Earth transformed: detailed mapping of global human modification from 1990 to 2017

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Abstract

Data on the extent, patterns, and trends of human land use are critically important to support global and national priorities for conservation and sustainable development. To inform these issues, we created a series of detailed global datasets for 1990, 2000, 2010, and 2015 to evaluate temporal and spatial trends of land use modification of terrestrial lands (excluding Antarctica). We found that the expansion and increase of human modification between 1990 and 2015 resulted in 1.6 M km$^2$ of natural land lost. The percent change between 1990 and 2015 was 15.2% or 0.61% annually -- roughly 178 km$^2$ daily. Over the pause of a deep breath, over 8 football pitches of natural lands were lost (~17 per minute). Worrisomely, we found that the global rate of loss has increased over the past 25 years. The greatest loss of natural lands from 1990-2015 occurred in Oceania, Asia, and Europe, and the biomes with the greatest loss were mangroves, tropical & subtropical moist broadleaf forests, and tropical & subtropical dry broadleaf forests. We also created a contemporary (~2017) estimate of human modification that included additional stressors and found that globally 14.5% or 18.5 M km$^2$ of lands have been completely modified -- an area greater than Russia. Our novel datasets are detailed (0.09 km$^2$ resolution), temporal (1990-2015), recent (~2017), comprehensive (11 change stressors, 14 current), robust (using an established framework and incorporating classification errors and parameter uncertainty), and strongly validated. We believe these datasets will support better understanding of the profound transformation wrought by human activities and provide foundational data on the amounts, patterns, and rates of change to inform planning and decision making for environmental mitigation, protection, restoration, and adaptation to climate change. The datasets generated from this work are available at https://doi.org/10.5061/dryad.n5tb2rbs1 (Theobald et al. 2020).
Introduction

Humans have transformed the earth in profound ways (Marsh 1885; Jordan et al. 1990; Vitousek et al. 1997), contributing to global climate change (IPCC 2019), causing global habitat loss and fragmentation, and contributing to declines in biodiversity and critical ecosystem services (IPBES 2019). Addressing the consequences of rapid habitat loss and land use change are essential for implementation of various international initiatives, including the Convention on Biological Diversity 2020 Aichi Biodiversity targets, the United Nations 2030 Sustainable Development Goals (esp. Goal 15; Secretariat of the Convention on Biological Diversity, 2010), the Bonn Challenge (Verdone & Seidl, 2017), and the Global Deal for Nature (Dinerstein et al. 2019). Foundational to addressing these goals is a firm understanding of the rates, trends, and amount of these land use changes. Efforts to date (Klein Goldewijk et al. 2007; Venter et al. 2016; Geldman et al. 2019; Kennedy et al. 2019a) have been limited due to the unavailability of contemporary, temporally comparable, and high-resolution data.

Here we describe a new dataset that maps the degree of human modification of terrestrial ecosystems globally, for recent changes from 1990 to 2015, and for contemporary (circa 2017) conditions. We mapped human activities that directly or indirectly alter natural systems, which we call anthropogenic drivers of ecological stress or “stressors” (following Salafsky et al., 2008; Theobald 2013). Similar to other efforts (Sanderson et al. 2002; Theobald 2010, 2013; Geldmann et al. 2014; Venter et al. 2016; Kennedy et al. 2019a), we augmented remotely-sensed data with traditionally-mapped cartographic features. This is because remotely sensed imagery has limitations for this application – especially prior to ~2010 – including obstructions by vegetation canopy (e.g., some roads, trails), inability to detect small or narrow features (e.g., towers, wind turbines, powerlines), or can require human-interpretation to classify efficiently.

We mapped the degree of human modification based on an established approach that has been applied nationally, internationally, and globally (Theobald 2010, 2013; Gonzalez-Abraham et al. 2015; Kennedy et al. 2019a). It uses an existing classification system (Salafsky et al., 2008) to: (a) ensure parsimony; (b) distinguish two spatial components (area of use and intensity of use); (c) use a physically-based measure that is needed to estimate change (Gardner and Urban 2007); (d) incorporate spatial and classification uncertainty; and (e) combine multiple stressors into an overall measure that assumes additive but monotonic relationships and addresses the correlation among variables (Theobald 2010). The resulting quantitative estimate of human modification has values ranging from 0 to 1 that support robust landscape assessments (Schultz 2001; Hajkowicz and Collins 2007).

To understand temporal landscape change, we calculated the degree of human modification – denoted by $H$ – for the years 1990, 2000, 2010, and 2015 using methods and datasets that minimize noise and bias. Second, we included additional stressors not incorporated previously, including disturbance of natural processes due to reservoirs, effects from air pollution, and human intrusion (Theobald 2008). Third, we calculated human stressors using up to two orders of magnitude finer resolution data (0.09 vs. 1-86 km$^2$) than past efforts (Ellis and Ramankutty 2008; Geldmann et al.
2014; Haddad et al. 2015; Venter et al. 2016; Geldmann et al. 2019b; Kennedy et al. 2019a). This higher resolution reduces the loss of information of the spatial pattern within a pixel, better identifies rare features, facilitates the application of these data for species and ecological processes that often occur at a fine-scale, and improves the utility and relevance of these products for policy makers, decision makers, and land use managers.

Calculating \( H \) as a real value across the full gradient of landscape changes is valuable because it can be applied rigorously to a variety of questions, including discerning the heterogeneity of human uses that are often lumped within broad classes like “urban”, capturing the extent and pattern of the agricultural lands typically occurring beyond urban centers and protected areas, and delineating areas of low modification – all of which are useful for conservation prioritization and planning efforts (Kennedy et al. 2019a, 2019b). Here, we describe the technical methods and briefly report on results on the temporal trends and current spatial patterns of human modification across all terrestrial lands, biomes and ecoregions (Dinerstein et al. 2017). Because conservation organizations often use this type of data to focus their activities on specific regions (e.g., Jantke et al. 2019), we provide rankings by biome and ecoregion and briefly compare our results to other available results.

2 Methods

2.1 Overview

We calculated the degree of human modification using the Direct Threats Classification v2 (Salafsky et al. 2008; cmp-openstandards.org), which defines a stressor as the proximate human activities or processes that have caused, are causing, or may cause impacts on biodiversity and ecosystems. Table 1 lists the specific stressors and data sources we included in our maps: urban/built-up, crop and pasture lands, livestock grazing, oil and gas production, mining and quarrying, power generation (renewable and non-renewable), roads, railways, power lines and towers, logging and wood harvesting, human intrusion, reservoirs, and air pollution.

To estimate temporal change in \( H \) from 1990 to 2015, we followed criteria established (Geldmann et al. 2014) and included 11 stressors for which we could obtain global data with fine-grained resolution (<1 km\(^2\)), and that provided consistent and comparable repeated measurements, especially in regards to the data source, methods used, and appropriate time frame (Table 1). We included current major roads and railways as a static layer in the temporal maps because in most cases some form of road existed prior to our baseline year of 1990 (except for the relatively rare, though important, new highway constructed).

To estimate the current amount of \( H \) circa 2017 year (median=2017, min=2012, max=2019), we included three additional stressors, including grazing, oil and gas wells, and powerlines. We note that we were not able to map stressors for invasive species or pathogens and genes, geologic events, or climate change. This was because suitable temporal global data were not available to capture stressors due to invasive species or pathogens and genes; the majority of geological events are not directly caused
by humans; and climate change is better modeled as separate process distinct from the effects of direct human activities and has a plethora of research on this topic (Geldmann et al. 2014; Titeux et al. 2016).

For each stressor \( s \) we quantified the degree of human modification as:

\[
H_s = F_s \cdot p(C_s) \cdot I_s,
\]

(1)

where \( F \) is the proportion of a pixel occupied (i.e. the footprint) by stressor \( s \), \( p(C_s) \) is the probability that a stressor occurs at a location to account for spatial and classification uncertainty, and \( I \) is the intensity. Importantly, \( F \) and \( I \) have a direct physical interpretation (Gardner and Urban 2007), are well-bounded and range from 0-1, and values are a “real” data-type. Consequently, \( H \) provides the basis for unambiguous interpretation to assess landscape change (Hajkowicz and Collins 2007; Riitters et al. 2009). Specific formulas used to map raw stressor data as indicator layers are provided below. Table 2 details our estimates of intensity values for each stressor (modified from Theobald 2013 and Kennedy et al. 2019a), which is used to differentiate land uses that have varying impacts on terrestrial systems (e.g., grazing is less intensive than mining). Our intensity values were informed by standardized measures of the amount of non-renewable energy required to maintain human activities (Brown and Vivas 2005) and found to generally correlate with species responses to land use where examined (Kennedy et al. 2019a).

We generated datasets that represent temporal changes between 1990 and 2015 and for current (~2017) conditions by combining stressor layers using the fuzzy algebraic sum (Bonham-Carter, 1994; Malczewski 1999; Theobald 2013), which is calculated as:

\[
H = 1 - \prod_{n=1}^{n} (1 - H_s),
\]

(2)

where \( n \) is the number of stressors \( s \) included. Of critical importance, the fuzzy sum formula is an increasing function that calculates the cumulative effects of multiple stressors in a way that minimizes the bias associated with non-independent stressors and assumes that multiple stressors accumulate (Theobald 2010, 2013; Kennedy et al. 2019a). This differs substantially from simple additive calculations that are commonly used (Halpern et al. 2008; Halpern and Fujita 2013; Venter et al. 2016), but assume that stressors are independent and results in a metric that is sensitive to the number of stressors included in the model (Malczewski 1999).

We mapped human modification of all terrestrial lands (excluding Antarctica) and included lands inundated by reservoirs, but excluded other rivers and lakes. An often overlooked but critical aspect to understand human modification is how water is mapped, especially for the interface between land and coastlines, lakes, reservoirs, and large rivers. We mapped non-reservoir areas dominated by water (i.e., oceans, lakes, reservoirs, and rivers) by processing data on ocean from the European Space Agency’s Climate Change Initiative program (ESA CCI; 150 m, circa 2000) and surface waters using the Global Surface Water dataset (GSW; 30 m; Pekel et al. 2016). We identified inland water bodies (i.e. lakes, reservoirs, rivers, etc.) using ESA CCI non-ocean pixels that were at least 1 km interior of the land-ocean interface. We identified interior water pixels using GSW with at least 75% water occurrence from 1984-2019 and that were at least 0.0225 km² in area (to remove small lakes,
ponds, and narrow streams). As a result, inland water bodies and the ocean-land interface are much clearer, more consistent, and better aligned.

We summarized our estimates of human modification across all terrestrial lands, biomes, and ecoregions (defined by Dinerstein et al. 2017) and here report median ($H_{med}$) and mean ($H_{mean}$) statistics. We summarized results of temporal trends using the mean annualized difference ($H_{mad}$), calculated as the mean value across each analytical unit (e.g., biomes, ecoregions) of the annualized difference assuming a linear trend ($H_{ad}$):

$$H_{ad} = (H_u - H_t)/(u - t),$$

where $u$ and $t$ are the years of the datasets (e.g., $u$=2015, $t$=1990) and $u > t$. When discussing trends between 1990 and 2015, we emphasize the mean statistic because it better captures locations where $H$ values have changed (mostly increasing over time), partly due to land uses with high values (e.g., urbanization $\sim$0.8) that are not well represented in the median statistic. We calculated the increase in $H$, or conversely the amount of natural habitat loss, as the per-pixel value times the pixel area, summed across a given unit of analysis. This assumes that any increase in the level of human modification causes natural land loss regardless of the original $H$ level. We also report the median statistic because, as is typical of spatial landscape data, the distribution of $H$ values is skewed to the right. Finally, we compared our results of $H_{mad}$ to those calculated on the Human Footprint (HF for 1993-2009; Venter et al. 2016) and the temporal human pressure index (THPI for 1995-2010; Geldmann et al. 2019b).

2.2 Stressors mapped

2.2.1 Urban and built-up

To map built-up areas that are typically found in urban areas and dominated by residential, commercial, and industrial land uses, we used the most recent version of the Built-up Grid from the Global Human Settlements Layers dataset (GHSL R2018A; Pesaresi et al. 2015). The degree of human modification that is contributed by built-up areas, $H_{bu}$, is:

$$H_{bu} = F_{bu} \cdot p(C_{bu}) \cdot I_{bu},$$

where $F_{bu}$ measures the proportion of the area of a pixel classified as built-up, $p(C_{bu})$ applies the GHSL-reported confidence mask (for 2014) for locations of the built-up areas (for the target year; Pesaresi et al. 2015) and $I_{bu}$ is the intensity factor specified in Table 2.

2.2.2 Agriculture

We mapped agriculture stressors by identifying land cover classes associated with crop and pastureland from ESA CCI land cover datasets (ESA CCI 2015; Perez-Hoyos et al. 2017; Li et al. 2018) available at 0.09 km$^2$ for 1992, 2000, 2010, and 2015. We merged the cropland and pastureland stressors because these two classes are combined in the ESA land cover data, and they are challenging to distinguish even at higher resolution (~30 m, Wickham et al. 2017). To incorporate classification errors associated with all cover classes, we multiplied the footprint $F_{cp}=1.0$ times the probability $p(C_{cp})$ that a pixel with cover class $C$ was found to be cropland or pasture, $C_{cp}$, by interpreting reported accuracy assessment results (ESA CCI 2017, in Table 3). To reduce the effects of
scattered pixels that have some probability of being mapped as cropland-pastureland (e.g., misclassified pixels high-elevation tundra or alpine areas), we multiplied $p(C_{cp})$ by the proportion of lands estimated to be in crops from the Unified Cropland Layer (Waldner et al. 2016), $v$ so that:

$$p(C_{cp})' = p(C_{cp}) \times v,$$

and also reduced the value of $p(C_{cp})'$ based on patch size $A$, assuming that accuracy declines rapidly with cropland/pastureland small “patches” ($A < 1$ km$^2$) using:

$$p(C_{cp})'' = (p(C_{cp}))^2, A < 1.$$  

We then calculated $H_{cp}$ as:

$$H_{cp} = F_{cp} \times p(C_{cp})'' \times I_{cp}. \quad (7)$$

We developed spatially-explicit estimates of agricultural intensity based on land management, such as cropping and number of rotations, tilling, and cutting operations because these activities typically vary geographically (van asselen and Verburg 2012; Kehoe et al. 2017). We followed existing methods (Chaudhary and Brooks 2018) to estimate three intensities of agricultural land use -- minimal, light, and intense -- and then mapped them using cover types from Global Land Systems v2 dataset (GLS; Kehoe et al. 2017) by estimating intensity values ($I$) for each of the agricultural intensity types (Table 2). Although GLS v2 represents conditions circa 2005, we incorporated temporal changes by weighting the proportion of agricultural lands from the time-varying ESA CCI land cover datasets.

To estimate the modification associated with the grazing of domestic livestock ($H_{au}$), we used the Gridded Livestock of the World v3 (Robinson et al. 2014; Gilbert et al. 2018a, Gilbert et al. 2018b) that maps the density of animals per km$^2$ ($G$) for eight types of livestock ($j$): buffaloes, cattle, chickens, ducks, goats, horses, pigs, and sheep. To calculate the overall footprint of grazing ($F_{au}$), we summed the weighted densities by global averages of livestock unit (LU) coefficients ($w = 0.84, 0.67, 0.01, 0.01, 0.10, 0.84, 0.23, 0.10$, listed respectively for each livestock species stated above). We used a lower threshold found at 10% to remove values <1.0 LUs/km$^2$ (similar to Jacobson et al. 2019) and 1000 LUs/km$^2$ as an upper threshold because it is a common breakpoint between grazing and industrial feedlots (Gerber et al. 2010). We assumed (here, and below unless otherwise provided) no uncertainty ($p(C_{au}) = 1.0$), because we lacked explicit data to do so. We then $log_{10}$ transformed and max-normalized (Kennedy et al. 2019a) to obtain 0-1 values, and calculated the mean $H_{au}$ using a 10 km radius moving window to reduce the effects of the coarser-resolution pixels:

$$F_{au} = \sum_{j=1}^{8} G_{wj} \times \text{max(1000)}, \text{min(1)} \quad (8)$$

$$H_{au} = \left( \frac{\log(F_{au} + 1)}{\log(1000)} \right) \times p(C_{au}) \times I_{au} \quad (9)$$

2.2.3 Energy and extractive resources

To estimate stressors associated with extractive energy production, we mapped gas flares derived from “night-time lights” using data from the Visible Infrared Imaging Radiometer Suite from the Suomi National Polar-orbiting Partnership (VIIRS; Elvidge et al. 2013). Roughly 90% of gas flares occur at locations where oil and gas are extracted (Elvidge et al. 2015). We used point data processed specifically to identify gas flares in VIIRS for 2012/2013 (Elvidge et al. 2016). For each flare, we approximated a footprint of 0.057 km$^2$ per well head (Allred et al. 2015). It is common to
approximate the footprint of points (and lines) using a simple “buffer”, which implicitly assumes no location error and no distance-decay from the point of origin. Such a buffer approach essentially centers a cylinder on each data point, where volume \( V \) equals the approximate footprint and height \( h \) and a perfect certainty of 1.0. Here, however, we assumed some uncertainty in the location of the point and that the effects associated with a feature such as an oil/gas well-deal diminish with distance. That is, rather than use a cylinder with volume \( V \) (or similarly a simple uniform buffer away from linear features, e.g. powerlines or roads), we used a conic shaped kernel centered on the point to calculate the uncertainty \( p(C_{og}) \), where the height of the cone \( h=0.5 \) represents a conservative estimate of spatial accuracy (Theobald 2013). We derived the cone radius \( D=0.329 \) km by setting \( V \) to the footprint of 0.057 km\(^2\):

\[
D = \sqrt{\frac{3}{2}} \frac{V}{\pi},
\]

Thereby the uncertainty parameter for each point is calculated using:

\[
p(C_{og}) = 3h/\pi D^2.
\]

We assigned the value of \( p(C_{og}) \) that overlapped the center of each pixel, with max \( p(C_{og}) = 1.0 \). Human modification was then calculated as:

\[
H_{og} = F_{og} \cdot p(C_{og}) \cdot I_{og}.
\]

### 2.2.5 Mines and quarries

To estimate modification due to mines and quarries, we derived locations represented as points from a global mining dataset \((n=34,565)\; S&P \; 2018; \; Valenta \; et \; al. \; 2019\). We retained surface mines that were constructed, construction started, in operation, in the process of being commissioned, or residual production \((n=22,705)\). For the temporal change analysis, we removed locations that did not have a specified year of construction \((n=3,634)\). We calculated the mean disturbed area and associated infrastructure of a mine by intersecting mine point locations with 441,623 polygons that represent footprints of quarries/mines (OpenStreetmap, 2016). For four types of mines: coal; hard-rock (bauxite, cobalt, copper, gold, iron ore, lead, manganese, molybdenum, nickel, phosphate, platinum, silver, tin, U, O\(_3\), and zinc); diamonds; and other (antimony, chrome, graphite, ilmenite, lanthanides, lithium, niobium, palladium, tantalum, and tungsten), we estimated the mean area \((a)\) to be: 12.95 km\(^2\) \((n=647)\) for coal, 8.54 km\(^2\) \((n=860)\) for hard-rock, 5.21 km\(^2\) \((n=39)\) for diamonds, and 3.40 km\(^2\) \((n=27)\) for other. Finally, following equations 8 and 9, we calculated \(p(C_{m})\) for each of the four mining types using \( D \) of 4.973, 4.038, 2.548, and 3.154 km, respectively, and calculated \(H_m\) as:

\[
H_m = F_m \cdot p(C_{m}) \cdot I_m.
\]

### 2.2.6 Power plants

To estimate the effects of where energy is produced, we mapped the location of power plants represented as points \((n=29,903)\; WRI \; 2019\). For the temporal change analysis, we removed locations that did not have a specified year of construction \((n=16,288)\). We estimated \(p(C_{pp})\) using a conic-shaped kernel (Eqs. 8 and 9) and \(h=0.5\). We mapped both non-renewable energy forms \((H_{pp})\); coal, oil, natural gas and renewable energy forms \((H_{ppr})\); geothermal, hydro, solar, wind), where we assumed \(F_{pp}=1\) and calculated a single \(p(C_{pp})\) for both non-renewable and renewable energy sectors with \(D_{pp}=1224\) m (following Theobald 2013):

\[
H_{pp} = F_{pp} \cdot p(C_{pp}) \cdot I_{pp}.
\]
2.2.7 Transportation and service corridors

For transportation, we mapped roads and railways using OpenStreetMap highway linear features (OpenStreetMap, 2019). We calculated the footprint for the following transportation types: major (motorway, primary, secondary, trunk, link), minor (residential, tertiary, tertiary-link), two-track roads and railways as:

\[ H_{pr} = F_{pr} \cdot p(C_{pr}) \cdot I_{pr} \]

where \( F_{pr} = \sum_{i=0}^{c} \frac{w_i}{\alpha} \cdot \mu \),

\[ H_{rr} = F_{rr} \cdot p(C_{rr}) \cdot I_{rr} \]

where \( w_i \) is the estimated width of a road of type \( i \) from Table 2, \( \alpha \) is the pixel width (i.e., 300 m), and \( \mu = 0.79 \) to adjust for the fractal dimension of road lines crossing cells (Theobald 2000) because road lines often cross pixels at random angles. If a divided highway is represented as two separate lines, then each is represented independently. Also, if a cell has two or more roadway types cross it (e.g., where a secondary road joins a highway), the fuzzy sum of \( H_{rr} \) for both roads is calculated. Note that use of roads is incorporated into the “human intrusion” stressor (described below).

To map the modification associated with above-ground powerlines \( (H_{pl}) \), we used:

\[ H_{pl} = F_{pl} \cdot p(C_{pl}) \cdot I_{pl} \]

where \( F_{pl} \) is calculated using a 500 m buffer (Theobald 2013), and \( p(C_{pl}) \) is calculated using \( h = 0.5 \), and \( I_{pl} \) is the estimate of intensity.

To estimate a stressor associated with electrical infrastructure and energy use \( (H_{nl}) \), we mapped “night-time lights” using the Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS; Elvidge et al., 2001) “stable” lights dataset. We included this as a distinct stressor from the energy extraction stressor (oil and gas flares, discussed above) because gas flares are derived by finding anomalies (high values) in the images rather than from the “stable lights” product, and the footprints associated with the flares are an extremely small fraction of the overall extent of energy infrastructure.

To maximize temporal consistency, we used the intercalibrated DMSP/OLS dataset (Zhang et al. 2016; Li and Zhou 2017) and extended their approach for 2013 (using \( a = 1.01 \), \( b = 0.00882 \), \( c = -0.965 \); Zhang et al. 2016). DMSP/OLS values, \( L \), are expected to range from 0 to 63, but because max values differed yearly (ranging from 57.87 - 66.16), we normalized all images (1992-2013) to range from 0 to 1.0 using the max-adjusted value for each year \( (L') \). To reduce the effects of noise in the images in areas with low-light and in high northerly latitudes, we removed nighttime light values when \( L' < 0.077 \) – that is, we set values to null when they were below the 25th percentile of the global terrestrial distribution compared to the often used noise threshold of \( L=5 \) (following Elvidge et al. 2001).

To adjust for inter-annual spatial-misalignment errors (Elvidge et al. 2013), we adjusted the normalized DMSP image for 2013 to align with the 2013 VIIRS product by identifying sharply contrasting and consistent signals at 10 locations \( (n=10) \) distributed across the continents. We then
visually compared each of the images from 1992-2012 to the DMSP image for 2013 and shifted the images to align them (averaged shift in meters: $x=359.5, y=476.2$). To further reduce inter-annual variability, we averaged image values at each pixel using a 3-year “tail” and used a rank-ordered-centroid weighting (Roszkowska 2013) such that the spatially-aligned and temporally-smoothed nightlight value $Y$ for year $t$ is:

$$Y_t = (L_t' \cdot 0.62) + (L_{t-1}' \cdot 0.26) + (L_{t-2}' \cdot 0.12) .$$  \hspace{1cm} (19)

Finally, to reduce the blooming effects and to take advantage of the higher-quality VIIRS-based nightlights (i.e. higher spatial resolution, reduction of saturated pixels), we sharpened DMSP nightlight values $Y_t$ using the VIIRS brightness value $y$ to be proportional to the ratio of the DMSP values:

$$Y_t' = Y_t \cdot (L_t' + L_{2013}) .$$ \hspace{1cm} (20)

We then transformed $Y_t'$ following Kennedy et al. (2019a), capping values above 126.0 (the 99.5 percentile of global values):

$$H_{nl} = (\log_{10} (1 + Y_t') / 2.104)) \cdot p(C_{nl}) \cdot I_{nl} .$$ \hspace{1cm} (21)

2.2.8 Logging

To estimate stressors on forested lands, we used maps of forest loss (Curtis et al. 2018) associated with commodity-driven deforestation, shifting agriculture, and forestry. (Note that we excluded wildfire as a stressor because of the challenges of attributing wildfires to human causation—especially over global extent, and urbanization because it is measured directly by the built-up stressor). We then identified locations where forest was lost due to one of the three mapped stressors (using v1.6, updated to 2018; Hansen et al. 2013) prior to the year of our estimated human modification map, and applied the intensity value associated with that stressor (Table 2). Thus, $H_{fr} = F_{fr} \cdot p(C_{fr}) \cdot I_{fr}$, \hspace{1cm} (22)

where $F_{fr}$ is pixels of forested loss in a given year, and $I_{fr}$ is an estimate of intensity associated with the cause of forest loss.

2.2.9 Human intrusion


Accessibility measured in travel time in minutes is calculated from each mapped settlement point $j$ (e.g., cities, towns, villages) from GRUMP v1.01 and GPW v4 (CIESIN 2017, 2018). This approach is much less sensitive to arbitrary thresholds of city/town size (e.g., 50,000 residents), often used due to computational constraints (e.g. Nelson 2008; Weiss et al. 2018). Second, to estimate “intrusion” of people to adjacent areas from a given settlement, we estimated the number of people (using population estimates at settlement $j$) at a given location ($X$; ~population density: people/km$^2$)
following the assumption that the human density halved with every 60 minutes traveled (Theobald 2008, 2013). The resulting intrusion map for each settlement was then summed to account for typical overlaps of intrusion from nearby settlements. We assumed that there is a limit at very high population densities and so we capped the maximum value of intrusion, \( X \), at 1,000,000 then max-normalized using a square-root transform:

\[
F_i = X_i^{0.5} \times 0.001, \quad (23)
\]

\[
H_i = F_i \times p(C_i) \times I_i, \quad (24)
\]

Note that accessibility was calculated using estimates of travel time along roads and rails, as well as off-road through different features of the landscape, using established travel time factors (Tobler 1991) and presuming walking off-trail or via boats on freshwater or along ocean shoreline (Nelson 2008; Theobald et al. 2010; Weiss et al. 2018; Nelson et al. 2019). This included effects of international borders following Weiss et al. (2018), and accessibility to lands was calculated across oceans.

2.2.10 Natural systems modification

Dams and their associated reservoirs flood natural habitat and strongly impact the natural flow regimes of the adjacent rivers (Grill et al. 2019). We mapped the footprint of reservoirs \( F_r \) created from 6,849 dams from the Global Reservoirs and Dams database (GRanD v1.3; Lehner et al. 2011; http://globaldamwatch.org/grand/).

\[
H_r = F_r \times p(C_r) \times I_r, \quad (25)
\]

2.2.11 Pollution

We estimated the stress of air pollution by using data on nitrogen oxides (\( \text{NO}_x \)) through time from the Emissions Database for Global Atmospheric Research (EDGAR v4.3.2; Crippa et al. 2018). We selected \( \text{NO}_x \) because it is a strong contributor to acid rain/fog and tropospheric ozone and because atmospheric levels are predominantly from human-sources (Delmas et al. 1997). We used the 99th percentile (46,750 M tonnes) as the maximum value and then max-normalized (\( F_{\text{nox}} \)) and adjusted using the intensity value \( I_{\text{nox}} \):

\[
H_{\text{nox}} = F_{\text{nox}} \times p(C_{\text{nox}}) \times I_{\text{nox}}, \quad (26)
\]

2.3 Uncertainty and validation analyses

To understand the uncertainty of our results associated with our estimated intensity values (Table 2), following Kennedy et al. (2019b), we re-calculated \( H \) where \( I_i \) was randomized between the minimum and maximum intensity values (at 1 km\(^2\) resolution for computational efficiency). We quantified the mean and standard deviation of the resulting global \( H \) values for \( n=50 \) randomizations.

We also assessed the accuracy of our maps following validation procedures described in Kennedy et al. (2019a, 2019b, 2019c). Because historical “ground truth” human modification data in comparable form are not widely available, we restricted our analysis to test the contemporary (~2017) conditions map of human modification that included all stressor layers. We used the validation data from Kennedy et al. (2019a), which is an independent validation dataset that quantified the degree of...
human modification from visual interpretation of high resolution aerial or satellite imagery across the world. We selected plots using the Global Grid sampling design (Theobald 2016), a spatially-balanced and probability-based random sampling that was stratified on a five-class rural to urban gradient using “stable nighttime-lights” 2013 imagery (Elvidge et al., 2001). Within each of 1,000 ~1 km² plots, we selected 10 simple-random locations to capture rare features and heterogeneity in land use and land cover (for a total of 10,000 sub-plots), which were separated by a minimum distance of 100 m. The spatial-balanced nature of the design maximizes statistical information extracted from each plot because it increases the number of samples in relatively rare areas that are likely of interest (in contrast to simple random sampling) – especially for urbanized and growing cities (Theobald, 2016).

2.4 Processing platform

We processed, modeled, and analyzed the spatial data using the Google Earth Engine platform (Gorelick et al. 2017). We calculated all distances and areas using geodesic algorithms in decimal degrees (EPSG: 4326). We summarized areas and percentages after projecting the data to Mollweide equal-area (WGS84) to simplify calculations. All datasets and maps conform to the Google Earth Engine terms of service. We used program R 3.6.1 (R Core Team 2019) to generate Fig. 2.

3 Results

Below we describe the temporal and spatial trends of human modification by continents (Table 4), biomes (Table 5), and ecoregions (Fig. 2).

3.1 Changes from 1990-2015

The mean value of $H$ for global terrestrial lands increased from 0.08221 in 1990 to 0.09458 in 2015, a percentage change of 15.04% (0.60% annually; Table 4). This equates to 1.6 M km² of natural lands lost – roughly 177 km² daily or 17 football pitches per minute (i.e. an international football field). Increases in human modification occurred across the globe and across urban and rural locations. We found that the largest increases in $H_{mad}$ occurred in Oceania, followed by Asia and Europe. Australia had the lowest increase followed by North and South America (Table 4). The biomes that exhibited the greatest increases were mangroves; tropical & subtropical moist broadleaf forests; and tropical & subtropical dry broadleaf forests; while the biomes with the smallest increases were tundra; boreal forests/taiga; and deserts and xeric shrublands. Maps of changes in $H_{mad}$ between 2015 and 1990 for each ecoregion are shown in Fig. 1a, relative to HF (Fig. 1b) and THPI (Fig. 1c). Figure 2 shows the ratio of natural land loss between 1990 and 2015, for each ecoregion and grouped by biome, in the context of the contemporary extent of human modification. We found most ecoregions (n=814) had increased in human modification, while the few (n=32) that had decreased were concentrated in higher latitudes and in more remote areas. We also found that changes in $H_{mad}$ have increased over time, from 0.00042 to 0.00051 to 0.00062, during 1990-2000 to 2000-2010 to 2010-2015. The percent change has also increased over time from 0.51% to 0.59% to 0.68%.
3.2 Contemporary extent

We found that about 19.1 M km$^2$ of natural lands were lost by ~2017 – about 14.6% of land globally (Table 4). South America was the most transformed (28.7%), followed by North America (16.8%), while Australia (5.0%) and Africa (10.7%) were the least transformed. Broad-scale patterns of the extent of human modification in ~2017 are shown in Fig. 3.

Terrestrial lands with very low levels of human modification ($H<0.01$) are concentrated in less productive and more remote areas in high latitudes and dominated by inaccessible permanent rock and ice or within tundra, boreal forests, and to a lesser extent montane grasslands. Table 5 shows that the biomes with the highest levels of $H$ in ~2017 were temperate broadleaf and mixed forests ($H=0.374$); tropical & subtropical dry broadleaf forests ($H=0.331$); and Mediterranean forests, woodlands & scrub ($H=0.290$). The five least modified biomes were tundra (mean $H=0.002$); boreal forests/taiga ($H=0.021$); deserts and xeric shrublands ($H=0.057$); and montane grasslands and shrublands ($H=0.089$).

We found that in ~2017, 51.0% of lands had very low human modification (mean $H \leq 0.01$; 66.8 M km$^2$), 13.3% had low human modification ($0.01 < H \leq 0.1$; 17.4 M km$^2$), 21.0% had moderate human modification ($0.1 < H \leq 0.4$; 27.6 M km$^2$), 12.3% had high human modification ($0.4 < H \leq 0.7$; 16.1 M km$^2$), and 2.4% had very high human modification ($0.7 < H \leq 1.0$; 3.2 M km$^2$) (following the thresholds from Kennedy et al. 2019a). We found that ~4.2% of lands have no evidence of human modification ($H < 0.00001$; 5.5 M km$^2$), based on our estimate of the level of precision (~0.00001) given the data inputs.

3.3 Comparisons

We compared our work to earlier efforts to determine if overall trends and extents were generally consistent and resulting priorities of biomes and ecoregions were similar. Globally, $H_{mad}$ from 1990-2015 ($t=1990, u=2015$) was 0.00049, while for HF and THPI it was higher ($HF_{mad}=0.00056$, $THPI_{mad}=0.00081$). Perhaps more important is that the variability of the mean annualized difference values in the HF and THPI was 2.3 and 3.2 times that of $H$. By continent, we found that $H_{mad}$ increased the most in Oceania, followed by Asia, Europe, Africa, South America, North America, and Australia. Continental ranks by THPI followed $H$ roughly, though HF differed more substantially (Table 5). $H_{mad}$ increased for all continents, but $HF_{mad}$ showed declines in modification for Europe and South America, while $THPI_{mad}$ showed a decline for North America.

We also found the ranking of biomes by mean annualized difference for HF and THPI were fairly different from ranks developed from $H$ values (Table 6). Of the three biomes with the largest increase for $H_{mad}$, two of them were also identified by HF (tropical & subtropical dry broadleaf forests and tropical & subtropical moist broadleaf forests) and none of them by THPI. Of the five biomes with the largest increase for $H_{mad}$, three of them were also identified by HF and THPI. The biomes that had the greatest disagreement amongst the ranking of $H$, HF, and THPI were mangroves; tropical & subtropical coniferous forests; and tropical & subtropical dry broadleaf forests. The results for
ecoregions shown in Fig. 1 are even more striking, as the mean annualized difference values for HF and THPI were inconsistent with our results. Of the 814 ecoregions that had increases in $H_{\text{mad}}$, a decrease in modification was found for 201 ecoregions in $H_{\text{mad}}$ and 202 for $THPI_{\text{mad}}$, and for the 32 ecoregions that were found to have decreases in $H_{\text{mad}}$, an increase in modification was found for 20 in HF and 22 in THPI.

In terms of the overall amount of recent (~2017) human modification globally, we found that 14.5% of terrestrial lands globally have been modified -- which is roughly similar to HF (12.3% for ~2009; Venter et al. 2016) and the degree of human modification at 1-km resolution (H1k; 19% for ~2016; Kennedy et al. 2018, 2019a). The ranks of the extent of modification by biomes, however, were very similar between H, H1k, and HF. In general, H had intermediate modification levels compared to H1k and HF: with H1k levels being slightly higher (difference between 0.00 min to 0.09 and average difference of 0.05 by biome) and HF being slightly lower (difference between 0.00 min to 0.13 max and average difference of 0.04 by biome) (Table 6). The global estimate for H1k was likely higher than H because H1k did not limit the livestock stressor at LU km$^{-1}$ <1.0, used a slightly higher value for the low-threshold on the electrical infrastructure and energy use stressor (i.e. “nightlights”), and reported results that incorporate uncertainty in estimates of intensity. The biggest differences in rankings between the H and the HF were for temperate and broadleaf mixed forests (and see comparisons of H1k and HF in Kennedy et al. 2019a, 2019b).

3.4 Uncertainty and validation analyses

To examine the uncertainty associated with our intensity estimates, we calculated across all terrestrial lands the mean $H$ value on datasets generated with intensity values drawn from a uniform random distribution between the minimum and maximum estimates. We generated 50 randomized datasets and found the mean of the randomized maps was 0.14306 and the standard deviation was ±0.00106 (compared to our best-estimate of 0.14605). The lowest possible mean $H$ value calculated with the minimum estimate for all stressors was 0.10686 and the highest possible value using the maximum estimate was 0.18493.

We found strong agreement between $H$ for ~2017 and our validation data ($r=0.783$), with an average root-mean-square-error of 0.22 and a mean-absolute-error of 0.04, for the 926 ~1 km$^2$ plots (9,260 sub-plots). There were 726 plots within ±20% agreement, while for 161 plots $H$ was estimated higher than our visual estimate from the validation data (and 39 plots lower). Estimates of $H$ were biased high, likely because the stressors for the “human intrusion” and electrical infrastructure (based on nighttime lights) are not readily observable from the aerial imagery used to generate the validation data.
4 Discussion

4.1 Summary

We found rapid and increasing human modification of terrestrial systems, resulting in the loss of natural lands globally. Our findings foreshadow trends and patterns of increased human modification, assuming future trends in the next 25-30 years continue as they have recently. Thus, our study reinforces calls for stronger commitments to help reduce habitat loss and fragmentation (Kennedy et al. 2019a, Jacobson et al. 2019) – which should be considered in conjunction with current commitments (e.g., to reduce CO$_2$ emissions through the Paris climate accord; Baruch-Mordo et al. 2019; Kiesecker et al. 2019). We believe that the comparisons of ecoregions and biomes shown in Fig. 2 offer valuable contextual information that provides initial guidance on conservation strategies that may be most appropriate (Kennedy et al. 2019a). Also, it is important to consider the relative importance of each ecoregion towards meeting representation goals by ecoregion (Dinerstein et al. 2017) or ecosystem (Jantke et al. 2019), as well as considering additional stresses caused by climate change (Costanza and Terando 2019). We emphasize that although global, continental, biome, and ecoregional summaries provide a general idea of trends and patterns, our work here supports robust estimates at country and within ecoregional patterns of the gradient of human modification, especially when placed within a broader structured decision making framework (Tullock et al. 2015).

Our datasets of human modification provide the most granular, contemporary, comprehensive, high-quality, and robust data currently available to assess temporal and spatial trends of global human modification. Our work is grounded in a structured classification of stressors, uses an internally-consistent model, evaluates uncertainty, and incorporates refinements to minimize the effects of scaling and classification errors. Our validation approach uses an independent and spatially-balanced random sample design to provide strong support for the quality of our findings (Kennedy et al. 2019c).

Our overarching goal in producing and publishing these datasets is to support detailed quantification of the rates and trends, as well as the current extent and pattern, to understand the gradient of the degree of human modification across the continuum from low (e.g., wilderness) to high (e.g., intense urban). Beyond the basic findings presented here, we believe there are many potential applications of these datasets, including: examining temporal rates and trends of land modification in and around protected areas (e.g., Geldmann et al. 2019a); estimating fragmentation for all ecoregions and biomes (Kennedy et al. 2019a, Jacobson et al. 2019); and evaluating conservation opportunities and risks (e.g., the conservation risk index; Hoekstra et al. 2005). We also note that the human modification approach allows, in a straightforward and logically consistent way, inclusion of additional stressors and higher resolution datasets that may become available over time or may be available for specific, local areas.
4.2 Caveats

As with any model, we recognize there are limitations of our work. We did not include data for all human stressors, typically because of incomplete global coverage or too-coarse mapping units (Klein Goldewijk et al. 2007; Geldmann et al., 2014), an inability to discern human-induced versus natural disturbances (e.g.; wildfires), or uncertainty in the location and directionality of its impact (e.g.; climate change on terrestrial systems; Geldmann et al., 2014). Although our datasets described here have order-of-magnitude higher resolution than previous temporal maps, estimates of $H$ generated for areas less than roughly 100 km$^2$ should be used with caution. Stressors that are particularly important to improve include effects of grazing (currently coarse data and very broad expanse), pasture land, invasive species, and climate change (especially effects of sea-level rise), and we encourage future work to focus on developing appropriate datasets and approaches to include or better capture these stressors. Key datasets we believe should be improved include transportation networks (e.g., Van Etten 2019) that are comparable through time; livestock grazing, rangelands, croplands, and pasturelands and their intensity of use; resource extraction (especially mining footprints); and temporal trends in gas flares, utility-scale solar plants, electrical substations, etc.

4.3 Data availability

The datasets generated from this work are available at [https://doi.org/10.5061/dryad.n5tb2rbs1](https://doi.org/10.5061/dryad.n5tb2rbs1) (Theobald et al. 2020). All other datasets used in our work are open-source data cited within.

Author contributions

DT, CK, BC, JO, SBM, JK conceived the paper; DT, CK, JO, BC prepared data; DT implemented the model; DT, CK, BC, SBM conducted summary analyses; DT, CK, BC, JO, SBM, JK developed recommendations; all contributed to writing the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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### Tables

Table 1. Overview of stressors, datasets, spatial resolution, and years data were available and used in the maps of human modification. Stressor classification levels in parentheses correspond to those within the Direct Threats Classification v2 (Salafsky et al. 2008). Acronyms of source data are bolded in Source column for reference throughout the paper.

<table>
<thead>
<tr>
<th>Class</th>
<th>Stressor*</th>
<th>Source</th>
<th>Resolution (km²)</th>
<th>Year(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban &amp; built-up (1)</td>
<td>Built-up (1.1, 1.2)</td>
<td>Global Human Settlement Layer version R2018A (GHSL; Pesaresi et al. 2015)</td>
<td>0.0009 - 0.9</td>
<td>1990, 2000, 2010*, 2015</td>
</tr>
<tr>
<td>Agriculture (2)</td>
<td>Croplands &amp; pasturelands (2.1)</td>
<td>European Space Agency Climate Change Initiative land cover (ESA CCI; Li et al. 2018)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unified Cropland Layer (UCL; Waldner et al. 2016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Global Land Systems v2 (GLS; Kehoe et al. 2017)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Grazing (2.3)</td>
<td>Gridded Livestock of the World v3 (GLW; Robinson et al. 2014; Gilbert et al. 2018a, Gilbert et al. 2018b)</td>
<td>10</td>
<td>2010</td>
</tr>
<tr>
<td>Energy production &amp; mining (3)</td>
<td>Oil &amp; gas production (3.1)</td>
<td>Nighttime flares from Defense Meteorological Program/Operational Line-scan System (DMSP/OLS, Elvidge et al. 2009) and Visible Infrared Imaging Radiometer Suite (VIIRS, Elvidge et al. 2016)</td>
<td>0.25 - 1.0</td>
<td>2016</td>
</tr>
<tr>
<td></td>
<td>Transport &amp; service</td>
<td>OpenStreetMap highway, minor, and two-track features (OSM;</td>
<td>1:10-25000</td>
<td>2019</td>
</tr>
<tr>
<td>Category</td>
<td>Description</td>
<td>Resolution</td>
<td>Start Year</td>
<td>End Year</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------------</td>
<td>------------</td>
<td>----------</td>
</tr>
<tr>
<td>Corridors (4)</td>
<td>OpenStreetMap 2019</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Railways (4.1)</td>
<td>OSM railway features (OpenStreetMap 2019)</td>
<td>~1:10-25000</td>
<td>2019</td>
<td></td>
</tr>
<tr>
<td>Powerlines (4.2)</td>
<td>OSM power line features (OpenStreetMap 2019)</td>
<td>~1:10-25000</td>
<td>2019</td>
<td></td>
</tr>
<tr>
<td>Electrical infrastructure (4.2)</td>
<td>Nighttime lights from DMSP/OLS and VIIRS (Elvidge et al. 2001; Doll 2008; Elvidge et al. 2013; Zhang et al. 2016)</td>
<td>0.25 - 1.0</td>
<td>1992, 2000, 2010, 2015, 2018</td>
<td></td>
</tr>
<tr>
<td>Biological harvesting (5)</td>
<td>Logging &amp; wood harvesting (5.3)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Natural system modifications (7)</td>
<td>Reservoirs (7.2)</td>
<td>~1:25000</td>
<td>1990, 2000, 2010, 2017</td>
<td></td>
</tr>
<tr>
<td>Pollution (9)</td>
<td>Air pollution (9.5)</td>
<td>~100</td>
<td>1990, 2000, 2010, 2012</td>
<td></td>
</tr>
</tbody>
</table>

*Based on interpolation.
Table 2. Estimates of the intensity value for each stressor. “Best” estimates were determined from Brown and Vivas (2005), Theobald (2013), Kennedy et al. (2019a), or expert judgement, and are bracketed by a minimum and maximum range, following the lowest-highest-best estimate elicitation procedure to reduce bias (McBride et al., 2012). Results presented here use the best estimate, while minimum and maximum estimates are used to specify the range of possible randomized intensity values in the uncertainty analysis.

<table>
<thead>
<tr>
<th>Class</th>
<th>Stressor</th>
<th>Minimum</th>
<th>Best</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban &amp; built-up</td>
<td>Built-up areas&lt;sup&gt;3,4&lt;/sup&gt;</td>
<td>0.69</td>
<td>0.85</td>
<td>1.00</td>
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<td>Agriculture</td>
<td>Cropland/pasture&lt;sup&gt;1&lt;/sup&gt;</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Minimal&lt;sup&gt;4&lt;/sup&gt;</td>
<td>0.29</td>
<td>0.34</td>
<td>0.39</td>
</tr>
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<td></td>
<td>- Light&lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.35</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>- Intense&lt;sup&gt;3,4&lt;/sup&gt;</td>
<td>0.60</td>
<td>0.65</td>
<td>0.70</td>
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<td>Livestock grazing&lt;sup&gt;1&lt;/sup&gt;</td>
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<td>0.37</td>
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<td>Energy production &amp; mining</td>
<td>Oil &amp; gas production&lt;sup&gt;1,3&lt;/sup&gt;</td>
<td>0.70</td>
<td>0.85</td>
<td>1.00</td>
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<td></td>
<td>Mining&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.83</td>
<td>0.91</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Power generation&lt;sup&gt;1&lt;/sup&gt;</td>
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<td>(non-renewable)</td>
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<tr>
<td></td>
<td></td>
<td>0.70</td>
<td>0.85</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Power generation (renewable)&lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.70</td>
<td>0.80</td>
<td>0.90</td>
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<td>Transportation &amp; service corridors*</td>
<td>Major roads&lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.78 (20)</td>
<td>0.80 (30)</td>
<td>0.83 (40)</td>
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<td></td>
<td>Minor roads&lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.39 (15)</td>
<td>0.44 (20)</td>
<td>0.50 (25)</td>
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<td>Two-track roads&lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.10 (3)</td>
<td>0.15 (5)</td>
<td>0.20 (10)</td>
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<td></td>
<td>Railways&lt;sup&gt;1&lt;/sup&gt;</td>
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<td>0.80 (20)</td>
<td>0.83 (25)</td>
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<td></td>
<td>Powerlines&lt;sup&gt;2&lt;/sup&gt;</td>
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<td>0.15</td>
<td>0.20</td>
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<td></td>
<td>Electrical infrastructure&lt;sup&gt;3&lt;/sup&gt; (night-time lights)&lt;sup&gt;3&lt;/sup&gt;</td>
<td>0.20</td>
<td>0.35</td>
<td>0.50</td>
</tr>
<tr>
<td>Biological harvesting</td>
<td>Logging &amp; wood harvesting&lt;sup&gt;3,4,3,4&lt;/sup&gt;</td>
<td>0.60</td>
<td>0.65</td>
<td>0.07</td>
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<td>- Commodity-driven&lt;sup&gt;4&lt;/sup&gt;</td>
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<td>0.30</td>
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<td></td>
<td>- Shifting agriculture&lt;sup&gt;14&lt;/sup&gt;</td>
<td>0.10</td>
<td>0.20</td>
<td>0.30</td>
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<tr>
<td></td>
<td>- Forestry&lt;sup&gt;14&lt;/sup&gt;</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Human intrusion</td>
<td>Human intrusion(^3, 4)</td>
<td>(0.20)</td>
<td>(0.35)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>-----------------</td>
<td>---------------------------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
</tr>
</tbody>
</table>

*Assumed width of roads and railways (meters) provided in parentheses. Use of roads is incorporated into estimates of human “intrusion”.

**Causes of forest loss due to wildfire was not included because of the challenges in understanding human-causation/suppression, especially over a global extent. Also, cause of loss due to urbanization was not included in this stressor because it is incorporated directly in the built-up stressor.

***Minimum value is half of best, maximum is twice of best.
Table 3. Probability of a land cover type being classified as cropland or pasture, calculated using the producer’s accuracy, which is how often features on the ground are classified, or the probability that a certain pixel is classified as a given land cover class. Probabilities of being cropland or pasture cover type \( C_{cp} \) are adjusted based on patch size \( A \) for patches with \( A < 1 \) km\(^2\), where \( p(C_{cp}) = C_{cp} \times A_{cp}^{2} \).

<table>
<thead>
<tr>
<th>Value</th>
<th>Name</th>
<th>Crop/pastureland weight</th>
<th>Probability crop/pastureland</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Cropland, rainfed</td>
<td>1</td>
<td>0.887</td>
</tr>
<tr>
<td>20</td>
<td>Cropland, irrigated</td>
<td>1</td>
<td>0.893</td>
</tr>
<tr>
<td>30</td>
<td>Mosaic cropland (&gt;50%)</td>
<td>0.5</td>
<td>0.387</td>
</tr>
<tr>
<td>40</td>
<td>Mosaic cropland (&gt;50%)</td>
<td>0.25</td>
<td>0.366</td>
</tr>
<tr>
<td>50</td>
<td>Tree (&gt;15%), broadleaved, evergreen</td>
<td>0</td>
<td>0.038</td>
</tr>
<tr>
<td>60</td>
<td>Tree (&gt;15%), broadleaved, deciduous</td>
<td>0</td>
<td>0.070</td>
</tr>
<tr>
<td>70</td>
<td>Tree (&gt;15%), needleleaved, evergreen</td>
<td>0</td>
<td>0.016</td>
</tr>
<tr>
<td>80</td>
<td>Tree (&gt;15%), needleleaved, deciduous</td>
<td>0</td>
<td>0.000</td>
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<td>90</td>
<td>Tree, mixed leaf type</td>
<td>0</td>
<td>0.000</td>
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<tr>
<td>100</td>
<td>Mosaic tree/shrub (&gt;50%)</td>
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<td>0.345</td>
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<tr>
<td>110</td>
<td>Mosaic herbaceous (&gt;50%)</td>
<td>0</td>
<td>0.091</td>
</tr>
<tr>
<td>120</td>
<td>Shrubland</td>
<td>0</td>
<td>0.104</td>
</tr>
<tr>
<td>130</td>
<td>Grassland</td>
<td>0</td>
<td>0.176</td>
</tr>
<tr>
<td>140</td>
<td>Lichens and mosses</td>
<td>0</td>
<td>0.000</td>
</tr>
<tr>
<td>150</td>
<td>Sparse vegetation (&lt;15%)</td>
<td>0</td>
<td>0.032</td>
</tr>
<tr>
<td>160</td>
<td>Tree, flooded</td>
<td>0</td>
<td>0.043</td>
</tr>
<tr>
<td>170</td>
<td>Tree, flooded saline</td>
<td>0</td>
<td>0.000</td>
</tr>
<tr>
<td>180</td>
<td>Shrub/herbaceous flooded</td>
<td>0</td>
<td>0.000</td>
</tr>
<tr>
<td>190</td>
<td>Urban areas</td>
<td>0</td>
<td>0.120</td>
</tr>
<tr>
<td>200</td>
<td>Bare</td>
<td>0</td>
<td>0.011</td>
</tr>
<tr>
<td>210</td>
<td>Water</td>
<td>0</td>
<td>0.018</td>
</tr>
<tr>
<td>220</td>
<td>Permanent snow &amp; ice</td>
<td>0</td>
<td>0.000</td>
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Table 4. Summary of estimates of the degree of human modification ($H$) and the mean annualized difference between 5- or 10-yr increments for which change over time can be calculated (1990, 2000, 2010, and 2015), and $H$ values for the contemporary dataset (~2017, all stressors). Mean annualized mean difference is calculated as the mean value across the continents of the difference in $H$ values divided by the number of years (e.g., $H_{\text{ann}} = [H_{2015} - H_{1990}] / 25$).

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Africa</td>
<td>0.0457</td>
<td>0.0489</td>
<td>0.0515</td>
<td>0.0530</td>
<td>0.00032</td>
<td>0.00026</td>
<td>0.00030</td>
<td>0.00029</td>
<td>0.0056</td>
<td>0.1073</td>
<td>0.1730</td>
</tr>
<tr>
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<td>0.0915</td>
<td>0.0988</td>
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<td>0.00059</td>
<td>0.00073</td>
<td>0.00075</td>
<td>0.00067</td>
<td>0.0056</td>
<td>0.1542</td>
<td>0.2286</td>
</tr>
<tr>
<td>Australia</td>
<td>0.0313</td>
<td>0.0324</td>
<td>0.0334</td>
<td>0.0341</td>
<td>0.00011</td>
<td>0.00011</td>
<td>0.00013</td>
<td>0.00011</td>
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</tr>
<tr>
<td>No. America</td>
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<td>0.0419</td>
<td>0.0461</td>
<td>0.0463</td>
<td>0.00011</td>
<td>0.00042</td>
<td>0.00005</td>
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<td>0.1680</td>
<td>0.1681</td>
</tr>
<tr>
<td>Oceania</td>
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<td>0.0475</td>
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<td>0.00105</td>
<td>0.00164</td>
<td>0.00093</td>
<td>0.0527</td>
<td>0.1592</td>
<td>0.1856</td>
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<tr>
<td>So. America</td>
<td>0.2378</td>
<td>0.2398</td>
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<td>0.2442</td>
<td>0.00020</td>
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<td>0.00026</td>
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<tr>
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<td>0.00042</td>
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<td>0.1451</td>
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Table 5. A comparison of the mean annualized difference of human modification values for changes from 1990 to 2015 (H, 1990-2015), human footprint (HF, 1993-2009; Venter et al. 2016), and the temporal human pressure index (THPI, 1995-2010, Geldmann et al. 2019). Mean annualized mean difference is calculated as the mean value of the difference in H values divided by the number of years (e.g., \( H_{\text{mad}} = \frac{H_{2015} - H_{1990}}{25} \)).

<table>
<thead>
<tr>
<th>Continent</th>
<th>H</th>
<th>HF</th>
<th>THPI</th>
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<tbody>
<tr>
<td>Africa</td>
<td>0.00029</td>
<td>0.00069</td>
<td>0.00106</td>
</tr>
<tr>
<td>Asia</td>
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<td>0.00085</td>
<td>0.00123</td>
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<tr>
<td>Australia</td>
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<td>0.00018</td>
<td>0.00012</td>
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<tr>
<td>Europe</td>
<td>0.00033</td>
<td>-0.00023</td>
<td>0.00024</td>
</tr>
<tr>
<td>North America</td>
<td>0.00022</td>
<td>0.00271</td>
<td>-0.00014</td>
</tr>
<tr>
<td>Oceania</td>
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<td>0.00113</td>
<td>0.00072</td>
</tr>
<tr>
<td>South America</td>
<td>0.00025</td>
<td>-0.00004</td>
<td>0.00024</td>
</tr>
<tr>
<td>Global</td>
<td>0.00050</td>
<td>0.00056</td>
<td>0.00081</td>
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</table>
Table 6. Summary of results by biome, comparing trends using the mean annualized difference for the human modification ($H_{mad}$), human footprint ($HF_{mad}$, Venter et al. 2016), and the mean temporal human pressure index ($THPI_{mad}$, Geldmann et al. 2019) score. Also provided are estimates of the proportion of terrestrial lands modified as estimated from Kennedy et al. (H1k; 2019), and HF (score was max-normalized to rescale to 0-1). The THPI dataset characterizes only change and so estimates of the proportion of lands modified in 2010 could not be provided. Mean annualized mean difference is calculated as the mean value across the continents and globally of the difference in $H$ values divided by the number of years.

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Boreal Forests/Taiga</td>
<td>0.000004</td>
<td>-0.000014</td>
<td>0.000001</td>
<td>0.0213</td>
<td>0.0374</td>
<td>0.0288</td>
</tr>
<tr>
<td>Deserts &amp; Xeric Shrublands</td>
<td>0.000010</td>
<td>0.000028</td>
<td>0.000032</td>
<td>0.0571</td>
<td>0.1059</td>
<td>0.0820</td>
</tr>
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<td>Flooded Grasslands &amp; Savannas</td>
<td>0.000022</td>
<td>0.000023</td>
<td>0.00012</td>
<td>0.2024</td>
<td>0.2480</td>
<td>0.1423</td>
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<td>Mangroves</td>
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<td>0.000047</td>
<td>0.000021</td>
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<td>0.1972</td>
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<tr>
<td>Mediterranean Forests, Woodlands &amp; Scrub</td>
<td>0.000033</td>
<td>0.000078</td>
<td>0.000012</td>
<td>0.2903</td>
<td>0.3373</td>
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<td>0.000059</td>
<td>0.000057</td>
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<td>Temperate Broadleaf &amp; Mixed Forests</td>
<td>0.000023</td>
<td>0.000027</td>
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<td>Tropical &amp; Subtropical Coniferous Forests</td>
<td>0.000032</td>
<td>0.000005</td>
<td>0.000247</td>
<td>0.2052</td>
<td>0.2606</td>
<td>0.1568</td>
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<tr>
<td>Tropical &amp; Subtropical Dry Broadleaf Forests</td>
<td>0.000046</td>
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<tr>
<td>Tropical &amp; Subtropical Grasslands, Savannas &amp; Shrubs</td>
<td>0.000020</td>
<td>0.000057</td>
<td>0.000084</td>
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<tr>
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<tr>
<td>Tundra</td>
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<td>0.000001</td>
<td>-0.000001</td>
<td>0.0023</td>
<td>0.0001</td>
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</table>
Figure captions

Figure 1. A comparison of the recent trends in human activities by ecoregion using the mean annualized difference estimated by: (a) human modification (H, from 1990-2015); (b) human footprint (for 1993-2009, Venter et al. 2016); and (c) temporal human pressure index (for ~1995-2010, Geldmann et al. 2019). Note: interactive maps are available at:
Figure 2. Graphs of the ratio of natural lands loss (2015:1990) and contemporary (~2017) degree of human modification (denoted as HM) for each of the 14 biomes and its ecoregions, globally. Note that ecoregions with change ratios ≥3.0 are placed on the maximum x-axis value (3.0).
Figure 3. The degree of human modification for circa ~2017: (a) globally; (b) central America; (c) Europe, and (d) Oceania. Note: interactive maps are available at: https://davidtheobald8.users.earthengine.app/view/global-human-modification-change.