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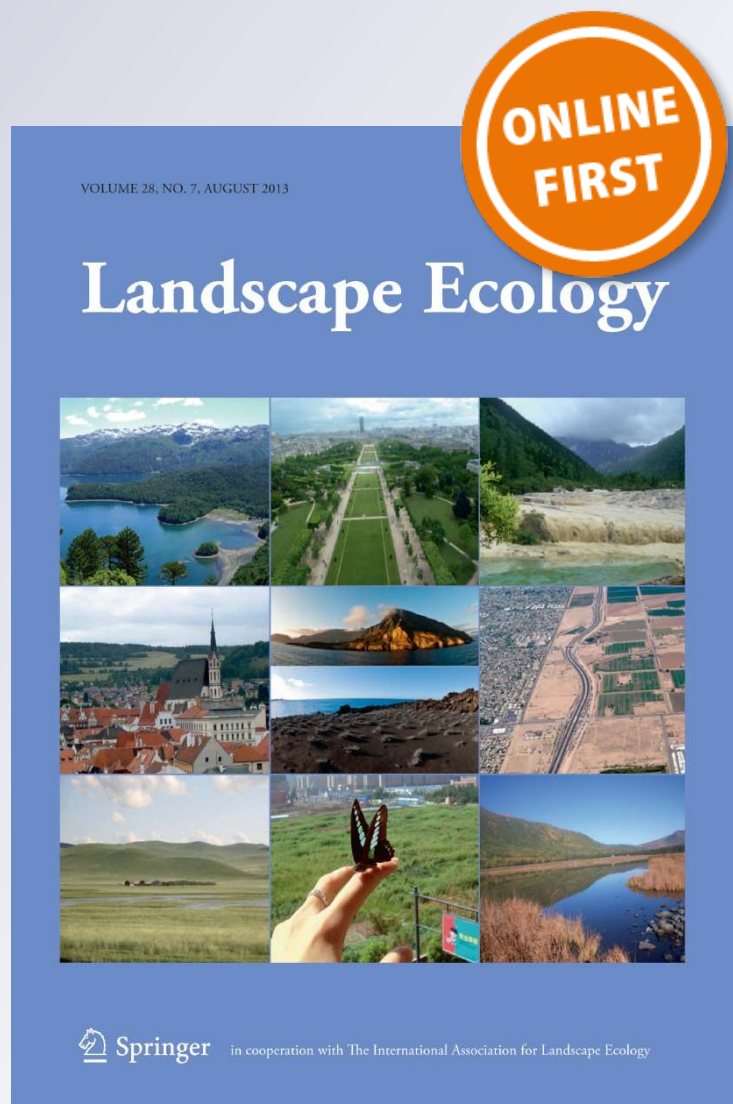
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RESEARCH ARTICLE

A general model to quantify ecological integrity for landscape assessments and US application

David M. Theobald

Abstract Increasingly, natural resources agencies and organizations are using measures of ecological integrity to monitor and evaluate the status and condition of their landscapes, and numerous methods have been developed to map the pattern of human activities. In this paper I apply formal methods from decision theory to develop a transparent ecological indicator of landscape integrity. I developed a parsimonious set of stressors using an existing framework to minimize redundancy and overlap, mapping each variable as an individual data layer with values from 0 to 1.0, and then combined them using an "increasive" function called fuzzy sum. A novel detailed land use dataset is used to generate empirical measures of the degree of human modification to map important stressors such as land use, land cover, and presence, use, and distance from roads. I applied this general framework to the US and found that the overall average degree of human modification was 0.375. Regional variation was fairly predictable, but aggregation of these raw values into terrestrial or watershed units resulted in large differences at local to regional scales. I discuss three uses of these data by land managers to manage protected areas within a dynamic landscape context. This approach generates an internally-valid model that has a direct, empirical, and physical basis to estimate the degree of human modification.

Introduction

Landscape ecologists and conservation scientists have often characterized landscape and ecological systems in terms of composition, structure, and function (Noss 1990). Building on this framework, Parrish et al. (2003) defined ecological integrity of a landscape as the ability of an ecological system to support and maintain a community of organisms that has species composition, diversity, and functional organization comparable to those of natural habitats within a region. High integrity refers to a system with natural evolutionary and ecological processes, and minimal or no influence from human activities (Angermeier and Karr 1994; Parrish et al. 2003). Species-specific approaches typically develop ecological indicators that attempt to measure attributes of a species or community, such as population size or species diversity. A complementary, and more general, approach is to develop indicators of the absence of human modification of habitat and alteration of ecological

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processes. An *ecological indicator* is a measurable attribute that provides insights into the state of the environment and provides information beyond its own measurement (Noon 2003). Indicators are usually surrogates for properties or system responses that are too difficult or costly to measure directly (Leibowitz et al. 1999).

Increasingly, natural resources agencies and organizations are monitoring and evaluating the status and condition of their lands and waters by measuring the ecological integrity of landscapes (e.g., Canada National Parks Act, Lindenmayer et al. 2000, IUCN 2006; Fancy et al. 2008; Borja et al. 2008; the 2012 US Forest Service Forest Planning Rule). For example, some measure of ecological integrity is typically used when assessing the current status and likely future condition of coarse-filter conservation elements that are key to the Bureau of Land Management's (BLM) Rapid Ecological Assessments (REAs) "landscape approach." Additional examples include the National Park Service's Natural Resource Condition Assessments, the Western Governor's Association (WGA) initiative on Wildlife Corridors and Crucial Habitat (www.westgov. org/initiatives/wildlife) and the US Fish & Wildlife Service's Landscape Conservation Collaboratives (LCCs; www.fws.gov/science/shc/lcc.html).

Many composite scoring systems have been used as an indicator of ecological integrity by mapping the influence of human activities on natural landscapes, including wildness (Aplet et al. 2000) and the human footprint (Hannah et al. 1995; Sanderson et al. 2002; and Leu et al. 2008; Woolmer et al. 2008). These provide general maps of human influence and have been useful, but two improvements have been offered recently (Gardner and Urban 2007; Riitters et al. 2009; Theobald 2010). First, landscape ecologists have established that proportion of cover is a fundamental metric (Gardner et al. 1987; Gardner and Urban 2007) because no other landscape metric can be interpreted independently of it (Neel et al. 2004; Wickham et al. 2008), and it provides the basis for unambiguous interpretation needed to assess landscape change (Riitters et al. 2009). Second, ad hoc scoring systems such as the human footprint are limited because the final score typically has no direct physical basis, conversion of quantitative values to ordinal categories can violate mathematical axioms, and colinearity of individual factors leads to difficulty when interpreting results (Schultz 2001). Formal methods are available

from decision theory to provide transparent accountable indicators, such as multiple criteria analysis (Hajkowicz and Collins 2007).

My goal in this paper is to describe the development and applications of a quantitative, empirically-based measure of ecological integrity that is suitable for landscape-level assessments. To achieve this goal, I extend previous work (Theobald 2010; Theobald et al. 2012) and provide a formal analytical method that allows compensatory or additive effects when considering multiple stressors to: (a) describe common human modification stressors to landscapes in the US and their data sources; (b) estimate the degree of human modification that can be attributed to each stressor; (c) combine the stressors into an overall estimate of human modification; (d) incorporate spatial and landscape context into the measure; (e) validate the estimates using a national dataset of watershed condition; (f) examine the consequence of three common methods to aggregate landscape data into management-relevant decision-making units; and (g) describe general results and initial applications of this dataset. I develop a comprehensive list of common stressors and datasets used to represent them in the "Methods" section, provide basic summaries and comparison to validation data in the "Results" section, and describe some uses and ways ecological integrity maps are commonly applied by land management agencies in the "Discussion" section.

Methods

To calculate the degree of human modification I conducted three major analysis steps. First, I distinguished the magnitude (or intensity) of impact from the spatial extent (or footprint) of a given activity at a given location. Values for both the intensity and footprint range from 0.0 (low) to 1.0 (high). Second, I used an existing framework that catalogues and organizes multiple stressors into a comprehensive but parsimonious list of stressors and the spatial databases used to represent them. I generated a data layer for each stressor for which both spatial data and estimates of intensity and footprint were readily available or made. Finally, I combined the multiple stressor layers into a single, overall metric of the degree of human modification that ranges in values of 0.0 (low modification) to 1.0 (high modification).

Similar to existing approaches to map the effects of human activities on ecological integrity, for many of the stressors I relied on impacts estimated by experts documented in the literature and/or considered to be standard. However, a critical advance in this paper is that I developed empirical estimates of the degree of human modification for the key stressors on land cover, roads, and road use (based on findings of Woolmer et al. 2008) using a detailed land use dataset generated from interpretation of aerial photography. After detailing the methods used in each of the three steps to calculate the degree of human modification, I describe how I evaluated the model and some applications of the resulting data layer. The spatial datasets for each stressor were processed at 30 m resolution unless otherwise noted, and the final human modification dataset and applications of it were produced at 90 m resolution.

Estimating human modification

When measuring the degree of human modification h, I distinguished two factors of an activity at a given place: magnitude and footprint. The intensity I (or magnitude) is the degree to which an activity at a location modifies an ecological system. This helps to differentiate effects of different types of land uses—for example, using a patch of land as pasture is likely to have a lower overall effect on the ecological integrity than conversion to a parking lot. The second factor in measuring the degree of human modification is the footprint F, or the areal extent of a given human activity. In practice, the footprint is measured as the proportion of a raster cell that is occupied by a given land use. Thus, the overall effect at a location is $h = IF$, where a value of 0.0 has no human modification and a value of 1.0 has high modification. Although somewhat simplified, this equation is critical because h has a direct physical interpretation, and its value remains a ratio data type so that differences within the range are meaningful (i.e. a value of 0.8 is twice the effect of 0.4).

Estimates of I and F were made from two different sources: expert opinion or empirical datasets. Table 1 details the data sources used to represent each stressor, as well as the source of the estimates of I and F. For about half of the stressors reasonable parameters were estimated using common expert-based values, but to

the extent possible, I and F were quantified using empirical estimates of modification.

For the empirically-based stressors, I estimated I as a value from 0.0 to 1.0 based on the relative amount of energy required to maintain a particular land use type (Table 2; Brown and Vivas 2005). The footprint F was calculated as the magnitude-weighted proportion of cells of land cover type c that overlap with polygons from a detailed land use dataset, which was generated interpreting land uses from recent high-resolution (<1 m) aerial photography sampled at $\sim$6,000 random locations across mainland US. For each sample location or "chip" (roughly 600 m $\times$ 600 m), a trained photo interpreter mapped polygons of each land use type following an established protocol (Leinwand et al. 2010). To quantify F for the roughly 577 ecological system classes in the USGS Gap land cover dataset, I intersected the centers of the cells that overlap polygons found within each chip, resulting in $\sim$400 data points in each chip. I then combined each of the natural ecological system classes into their level 3 "formation" level (Grossman et al. 1998). For human-dominated formations (Developed and Urban and Agricultural Vegetation), I maintained the detailed ecological land type. To account for bioregional variability in these broad formations and human-dominated land cover classes, the 41 formation groups were intersected with eight eco-division-groups generated based on ecodivisions that characterize both climate and biogeographic history at a sub-continental scale (Grossman et al. 1998). I then calculated the mean and standard deviation of h for each of the resulting 86 formation/ecodivision-group classes (Table 3). For formation/ecodivision group classes for which there were less than 100 data points coming from a minimum of 10 chips, I manually re-grouped these types into most similar class, first grouping across similar ecodivision groups, then formation. The final dataset had 241 unique combinations of land cover and ecodivisional classes. Note that not all formations were found in all ecodivision classes.

The detailed land use dataset was also used to derive a empirical estimates of human modification as a function of distance from interstates and highways, in 150 m increments. h was set to 0 at a distance of $\geq$20 km because there were fewer than 30 chips that contributed data to the calculation. Figure 1 shows a strong relationship ($r^2 = 0.98$) between the impact to the distance from major roads.

Table 1 The list of stressors incorporated in the development of the degree of human modification dataset, based on the Conservation Measures Partnership framework (Salafsky et al. 2008)

Human modification activities framework		Stressor in human modification		Parameters*		
Level 1	Level 2	Name	Data source and scale	Source	Intensity value (I)	Footprint value (F)
Residential and comm. development	Commercial and industrial areas	Urban	Fry et al.[a] (2011); Table 3, 90 m	E	Table 3	1.0
	Housing and urban areas	Residential density	Bierwagen et al. (2010); Theobald (2005) and Leinwand et al. (2010); 90 m	E	Leinwand et al. (2010)	1.0
Agriculture	Tourism and recreation areas[b]	Urban	Fry et al.[a] (2011); 90 m	E	Table 3	1.0
	Annual and perennial non-timber crops	Croplands	Fry et al. (2011); 90 m	E	Table 3	1.0
	Wood and pulp plantations	Plantations	US Geological Survey Gap Analysis Program (2011); 90 m	E	Table 3	1.0
	Livestock farming and ranching[c]					
	Marine and freshwater aqua-culture[d]					
Energy production and mining	Oil and gas drilling	Oil and gas wells	Copeland et al. (2009)	X	0.5	KD = 1.0
	Mining and quarrying	Mining	USGS Mineral Resources Data System (http://tin.er.usgs.gov/mrds/); USGS Topographic Change (http://topochange.cr.usgs.gov/)	X	0.25	KD = 0.5
	Renewable energy	Wind turbines	Federal Aviation Administration (https://oeaaa.faa.gov/oeaaa/external/portal.jsp)	X	0.17	KD = 0.5
Transportation and service corridors	Roads and railroads	Road type	TIGER (http://www.census.gov/geo/maps-data/data/tiger.html); Highways = 30 m, Secondary = 15 m, Local = 10 m 4WD/ dirt = 3 m; Railways = 30 m; 30 m cell	E	1.0	Hiwy = 1.0 Sec. = 0.5 Local = 0.3 4WD = 0.1 Rlwy = 1.0
	Highway traffic		FHA (2010)—AADT (cars per day); Estimated at 50 % max for AADT = 100,000 (Theobald 2010);	X	0.5	KD = 1.0
	Utility and service lines	Utility powerlines	Electric power from Platts (http://www.platts.com/products/gis-data);	X	0.17	KD = 0.5
		Towers	FCC (2012)	X	0.25	KD = 0.25
	Shipping lanes[d]					
	Flight paths[c]					
Biological resource use	Hunting and collecting terrestrial animals[e]					
	Gathering terrestrial plants[e]					
	Logging and wood harvesting[f]					
	Fishing and harvesting aquatic resources[d]					

Table 1 continued

Human modification activities framework		Stressor in human modification		Parameters*		
Level 1	Level 2	Name	Data source and scale	Source	Intensity value (I)	Footprint value (F)
Human intrusions and disturbance	Recreational activities	Distance to major roads	FHA (2010); Theobald (2010); 90 m	E	1.0	Figure 1
	War, civil unrest and military exercises[c]					
	Work and other activities[e]					
Natural system modifications	Fire and fire suppression[c]					
	Dams and water use[d]					
Invasive species and disease	Invasive non-native species	Cover dominated by introduced species	USGS Gap Analysis Program (2011); (five classes include introduced vegetation types)	E	Table 3	1.0
	Problematic native species[c]					
	Introduced genetic material[c]					
Pollution	Household sewage and urban waste water[e,g]					
	Industrial and military effluents[e,g]					
	Agricultural and forestry effluents[c]					
	Garbage and solid waste[c]					
	Air-borne pollutants[e,g]					

Note that a comprehensive list of the first and second levels of classes in the framework is provided, and data gaps exist when no readily-available dataset was identified to map a stressor

* *Source of estimation E* empirical, *X* expert-opinion. *KD* kernel density with radius in kilometers. Values used to parameterize the calculation of *h*

[a] NLCD was filtered to remove the built-up land cover types that were "burned-in" on the basis of rural highways

[b] Some intense tourist and recreation uses are mapped in land cover datasets, but lower intensity tourism and recreation such as ski areas often are not included

[c] No nationally consistent, readily-available dataset is known

[d] Not applicable for terrestrial-based ecosystems

[e] Partially addressed by distance to major roads

[f] Partially addressed by plantations

[g] Partially addressed by residential and commercial development

Table 2 Estimated magnitude (*I*) values (0 → 1.0) for different land use types, from cross-walking categories to Brown and Vivas (2005)

Description	Magnitude
Undeveloped	0.0
Residential	0.7
Mixed use developed	0.9
Agriculture	0.5
Resource extraction	0.8
Industrial	1.0
Recreation	0.2
Transportation	1.0
Unknown[a]	0.3

[a] But human modified—estimated to be 0.3 because it reflects clear signs of human modification but from miscellaneous and unknown types of activities

Stressors framework and spatial datasets

The Conservation Measures Partnership (CMP) framework catalogues and organizes multiple sources of stressors or threats associated with different human activities (Salafsky et al. 2008). Organizing the multiple stressors that can influence a landscape using this existing framework helps to minimize redundancy and potential overlap. It also results in a comprehensive but parsimonious list of roughly a dozen different major threats that are further broken down into classes (or stressors) that I mapped as variables (Table 1). Each variable is represented as an individual data layer, with values that range from 0 to 1.0 (no to complete impact).

I mapped residential and commercial development stressors from the National Land Cover Dataset 2006 (NLCD; Fry et al. 2011; www.mrlc.gov) using the developed cover classes that include commercial, industrial, and residential land uses. Housing density data from Bierwagen et al. (2010) were used to map residential areas, particularly because low-density residential areas (<1 dwelling unit per acre; dua) are largely unmapped in NLCD. Agricultural stressors were mapped from NLCD classes of cropland and pastureland. I was unable to locate a consistent, reliable, and readily-available dataset on livestock farming and ranching (i.e. grazing). Energy development stressors were mapped using a kernel density (KD) function applied to oil and gas well locations (Copeland et al. 2009) with a 1 km radius and maximum impact estimated to be 0.5. State natural resource experts (WGA Landscape Integrity working group) estimated a maximum impact of 0.25 for effects associated with active mines and quarries and 0.17 for wind tower/turbine locations (https://oeaaa.faa.gov), both with a 0.5 km radius. Transportation stressors (Forman et al. 2003; Fahrig and Rytwinski 2009) were mapped using several datasets. The physical footprint of roads and railroads was mapped using TIGER 2010 data (www.census.gov/geo/www/tiger), with average widths estimated empirically from aerial photography by road type. Road use was measured by highway traffic or average annual daily traffic (AADT; number of vehicles per day) from the National Transportation Atlas Database 2012 (www.bts.gov) by applying a KD with 1 km radius and an estimated maximum impact of 0.5 for AADT ≥100,000 (Theobald 2010). Utility power lines were mapped to current power line infrastructure locations with a KD of 0.5 km and maximum impact of 0.17. I mapped communication towers and antennae from the Federal Communications Commission's Antenna Structure Registration dataset (FCC 2012) by applying a KD of 0.25 km, assuming a maximum impact of 0.25. Potential stressors associated with airplane flight paths were not mapped, due to a lack of readily-available data and limited knowledge about their impacts to biodiversity.

I was able to only partially address effects associated with biological use stressors such as hunting, fishing, plant gathering, and timber logging. These resource extraction activities tend to be quite dispersed and because they are limited by accessibility to locate a resource and to transport materials back to process, I used a measure of impact as a function of the distance from major roads (state and county highways) as a proxy (Gelbard and Belnap 2003; Coffin 2007; Fahrig and Rytwinski 2009). I did not include maps associated with fire because spatial data are limited about the degree of human modifications to these natural processes. Data on dam (and reservoir) locations are readily available, but mapping their effects is challenging, in part because much of their ecological impact manifests in an indirect way at some distance from the dam, the data required to calculate the hydraulic residency time are limited (Poff and Hart 2002) and because mapping them requires processing complex hydrologic networks. I mapped land cover that was dominated by introduced species (i.e. invasive), as mapped by the five classes in the USGS Gap land cover v2 (USGS 2011) dataset. The importance of

Table 3 Empirical estimates (average values) of human modification derived by combining detailed land use dataset with the USGS Gap land cover v2 dataset

Formation class[a]	Pacific	IM basin	Rocky mtns.	Deserts	Great plains	Coastal	Appalachian	Northern/boreal forests
	1	2	3	4	5	6	7	8
Polar and alpine cliff, scree and rock vegetation			0.0023	0.0023	0.0023			0.0023
Alpine scrub, forb meadow and grassland	0.0007	0.0007	0.0007					0.0007
Temperate and boreal cliff, scree and rock vegetation			0.0185	0.0185	0.0165	0.0165	0.0165	0.0172
Cool semi-desert cliff, scree and rock vegetation	0.4	0.0046	0.0021	0.0021	0.0021	0.0021		0.0688
Warm semi-desert cliff, scree and rock vegetation	0.0087	0.0087	0.0087	0.0061	0.0061	0.0061		0.0072
Mediterranean cliff, scree and rock vegetation	0			0		0	0	0.0000
Cool temperate forest	0.0436	0.0074	0.0178	0.0119	0.1171	0.215	0.1289	0.0791
Lowland and montane boreal forest					0.053		0.053	0.0530
Warm temperate forest	0.0328	0.1024	0.0114	0.0071	0.0683	0.2203	0.2141	0.1088
Tropical (semi-) deciduous forest						0.1468		0.1468
Boreal grassland, meadow and shrubland	0.0687	0.0232	0.0413	0.0098	0.1454	0.3129	0.1961	0.1427
Temperate grassland, meadow and shrubland	0.0384	0.0384		0.0384		0.0384		0.1175
Mediterranean scrub	0.0962	0.0962		0.0962		0.0962		0.0384
Mediterranean grassland and forb meadow	0.0037	0.0122	0.0103	0.0203	0.0236	0.0236		0.0962
Cool semi-desert scrub and grassland	0.0222	0.0222	0.0222	0.0236	0.0853	0.1204		0.0156
Warm semi-desert scrub and grassland	0.1859	0.1859	0.1859	0.1859	0.1859	0.1859	0.1021	0.0574
Temperate and boreal scrub and herb coastal vegetation	0.0248	0.0248	0.0248			0.1859	0.1859	0.1859
Tropical wooded, scrub and herb coastal vegetation	0.0248		0.0248			0.1468		0.1859
Boreal flooded and swamp forest	0.1214	0.1214	0.1214		0.0985		0.0985	0.0985
Mangrove	0.1859	0.1859	0.1859					0.1468
Marine and estuarine saltwater aquatic vegetation				0.0248	0.0231	0.0364	0.0364	0.0306
Salt marsh						0.0364		0.0289
Temperate and boreal bog and fen					0.1214	0.1214	0.1214	0.1214
Temperate and boreal scrub and herb coastal vegetation				0.1859	0.1859	0.1859	0.1859	0.1859
Temperate flooded and swamp forest	0.0862	0.0439	0.0512	0.0861	0.1643	0.1468	0.1374	0.1008
Tropical flooded and swamp forest						0.1468		0.1468
Tropical Freshwater Marsh						0.0096		0.0096
Freshwater aquatic vegetation	0.0096					0.0096	0.0096	0.0096
Open water	0.0323	0.012	0.0013	0.0013	0.1088	0.0614	0.08	0.0414
Barren	0.0541	0.0541	0.0541	0.0541		0.0541	0.0541	0.0541
Current and historic mining activity	0.5887	0.3765	0.3469	0.4682	0.5328	0.4721	0.5474	0.4708

Table 3 continued

Formation class[a]	Pacific	IM basin	Rocky mtns.	Deserts	Great plains	Coastal	Appalachian	Northern/boreal forests
	1	2	3	4	5	6	7	8
Introduced and semi natural vegetation	0.0847	0.0556	0.09	0.09	0.2628	0.1649	0.1649	0.1649
Woody agricultural vegetation	0.419	0.419	0.419					0.4190
Herbaceous agricultural vegetation pasture	0.421	0.2315	0.2986	0.2806	0.3845	0.3475	0.3919	0.3428
Herbaceous agricultural vegetation cropland	0.4764	0.4201	0.351	0.4248	0.4574	0.4557	0.4335	0.4263
Recently disturbed or modified	0.2893	0.0029	0.1297	0.069	0.2885	0.3524	0.2855	0.2205
Developed, Open Space	0.2965	0.4064	0.2554	0.1379	0.4187	0.3953	0.397	0.3295
Developed, low intensity	0.5887	0.3765	0.3469	0.4682	0.5328	0.4721	0.5474	0.4708
Developed, medium intensity	0.6505	0.6505	0.6505	0.6505	0.6341	0.5329	0.6851	0.6366
Developed, high intensity	0.6033	0.6033	0.6033	0.6033	0.7303	0.6909	0.7621	0.6698
Average	0.20	0.16	0.15	0.15	0.22	0.19	0.23	0.19

Note these are calculated independently for each ecodivision grouping, ensuring that there were at least 100 data points that the estimates were based on, following methods described in Leinwand et al. (2010) and Theobald et al. (2012)

[a] This is the formation level for natural cover types from the National Vegetation Classification (Grossman et al. 1998)

invasive species and problematic native species in altering the condition of ecological systems is widely recognized, but a detailed, readily-available dataset on the location or proportion of these species is not available (Bradley and Marvin 2011). Also, note that stressors related to pollution were not directly included—although effects from these are partially included in our overall model because I directly map roads, urban areas, residential housing, and croplands.

Combining stress layers to overall degree of human modification

I used a method that minimizes bias associated with non-independence among multiple stressor/threats layers. That is, I assumed that locations with multiple threats have a higher degree of human modification than locations with just a single threat (assuming the same value), but the cumulative human modification score converges to 1.0 with multiple stressors. The specific algorithm is called a "fuzzy algebraic sum" (Bonham-Carter 1994) and the result is always at least as great as the largest contributing factor, so the effect is "increasive", but never exceeds 1.0 (Theobald 2013). The overall degree of human modification H_i at each cell i, with values that range from 0.0 (no modification, natural) to 1.0 (highly modified, un-natural) and is calculated as:

$$H_i = 1.0 - \prod_{j=1}^{k} \left(1 - h_j\right)$$

and let h = human modification score for individual stressor, with values ranging from 0.0 (no human modification, natural) to 1.0 (high degree of modification, un-natural), for $j = 1\ldots k$ data layers. For example, H_i for three layers of 0.6, 0.5, and 0.4, the computation would be: $H_i = 1.0 - ((1 - 0.6) \times (1 - 0.5) \times (1 - 0.4))$, or 0.88. Note that the final human modification layer where each raster cell value equals H_i is denoted as H. I also identified the stressor h_j that contributed the highest level impact at a given location, which I called "dominant."

Model evaluation and application

Because measures of ecological integrity commonly are used in spatially-explicit models, such as the

Fig. 1 The relationship of human modification to distance from major roads, fit using a 4th order polynomial trend line:
$y = -5E - 22x^5 + 4E - 17x^4 - 1E - 12x^3 + 2E - 08x^2 - 0.0001x + 0.387$
($R^2 = 0.98$)
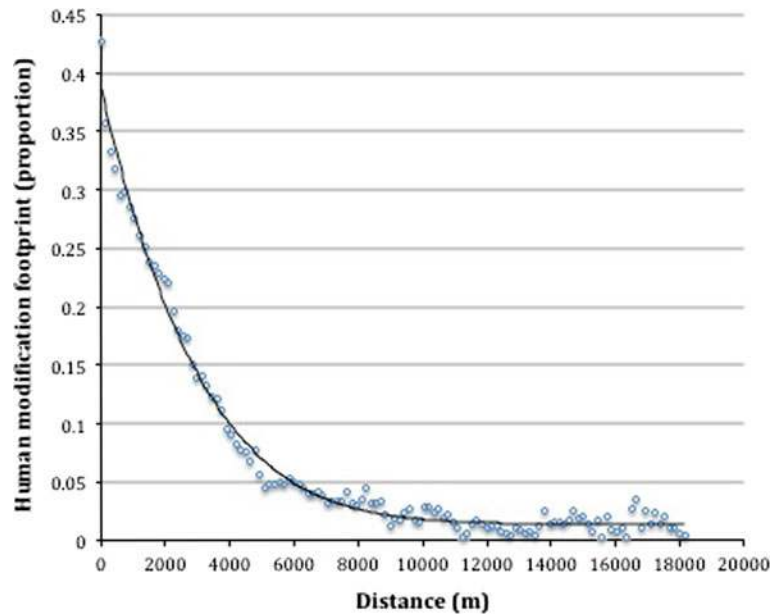
resistance layer for connectivity mapping (e.g., Carroll et al. 2012; McRae et al. 2012; Theobald et al. 2012), it is important to understand and evaluate the degree to which spatial processes are integrated into a measure and the spatial patterns that emerge, so that reasonable interpretations can be made. That is, most landscape integrity maps account for local or very fine scale (e.g., within a cell or nearby such as 500 m), but for some purposes are aggregated to watersheds (e.g., Esselman et al. 2011). Commonly in landscape ecology two dominant ecological processes have been discussed (Wiens 2002): those dominated by terrestrial processes (animal movement, wind dispersal, etc.) and those that are dominated by freshwater processes (i.e. hydrologic and riverine).

To evaluate the role of a presumed dominant ecological process in forming spatial pattern, I calculated and compared three ways to process the raw values in the human modification dataset. To represent *local* or in situ processes, I calculated the mean value of H from the 90 m dataset for each 12-digit HUCs, denoted as H_l. To represent a *watershed* perspective where hydrologic connectivity dominates but is not limited to downstream-only flows (and therefore this is not freshwater in the strict sense), I calculated a hierarchical watershed average value, denoted as H_w. That is, the mean H value within each HUC found within each 12, 10, 8, 6, and 4-digit layer was calculated, and then the mean H value at each raster

cell across the 5 layers was calculated. An important distinction here is that this approach does not assume that a given process can be adequately captured at a single scale (or even known adequately), but rather it makes use of a multi-scale averaging process that is more appropriate for general representation of landscape-level processes (Riitters et al. 2009; Theobald 2010). To represent a *terrestrial* perspective, I applied the multi-scale averaging approach and assumed that the dominant ecological processes were isotropic and therefore were represented by a moving *circular* windows, scaled in size equal to the average HUC area: 101, 545, 3981, 25426, and 42168 km² for HUC 12-4, denoted as H_t.

To compare the process perspectives, I calculated a Z-score by standardizing the H_l values in each HUC12 against the values from the local process layer. Locations with a large negative Z-score signify that the local scores are significantly higher and over-represent the impact compared to when areas are integrated according to either a watershed or terrestrial perspective. Locations with a large positive Z-score signify that the local scores (H_l) are significantly lower and under-represent the impact compared to the watershed (H_w) or terrestrial (H_t) maps.

I assessed how well the degree of human modification predicts a general indicator of field-level conditions from the EPA's Wadeable Stream Assessment (WSA) following the approach of Falcone et al.

(2010). I classified sites into two levels of disturbance: *reference* sites that were considered to be natural or least-disturbed conditions in their ecoregions (n = 1,699) and *disturbed* which were considered to be most heavily-modified by human activities (n = 440). I expected that there would be a significant difference between the human modification values within the reference sites versus the disturbed sites. I expected that the watershed characterization would have the best fit with the WSA sites, followed by terrestrial (because of spatial process), and the poorest fit with the local process (HUC12). Finally, I summarized findings by protection status level from the Protected Areas Database (http://gapanalysis.usgs.gov/padus/).

Results

For the conterminous US, I found the overall average degree of human modification H value was 0.3756 (SD = 0.243). Of course this varies regionally (Fig. 2; Table 4), and not surprisingly the intermountain west was least modified (H = 0.2216, SD = 0.193), while the Great Lakes region was most heavily modified by human activities (H = 0.5349, SD = 0.211). The general pattern of human modification also increases predictably as a function of decreasing protection

Table 4 Results of the degree of human modification within census regions (http://www.census.gov/geo/maps-data/maps/pdfs/reference/us_regdiv.pdf)

Region	Mean	SD
Pacific	0.2860	0.237
Intermountain West	0.2216	0.193
North Central	0.4715	0.185
South Central	0.4206	0.215
Great Lakes	0.5349	0.211
Northeast	0.4805	0.248
Southeast	0.5187	0.213

level, so that H in status 1 = 0.1556 (SD = 0.141), 2 = 0.2004 (SD = 0.176), 3 = 0.2021 (SD = 0.162), and 4 = 0.4349 (SD = 0.236).

Figure 3a–c show the degree of human modification mapped to examine results from different spatial processes: local (HUC12), watershed, and terrestrial. Figures 4a–c show the same data but zoomed into the Austin, Texas area as an example of the detailed patterns. At a continental extent, all three patterns are generally similar, but Fig. 5a and b show the departure from local values for both the watershed and terrestrial maps. Zooming into a narrower region (for example, Austin Texas; Fig. 5c, d) shows the fine-grained heterogeneity of these differences, including a difference in direction

Fig. 2 The degree of human modification (*H*) for the conterminous US at 90 m resolution, showing low levels of human activities in *green*, moderate levels in *yellow*, and high levels of human activities in *red*. *Note* major water bodies are included for reference, but water-based stressors are not included in a primary way. (Color figure online)
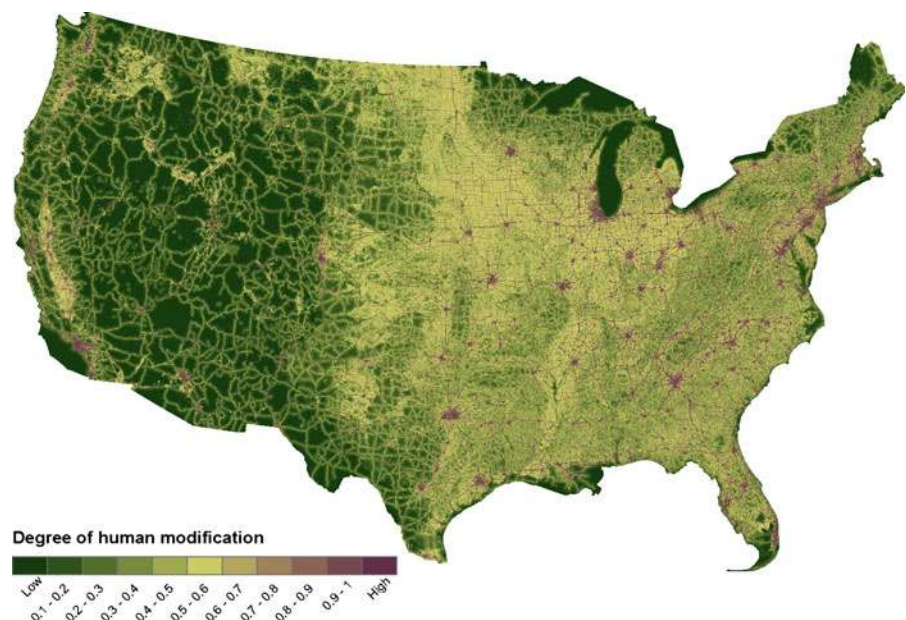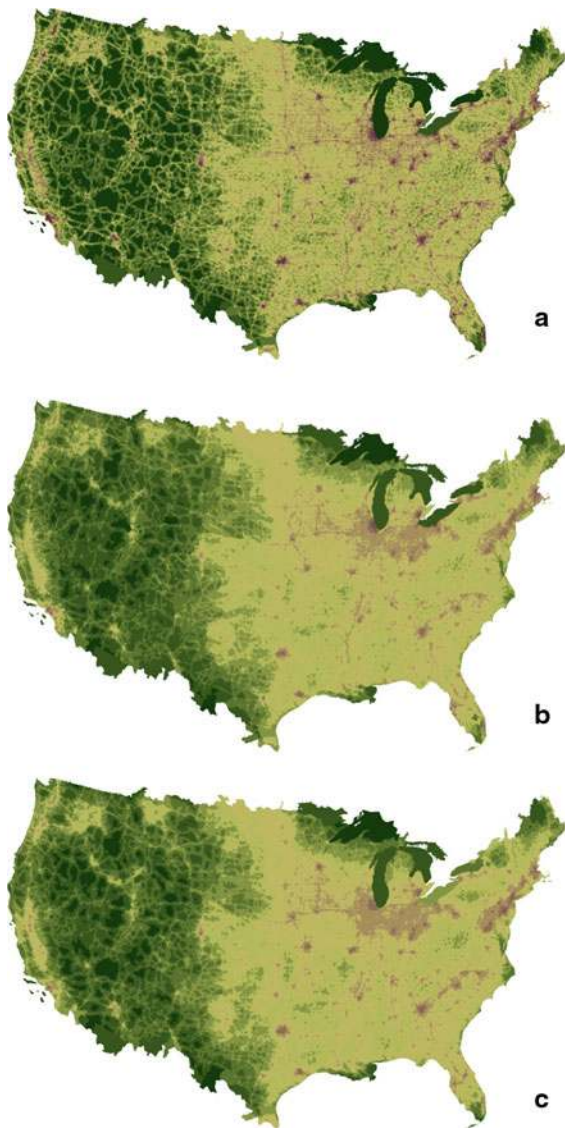
Fig. 3 Maps showing the degree of human modification (see Fig. 2 for legend), for different assumed ecological processes: **a** the "local" shown at a 12-digit hydrologic unit code; **b** "watershed" perspective by hierarchical averaging across HUC units 12, 10, 8, 6, and 4; **c** "terrestrial" using five moving windows sized equal to the average HUC units at the various scales

Fig. 4 A zoom-in map around Austin, Texas showing the degree of human modification, for different assumed ecological processes: **a** the "local"; **b** "watershed"; and **c** "terrestrial"

(under- vs. over-estimation) for some locations between watershed and terrestrial results.

Not surprisingly, I found that stressors associated with land uses that resulted in conversion to developed lands were dominant. Urban and residential density and agricultural activities were dominant for 44 % of the US, while impacts associated with distance from
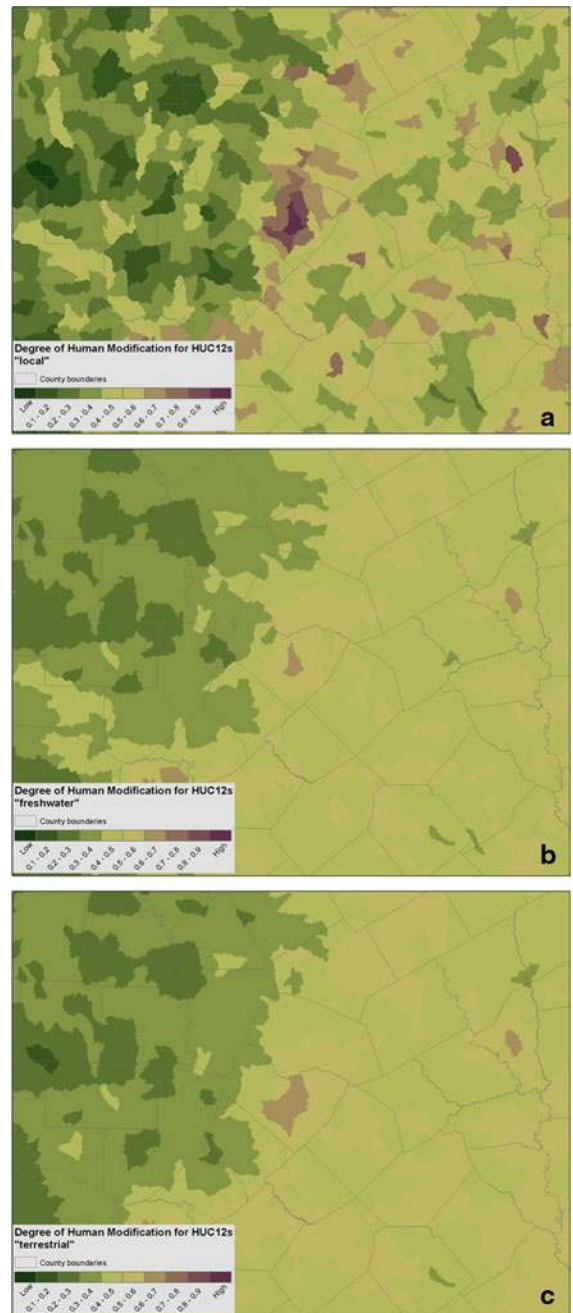
major roads dominated 51 %—particularly in the western US. For 2 % of the US, the road footprint was dominant, while effects associated with housing density was dominant in 0.3 %. Recall that the road footprint represents only the physical extent up to
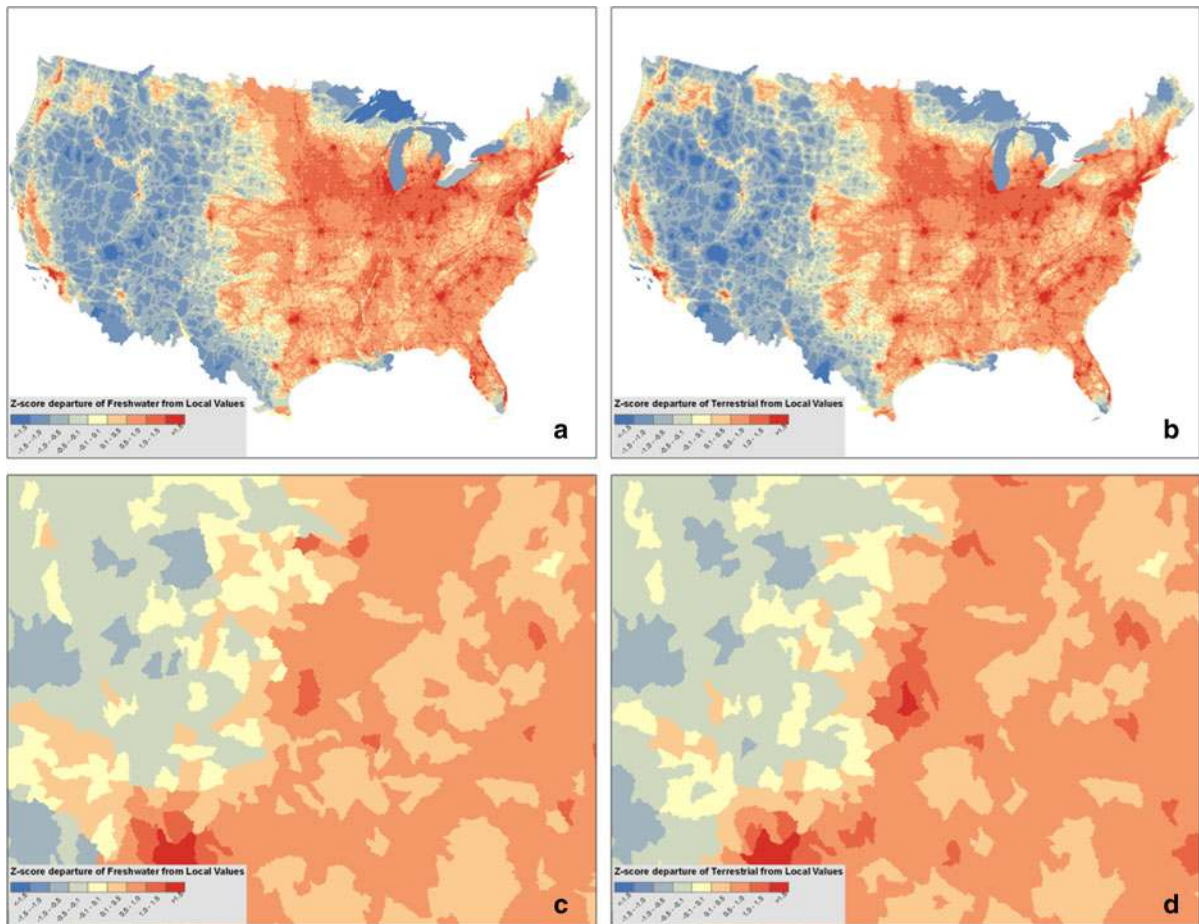
Fig. 5 A map showing the departure from local values for both **a** watershed and **b** terrestrial maps, as compared to local 12-digit HUC scores; **c** is freshwater near Austin, TX; and **d** is terrestrial near Austin, TX. That is, a Z-score was calculated by standardizing the h values in each HUC12 against the local values

30 m, and note that for most locations multiple stressors occurred together.

I compared results of H values (90 m resolution) from 2,139 WSA sites, and found that the mean value of H is less in reference sites (mean = 0.351, SD = 0.173) than disturbed sites (mean = 0.432, SD = 0.197). The distributions of reference to disturbed sites were significantly different using a Cramer–von Mises two-tailed test ($p = 0.005$) for all three forms: local ($W^2 = 6.558$), watershed ($W^2 = 3.495$), and terrestrial ($W^2 = 3.907$). Also, there is less variability in the watershed values for reference and disturbed sites (SD = 0.147, 0.161) as compared to the terrestrial (SD = 0.152, 0.164) and the local (0.173, 0.197) datasets, one indication that the watershed-process layer had the best fit with the validation dataset.

Discussion and application

The finding that about 38 % overall degree of human modification is roughly comparable with past estimates of human footprint and naturalness (34–35 %; Theobald 2010), though the variability of values in the current results has been reduced roughly in half. This is likely due to a tighter estimation of the degree of human modification.

Landscape integrity values changed substantially depending on what ecological process was assumed to be dominant. That is, for most urban and highly-modified locations (particularly in the eastern US), a map of local values tends to underestimate impacts because it does not consider any spill-over or influence from adjacent or nearby HUC12s. This assumption may be justified for

some situations where local-scale processes dominate. For other situations, such as potential effects of human activities on river water quality, clearly nearby (and especially upstream) impacts can strongly influence nearby (especially downstream) conditions. Note that even a simple isotropic assumption of spatial process can result in estimated values that are quite different from local conditions. Very fine-grained differences can occur—including a difference in direction (under- vs. over-estimation) for some locations between watershed and terrestrial results (e.g., Fig. 5d). The main point from this process comparison is that strongly different results can be obtained depending on the assumed ecological process and neighborhood or scale of analysis (Wiens 1989).

These results could be applied in three main ways by land management agencies. First, many programs directly use a measure of ecological integrity as a key variable in landscape assessments. For example, the results here could be used to update the BLM's REAs to provide a more consistent basis for their results. That is, using a comprehensive and empirically-based estimate of human modification would strengthen the findings of existing REAs and would enable consistency across the roughly dozen assessments. The degree of human modification results found here could also be used directly in the ongoing ecoregional landscape assessments conducted by the 16 LCCs, or to identify the large intact landscapes that is a primary data layer in the WGA Crucial Habitat Assessment Tool.

Second, the data layer here can be summarized to provide a measure of landscape context to inform management within a specific protected area (e.g., Hansen et al. 2011). As described earlier, Table 5 provides a summary of the degree of human modification averaged across each LCC, ranging from a low of 0.1835 for Great Basin and a high of 0.5797 in the Eastern Tallgrass Prairie and Big Rivers LCC. From a continental or national perspective, analyzing these scores in this way provides a robust and consistent measure of landscape integrity that can be used to roughly compare among broad units. Similar measures can be easily developed, for example for the 17 states in the WGA CHAT, the 32 networks of the National Park Service and the 14 ecoregions of the BLM's REAs.

A third type of use is to characterize the ecological context outside of existing protected areas to provide more locally-relevant and meaningful measures that

Table 5 Results of the degree of human modification within US Fish & Wildlife Service Landscape Conservation Collaboratives for the conterminous US

Name	Mean	SD
North Pacific	0.3143	0.230
California	0.3901	0.261
Great Northern	0.2150	0.193
Great Basin	0.1835	0.183
Southern Rockies	0.1962	0.176
Desert	0.1952	0.188
Plains and Prairie Potholes	0.4028	0.198
Great Plains	0.4269	0.184
Gulf Coast Prairie	0.4176	0.227
Upper Midwest and Great Lakes	0.3754	0.260
Eastern Tallgrass Prairie and Big Rivers	0.5797	0.173
Gulf Coastal Plains and Ozarks	0.4888	0.189
North Atlantic	0.4763	0.265
Appalachian	0.5014	0.211
South Atlantic	0.5406	0.210
Peninsular Florida	0.5150	0.259

can be used to inform the selection of conservation targets and/or help to prioritize specific locations of conservation action within each administrative unit—at the local, state or federal managerial unit. For example, Fig. 6 provides a depiction of areas of potential conservation opportunity that combines a regionalized landscape integrity score with a protection status score to help distinguish potential audiences and actions. That is, the H values at each location were standardized to the LCC so that importance is expressed relative to each LCC. Locations (in this case HUC12 s) with each LCC were then ranked to identify the 90th-percentile, the 75th, and the 50th (i.e. the median) as a rough classification of importance. These are portrayed in different colors for conservation status (Gap status level) 1&2 (highest protection level for biodiversity (i.e. biodiversity reserves), 3 (protected with some extractive activities), and 4 (unprotected, mostly privately-owned). Opportunities and actions differ with each status category (Wade et al. 2011); indeed, for each land owner and management unit as well, but those are beyond the scope of this paper. For example, status 1&2 will likely be focused on management of currently protected lands, rather than targeting specific locations to change management of status 3 lands to be more compatible with biodiversity protection—particularly those with high

Fig. 6 Potential conservation opportunities to conserve large, intact landscapes. Results are shown for three protection level status codes: parks and wilderness areas in Gap level 1&2 (*green*), multi-use public lands in Gap 3 (*blue*), and privately-owned lands without formal conservation protection in Gap 4 (*orange*). Deeper hues signify 12-digit HUCs with a lower degree of human modification (i.e. higher levels of landscape integrity), lighter hues signify a higher degree of human modification—areas without any colors (*white*) have a relatively high degree of human modification. (Color figure online)
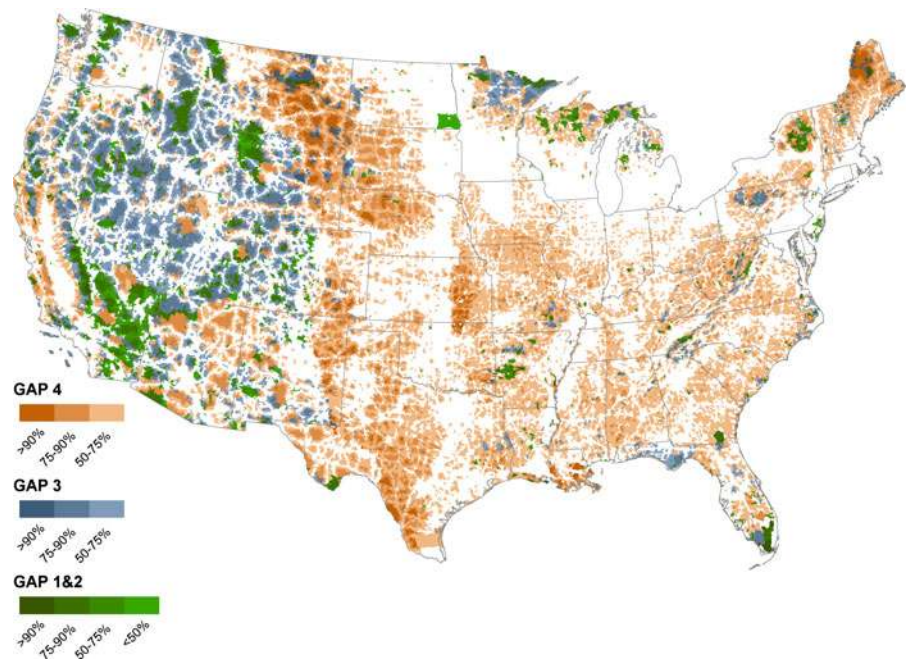
landscape integrity near a cluster of status 1&2, or perhaps providing corridors of higher protection to move between reserves. For status 4 lands, areas with high integrity ranks might be considered to have higher value in a prioritization for potential conservation purchase or easement programs. Although this approach is not intended to replace prioritization efforts by individual agencies and organizations, it does give an important complementary perspective by providing an integrated, synthetic, landscape view that crosses land ownership boundaries. Note that locations that are less than the mean standardized value are not portrayed in this map, but should not be interpreted as having no conservation value. Instead, these locations could be viewed through a restoration lens, by identifying those areas that contribute to overall improvements if local stressors to landscape integrity could be ameliorated (Baldwin et al. 2012).

I recognize that there was a practical and opportunistic aspect to the selection of stressors that were included in the final model, as not all stressors have reliable, publicly-available datasets available. A critical advantage of examining potential stressors within the broad framework is that insight can be gained into which threats were most important (impactful) and relevant, and the gaps are made explicit to identify future opportunities for data that would improve the overall human modification model. To that end, the

most critical datasets for future improvement to this landscape integrity dataset include stressors that effect disproportionately freshwater resources such as dams, irrigation, and pumping, the proportion of invasive species, likely shifts in biomes due to climate change, the intensity of domestic grazing, and hunting and fishing pressure. Although not emphasized in this paper, this approach supports the monitoring of status and trends in landscape integrity, as the main inputs are time dependent (cover, housing, roads, etc.) so that a landscape integrity dataset could be generated at a 5–10 year interval (e.g., Theobald 2010).

In this paper I developed and provided preliminary applications of an empirically-based, robust measure of ecological integrity at the landscape level. I found that the degree of human modification averaged to be about 0.38 across the US, with reasonable regional variation. Estimates of impact for roughly half of the stressors included here relied on values established by expert judgment, but more than 97 % of the US was dominated by a stressor whose impact was estimated using empirical data. Although improvements could be made to this approach, especially in terms of filling data gaps on invasive species and grazing/hunting intensity, the framework and methodology described here provides important improvements over existing, ad hoc approaches, to provide a foundation on which sound monitoring and evaluation of ecological

integrity can be based. Most importantly, landscape-level assessments of ecological integrity should be based on an internally consistent model, comply with decision theory principles, incorporate empirically-derived data to the maximum extent possible, explicitly state the incorporation of the assumed dominant ecological process, and provide validation of their results to the degree possible.

References

Angermeier PL, Karr JS (1994) Biological integrity versus biological diversity as policy directives. BioScience 44(10): 690–697

Aplet G, Thomson J, Wilbert M (2000) Indicators of wildness: using attributes of the land to assess the context of wilderness. In: McCool SF, Cole DN, Borrie WT, O'Loughlin J (eds) Wilderness science in a time of change conference. Proceedings RMRS-P-15-VOL-2, Ogden, UT. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, pp 89–98

Baldwin RF, Reed SE, McRae BH, Theobald DM, Sutherland RW (2012) Connectivity restoration in large landscapes: modeling landscape condition and ecological flows. Ecol Restor 30:274–279

Bierwagen B, Theobald DM, Pyke CR, Choate CA, Groth P, Thomas JV, Morefield P (2010) National housing and impervious surface scenarios for integrated climate impact assessments. Proc Nat Acad Sci USA 107(49):20887–20892

Bonham-Carter GF (1994) Geographic information systems for geoscientists: modeling with GIS. Pergamon, Oxford

Borja A, Bricker SB, Dauer DM, Demetriades NT, Ferreira JG, Forbes AT, Hutcings P, Jia X, Kenchington R, Marques JC, Zhu C (2008) Overview of integrative tools and methods in assessing ecological integrity in estuarine and coastal systems worldwide. Mar Pollut Bull 56:1519–1537

Bradley BA, Marvin DC (2011) Using expert knowledge to satisfy data needs: mapping invasive plant distributions in the western US. West North Am Nat 71(3):302–315

Brown MT, Vivas MB (2005) Landscape development intensity index. Environ Monit Assess 101:289–309

Carroll C, McRae B, Brookes A (2012) Use of linkage mapping and centrality analysis across habitat gradients to conserve connectivity of gray wolf populations in western North America. Conserv Biol 26:78–87

Coffin AW (2007) From roadkill to road ecology: a review of the ecological effects of roads. J Transp Geogr 15(5):396–406

Copeland HE, Doherty KE, Naugle DE, Pocewicz A, Kiesecker JM (2009) Mapping oil and gas development potential in the US intermountain west and estimating impacts to species. PLoS ONE 4(1):e7400

Esselman PC, Infante DM, Wang L, Wu D, Cooper AR, Taylor WW (2011) An index of cumulative disturbance to river fish habitats of the conterminous United States from landscape anthropogenic activities. Ecol Restor 29(1–2):133–151

Fahrig L, Rytwinski T (2009) Effects of roads on animal abundance: an empirical review and synthesis. Ecol Soc 14(1): 21. http//www.ecologyandsociety.org/vol14/iss1/art21/. Accessed 16 Sep 2013

Falcone JA, Carlisle DM, Weber LC (2010) Quantifying human disturbance in watersheds: variable selection and performance of a GIS-based disturbance index for predicting the biological condition of perennial streams. Ecol Indic 10: 264–273

Fancy SG, Gross JE, Carter SL (2008) Monitoring the condition of natural resources in US National Parks. Environ Monit Assess 151:161–174

Federal Communications Commission (FCC) (2012) Antenna structure registration. http://wireless.fcc.gov/antenna/index.htm?job=home. Accessed 16 Sep 2013

Federal Highway Administration (FHA) (2010) National Transportation Atlas Database 2010. DVD published by the Research and Innovative Technology Administration, Bureau of Transportation Statistics

Forman RTT, Sperling D, Bissonette JA, Clevenger AP, Cutshall CD, Dale VH, Fahrig L, France R, Goldman CR, Heanue K, Jones JA, Swanson FJ, Turrentine T, Winter TC (2003) Road ecology: science and solutions. Island, Washington, DC

Fry JA, Xian G, Jin S, Dewitz JA, Homer CG, Yang L, Barnes CA, Herold ND, Wickham JD (2011) Completion of the 2006 national land cover database for the conterminous United States. Photogramm Eng Remote Sens 77:858–864

Gardner RH, Urban DL (2007) Neutral models for testing landscape hypotheses. Landscape Ecol 22:15–29

Gardner RH, Milne BT, Turner MG, O'Neill RV (1987) Neutral models for the analysis of broad-scale landscape pattern. Landscape Ecol 1:19–28

Gelbard JL, Belnap J (2003) Roads as conduits for exotic plants in a semi-arid landscape. Conserv Biol 17:420–432

Grossman DH, Faber-Langendoen D, Weakley AS, Anderson M, Bourgeron P, Crawford R, Goodin K, Landaal S, Metzler K, Patterson KD, Pyne M, Reid M, Sneddon L (1998) International classification of ecological communities: terrestrial vegetation of the United States. The national vegetation classification system: development, status, and applications, vol 1. The Nature Conservancy, Arlington

Hajkowicz S, Collins K (2007) A review of multi-criteria analysis for water resource planning and management. Water Resour Manag 21(9):1553–1566

Hannah L, Carr JL, Lankerani A (1995) Human disturbance and natural habitat: a biome level analysis of a global data set. Biodivers Conserv 4:128–155

Hansen AJ, Davis CR, Piekielek N, Gross J, Theobald DM, Goetz S, Melton F, DeFries R (2011) Delineating the

ecosystems containing protected areas for monitoring and management. BioScience 61:363–373

IUCN (2006) Evaluating effectiveness: a framework for assessing management of protected areas, 2nd edn., Best practice protected area guidelines series No. 14IUCN, Gland and Cambridge

Leibowitz S, Cushman S, Hyman J (1999) Use of scale invariance in evaluating judgment indicators. Environ Monit Assess 58:283–303

Leinwand IIF, Theobald DM, Mitchell J, Knight RL (2010) Land-use dynamics at the public–private interface: a case study in Colorado. Landsc Urban Plan 97(3):182–193

Leu M, Hanser SE, Knick ST (2008) The human footprint in the West: a large-scale analysis of anthropogenic impacts. Ecol Appl 18(5):1119–1139

Lindenmayer DB, Margules CR, Botkin DB (2000) Indicators of biodiversity for ecologically sustainable forest management. Conserv Biol 14(4):941–950

McRae BH, Hall SA, Beier P, Theobald DM (2012) Where to restore ecological connectivity? Detecting barriers and quantifying restoration benefits. PLoS ONE 7(12):e52605

Neel MC, McGarigal K, Cushman SA (2004) Behavior of class-level landscape metrics across gradients of class aggregation and area. Landscape Ecol 19:435–455

Noon B (2003) Conceptual issues in monitoring ecological resources. In: Busch D, Trexler J (eds) Monitoring ecosystems: interdisciplinary approaches for evaluating ecoregional initiatives. Island Press, Washington, DC, pp 27–72

Noss RF (1990) Indicators for monitoring biodiversity: a hierarchical approach. Conserv Biol 4(4):355–364

Parrish JD, Braun DP, Unnasch RS (2003) Are we conserving what we say we are? Measuring ecological integrity within protected areas. BioScience 53(9):851–860

Poff NL, Hart DD (2002) How dams vary and why it matters for the emerging science of dam removal. BioScience 52(8):659–668

Riitters KH, Wickham JD, Wade TG (2009) An indicator of forest dynamics using a shifting landscape mosaic. Ecol Indic 9(1):107–117

Salafsky N, Salzer D, Stattersfield AJ, Hilton-Taylor C, Neugarten R, Butchart SHM, Collen B, Cox N, Master LL, O'Connor S, Wilkie D (2008) A standard lexicon for biodiversity conservation: unified classifications of threats and actions. Conserv Biol 22(4):897–911

Sanderson EW, Jaiteh M, Levy MA, Redford KH (2002) The human footprint and the last of the wild. BioScience 52(10):891–904

Schultz MT (2001) A critique of EPA's index of watershed indicators. J Environ Manag 62:429–442

Theobald DM (2005) Landscape patterns of exurban growth in the USA from 1980 to 2020. Ecol Soc 10(1):32. Available from: http://www.ecologyandsociety.org/vol10/iss1/art32/. Accessed 16 Sep 2013

Theobald DM (2010) Estimating changes in natural landscapes from 1992 to 2030 for the conterminous United States. Landscape Ecol 25(7):999–1011

Theobald DM (2013) Integrating land use and landscape change with conservation planning. In: Craighead L, Convis C (eds) Shaping the future: conservation planning from the bottom up. Esri, Redlands, pp 105–121

Theobald DM, Reed SE, Fields K, Soule M (2012) Connecting natural landscapes using a landscape permeability model to prioritize conservation activities in the US. Conserv Lett 5(2):123–133

US Geological Survey (2011) Mineral resources data system. http://tin.er.usgs.gov/mrds/. Accessed 16 Sep 2013

US Geological Survey Gap Analysis Program (2011) National land cover, version 2. http://gapanalysis.usgs.gov/gaplandcover/. Accessed 16 Sep 2013

Wade AA, Theobald DM, Laituri M (2011) A multi-scale assessment of local and contextual threats to existing and potential US protected areas. Landsc Urban Plan 101:215–227

Wickham JD, Riitters KH, Wade TG, Homer C (2008) Temporal change in fragmentation of continental US forests. Landscape Ecol 23:891–898

Wiens JA (1989) Spatial scaling in ecology. Funct Ecol 3:385–397

Wiens JA (2002) Riverine landscapes: taking landscape ecology into the water. Freshw Biol 47:501–515

Woolmer G, Trombulak SC, Ray JC, Doran PJ, Anderson MG, Baldwin RF, Morgan A, Sanderson EW (2008) Rescaling the human footprint: a tool for conservation planning at an ecoregional scale. Landsc Urban Plan 87:42–53