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# Mapping Change in Human Pressure Globally on Land and within Protected Areas

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**Abstract:** *It is widely accepted that the main driver of the observed decline in biological diversity is increasing human pressure on Earth's ecosystems. However, the spatial patterns of change in human pressure and their relation to conservation efforts are less well known. We developed a spatially and temporally explicit map of global change in human pressure over 2 decades between 1990 and 2010 at a resolution of 10 km$^2$. We evaluated 22 spatial data sets representing different components of human pressure and used them to compile a temporal human pressure index (THPI) based on 3 data sets: human population density, land transformation, and electrical power infrastructure. We investigated how the THPI within protected areas was correlated to International Union for Conservation of Nature (IUCN) management categories and the human development index (HDI) and how the THPI was correlated to cumulative pressure on the basis of the original human footprint index. Since the early 1990s, human pressure increased 64% of the terrestrial areas; the largest increases were in Southeast Asia. Protected areas also exhibited overall increases in human pressure, the degree of which varied with location and IUCN management category. Only wilderness areas and natural monuments (management categories Ib and III) exhibited decreases in pressure. Protected areas not assigned any category exhibited the greatest increases. High HDI values correlated with greater reductions in pressure across protected areas, while increasing age of the protected area correlated with increases in pressure. Our analysis is an initial step toward mapping changes in human pressure on the natural world over time. That only 3 data sets could be included in our spatio-temporal global pressure map highlights the challenge to measuring pressure changes over time.*

**Keywords:** effectiveness, human footprint, human population, IUCN management categories, protected area, stable nightlight

Mapeo del Cambio en la Presión Humana Global en Tierra y Dentro de Áreas Protegidas

**Resumen:** *Se acepta ampliamente que el principal conductor de la declinación observada en la diversidad biológica está incrementando la presión humana sobre los ecosistemas de la Tierra. Sin embargo, los patrones espaciales de cambio en la presión humana y su relación con los esfuerzos de conservación son menos conocidos. Desarrollamos un mapa temporal y espacialmente explícito del cambio global en la presión humana a lo largo de 2 décadas entre 1990 y 2010 y con una resolución de 10 Km$^2$. Evaluamos 22 series de datos espaciales que representaban diferentes componentes de la presión humana y los usamos para compilar un índice de presión humana temporal (THPI, en inglés) basado en 3 series de datos: densidad de población humana, transformación de suelo y la infraestructura de poder eléctrico. Investigamos cómo el THPI dentro de áreas protegidas estaba correlacionado con las categorías de manejo de la Unión Internacional para la Conservación de la Naturaleza (UICN) y el índice de desarrollo humano (HDI, en inglés) y cómo el THPI estaba correlacionado con la presión acumulativa con base en el índice original de la huella humana. Desde*

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*principios de los 90, la presión humana incrementó en 64% de las áreas terrestres; siendo los incrementos mayores en el sureste asiático. Las áreas protegidas también exhibieron incrementos generales en la presión humana, cuyo grado varió de acuerdo a la localidad y la categoría de manejo de la UICN. Sólo las áreas silvestres y los monumentos naturales (categorías de manejo Ib y III) exhibieron disminuciones en la presión. Las áreas protegidas sin una categoría asignada exhibieron los incrementos más grandes. Los valores altos de HID y la elevación media mayor se correlacionaron con reducciones mayores en la presión a lo largo de áreas protegidas, mientras incrementaban la edad del área protegida correlacionada con incrementos en la presión. Nuestro análisis es un paso inicial hacia el mapeo de cambios en la presión humana sobre el mundo natural a través del tiempo. El hecho de que solamente 3 series de datos pudieran incluirse en nuestro mapa de presión global espacio-temporal resalta el reto de medir los cambios de presión a través del tiempo.*

**Palabras Clave:** Área protegida, categorías de manejo UICN, efectividad, huella humana, luz nocturna estable, población humana

## Introduction

Biological diversity is in rapid decline (Barnosky et al. 2011), despite continued international commitments to protect 17% of the world's land area (i.e., the Aichi targets: CBD 2010) that have resulted in increasing efforts to reverse this negative trajectory (Butchart et al. 2010). One of the primary causes of this decline is increasing human pressure on natural systems (Millinium Ecosystem Assessment 2005). Understanding the extent and effects of pressures on nature is key for conservation science, especially when assessing where and how pressures increase or decrease relative to conservation interventions. However, understanding this is challenging for a number of reasons. First, human pressure is diverse, and its effects are intertwined, making representations based on aggregated indices challenging. Second, the impact of human pressure on ecosystems and species may vary considerably depending on a multitude of factors, so the specific effect cannot be inferred without understanding the system within which it works. This leads to very different ways of evaluating human pressure, depending on the scale and whether the focus is on the cause or the effect of the pressure.

Despite the challenges, there is a long history of mapping cumulative human pressure on the environment, dating back to McCloskey and Spalding (1989). Most products (e.g., anthropogenic biomes and the human footprint) are a composite of remotely sensed data on land use, human infrastructure, and human population density and address the terrestrial (Sanderson et al. 2002; Mittermeier et al. 2003; Ellis & Ramankutty 2008; Alkemade et al. 2009), marine (Halpern et al. 2008), and freshwater (Vörösmarty et al. 2010) realms. None of the existing products include all possible sources of human pressure on nature, either because spatial products for the omitted components do not exist or because the scale or quality of existing products prevents their inclusion. Thus, all spatial representations of human pressure are flawed if interpreted as comprehensive descriptions of human pressure on the natural environment. Further, all existing maps of human pressure on the environment are static and represent the current human pressure as it has built up through time, often from processes working over decades or even centuries. Although such maps are valuable for conservation planning and illustrating human impacts on nature, they provide limited information on where human pressure has increased, decreased, or remained the same over time; therefore, they do not delineate where conservation efforts may be working, failing, or may require additional effort.

We produced a methodologically consistent map of change in human pressure over 2 decades (1990s and 2000s). Because we aimed to evaluate pressure change, we used only data sources with repeated and comparable approaches. Our work is therefore more heavily constrained in terms of potential input data than previous static threat mapping exercises and excludes important components of human pressure that are not spatially explicit or temporally comparable. Our main aim was to provide a first assessment of temporal changes in pressure globally and to assess these changes in relation to protected areas. A secondary aim was to highlight the paucity of data on human pressures, particularly with an appropriate temporal resolution for conservation application.

## Methods

### Identification of Relevant Pressure Layers

First we assessed the layers included in the original human footprint index (Sanderson et al. 2002). However, the human footprint omits important pressures (e.g., bushmeat hunting, pollutants, nitrification, and socioeconomic factors) for which no spatial products existed. We therefore completed a review of spatial products that could be used to describe other types of pressures not included in the original human footprint. This resulted in the identification of 17 additional data sets (Table 1). Our aim was not to conduct a comprehensive review of all existing spatial data sets; rather, we wanted to investigate

**Table 1. Potential data sets that can be used to measure major human pressures affecting biodiversity at a global scale.**

| *Pressures* | *Data-set*[a] | *Reference* | *Spatial coverage* | *Temporal coverage* | *Notes* |
|---|---|---|---|---|---|
| Land use[b] | IGBP DISCover | Loveland et al. 2000 | global (1 $km^2$) | ~1992 | Based on reclassification of AVHRR remote sensed data; no repeated measures for this product |
| Land use | GLC2000 | Bartholomé et al. 2005 | global (1 $km^2$) | 2000 | Composite data sets based on classifying different remote sensing product into a series of discrete categories; no temporal repeat |
| Land use | GlobCover300 | Arino et al. 2007 | global (0.3 $km^2$) | 2004; 2009 | Composite data sets based on classifying different remote sensing product into a series of discrete categories; comparing across time is generally not recommended and should only be done after careful evaluation |
| Land use | HYDE | Klein et al. 2011 | global (8 $km^2$) | 10,000 BC; 2005 | Composite data sets based on classifying different remote sensing products combining these with FAO statistics |
| Land use | MODIS MCD12C1 | Friedl et al. 2010 | global (0.5 $km^2$) | 2001–2012 | Based on the MODIS Terra satellite; classified into 17 discrete landcover classes based on IGBP land cover classification; annual measurements |
| Land use | MODIS Global fire mapper | Giglio 2013 | global (1 $km^2$) | 2003–2012 | Monthly fire maps; included in the stable nightlight products with an annual average product; time period for MODIS fire-mapper is shorter than our combined product |
| Transport and access[b] | Vmap0 | NIMA 1997 | global | ~1995 | Combines remote sensing data and local inventories; coverage expected to have variable precision across the globe |
| Transport and access | gRoads | CIESIN 2005 | global | ~2010 | More comprehensive road map than Vmap0, but not comparable with Vmap over time |
| Pollutants | FAO maps | FAO 2012 | near global selected regions | 1970- 2011 2013 | Only on country level for the entire world, some gaps; based on retail values; included in HYDE 3.1 cropland data |
| Pollutants | Aura OMI | NASA 2013 | global | 2004 – daily | Measures of $NO_2$, $SO_2$, $O_3$, HCHO; daily measures from 2004 in the level 3 products; no yearly averaged products or general representations of the pollutants; daily values extremely variable and not comparable over time |
| Invasive species | IUCN global database | De Poorter & Browne 2005 | variable | None | Based on expert opinion; many species have only descriptive ranges |
| Disease | N/A | N/A | n/a | N/A | For some human and livestock diseases there has been a global mapping, including malaria |
| Climate change | Woldclim temperature and precipitation | Hijmans et al. 2005 | global (1 $km^2$) | 1965 - | No agreed form of baseline; no one interpretation of negative and positive changes |
| Human population[b] | GWPv3 | CIESIN 2000 | global (1 $km^2$) | 1990–2015 | Some products have lower spatial resolution; data based on modeling population census data from national inventories |

*Continued*

**Table 1. Continued.**

| *Pressures* | *Data-set*[a] | *Reference* | *Spatial coverage* | *Temporal coverage* | *Notes* |
|---|---|---|---|---|---|
| Human population | GRUMPv1 | CIESIN 2012 | global (1 $km^2$) | 1990–2015 | Some products have lower spatial resolution; data based on modeling population census data from national inventories; also included secondary model parameters |
| Human population | Landscan | Dobson et al. 2000 | global (1 $m^2$) | 1998 – annually | Uses number of secondary data sources to model population density; Landscan caution against a cell by cell comparison between yearly releases because input data sets are constantly improving, which in turn causes changes in the population distribution |
| Human population[b] | Stable nightlights | Elvidge et al. 1997 | global (1 $km^2$) | 1992 – annually | Annual average product; several versions and improvements exist. We used the newest version 4 which accounts for the inter-annual variation in signal detection. |
| Legislation and corruption | TI corruption index | CPI 2012 | global | 1980–2012 | Increasing global coverage, some countries still missing; changing methodologies impedes comparison |
| Education and livelihood | Human development index | UNDP 2011 | global | 1990–2012 | Only at country level; some smaller changes have been implemented; care should be taken when comparing across time |

[a] *Some products (e.g., Aura OMI) are aggregated into one row because resolution, extent, etc. are the same for all individual components.*
[b] *Included in the human footprint analysis of Sanderson et al. (2002).*

whether data sets across both space and time existed for other types of pressure than those included in the human footprint. We assessed the 17 data sets relative to 9 categories of globally important threat types based on existing threat classification systems (Salafsky et al. 2008; Balmford et al. 2009; Baldwin 2010): climate change, disease, education and livelihood, human population pressure, invasive species, properties of land and resources, legislation and corruption, pollutants, and transport and access (Table 1 & Supporting Information).

We defined 6 criteria to evaluate each data set for potential inclusion in our index of pressure change. First, data sets had to have global spatial coverage, the exception being data sets without data on polar regions. Second, data sets had to have at least 2 repeated measurements. Third, for data sets with repeated measurements, methods had to be consistent and comparable for all years. Fourth, data sets had to have sub-national or finer resolution to ensure the effect was captured by the spatial grain size of the data (e.g., the negative effects of most pollutants are local to the areas of use and cannot be extracted from national statistics). Fifth, seasonal variation within the data source had to be addressed so that observed changes between years was not a result of local temporal conditions (e.g., daily or even monthly averaged data products can be subject to seasonal changes that can often be greater than the long-term temporal changes). Sixth, data sets had to have a unidirectional response so that changes were associated with either increasing or decreasing pressure. This excluded all layers where an increase could either lead to reduced pressure or increased pressure depending on local conditions (e.g., increased temperatures as a result of climate change are predicted to have positive effects in some regions and negative effects in others).

### Retained Data Sets

The inter-calibrated stable night lights version 4 is globally mapped, applies an analogous method for all years, and has a unidirectional response in pressure (Elvidge et al. 2009; Elvidge et al. 2014). Stable night lights are measured on a scale from 0 to 63 (0, no light; 63, maximum light intensity) based on a threshold model of local conditions. We used data from 1995 and 2010 (Supporting Information).

The Gridded Population of the World (GPW) version 3 is a globally mapped human population data set developed using an analogous method for years 1995 and 2010 (Supporting Information). It has a unidirectional response of increasing pressure as human population density increases (Center for International Earth Science

Information Network 2005). The GPWv3 is based on the newest population estimate and applies a consistent method for all years and secondary data are not used for smoothing, which reduces the risk of population estimates varying for reasons other than real population changes (Balk & Yetman 2004).

The History Database of the Global Environment (HYDE) 3.1 contains a global layer on percentage of cropland at a resolution of approximately 10 km$^2$ (Goldewijk et al. 2007). This layer is built with a combination of satellite data from the International Geosphere Biosphere Programme (IGBP) (Loveland et al. 2000), the Global Land Cover 2000 (GLC2000) project (Bartholomé & Belward 2005), and agricultural statistics from the Food and Agriculture Organization (FAO) (FAO 2005). Estimated land use goes back several thousand years, but to keep the time span comparable to our other retained data sets, we used the newest estimates from 1990 and 2005, respectively (Supporting Information).

### Rejected Data Sets

The original human footprint analysis (Sanderson et al. 2002) used Land Cover version 2 based on data from 1992 to 1993 (Loveland et al. 2000). We evaluated this and GLC2000, GlobeCover300 (European Space Agency 2006), and MODIS (Friedl et al. 2010) as alternatives to the HYDE 3.1 cropland layer. Of the 3, GlobeCover300 and MODIS have been repeated, the former over 5 years (2004 and 2009) and the latter annually starting in 2001. Both are based on a categorical system of land cover classes (Supporting Information) which makes it complicated to assess the amount of change. The HYDE 3.1 cropland data, using a percentage measure, were therefore considered the best representation of land-use change for our purpose (Supporting Information).

Human infrastructure (roads and railways) were excluded because no temporally comparable layers exist. The original VMAP0 layers used in the 2002 human footprint analysis were based on national and sub-national data sources up till approximately 1995, without information on the date of road construction (National Imagery and Mapping Agency 1997). Improved products are being developed, such as gRoads v.1 (Center for International Earth Science Information Network 2013), that focus on expanding and improving the mapping of global road infrastructure. Current updates contain roads that were present before 1995 but not included on the older maps, so this product cannot be used to develop a credible measure of change in road and railway density.

All identified data layers of pollutants, invasive species, and diseases were excluded because they lacked sufficient spatial coverage. The FAO tabulates statistics on fertilizer and pesticide use for most countries but only at a country level, which was too coarse for our purposes. New maps are being developed based on remote sensing to estimate specific air pollutants such as nitrogen dioxide but only at regional and national levels, and no global products, or repeated measures, are planned (National Aeronautics & Space Administration 2013). No global, spatially explicit maps exist that show the distribution or changes in intensity of invasive non-native species. The International Union for the Conservation of Nature (IUCN) has established an invasive species specialist group and a global invasive species database (De Poorter & Browne 2005) that includes over 850 invasive species. However, information on species is mainly narrative and based on reported distributions within administrative units. Diseases pose a potentially significant threat to species, and their impact and distribution can be affected by human actions, but there is no global database on the distribution of all or a representative subset of diseases (Hurlimann et al. 2011). Mapping the distribution of diseases is also complicated by their often rapid evolution, the lack of good tools for consistent classification, and the fact that most mapped diseases that affect humans (e.g., malaria) are harmless to most other species.

The human development index (HDI) (United Nations Development Programme 2011), which has been calculated globally since 1990, Transparency International's corruption perception index (CPI), and infant mortality rates (United Nations Children's Fund 2011) were excluded because none were mapped at sub-national scale for the entire world. Furthermore, the CPI is based on national inventories that cannot be compared across years.

We also excluded all threats from climate change. Generally climate change is mapped as changes in temperature and precipitation that are not easily comparable between 2 years, and establishing a baseline from which to measure change needs more careful consideration before inclusion (Parmesan & Yohe 2003; Hoffmann & Sgro 2011). Products translating metrological components of climate change into threats have been developed only for the future and at regional scales (Ackerly et al. 2010). Furthermore, the effect of a changing climate is not unidirectional. Some habitats or species will benefit while others will not (Levinsky et al. 2007).

### Estimating Pressure Change

Data from our 3 retained global pressure layers were spatially aggregated to a resolution of 5.0 arc minutes (approximately 10 km$^2$ at the equator), the original resolution of the HYDE 3.1 cropland data. This aggregation caused some loss of resolution for the other 2 data sets (approximately 2.8 km$^2$ for stable nightlights and 5 km$^2$ for human population density). For each terrestrial pixel, we calculated the difference between values in the first and last year. This was done separately for the 3 layers. We transformed human population density to the square root. Data transformation of variables is a standard procedure for spatial pressure mapping, and it allows comparison between different data types and distributions (Halpern & Fujita 2013). We chose square-root transformation because it accounted for the expected declining impacts per person in densely populated areas (Hardin 1993) but still had a range distribution similar to the original data (Supporting Information). The result was 3 maps displaying the change in absolute values of human population density, stable nightlights, and land use, respectively.

These maps had very different data ranges (human population, -8,532 to 11,423 people per pixel; stable nightlights, -62 to 63 on an arbitrary scale; cropland, -86 to -70% change). To account for these inherent differences, values for each layer were standardized on a scale of -1 to 1, which allowed us to summarize these 3 different components of pressure. We used the same weighting as the original human footprint (Sanderson et al. 2002), giving equal weight to stable nightlights and human population while weighting land-use change at 0.8 (for justification, see Supporting Information). Finally, we combined the 3 layers by adding the values within each pixel and standardizing the resulting score on a scale of -100 to 100, where positive values mean increased human pressure and negative values mean decreased human pressure. This final product forms our temporal human pressure index (THPI), which measures changes in human pressure for the 3 data sets over 15 years from 1990 to 2010.

### Geographical Divisions of the World

The spatial extent of our analysis was restricted to 75° to -58° longitude and -180° to 180° latitude, based on DMSP-OLS stable nightlights full extent. All nonterrestrial areas were removed with the Global Self-consistent Hierarchical High-resolution Geography version 2.1 from the National Oceanic and Atmospheric Administration (Wessel & Smith 1996). All layers were projected using Mollweide equal area projection. We divided the world into biogeographical realms and biomes following Olson et al. (2001), although we combined Oceania and Australia (Supporting Information).

### Protected Areas

We used the World Database on Protected Areas (WDPA) from September 2013 for all information on size, shape, location, and IUCN management category of protected areas. All protected areas without information on date of establishment, as well as protected areas established after 1995, were excluded. Protected areas smaller than 2 times the resolution of the THPI (200 km$^2$) were removed. For overlapping protected areas with different IUCN categories, we did a stepwise erase; we removed the highest (lowest level of management) IUCN category and always assigned the strictest IUCN management category (Joppa & Pfaff 2009, 2011). After this pre-processing, we were left with a database of 8950 protected areas from 107 countries.

### Analyzing Change

The ArcGIS Zonal analysis tool was used to estimate the difference in average THPI scores among ecoregions of the world and among protected areas of different IUCN management categories. We used a linear regression model to examine the correlation between the human influence index (HII) (Sanderson et al. 2002) and change in THPI for biomes within realms, aiming to test how THPI compares with accumulated static human pressure. We used an analysis of covariance (ANCOVA) to test the effectiveness of protected areas at mitigating change in pressure as a function of protected area size, protected area age, mean slope of the protected area, mean elevation of the protected area, country level HDI, and IUCN management category. Final model selection was based on corrected Akaike information criterion ($AIC_c$) coefficients.

All spatial data management and analysis were conducted in ESRI ArcGIS 10.1, and all statistical analysis was conducted with R version 2.14.1.

## Results

### Global and Regional Changes

Human pressure increased in 64% of the world's terrestrial area over 15 years from the early 1990s to the late 2000s, especially in Southeast Asia and the Sahel region of Africa (Fig. 1). The accumulated human pressure (HII) in biomes within realms around 1995 (Sanderson et al. 2002, table 2) and THPI were significantly and positively correlated ($R^2 = 0.42$; $p < 0.001$) (Fig. 2).

### Changes within Protected Areas

Globally, protected areas exhibited an increase in human pressure over the 15 years (mean [SD] = 1.02 [9.61]), and there was considerable variation among regions. Protected areas in Southeast Asia had the highest increase (mean THPI = 5.57[9.15]), followed by Latin America (mean THPI = 2.62[7.83]), Sub-Saharan Africa (mean THPI = 2.46 [7.40]), and Euro-Asia (mean THPI = 0.84 [10.53]). Conversely, in North America (mean THPI = -2.47 [6.68]) and Australia and Oceania (mean THPI = -0.88 [5.30]) protected areas exhibited decreased human pressure.

Protected areas that lacked an IUCN category had the highest increases in pressure. Of the protected areas

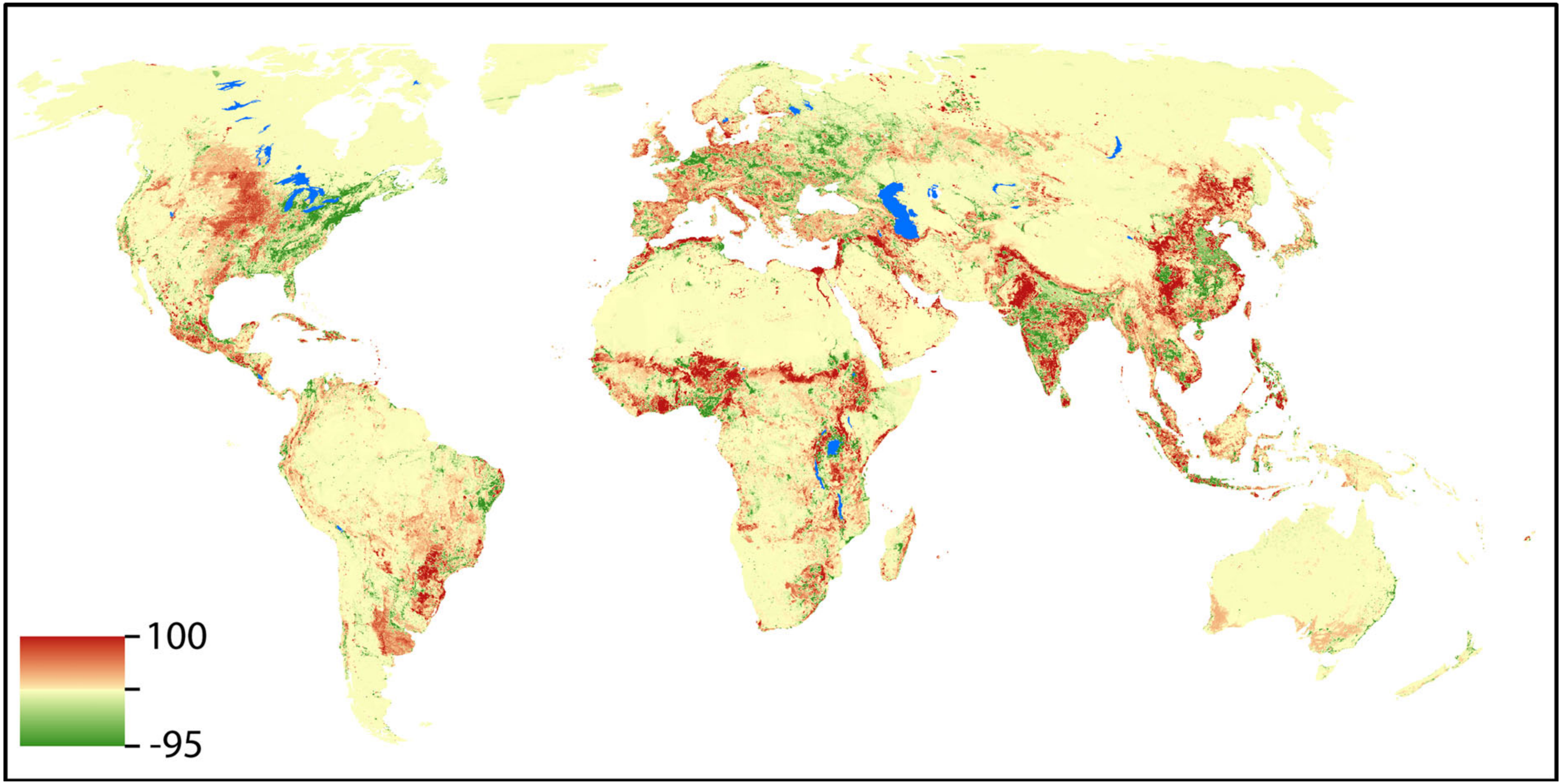


*Figure 1. Global distribution of the temporal human pressure index, over 15 years between 1990 and 2010 (red, increase in pressure, darkest shading is greatest increase; green, decreased pressure, darkest shading is greatest decrease; sand color, no change; blue, inland water). Change metrics were not calculated for North and South Poles (from 75° north and –58° south).*

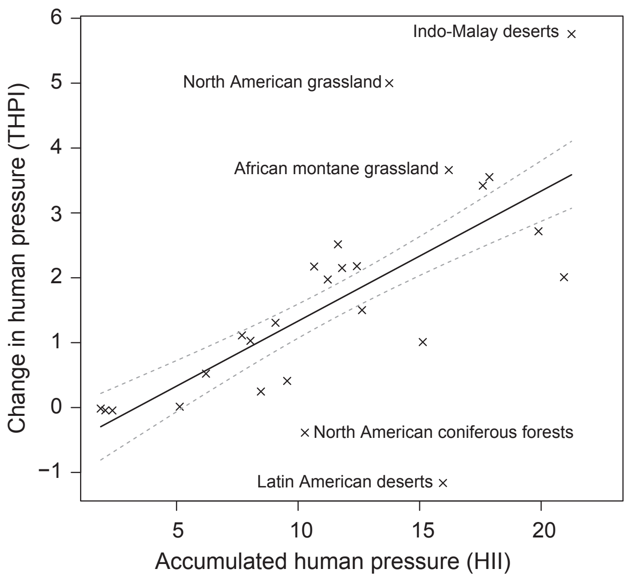


*Figure 2. Correlation between accumulated human pressure by circa 1995 (human influence index) (Sanderson et al. 2002) and changes in temporal human pressure index (THPI). Each point represents a biome within a realm. Biomes smaller than 0.5% of the total terrestrial area were removed to avoid extreme values from data outliers. Units are not directly comparable between the human influence index and THPI.*

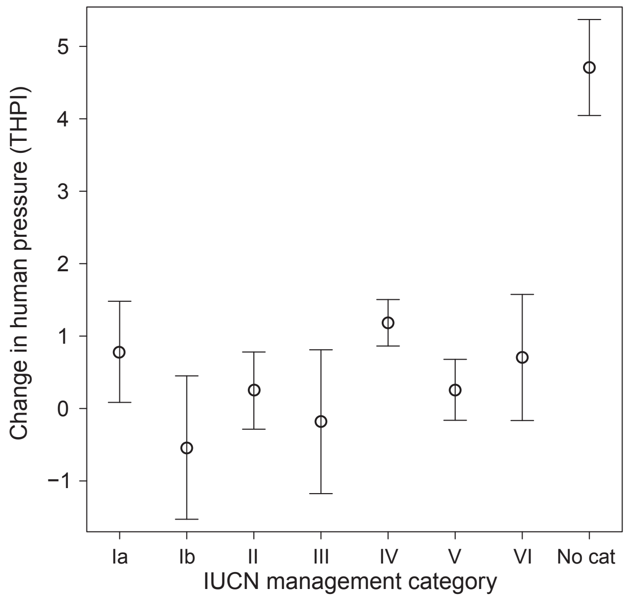


*Figure 3. Average change in temporal human pressure index (THPI) over 15 years in 8950 protected areas by their International Union for Conservation of Nature (IUCN) management category and in 1076 protected areas that lack an IUCN category. Positive THPI values indicate increased pressure. Error bars are standard deviation.*

assigned IUCN categories, category IV areas had the highest increases in pressure, whereas both categories Ib and III had a mean decrease in pressure (Fig. 3). However, no clear patterns emerged at the global level, and the regional patterns showed large differences both in the amount of change and the pattern of change between categories (Fig. 4).

Based on $AIC_c$ weights the preferred model to explain amounts of pressure change contained IUCN management category, log(protected area age), log(size of the protected area), log(mean elevation of the protected area), mean slope of the protected area, and country level HDI (Table 2). This model explained 9.14% of the total variation of the data. We found a significant effect of increasing HDI; protected areas in more developed countries had smaller increases in pressure (Fig. 5a). However increasing mean elevation (Fig. 5b), mean slope (Fig. 5c) and age of the protected area (Fig. 5d) were correlated with greater changes, such that older protected areas located in steeper areas experienced higher increases in human pressure.

## Discussion

Ours is the first to attempt to map terrestrial changes in human pressure globally at a scale that is meaningful for conservation planning and can be used to evaluate the impact of conservation interventions, such as protected areas. Our results show that the majority of the world has been subjected to increases in human pressure, with areas under the greatest pressure experiencing the greatest increases.

Our estimates exclude many important sources of pressure for which we could not find appropriate data layers, such as data on the use of bushmeat, extractive industries (e.g., logging, mining, and associated roads and other infrastructure), and climate change. These are examples of pressures that can lead to great damage to ecosystems and biological diversity, including in wilderness areas that do not necessarily have high population density, many night lights, or extensive agriculture. We therefore suspect that the Amazon and Congo basins, Indo-Malayan islands, and New Guinea may have had considerably higher increases in pressure than our THPI map shows (Supporting Information). Pressure from processes such as bushmeat hunting is not distributed evenly and is of particular concern in areas such as central and west Africa, where local people depend heavily on these resources for their subsistence (Davies & Brown 2007). In such places, many mammal species are often hunted to near extirpation (Coad et al. 2013) and protected areas offer limited relief (Geldmann et al. 2013). Likewise, climate change is not expected to impact all areas evenly but will instead affect species with low ability for adaptation, concentrated in regions such

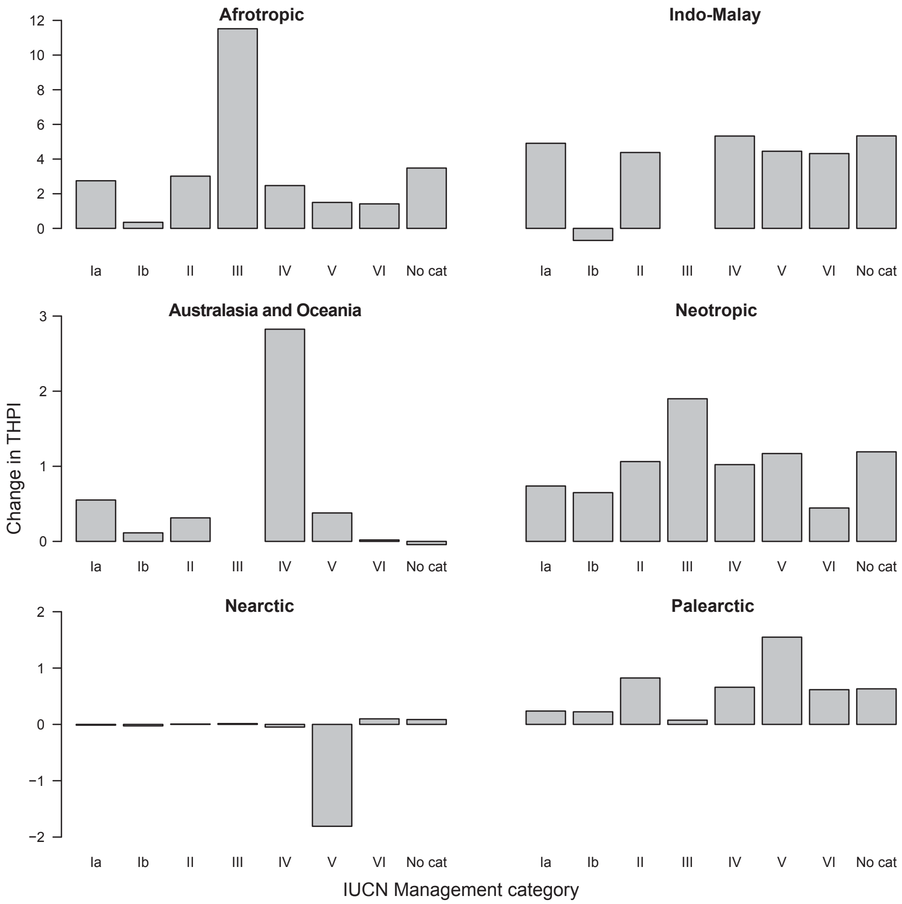


*Figure 4. Average change in temporal human pressure index (THPI) over 15 years between 1990 and 2010 in protected areas in different geographical regions on the basis of the International Union for Conservation of Nature management categories (positive values, increased pressure; negative values, decreased pressure). Geographical categories are based on WWF realms (Olson et al. 2001).*

as the Amazon, Mesoamerica, central Eurasia, the Congo basin, the Himalayas, and Sundaland (Malaysia, Indonesia, and southern Thailand) (Foden et al. 2013).

## Protected Areas

Habitat loss inside protected areas is lower in reserves that are more strictly managed (Scharlemann et al. 2010; Joppa & Pfaff 2011). However, our results indicate that the relationship between change in pressure and IUCN management categories is complex, and we found distinct regional patterns. Interestingly protected areas without a category had significantly higher increases in pressure than any of the IUCN categories. This could indicate that areas assigned an IUCN category, independent of which category, are areas receiving more attention on the ground.

Our results also suggest that national level socioeconomic and governance metrics may play a major role in the effectiveness of protected areas in reducing pressure because we found a strong significant correlation between increasing HDI and lower pressure increase. This is consistent with the results of previous studies that show the importance of socioeconomic drivers in delivering or maintaining effective reserves (e.g., Smith et al. 2003; Persha et al. 2011; Nolte et al. 2013).

However, we also found elements of protected area design and location to be of likely importance in promoting the effectiveness of reserves. Contrary to studies of deforestation inside protected areas (Geldmann et al. 2013), we found that as mean elevation and mean slope increased change in pressure increased. This could be driven by human expansions into steeper areas from more heavily occupied lowland areas. Thus, while the accumulated pressure might still be higher in the lowland, changes are seen more dramatically in some steeper regions, for example, on the fringes of already existing urban settlements (Kabisch & Haase 2011). We also found older protected areas had higher mean increases in pressure than newer areas. Newer protected areas are often established in remote areas with little predisposition for human impacts (Butchart et al. 2012). Such patterns would likely lead to older areas being located closer to already existing human activities; thus, these older areas would be more likely to experience relatively higher levels of pressure.

## Challenges

There were 6 major challenges to interpreting our results. First, for all 3 data sources, increases in values corresponded to increases in pressure. However, this

**Table 2. Parameter estimates for ANCOVA model of protected area performance.**

| *Parameter*[a] | *Estimate* | *SE* | *t* | *p* |
|---|---|---|---|---|
| Intercept | −0.753 | 1.543 | −0.488 | 0.625 |
| IUCN category Ib | −1.533 | 0.613 | −2.498 | 0.012* |
| IUCN category II | −0.811 | 0.451 | −1.800 | 0.072 |
| IUCN category III | −0.881 | 0.621 | −1.418 | 0.156 |
| IUCN category IV | 0.624 | 0.396 | 1.577 | 0.115 |
| IUCN category V | −0.443 | 0.418 | −1.060 | 0.289 |
| IUCN category VI | −0.227 | 0.568 | −0.399 | 0.690 |
| IUCN category No cat | 4.132 | 0.506 | 8.171 | <0.001*** |
| Log(PA age) | 0.969 | 0.266 | 3.643 | <0.001*** |
| Log(size) | 0.107 | 0.048 | 2.219 | 0.026* |
| Log(Mean elevation) | 0.491 | 0.118 | 4.180 | <0.001*** |
| Mean slope | 0.545 | 0.038 | 14.188 | <0.001*** |
| HDI | −8.542 | 0.898 | −9.512 | <0.001 |

[a] *Categories are International Union for Conservation of Nature (IUCN) management categories. For IUCN categories, significance indications relates to whether the individual categories are significantly different from category Ia. See partial effect plot (Fig. 3) for the differences between all categories. Abbreviations: PA age, age of establishment of the protected area; HDI, human development index.*

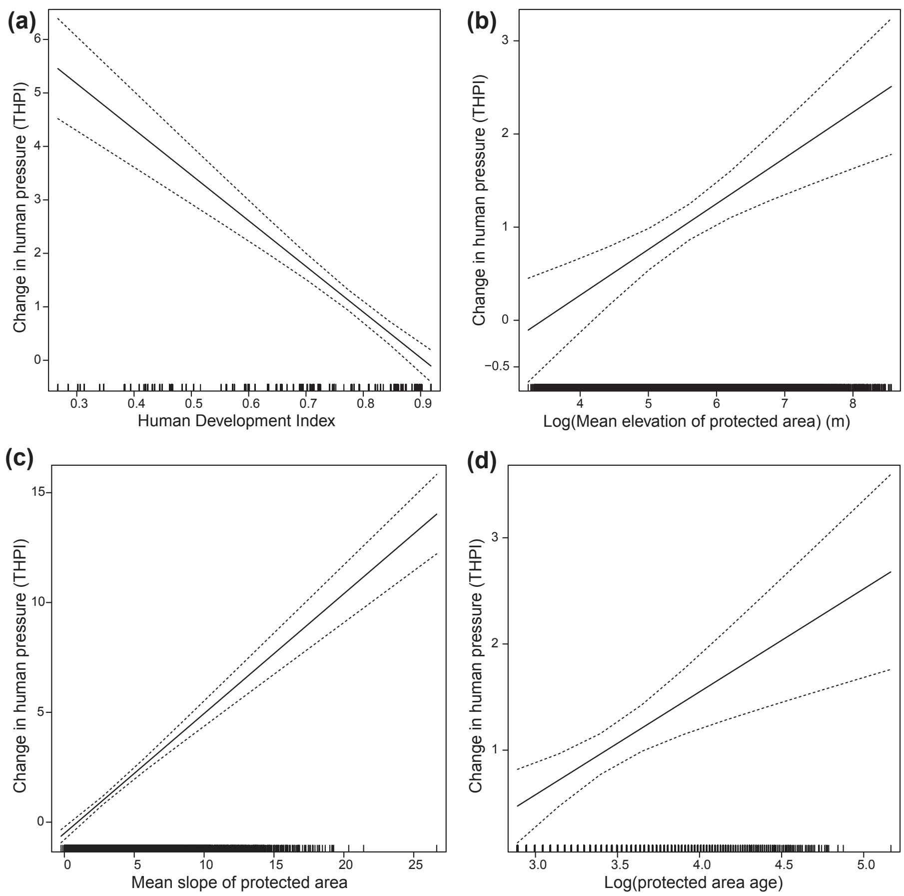


*Figure 5. Partial effect plots for analysis of covariance to evaluate the correlation between change in temporal human pressure index (THPI) and the (a) human development index, (b) elevation of the protected area, (c) slope of protected area, and (d) age of protected area. All correlations were significant (Table 2).*

relationship was not necessarily linear, and studies have suggested that per capita increase, for example, of $CO_2$ (Dietz & Rosa 1997) or material consumption (Bringezu et al. 2004), levels off or even declines with increasing economic wealth and technological advances (Shafik 1994). Thus, translating the THPI scores into actual impact measures is far from trivial, and the THPI, like previous static maps, measures input, which will often require local and context-specific interpretation before translating into impact (Halpern & Fujita 2013).

Second, the underlying driver of change may not always have the same impact on the ground. For example, besides electrical outlets, stable nightlights capture gas flares and other sites of resource extraction (Elvidge et al. 2009; Ghosh et al. 2010), as well as wild fires (Elvidge et al. 2001; Chand et al. 2007). Likewise, expansion of cropland will have very different ecological impacts depending on the intensification and accompanying technologies associated with increase in area (Ray et al. 2012).

Third, when examining composite data layers, one major challenge is weighting the influence of one source compared with another. This is an unavoidable issue when mapping cumulative inputs from pressures and is particularly challenging for data sources where weights depend on idiosyncratic decisions and expert opinion (Malczewski 2006; Halpern & Fujita 2013). In such cases, it is instrumental that the method is transparent and the assumptions clearly stated (Game et al. 2013; Halpern & Fujita 2013). Following Sanderson et al. (2002), who used an expert-driven process based on quantitative parameters, we used the same weighting between the individual components. A similar approach was used in producing a marine static pressure layer (Halpern et al. 2008). Expert-derived indices are not a guarantee of a correct assessment, but it does allow for subsequent evaluation and is often the only option.

Fourth, though the 3 data sources are independent products and describe distinct sources of pressure, they will be intercorrelated. Areas of high population density will be predisposed to have higher values of stable nightlight or agricultural production (Supporting Information).

Fifth, our map is at 10 km$^2$ grid scale. Yet some impacts originating from the 3 layers may have an effect on much larger scales, making the individual pixel values a poor unit for comparison.

Sixth, although we were able to present a temporally and spatially explicit map of change in human pressure, it does not include many instrumental drivers of declines in biological diversity or habitat loss. Thus, our map is not comprehensive and neither is the representation of pressure and understanding of the elements not included is essential when interpreting the results.

### Paucity of Data

Our objective was to map changes in anthropogenic pressure on land over time with available and appropriate data of an acceptable quality and a sufficient spatial resolution. Few of the assessed data sets met our criteria for inclusion because they were either not sufficiently spatially resolved, had limited coverage, or were not comparable over time. As a consequence of the paucity of appropriate data, our pressure change metric is simple (3 elements). Despite that, we believe our efforts are a relevant first step for mapping change in human pressure—all 3 components affect nature—and our map can provide the initial architecture for a more comprehensive spatio-temporal data set into the future.

We suggest that the current paucity of appropriate data to map spatial and temporal patterns of threat is to some extent a reflection of methods more than scientific questions driving data generation. We acknowledge the need for improvement in methods; however, we also see a need for more data generation that allows for comparison over time. The advances in methods for data collection increases the availability of large-scale data sets as well as our knowledge about the world today, but they often neglect that conservation science is based on understanding effects and thus changes over times of both pressures and responses (Dornelas 2010; Magurran & Dornelas 2010). We see a need for an increased focus on spatial data that can be compared over time, even if this comes at the expense of quality. Our analysis here is a step toward this goal, and it highlights the challenge to creating an overall representation of human pressures and their changes around the world at scales that can be applied to conservation decision making.

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## Supporting Information

An explanation of threat categorization, our geographic division of the world, validation of data layers, types of responses to changes in an independent variable, frequency distribution of THPI scores, correlation between frequency scores of transformed values and original values for human population density, a description of HYDE 3.1 cropland product, and excluded land cover maps (Appendix S1) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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