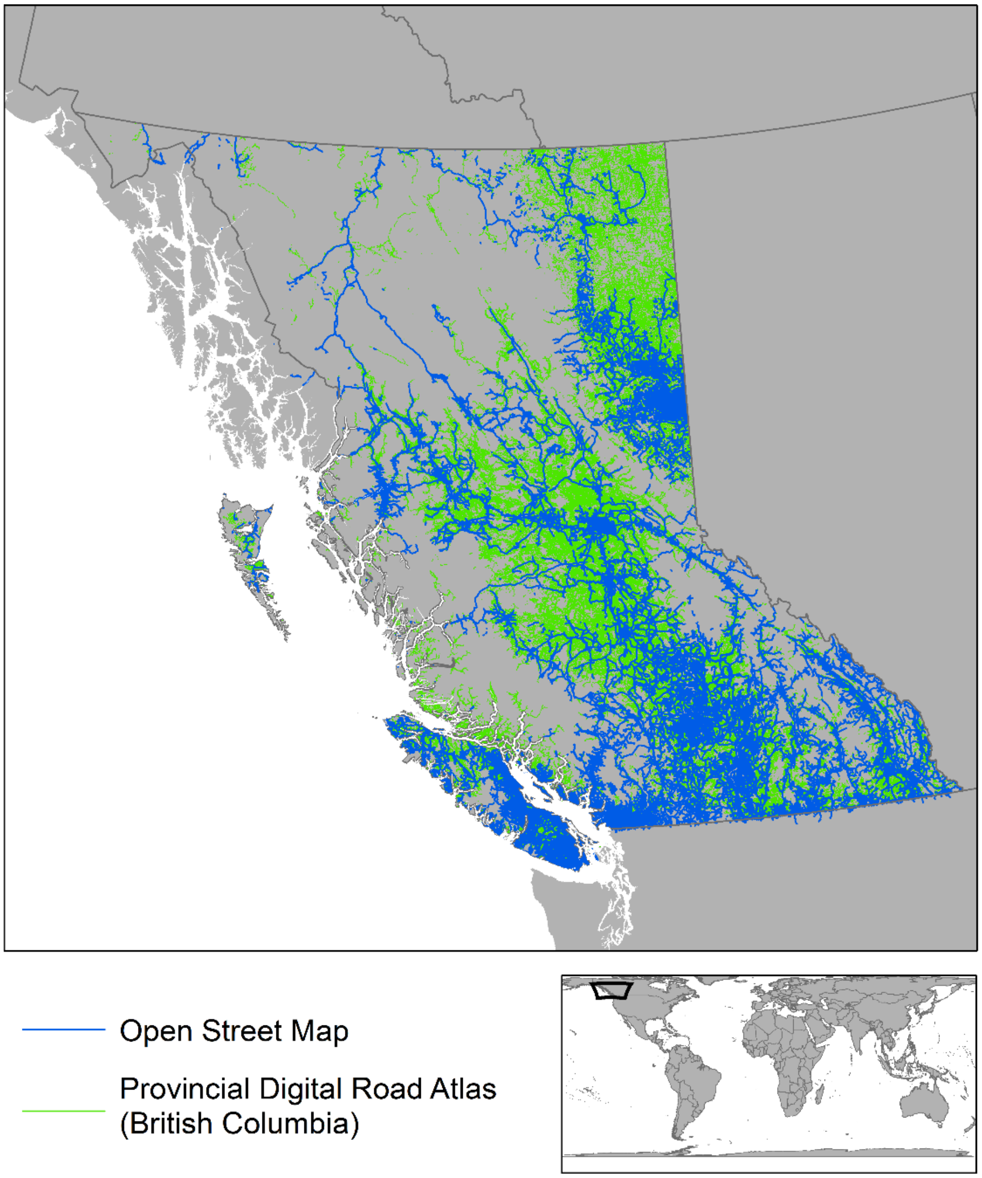


Figure S1. A map overlaying the Open Street Maps data (blue) and provincial government data (green) for roads and other linear infrastructure associated with resource access.

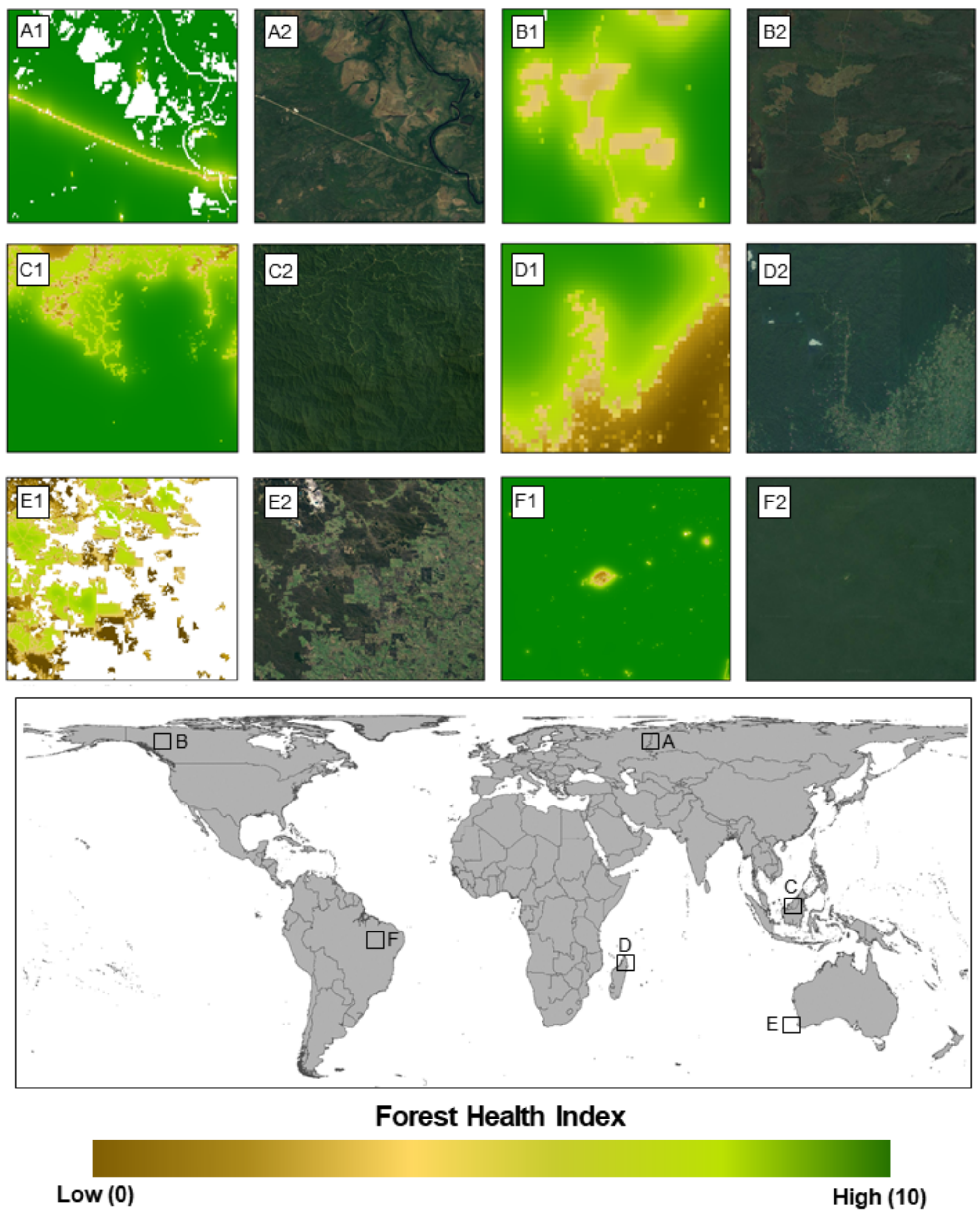


Figure S2. A global map of Forest Health for 2019. Highlighted regions show **A.** A remote road in Russia, **B.** Clearcut logging in Canada, **C.** Selective logging in Borneo, **D.** Swidden agriculture in Madagascar, **E.** Forest fragmentation in Western Australia, **F.** Remote settlements in the Brazilian Amazon.