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Managing the middle: A shift in conservation priorities based on the global human modification gradient

Christina M. Kennedy[1,*] | James R. Oakleaf[1,*] | David M. Theobald[2] | Sharon Baruch-Mordo[1] | Joseph Kiesecker[1]

[1]Global Lands Program, The Nature Conservancy, Fort Collins, Colorado
[2]Conservation Science Partners, Fort Collins, Colorado

Correspondence
Christina M. Kennedy, Global Lands Program, The Nature Conservancy, Fort Collins, CO.
Email: ckennedy@tnc.org

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Abstract

An increasing number of international initiatives aim to reconcile development with conservation. Crucial to successful implementation of these initiatives is a comprehensive understanding of the current ecological condition of landscapes and their spatial distributions. Here, we provide a cumulative measure of human modification of terrestrial lands based on modeling the physical extents of 13 anthropogenic stressors and their estimated impacts using spatially explicit global datasets with a median year of 2016. We quantified the degree of land modification and the amount and spatial configuration of low modified lands (i.e., natural areas relatively free from human alteration) across all ecoregions and biomes. We identified that fewer unmodified lands remain than previously reported and that most of the world is in a state of intermediate modification, with 52% of ecoregions classified as moderately modified. Given that these moderately modified ecoregions fall within critical land use thresholds, we propose that they warrant elevated attention and require proactive spatial planning to maintain biodiversity and ecosystem function before important environmental values are lost.

KEYWORDS
Bonn challenge, connectivity, conservation planning, cumulative impact assessment, ecological integrity, habitat restoration, Half-Earth, human footprint, intermediate disturbance, land use policy, landscape fragmentation threshold, landscape gradient, protected areas, Sustainable Development Goals, wilderness

1 | INTRODUCTION

Humans have dramatically transformed the terrestrial biosphere (Ellis, Klein Goldewijk, Siebert, Lightman, & Ramankutty, 2010), impacting global biodiversity (Newbold et al., 2015), the functioning and stability of Earth's ecosystems (Steffen et al., 2015), and the provisioning of ecosystem services upon which we depend (Millennium Ecosystem Assessment, 2005). The global community has responded by developing a number of international initiatives to reconcile human development with conservation. For example, the *Convention on Biological Diversity* (CBD) 2020 Aichi Biodiversity Targets establishes the protection of 17% of global terrestrial lands (Target 11), the restoration of 15% of degraded ecosystems (Target 15), and the maintenance of human impacts within “safe ecological limits” (Target 4; Secretariat of the Convention on Biological Diversity, 2010). The United Nations 2030 *Sustainable Development Goals* (SDGs) calls for the protection, restoration, and sustainable use of ecosystems and the halting and reversal of land degradation and biodiversity loss (Goal 15; Cowie et al., 2018). Alongside these multilateral agreements are complementary efforts, such as the *Bonn Challenge* that aims to restore 350 million hectares of degraded land globally by 2030 (Verdone & Seidl, 2017), and the *Nature Needs Half* (NNH) initiative that aspires to protect 50% of terrestrial lands to

*Authors contributed equally.

conserve the world's biodiversity (Dinerstein et al., 2017). Critical to successful implementation of these initiatives is the ability to gauge the current condition of terrestrial ecosystems, including the extent and configuration of minimally altered lands.

Previous global assessments have largely focused on habitat conversion to develop conservation priorities (Dinerstein et al., 2017; Olson & Dinerstein, 2002; Watson, Jones, et al., 2016) or to identify possible tipping points or safe ecological limits (Steffen et al., 2015). Determining the extent of natural or converted lands alone, however, fails to capture the variety of human activities that range from agriculture, urban settlement, roads, energy, and mining: all of which vary in their spatial distributions and degrees of influence on biodiversity and ecosystem functioning. In addition, it does not account for the cumulative effects of multiple human activities. Individual impacts when in isolation can be negligible, but when they accumulate from several development projects co-occurring in a region, dire outcomes for biodiversity and ecosystems can result (Raiter, Possingham, Prober, & Hobbs, 2014).

Here, we provide a comprehensive and continuously scaled spatial assessment of the estimated impact of 13 anthropogenic stressors across all terrestrial lands, biomes, and ecoregions. To do so, we used the human modification (HM) model (Theobald, 2013), which accounts for the spatial extent, intensity, and co-occurrence of human activities to derive the potential magnitude of impact on terrestrial systems for a parsimonious list of stressors (Salafsky et al., 2008). Using the most recent, spatially explicit global datasets (median year of 2016), for each 1 km^2 area globally, we map the physical extent of human settlement (population density and built-up areas), agriculture (cropland and livestock), transportation (major roads, minor roads, two tracks, and railroads), mining, energy production (oil wells and wind turbines), and electrical infrastructure (powerlines and nighttime lights). We then weight their spatial extents by their intensity levels, as informed by independent measures of the non-renewable energy required to maintain different land use activities (Brown & Vivas, 2005). The result is an empirically based, continuous 0–1 metric that reflects the proportion of a landscape modified by humans, which is a fundamental indicator of ecological function (Gustafson & Parker, 1992).

Relative to previous global terrestrial threat maps (Ellis et al., 2010; Geldmann, Joppa, & Burgess, 2014; Venter et al., 2016), we incorporate more recent global-scale datasets and a greater number of anthropogenic drivers. We include a greater coverage of transportation infrastructure that is known to trigger human encroachment and accelerate ecosystem degradation (Ibisch et al., 2016) and extractive activities that increasingly cause large-scale land change (Kiesecker & Naugle, 2017) and have high impact on biodiversity (Schulze et al., 2018). Unlike other approaches that rely on categorical land system mapping (Van Asselen & Verburg, 2013; Ellis & Ramankutty, 2008) or ad hoc categorical scoring (Sanderson et al., 2002), our cumulative human modification map (HM_c) supports thresholding along a continuous gradient of land modification values to evaluate landscape structure (Verburg, Asselen, Zanden, & Stehfest, 2013): a component essential for robust cumulative impact assessments (Halpern & Fujita, 2013) and fragmentation analyses (Haddad et al., 2015; Halpern & Fujita, 2013; Taubert et al., 2018).

We apply the HM_c map to provide an update of the extent to which human activities have modified terrestrial lands globally. We characterize the degree of human modification of ecosystems and quantify the amount and spatial configuration of low modified lands (i.e., natural areas relatively free from human alteration). We show clear differences in terrestrial modification across biomes and ecoregions and strong variability within each. We llustrate how this gradient metric provides novel insights to prioritize global conservation and mitigation efforts. We find that moderately modified ecosystems dominate the terrestrial biosphere and fall within critical land use thresholds. Thus, we highlight these regions as timely conservation priorities, where proactive spatial planning is urgently needed to maintain biodiversity and ecosystem function before important environmental values are lost.

2 | MATERIALS AND METHODS

2.1 | Stressor data

We considered human activities that directly or indirectly alter or impact natural lands based on an existing threat classification system (Salafsky et al., 2008). We identified five major categories of stressors for which we could acquire global spatial data on indicators (or proxies) at resolution of 1 km^2: (a) human settlement (population density, built-up areas), (b) agriculture (cropland, livestock), (c) transportation (major roads, minor roads, two tracks, railroads), (d) mining and energy production (mining, oil wells, wind turbines), and (e) electrical infrastructure (powerlines, nighttime lights). We limited our assessment to stressors for which we could assemble global coverage on spatially explicit features from publicly available data produced at 1-km^2 or at scale supportive of this resolution (i.e., >1:2,000,000). We selected this resolution to promote spatial consistency in stressor mapping and to capture heterogeneity in stressor values within units relevant for global-scale assessments (Halpern & Fujita, 2013; Verburg et al., 2013). For each stressor, we relied on the most recent data to capture contemporary land status, with median and mean dates of 2016 and 2014, respectively.

We integrated data derived from remotely sensed imagery and ground-based inventories, an approach deemed useful to measure land use intensity (Kuemmerle et al., 2013). For human settlement, we used population density from the 2015 UN-adjusted, Gridded Population of the World dataset (Doxsey-Whitfield et al., 2015), and built-up areas from the Global Human Settlements Layer (Pesaresi et al., 2013). For agriculture, the Unified Cropland Layer (Waldner et al., 2016) provided our cropland estimates, while the Gridded Livestock of the World v2 database (Robinson et al., 2014) identified livestock densities. For transportation that included major roads, minor roads, two tracks, and railroads, we used OpenStreetMap (OSM) data (Retrieved from www.openstreetmap.org on 02/1/2016; Barrington-Leigh & Millard-Ball, 2017), augmented with gRoads v1 (Center for International Earth Science Information Network, CIESIN, Columbia University & Information Technology Outreach Services, ITOS, University of Georgia, 2013) and Digital Chart of the World (DCW) vMap0 (Danko, 1992) for both roads and railways, respectively. For mining and energy production, we again used OSM data to calculate the proportion of each 1-km^2 cell comprised of mining, oil wells, or wind turbines. For electrical infrastructure, we mapped above-ground powerlines using OSM data augmented with DCW data and nighttime lights using the most recent version of the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) nighttime lights (Elvidge et al., 2001). We examined the spatial overlap and the correlations of the 1-km^2 spatial extent of each of the 13 human stressor indicators in the HM_c map. Overall stressors were only weakly spatially correlated ($r \leq 0.58$) and had low spatial overlap ($\leq$38%, except 86% between livestock and human population) (see SI “Stressor correlations and spatial overlap” section). Further details on the source layers, their resolutions and data processing are provided in the Supporting Information Appendix S1, Methods section.

2.2 | Human modification model

We mapped the cumulative degree of human modification across global terrestrial lands building on an established approach (Theobald, 2013). HM_c was calculated as the per-pixel (1 km^2) product (HM_s) of the spatial extent (H_e) and expected intensity of impact (H_i) across 13 human stressors (s) (e.g., human settlement, agriculture, energy production), such that $HM_s = H_e \times H_i$. Stressors were then aggregated to a cumulative score using a “fuzzy algebraic sum” (Bonham-Carter, 1994):

$$\mathrm{HM_C} = 1.00 - \prod_{s=1}^{n} (1 - (\mathrm{HM_S})).$$

The fuzzy sum is an increasive function that assumes the contribution of a given factor decreases as values from other stressors co-occur. This approach ensures that HM_c values are at least as large as the largest stressor indicator value, but that the additional contribution of a given indicator decreases as values from other indicators overlap, and ultimately converge to 1.00 (regardless of the number of stressors), thereby supporting the principle of parsimony and calibrating landscape impacts as a continuous gradient that better capture real-world patterns and conditions (Perkl, 2017). Aggregating individual factors for the mapping of landscape integrity or human modification through the fuzzy sum formula has seen increased use (Bui, Pradhan, Lofman, Revhaug, & Dick, 2012; Perkl, 2017) since its mainstream introduction (Malczewski, 1999).

Prior to summation, both H_e and H_i values were scaled from 0.00 to 1.00. H_e values were rescaled based on the proportion of converted land for built-up areas, cropland, roads, powerlines, oil wells, wind turbines, mines, or the log[X + 1] transformed values for human population, livestock numbers, nighttime lights (see section below). H_e values were determined from spatially explicit datasets and published information on average physical footprint sizes (see Supporting Information Table S1). H_i values ranged from 0.00 (none) to 1.00 (high) and represented the relative levels of human-induced impacts on biological, chemical, and physical processes of lands. Where possible, H_i values were based on a generalized land use coefficient, termed Landscape Development Intensity (LDI), that captures the per-unit amount of non-renewable energy required to maintain a human activity (Brown & Vivas, 2005) (See Supporting Information Appendix S1, Methods for further details on this metric). Unlike human threat index-scoring approaches that have relied on ordinal or interval scales (Sanderson et al., 2002; Venter et al., 2016), H_i values are measured on a ratio scale with meaningful differences: for example, 0.00 indicating no impact and 0.25 indicating half the intensity of impact of 0.50. We accounted for the uncertainty in H_i by randomly selecting values from a uniform distribution (100 iterations) between a reported MIN and MAX range of intensity values (Supporting Information Table S2). The final cumulative HM_c map was the average of all generated HM_c values and had values ranging from 0.00 (no modification) to 1.00 (highly modified land), thereby resembling a likelihood value. See Supporting Information Appendix S1, Methods for further details on this model and its assumptions.

2.3 | Data projection and representation

We analyzed all terrestrial lands excluding Antarctica. We identified terrestrial lands using the ESA CCI land cover dataset (Defourny et al., 2016) and selected 1 km^2 cells with at least one 300-m cell identified as terrestrial land. Prior to any processing, all spatial data were converted to the Mollweide projection with WGS84 datum. We projected continuous value raster datasets using bilinear resampling and nominal-valued raster datasets using a nearest neighbor routine. All vector datasets were projected prior to converting data to raster format. All spatial data processing was performed using ESRI's ArcGIS v10.4 software with the Spatial Analyst extension for raster analysis.

2.4 | Regional variation in HM_c

To inform global and regional decision-making and to facilitate comparisons with other terrestrial maps (see Supporting Information Appendix S1, material for details), we summarized the HM_c per biome and ecoregion. Biomes and ecoregions are natural boundaries widely used to guide conservation prioritization (Dinerstein et al., 2017; Hoekstra, Boucher, Ricketts, & Roberts, 2005; Olson & Dinerstein, 2002). Ecoregions define geographically distinct assemblages of species and natural communities within biomes and are considered ecosystems of regional extent. For spatial boundaries, we used the revised Ecoregions 2017 (Dinerstein et al., 2017), but excluded those ecoregions within the Antarctic Realm, classified as “Rock and Ice,” and with <100 km^2 of HM_c data coverage (leaving 803 ecoregions within 14 biomes and 7 biogeographic realms; Hoekstra et al., 2005; Venter et al., 2016; Watson, Shanahan, et al., 2016). For a spatial map of ecoregions, biomes, and biogeographic realms, see http://ecoregions2017.appspot.com/ (Dinerstein et al., 2017).

We calculated the minimum, maximum, mean (±*SD*), median (±MAD), and the distribution of HM_c values across all lands globally and for each biome and ecoregion. Based on the global, non-normal, distribution of HM_c values (median = 0.1 ± 0.1 MAD) and in a manner consistent with literature (Alkemade et al., 2009; Brown & Vivas, 2005; Gustafson & Parker, 1992), we binned median HM_c values into four modification classes: "low" ($0.00 \le HM_c \le 0.10$), "moderate" ($0.10 < HM_c \le 0.40$), "high" ($0.40 < HM_c \le 0.70$), and "very high" ($0.70 < HM_c \le 1.0$). We assigned low modification to areas with median HM_c values on the lower half of the distribution globally (≤0.1). We assigned moderate modification to those areas with median HM_c values on the higher half of the distribution globally but not >0.4. We used HM_c = 0.4 to demarcate a transition from a moderate to a highly modified state, because it matches the critical habitat threshold of ~0.60 based on percolation theory (Gustafson & Parker, 1992): a framework used to analyze fragmentation structure (Taubert et al., 2018) and shown to empirically relate to species threshold responses to habitat loss (Swift & Hannon, 2010). This value also corresponds to low-intensity agriculture in our assessment, thus, approximates a transition to a human-dominated state. Finally, we based the high to very high breakpoint (0.7) on equal binning of the interval values in a manner consistent with empirical syntheses (Alkemade et al., 2009; Brown & Vivas, 2005). Applying categories to the continuous HM_c value aids in the interpretation of land patterns, with our rationale detailed in the Supporting Information Appendix S1. At the same time, thresholding continuous HM_c values remains flexible and can be evaluated empirically to delineate "natural" or "wild" locations or other breakpoints as determined by ecosystem-specific responses.

2.5 | Characterizing land fragmentation

We calculated the median (±MAD) Euclidean distance away from low modified areas ($HM_c \le 0.1$) to those with higher degree of human modification ($HM_c > 0.1$) and characterized the edge distance distributions (i.e., using threshold (t) of 0.1). We applied the Euclidean distance to edge because it is a widely used fragmentation metric and recently applied to assess forested biomes (Haddad et al., 2015). We calculated distances (after removing rock and ice and water bodies) using an equidistant global projection based on cell centroids, but then subtracted these distances by the cell width (1,000 m) to capture cell adjacencies as 0 m from an edge. Given the 1-km resolution of the HM_c map, the 0–1 km edge distance represents adjacency to modified lands. These distances were then reprojected back into Mollweide coordinate system using bilinear interpolation. We calculated distances across all 1 km^2 cells globally and across all biomes and ecoregions classified as low, moderate, high, and very high. In addition to the 0.1 threshold (t), we also calculated edge distances across the gradient of HM_c values (i.e., $t > 0$ to > 0.9, in increments of 0.1). Although the median distance from modified lands increases with higher degrees of modification (from $t = 0$ to $t > 0.9$), the general patterns for biome and ecoregion classifications were consistent (Supporting Information Figure S16). Therefore, we focused on the results for low modified lands ($t > 0.1$). We note that low modified lands are those areas with low mapped human influence and are not necessarily equivalent to the extent of native vegetation in a region.

2.6 | Validation procedures

We assessed the accuracy of the mapped HM_c values based on independent visual interpretation of high-resolution imagery, building on established methods (Wickham et al., 2017) and other global analyses (Fritz et al., 2017). We relied on aerial or satellite imagery using Google Earth (majority date of 2015 and majority resolution of <5 m except for urban areas represented typically at ~1 m). We selected 1,000 plots (~1 km^2 "chip") using the Global Grid sampling design (Theobald, 2016), which provided a spatially balanced and probability-based random sample across the global land extent (excluding Antarctica) that was stratified on a rural to urban gradient using "stable night-lights" imagery (Elvidge et al., 2001). Per plot, we selected 10 simple-random locations (for a total of 10,000 subplots) and recorded several land attributes using the Global Land Use Emergent Database (GLUED) protocol (Global Land Use Emergent Database Group, 2016), identifying land cover class, land use class, dominant and secondary human stressor, and percent human modified. Similar to the HM_c map, the GLUED protocol also measures the degree of human modification as the product of the spatial extent (H_e) and its intensity (H_i): where H_e is the percent area modified by a human activity within a 100 m radius, and H_i is an estimate of the intensity of land use and/or features modifying an area based on expert-informed guidelines. The final degree of HM was determined using a lowest-highest-best estimate elicitation procedure, shown to reduce bias in expert assessments (Speirs-Bridge et al., 2010). We evaluated the mapped HM_c relative to the visual estimates based on correlation coefficients and mean absolute error (MAE). These metrics were calculated after removing locations dominated by water and averaging best-guess estimates for plots with more than three subplots (N = 989 plots, 9,846 subplots). We also determined the number of mapped HM_c values and GLUED estimates within agreement and scored ±20% as a match (following Venter et al., 2016). See the "Technical validation" section in the Supporting Information Appendix S1 for further details.

2.7 | Data availability

The 1-km^2 resolution HM_c map is publicly available on figshare (Kennedy, Oakleaf, Theobald, Baruch-Mordo, & Kiesecker, 2018). Similar to other global threat datasets, it was designed to assess macro-ecological patterns resulting from human stressors at broad spatial extents (e.g., across countries, ecoregions, biomes as done in our analysis and others) (Geldmann et al., 2014; Halpern et al., 2008; Venter et al., 2016). It can also be used to prioritize where more refined landscape assessments are needed to evaluate resource condition, spatial structure, and connectivity (Dickson et al., 2017; McGuire, Lawler, Mcrae, Nuñez, & Theobald, 2016; Perkl, 2017). Our analytic approach offers a repeatable, consistent, and transparent method that can be readily adapted using more detailed and finer-scale datasets for land use planning (Theobald, Monahan, et al., 2016; Theobald, Zachmann, et al., 2016).

2.8 | Comparison of HM_c with other global threat maps

We outlined the methodological differences between the HM_c map and the 2009 Human Footprint (HF) map (Venter et al., 2016) and compared their outputs based on (a) a standardized 0–1 range of values, (b) their original range of values, and (c) original values binned into five classes of none (no presence of stressor), low, moderate, high, and very high according to each study's protocol. First, we compared the global and ecoregional score distributions using the normalized HF, where we compared means, medians and calculated Pearson's correlation on the values. Second, we compared pixel and ecoregional classifications resulting from the original HF scores and HM_c values, using their respective 5-category classification scheme. Alongside a comparison with the 2009 HF map, we also examined the distribution of the HM_c values within anthropogenic biomes (available at: http://ecotope.org/anthromes/maps/; Ellis et al., 2010) and categorized ecoregions based on the thresholds of low modified (natural) lands following the *Nature Needs Half* analysis by Dinerstein et al. (2017). Given the greater similarity between the HM_c and 2009 HF maps in their non-categorical approach, we present only the results for this comparison in the main text. Detailed comparisons of the HM_c map with the 2009 Human Footprint (HF) map (Venter et al., 2016), Anthromes map (v2) (Ellis et al., 2010), and *Nature Needs Half* ecoregional assessment (Dinerstein et al., 2017) can be found in the Supporting Information Appendix S1.

3 | RESULTS

3.1 | Global degree of land modification and biome variation

The HM_c of terrestrial lands (excluding Antarctica) was on average 0.19 (±0.22 1*SD*), with a median of 0.10 (±0.10 1MAD). Strikingly,

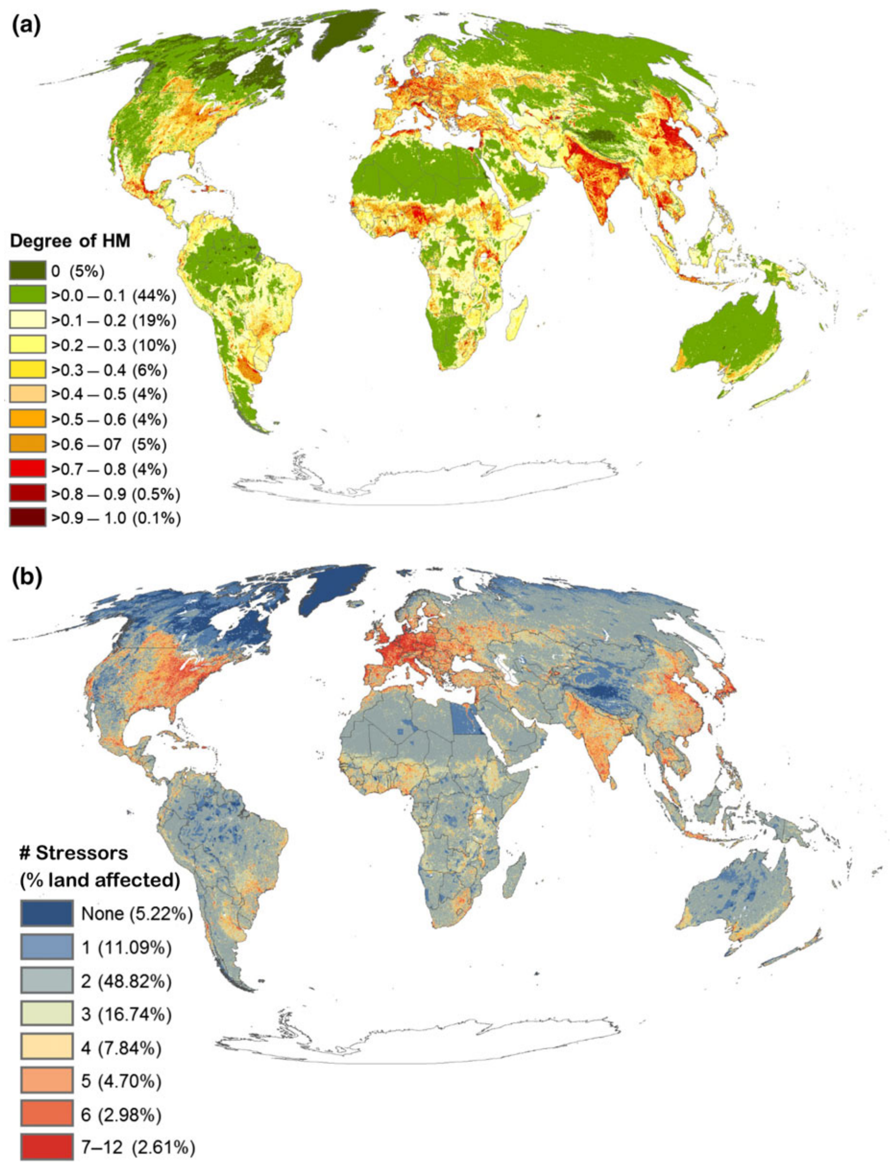

FIGURE 1 (a) Cumulative human modification (HM_c) across global terrestrial lands, categorized as low ($0.00 \le HM_c \le 0.10$), moderate ($0.10 < HM_c \le 0.40$), high ($0.40 < HM_c \le 0.70$), and very high ($0.70 < HM_c \le 1.00$). (b) Spatial distribution of the number of overlapping human stressors (out of 13 total) per 1-km^2 area, and the percentage of terrestrial lands affected globally (in parentheses)

95% of lands (127.22 million km^2) had some indication of human activities ($HM_c > 0$; Figure 1a). The 5% of unmodified lands (HM_c = 0; 6.96 million km^2) are concentrated in less productive and remote areas in high latitudes and dominated by inaccessible permanent rock and ice or within tundra, boreal forests, and to lesser extent montane grasslands. Forty-four percent of terrestrial lands had a low degree of human modification ($0 < HM_c \leq 0.1$; 58.96 million km^2), and largely reside within the world's deserts and boreal forests (Figure 2a). Consequently, the five least modified biomes are *tundra*, *boreal forests or taiga*, *deserts and xeric shrublands*, *temperate coniferous forests*, and *montane grasslands and shrublands*. These biomes had median HM_c values ≤0.1 and were dominated by low modified lands that largely reside ≥10 km away from more modified edges (Figures 2b and 3, Supporting Information Table S7).

The remainder of the world's lands had a moderate to high degree of modification: with 34% categorized as moderate ($0.1 < HM_c \leq 0.4$; 45.63 million km^2), 13% categorized as high ($0.4 < HM_c \leq 0.7$; 17.13 million km^2), and 4% categorized as very high modification ($0.7 < HM_c \leq 1.0$; 5.49 million km^2). *Tropical and subtropical grasslands, savannas, and shrublands*, *tropical and subtropical moist broadleaf forests*, *flooded grasslands and savannas*, and *tropical and subtropical coniferous forests* biomes exhibited intermediate modification: with median HM_c values ~0.20, high percentages (47%–64%) of moderately modified lands, and up to 25% of highly to very highly modified lands (Figure 3a). The most modified biomes are *temperate broadleaf and mixed forests*, *tropical and subtropical dry broadleaf forests*, *Mediterranean forests, woodlands, and scrub*, *mangroves*, and *temperate grasslands, savannas, and shrublands*. These five biomes had median HM_c values ranging from 0.22 to 0.38, with 28%–48% of their land surface under high to very high modification (Figure 3a). Across all biomes, *tropical and subtropical coniferous forests*, *tropical and subtropical dry broadleaf forests*, *mangroves*, and *flooded grasslands and savannas* are the most fragmented: with ~30%–36% of their low modified lands located adjacent to a modified edge, and 60%–69% within 5 km (Figure 3b).

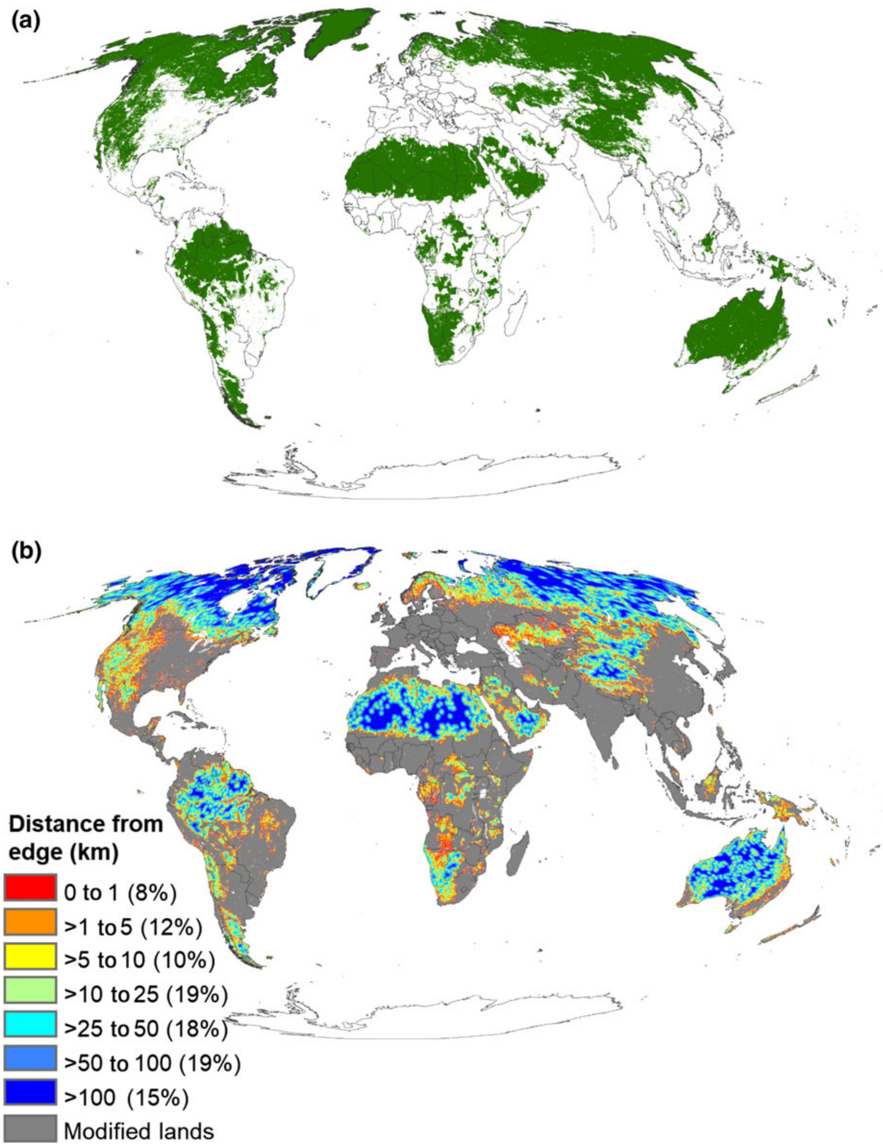

FIGURE 2 Global maps of (a) low modified lands ($HM_c \leq 0.10$), and (b) their median distance (in km) to areas of higher modification ($HM_c > 0.1$). Given the 1-km^2 resolution of the HM_c map, the 0–1-km edge distance represents adjacency to modified areas. See Supporting Information Figures S14 and S15 for ecoregional distributions of the percentage of low modified lands and their median distance to modified edges, respectively

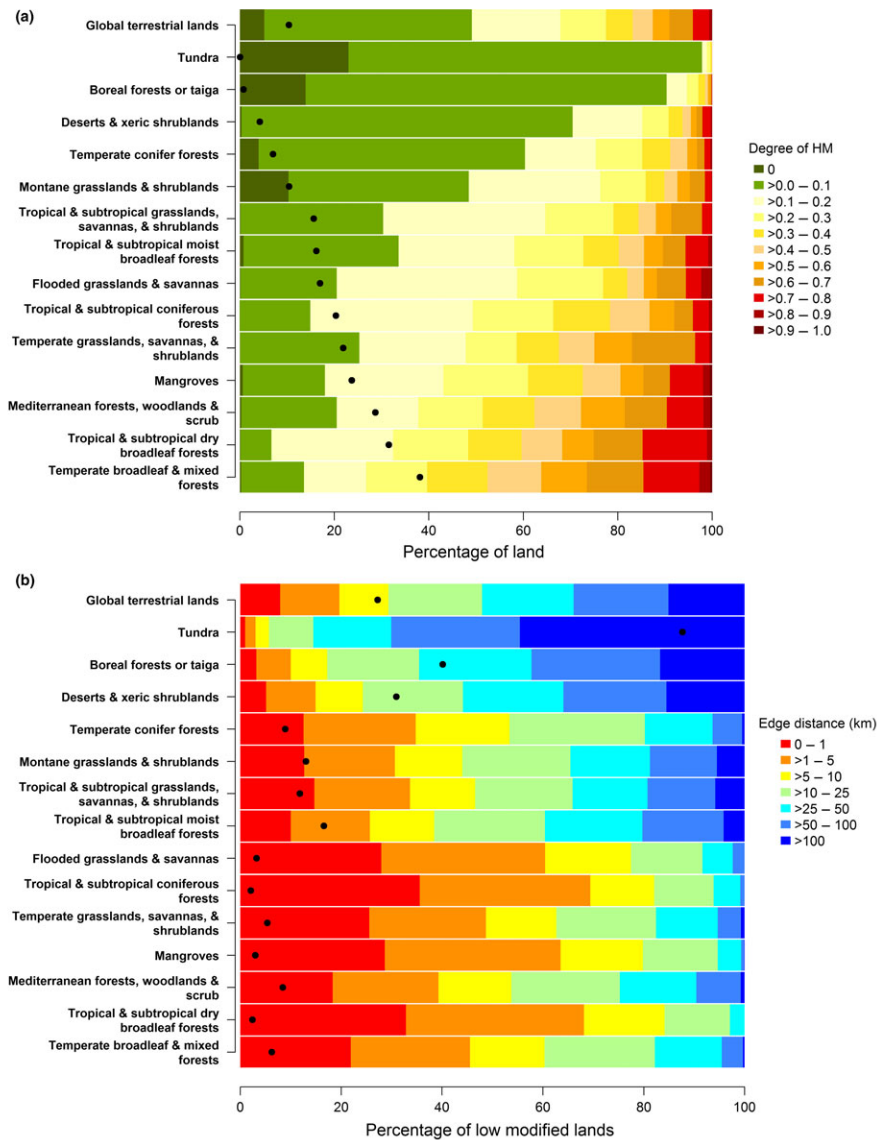

FIGURE 3 (a) Percentage of terrestrial land along the gradient of cumulative human modification (HM_c) per biome relative to globally. (b) Percentage of low modified lands within edge distance classes (km) per biome relative to globally based on Figure 2b. Median HM_c and median edge distances indicated by black dots, respectively. Given the 1-km^2 resolution of the HM_c map, the 0–1-km edge distance represents adjacency to modified areas. See Supporting Information Table S7 for the degree of HM_c across all biomes

3.2 | Cumulative and dominant stressors

The vast majority of the terrestrial surface, 84%, experiences multiple human stressors (Figure 1b). Eighty-two percent of low and moderately modified lands had one to two overlapping stressors, whereas 65% of high and 92% of very highly modified lands had ≥4 overlapping stressors. On average, the number of stressors declines with declining modification: 5.45 (±1.53), 4.46 (±1.48), 2.68 (±1.01), 1.64 (±0.78) stressors co-occur on very high, high, moderate, and low modification lands, respectively. Cumulative stressors are concentrated in North America and Europe, and to a lesser extent in the most developed regions of Southern and Eastern Asia, Central America, and Southern and Western Africa. When stressors spatially co-occurred, they were positively correlated, except for agriculture and human settlement, roads, or built-up areas (see Supporting Information Appendix S1 "Stressor correlations and spatial overlap" section and Supporting Information Tables S5 and S6).

Dominant drivers were, unsurprisingly, those that cause the largest land conversion: 48% of lands were predominately modified by human settlement (47.47 million km^2 by human population and 525.22 thousand km^2 by built-up areas) and 40% by agriculture (35.42 million km^2 by livestock and 18.35 million km^2 by cropland). The distributions of dominant stressors were spatially heterogeneous: for example, human settlement was mapped as the dominant driver in large regions of Africa, Eastern Europe, and Western and Southeastern Asia, and agriculture in large parts of North America, South America, Western Europe, Eastern Asia, and Australia (see Supporting Information Tables S5, "Dominant stressors" section and Supporting Information Figure S13).

3.3 | Ecoregion variation and classification

Over half of ecoregions (52%, N = 419) are classified as moderately modified, 30% of ecoregions (N = 238) are classified as low modification, and 19% (N = 133) of ecoregions are classified as either high (17%) or very high (2%) modification (Figure 4). In the following sections, we characterize this ecoregional gradient based on their degree of modification across all lands, their amount and

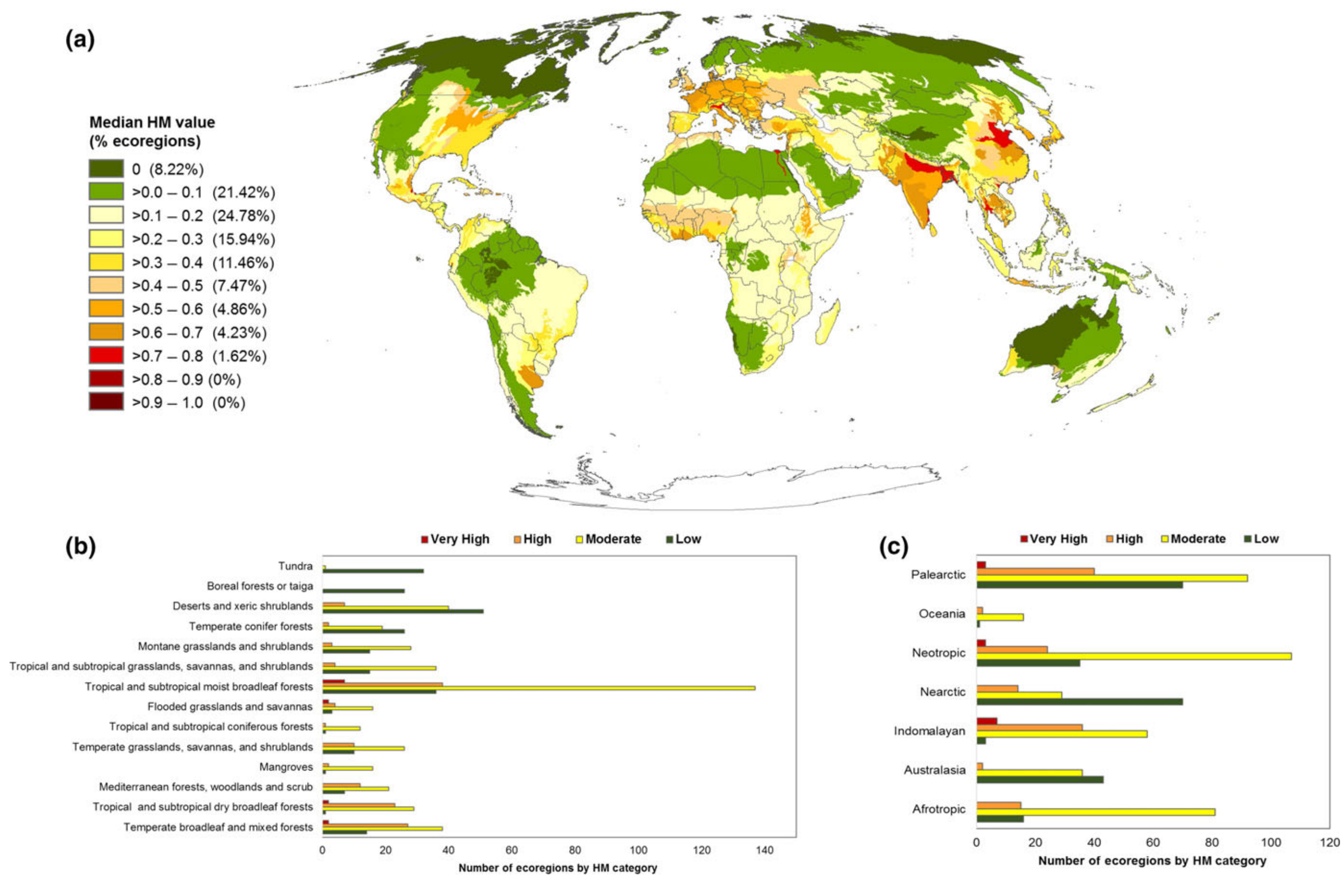

FIGURE 4 Cumulative human modification (HM_c) of the terrestrial ecoregions of the world based on their (a) median HM_c score (with percentages), and their distributions within (b) the 14 terrestrial biomes and (c) the seven terrestrial biogeographic realms

fragmentation of low modified (natural) lands, and their frequency within biomes and realms.

3.3.1 | Low modified ecoregions

On average, 83% (±16.33) of the terrestrial surface of low modified ecoregions is in low modification. Seventy-six percent of these ecoregions (*N* = 181) have ≥70% of low modified lands, and all ecoregions have >50% low modified lands (Figure 5a–d and Supporting Information Figure S14b). These low modified lands commonly reside 34.86 ± 27.41 km away from more modified areas, and only 5% are within ≤1 km of a modified edge (and 14% within ≤5 km) (Supporting Information Figure S15). Although all biomes and all biogeographic realms retain some percentage of low modified ecoregions, four biomes and two realms have only one to three remaining (Figure 4b,c): one in the *tropical and subtropical dry broadleaf forest* biome (*New Caledonia dry forests* ecoregion) (Figure 5c), one in the *mangroves* biome (*New Guinea mangroves* ecoregion), one in the *tropical and subtropical coniferous forests* biome (*Bahamian pineyards* ecoregion), three in the *flooded grasslands and savannas* biome (*Etosha Pan halophytics*, *Saharan halophytics*, and *Makgadikgadi halophytics* ecoregions; Figure 5b), one in the Oceania realm (*Hawai'i tropical high shrublands* ecoregion), and three in the Indomalayan realm (*Northern Triangle temperate and subtropical forests and Borneo montane rain forests* ecoregions) (Supporting Information Table S8).

3.3.2 | Moderately modified ecoregions

Moderately modified ecoregions have on average 70% (±17) of their lands in a moderate degree of degradation, and only 15% (±15) in low modification (Figure 5e–h). Most (75%, *N* = 313) have ≤20% of low modified lands, and none have >50% of low modified lands (Supporting Information Figure S14b). Further, most of these low modified lands (54%) are located ≤5 km from a modified edge (median: 4.21 ± 4.01 km), and 26% within 1 km (Supporting Information Figure S15). Within the range of habitat amount (i.e., 0%–50% of low modified lands) and fragmentation (i.e., 0 – 25 km edge distance) considerable variation exists, but most of these ecoregions have small amounts of low modified land and high levels of fragmentation across biomes, continents, and realms (Figure 6). *Mangroves and tropical and subtropical coniferous forests* biomes contain the largest percentage of moderately modified ecoregions (84% and 86%, respectively). However, these ecoregions are most common in all biomes and realms, except for the four least modified biomes (*tundra*, *boreal forests or taiga*, *deserts and xeric shrublands*, *and temperate conifer forests*) and two realms (Nearctic and Australasia).

3.3.3 | Highly modified ecoregions

Highly modified ecoregions tend to be a mixture of highly modified (50% ±12), moderately modified (27% ±12), and very highly modified (21% ±13) lands (Figure 5i-l). Very highly modified ecoregions are dominated by very highly modified lands (70% ±12) and to lesser extent highly modified lands (23% ±12; Figure 5m–p). On average, these ecoregions have <1% (±3) of low modified lands, with a maximum of 23% in highly modified and 9% in very highly modified ecoregions (Supporting Information Figure S14b). These few remaining natural areas are located in close proximity to disturbed areas. Approximately 50% are adjacent to modified areas and ~85% are within 5 km; and median edge distances are 0.72 ± 0.72 km and 1.42 ± 1.39 km for high and very highly modified ecoregions, respectively (Supporting Information Figure S15). Highly modified ecoregions are found in all realms and all biomes, except for *tundra and boreal forests or taiga*, but most are concentrated within three biomes (31% in *tropical and subtropical moist broadleaf forests*, 20% in *temperate broadleaf and mixed forests*, and 17% in *tropical and subtropical dry broadleaf forests*) and three realms (30% in Indomalayan, 30% in Palearctic, and 19% in Neotropic).

3.4 | Validation

We found strong agreement between our mapped HM_c values and those determined from independent visual interpretation of high-resolution images. For the 989 ~ 1 km^2 plots (9,846 subplots) analyzed, the mapped and visual scores were strongly correlated (r = 0.78), with an average error of ~14% (MAE =14.18). Relative to visual estimates, 707 plots (71%) were within ±20% agreement (Supporting Information Figure S3); 212 plots (21%) had higher mapped HM_c values (false positive); and 70 plots (7%) had lower mapped HM_c values (false negative). Higher mapped HM_c values largely occurred at high levels of development (Supporting Information Figure S4) and were driven by human population densities (which are not directly observable from aerial images) and nighttime lights (resulting from lit "spillover" areas from intense human development into adjacent undeveloped lands).

3.5 | Comparison of HM_c with the 2009 HF map

Relative to the 2009 HF map, the HM_c map includes a greater coverage of human stressors (13 stressors vs. 8 stressors included in the HF); reflects more recent land change (2016 median date of input stressor layers vs. 2009 for the HF); and captures the physical extents of human activities at a finer resolution by mapping the proportion of land converted at ≤1 km, without buffering features such as roads, navigable waterways, and coastlines. At a global scale, we found that the HM_c and normalized HF 2009 maps were strongly correlated (r = 0.77); but the HM_c values (mean ± 1 SD = 0.19 ± 0.22; median = 0.10) tended to be higher than the normalized HF values (mean ± 1 SD = 0.12 ± 0.14, median = 0.08; Supporting Information Figures S5 and S6). At regional (ecoregional) scales, these maps produced substantially different spatial land patterns, with lower correlations than at the aggregate global scale and low overlap between low modified lands (0.04%–40%; Supporting Information Figure S9a,b). Further, the HM_c map delineated 2.3 times more low modified areas than the HF map and captured smaller fragments (77% vs. 43% of patches were ≤5 km^2 by HM_c map and HF map, respectively) that could provide stepping stone habitats or facilitate landscape permeability or connectivity (Supporting Information Figure S10). Based on the classified HM_c map, the world is dominated by moderately modified lands (52%), whereas the HF map classifies the vast majority of the world (72% of ecoregions) as high or very highly modified (Supporting Information Figures S7–S9). These different results underscore that input data layers that feed into global assessments, and how they are combined and thresholded, significantly influence map outcomes with important implications for subsequent policy recommendations.

4 | DISCUSSION

The global map of human modification, HM_c, represents the most current and comprehensive quantification of the influence of cumulative human activities on Earth's terrestrial lands. We find that land modification is higher than previous assessments (Ellis et al., 2010; Geldmann et al., 2014; Venter et al., 2016), that less of the world's land remains unaffected by humans (5% relative to a recent estimate of 19%; Venter et al., 2016; Watson, Shanahan, et al., 2016), and that moderately modified ecosystems dominate the terrestrial biosphere (see Supporting Information Appendix S1 for map comparisons). At the same time, we show that only 8% of low modified lands (i.e., natural areas relatively free from human alteration) are located within 1 km (or adjacent) to a modified edge and 20% are within 5 km, which extends our understanding of global fragmentation beyond forested biomes (Haddad et al., 2015; Taubert et al., 2018).

Our analysis supports the *tropical and subtropical dry broadleaf forests* biome as one of most threatened, also identified by Dinerstein et al. (2017) and Watson, Jones, et al. (2016) based on levels of habitat conversion relative to protection. Based on the HM_c, this biome has the lowest percentage of low modified lands (7%), the second highest percentage of highly modified lands (40%), and the greatest adjacency to modified areas (68% of low modified lands are within 5 km of an edge). It also has the highest percentage of highly modified ecoregions (45%) and only one low modified ecoregion left. Alarmingly, we further find that half of the world's biomes have some cause for concern: either because they have little remaining low modified lands (i.e., six biomes contain ≤20%), retain only a handful of low modified ecoregions (i.e., six biomes have ≤10 ecoregions), or are potentially vulnerable to fragmentation effects (i.e., four biomes have 60%–69% of natural lands in close proximity to disturbed areas). Of the 803 ecoregions analyzed, strikingly, 30% and 50% of ecoregions retain ≤1% and ≤10% of low modified lands, respectively. Based on IUCN Red List of Ecosystems (Keith et al., 2013) and *Nature Needs Half* (Dinerstein et al., 2017) criteria, we

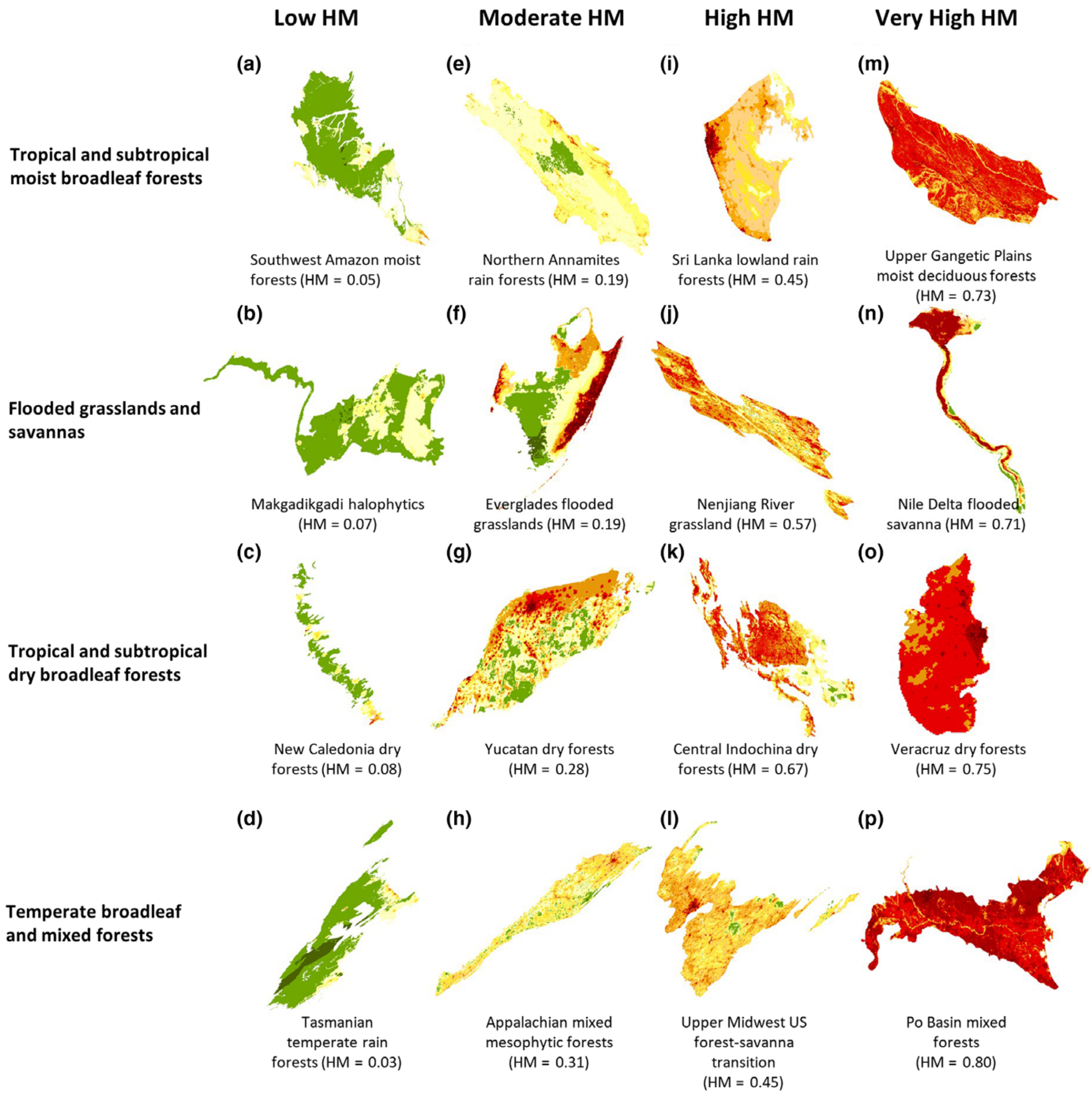

FIGURE 5 The gradient of land modification across representative ecoregions classified as low (0.00 ≤ median HM_c ≤ 0.10) (a–d), moderate (0.10 < median HM_c ≤ 0.40) (e–h), high (0.40 < median HM_c ≤ 0.70) (i–l), and very high (0.70 < median HM_c ≤ 1.00) (m–p) within the four biomes with all four modification classes. Each 1 km^2 area is color-coded corresponding to its HM_c score as depicted in Figure 1. Note that the maps vary in scale. See Supporting Information Appendix S1, Results section for details on the ecoregions depicted in this figure, and Supporting Information Table S8 for the degree of HM across all 803 ecoregions included in our analysis

classify 57% ecoregions to be Critically Endangered/Nature Imperiled (relative to 24% from Dinerstein et al. (2017)) and 14% of ecoregions to be Endangered/Nature Could Recover (relative to 27% from Dinerstein et al. (2017); Supporting Information Figure S17).

We find that less than a third of terrestrial ecoregions have a low degree of land modification and remain relatively free from human modification. These ecoregions retain most of their natural lands, which are often distant from human settlements, agriculture, and other modified environments. Thus, they represent vital areas where biodiversity and ecological processes are expected to be relatively intact and resilient (Keith et al., 2013; Swift & Hannon, 2010) and regional-scale ecosystems services may be supported (e.g., climate regulation, carbon sequestration, and water provisioning; Watson et al., 2018). Opportunity exists in these regions to set-aside large expanses of natural lands from human use to expediently meet conservation aspirations, such as those under the CBD, Aichi targets,

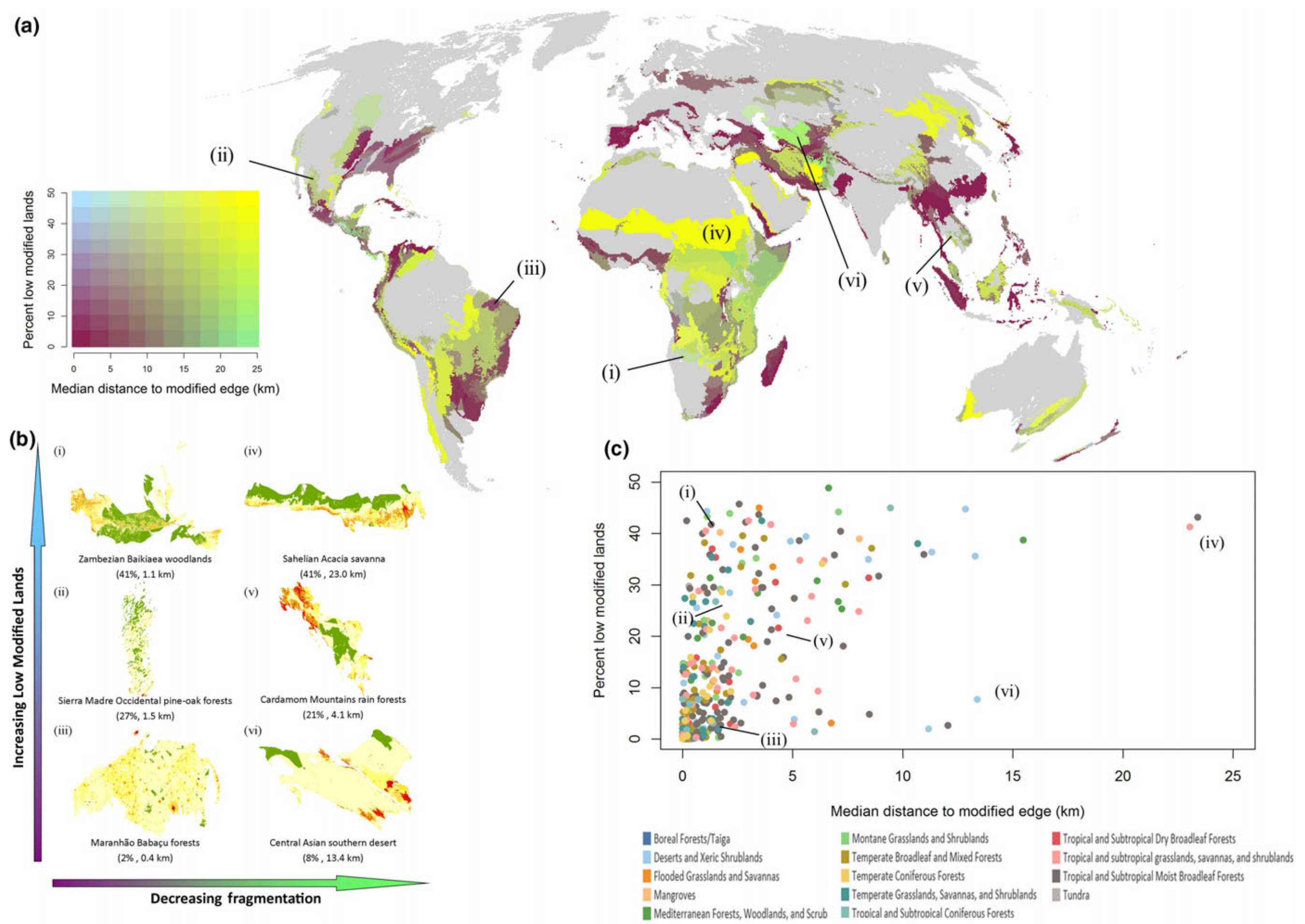

FIGURE 6 The relationship between the percentage of low modified lands ($HM_c \leq 0.1$) and their median distance (in km) to modified areas ($HM_c > 0.1$) for (a) all moderately modified ecoregions and (b) representative moderately modified ecoregions, shown in location and (c) as a scatter plot. Moderately modified ecoregions are those with median HM_c values on the lower half of the distribution globally but not >0.4, a critical habitat threshold based on percolation theory (Gustafson & Parker, 1992). Low modified lands are those areas with relatively low mapped human influence and are not necessarily equivalent to the extent of native vegetation. See Supporting Information Appendix S1, Results section for details on the ecoregions depicted in this figure

or NNH, especially where they also harbor rare, threatened, or biodiverse species or ecosystems. Spatial land planning by governments, private landowners, and civil society groups in these low modified ecoregions should focus on preventing and confining habitat loss, such that these ecoregions remain above critical landscape fragmentation thresholds (Desmet, 2018). Encouragingly, all biomes and all realms retain some low modified ecoregions, but the few strongholds that remain within biogeographic regions warrant special attention.

At the other end of the spectrum are one-fifth of ecoregions that are extensively altered by human activities. These highly modified ecoregions are dominated by dense human settlements, agricultural land uses, networks of infrastructure, and other industrial activities. These lands are commonly subject to five or more human stressors simultaneously. More than 80 percent of these ecoregions retain 1% or less of low modified lands, and all fall below habitat thresholds expected to maintain native biodiversity over the long-term (Keith et al., 2013; Swift & Hannon, 2010). Furthermore, the few remaining natural areas are surrounded by high levels of development. Dinerstein et al. (2017) acknowledge that in such heavily altered ecoregions, a *Half Protected* goal is simply "inconceivable." Thus, a more viable mitigation pathway to reconcile economic and environmental goals is likely within an ecosystem services paradigm: that is, restoring benefits that natural systems provide to humans, such as nutrient retention, soil fertility, carbon sequestration, pollination services, flood mitigation (Tallis, Kennedy, Ruckelshaus, Goldstein, & Kiesecker, 2015). Restored habitat, particularly in degraded landscapes, often fail to fully recover lost biodiversity or only after considerable time lags (Benayas, Newton, Diaz, & Bullock, 2009). At the same time, rehabilitation of degraded lands can regain many ecosystem features, particularly certain ecosystem services (Benayas et al., 2009) even in relatively short timeframes (Jones & Schmitz, 2009). Global initiatives, such as *The Bonn Challenge*, are advancing large-scale restoration within degraded forest ecosystems to enhance ecosystem functions and services to support human well-being (Lamb, 2014). Under such initiatives, spatial land planning within highly modified ecoregions will require not only restoring and connecting the few remaining natural areas, but more importantly, managing and improving the dominant, intervening human land uses to minimize negative effects on biodiversity and ecosystems (Driscoll, Banks, Barton, Lindenmayer, & Smith, 2013; Kennedy, Zipkin, & Marra, 2017).

The majority of the world's ecoregions fall within the middle of these low and high extremes, including 65% prioritized for exceptional concentrations of species diversity and endemism (i.e., Global200 ecoregions; Olson & Dinerstein, 2002). These are moderately modified regions comprised of natural remnants altered to varying degrees amidst a human-modified matrix. Most of these lands are subject to only one or two anthropogenic stressors, but a gradient of land use intensity exists. Notably, these ecoregions retain up to 50% of low modified lands that vary considerably in spatial configuration. Thus, they fall within a critical range where habitat loss (Swift & Hannon, 2010) and habitat fragmentation (Gustafson & Parker, 1992; Taubert et al., 2018) thresholds occur, and where there can be irreversible regime shifts in biodiversity (Pardini, Arruda, Gardner, Prado, & Metzger, 2010) and in the provision of ecosystem services (Mitchell, Bennett, & Gonzalez, 2015). These findings are consistent with a recent continent-wide assessment that suggest that global tropical forest fragmentation is close to a critical threshold (Taubert et al., 2018).

Circumventing losses and managing trade-offs among economic activities, biodiversity, and ecosystem services are vital in these moderately modified ecoregions and required under the SDGs (Cowie et al., 2018). Because these moderately modified regions are expected to exhibit higher variability in landscape structure and fragmentation than the low or highly modified ecoregions (Villard & Metzger, 2014), multi-objective spatial planning (Kennedy et al., 2016) and optimal habitat protection and restoration strategies (Possingham, Bode, & Klein, 2015) are needed to maintain critical levels of habitat amount and configurations and ensure viable conservation outcomes. These are regions that, without distinct recognition of their vulnerability to further land change, may fall through the cracks under current conservation schemes (Brooks et al., 2006). Further prioritization of these moderately modified ecoregions could account for their conflicts or opportunities for conservation intervention, for example, by considering their risk to future development (Oakleaf et al., 2015), their socioeconomic and political climate (Carter et al., 2017) and private landownership and tenure systems (Robinson et al., 2018), among other factors likely to influence sustainable outcomes (Tulloch et al., 2015). We propose that these are key areas to direct research to improve cross-system knowledge on the ecological risks of cumulative development impacts and stressor interactions, and the potential land use thresholds or safe ecological limits for both conservation and ecosystem services.

We caution that our results be interpreted in light of the following assumptions and limitations. First, while the HM_c maps 13 different stressors, it does not account for all human threats (Salafsky et al., 2008): in particular timber production, recreation, pastureland, pollution, and invasive species due to data limitations (Geldmann et al., 2014; Kuemmerle et al., 2013). We also did not consider climate change due to the uncertainty in the location and directionality of its impact on terrestrial systems (Geldmann et al., 2014) and its diffuse nature making it unstoppable by localized human intervention (Tulloch et al., 2015). Further, the interaction between land use and climate change on ecosystems may be better characterized through a coupled modeling process (Prestele et al., 2017). Although some of the missing stressors may be associated with and captured by those included (Perkl, 2017), we likely underestimated human impacts (e.g., northern high latitudes most affected by climate change). Second, although our use of OpenStreetMap data vastly improved the detail, accuracy, and coverage of transportation, energy, and mining sectors that are difficult to detect by satellite imagery but cumulatively cause significant impacts (Ibisch et al., 2016), these data are not globally complete (Barrington-Leigh & Millard-Ball, 2017). Third, we weighted stressors based on standardized measures of human-induced impacts on biological, chemical, and physical processes of lands (Brown & Vivas, 2005). While this metric has theoretical, empirical support for its use as a land use intensity metric (Brown & Ulgiati, 1997) and has been used to rank disturbance of watersheds and wetlands (Brown & Vivas, 2005) and to gauge the sustainability of nations (Siche, Agostinho, Ortega, & Romeiro, 2008), as with most models requiring empirical parameterization, uncertainties remain (Hau & Bakshi, 2004). However, our land use intensity weights have been verified in US landscapes (Theobald, 2013) and fall in line with species responses to land use where examined (Supporting Information Table S3). Fourth, our integration of different stressors assumes they act in an accumulative but mitigative fashion, which is in line with empirical evidence that suggests that interactions among impacts may be more commonly non-additive than additive (Crain, Kroeker, & Halpern, 2008; Darling & Côté, 2008). Although we lack complete understanding of the cumulative effects of multiple stressors, our approach creates a parsimonious index that minimizes potential bias from correlation of stressors and is robust to the addition of stressors as new data become available. Fifth, we categorized the continuous HM_c values into low-to-very high classes to aid in the interpretation of macro-ecological (ecoregional) patterns, as informed by the global distribution of HM_c values, empirical land intensity metrics (Alkemade et al., 2009; Brown & Vivas, 2005), and theoretical (Desmet, 2018; Gustafson & Parker, 1992) and empirical thresholds to habitat loss (Swift & Hannon, 2010; Yin, Leroux, & He, 2017). We acknowledge, however, that threshold responses to land use intensity and human activity will be species- or region-specific (Swift & Hannon, 2010) and may be at even lower levels than previously thought (Betts et al., 2017). Despite this fact, our binning of HM_c values produced spatial patterns of the degree and percentages of land modification and the number of stressors that appear meaningful. Further we provide the HM_c based on the original 0.00–1.00 values to provide flexibility in its use as continuous metric or to threshold based on user needs (Kennedy et al., 2018). As our understanding improves on how human activities interact to affect ecosystems, our modeling and thresholding can be updated accordingly. Despite these limitations, we find strong agreement between our mapped and independent visual estimates of human modification.

Our assessment reveals that the vast majority of the land surface is subject to multiple stressors. This finding mirrors that for oceans (Halpern et al., 2008) and reinforces that designing effective land use planning and mitigation strategies in the Anthropocene require an improved understanding of the cumulative impacts from different types of development including how stressors interact with one another (Crain et al., 2008; Darling & Côté, 2008), and the levels of development and spatial configurations that may push natural systems over ecological thresholds or tipping points (Kennedy et al., 2016; Taubert et al., 2018). A first step is improved cumulative impact assessments at multiple spatial scales (Canter & Ross, 2010); our analytical approach offers a robust and generalizable measure of cumulative human alteration of lands that can be applied at global (this study and Crooks et al., 2017), national (Theobald, 2013), and regional (Theobald, Zachmann, et al., 2016) levels.

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CONFLICT OF INTEREST

The authors declare no competing financial interests.

AUTHOR CONTRIBUTIONS

C.M.K., J.R.O., and D.M.T. conceived and designed the study; J.R.O. and C.M.K. aggregated the input data, developed the model, and conducted analyses and model comparisons; D.M.T., C.M.K., and J.R.O. conducted model validation; C.M.K, J.R.O., and S.B.-M. produced the figures and tables; C.M.K, J.R.O., D.M.T., S.B.-M., and J.K. interpreted the results; C.M.K. designed and wrote the paper; C.M.K, J.R.O., D.M.T., J.K., and S.B.-M. revised the paper.

ORCID

Christina M. Kennedy https://orcid.org/0000-0001-8902-8728

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