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RESEARCH ARTICLE

A landscape index of ecological integrity to inform landscape conservation

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Abstract
Context Conservation planning is increasingly using "coarse filters" based on the idea of conserving "nature's stage". One such approach is based on ecosystems and the concept of ecological integrity, although myriad ways exist to measure ecological integrity.
Objectives To describe our ecosystem-based *index of ecological integrity* (*IEI*) and its derivative *index of ecological impact* (*ecoImpact*), and illustrate their applications for conservation assessment and planning in the northeastern United States.
Methods We characterized the biophysical setting of the landscape at the 30 m cell resolution using a parsimonious suite of settings variables. Based on these settings variables and mapped ecosystems, we computed a suite of anthropogenic stressor metrics reflecting intactness (i.e., freedom from anthropogenic stressors) and resiliency metrics (i.e., connectivity to similar neighboring ecological settings), quantile-rescaled them by ecosystem and geographic extent, and combined them in a weighted linear model to create IEI. We used the change in IEI over time under a land use scenario to compute *ecoImpact*.

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Results We illustrated the calculation of *IEI* and *ecoImpact* to compare the ecological integrity consequences of a 70-year projection of urban growth to an alternative scenario involving securing a network of conservation core areas (reserves) from future development.

Conclusions *IEI* and *ecoImpact* offer an effective way to assess ecological integrity across the landscape and examine the potential ecological consequences of alternative land use and land cover scenarios to inform conservation decision making.

Keywords Landscape pattern · Landscape metrics · Ecological assessment · Conservation planning · Landscape conservation design · Coarse filter

Introduction

Unrelenting human demand for commodities and services from ecosystems raises questions of limits and sustainability. Many scientists believe that the earth is facing another mass extinction as a consequence (Pimm et al. 1995; Ceballos et al. 2015). Indeed, current global extinction rates for animals and plants are at least 100 times higher than the background rate in the fossil record (Ceballos et al. 2015). A number of factors have been implicated as key drivers of this global biodiversity crisis, but chief among them is anthropogenic habitat loss and fragmentation (Sala et al. 2000; Pereira et al. 2010; Haddad et al. 2015; Newbold et al. 2015). In response, land use planners and conservationists are seeking better ways to proactively conserve the most significant natural areas before they are lost or irreversibly degraded, but it is difficult to prioritize areas that are in the greatest need of protection, or determine which ones provide the greatest ecological value for the cost of protection. Analyzing a landscape's ecological/biodiversity value requires integrating vast amounts of site-specific information over varying spatial scales. Conservation organizations, which collectively spend billions of dollars each year to protect and connect natural areas (Lerner et al. 2007), increasingly need tools to effectively target conservation.

To meet the growing need for targeting conservation action, a variety of approaches have been developed for evaluating the human footprint (e.g., Sanderson et al. 2002; Theobald 2013; Venter et al. 2016) and selecting lands and waters for conservation protection (e.g., Williams et al. 2002; Ortega-Huerta and Peterson 2004; Belote et al. 2017). Important questions about the various approaches persist and include the appropriate type or level of diversity on which to focus (e.g., individual species, biotic communities, ecological systems, or geophysical settings), the criteria by which areas should be selected, specific protocols for optimizing reserve selection, and the amount of protected area needed to achieve conservation goals. Over time, focus has shifted from isolated reserves to interconnected reserve networks selected based on landscape ecology principles (e.g., Soulé and Terborgh 1999; Briers 2002; Cerdeira et al. 2005; Beier 2012), and from single species to multi-species and, more recently, ecosystem- and geophysical-based approaches that seek to conserve "nature's stage" (e.g., Hunter et al. 1988; Pickett et al. 1992; Noss 1996; Anderson and Ferree 2010; Beier et al. 2015; Wurtzebach and Schultz 2016). These approaches emphasize retaining representative ecological and/or geophysical settings instead of focal species, and as such provide a "coarse filter" (sensu Hunter et al. 1988) for biodiversity conservation. The use of such a coarse filter is touted as being proactive for species conservation because if ecological settings (which provide the habitat that species depend on) remain intact, most species will also be conserved (e.g., Scott et al. 1993). Moreover, it is assumed that if ecological settings remain intact, critical ecological and evolutionary processes, such as nutrient and sediment transport, interspecific interactions, dispersal, gene flow and disturbance regimes, will also be maintained and provide the necessary environmental stage for climate adaptation to occur (Beier 2012; Beier et al. 2015). This prospect is appealing because biological diversity (with shifting composition) could be conserved under changing environmental conditions with the same expenditure of funds and commitment of land to conservation and without specific and detailed knowledge of every species of interest.

While the general concept of focusing on nature's stage is both appealing and intuitive, there are many different approaches for doing so. One approach has been to focus solely on the geophysical environment without attention to the biota, and identify and prioritize representative, diverse and connected geophysical settings based on one or more metrics (e.g., Anderson et al. 2014; Beier et al. 2015). Here the goal is to conserve the abiotic stage and allow the biota to change and “play out” on this stage over time, especially in response to climate change (Beier and Brost 2010; Beier 2012). For example, Anderson et al. (2014) measured site resiliency using a combination of two metrics: (1) landscape diversity, which refers to the number of microhabitats and climatic gradients available within a given area based on the variety of landforms, elevation range, soil diversity, and wetland extent and density, and (2) local connectedness, which refers to the accessibility of neighboring natural areas. This measure of site resiliency is agnostic to the distribution of biota and explicit climate change projections, but is somewhat sensitive to the impacts of human development via the fragmentation of natural areas. This approach has been shown to perform well as a surrogate for species diversity (Anderson et al. 2014).

An alternative approach, but not without its critics (e.g., Brown and Williams 2016), has been to focus on ecosystems, with attention to both the biotic as well as geophysical environment, and use the concept of ecological integrity to identify and prioritize places of conservation value (e.g., Tierney et al. 2009; Theobald 2013; Wurtzebach and Schultz 2016; Belote et al. 2017). Here the goal is to conserve the “ecological stage” by focusing on places with high ecological integrity that can sustain the biota and critical ecological processes. Ecological integrity is broadly defined 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; an ecological system has integrity when its dominant ecological characteristics (e.g., elements of composition, structure, function, and ecological processes) occur within their natural ranges of variation and can withstand and recover from most perturbations imposed by natural environmental dynamics or human disruptions.” (Parrish et al. 2003, p. 852).

As part of a broader framework for biodiversity conservation in the northeastern United States that we developed initially under the auspices of the Conservation Assessment and Prioritization System (CAPS) project (www.umasscaps.org) and expanded for the Designing Sustainable Landscapes (DSL) project in collaboration with the North Atlantic Landscape Conservation Cooperative (NALCC, McGarigal et al. 2017), we developed an ecosystem-based, landscape ecological approach for quantitatively evaluating the relative ecological integrity, and thus the biodiversity conservation value of every raster cell over varying extents (e.g., watershed, ecoregion, state) across the Northeast. Our approach is based on a modified concept of ecological integrity, which we define as the ability of an area to support native biodiversity and the ecosystem processes necessary to sustain that biodiversity over the long term. Importantly, our definition emphasizes the maintenance of ecological functions rather than the maintenance of a particular reference biotic composition and structure, and thus accommodates the modification or adaptation of systems (in terms of biotic composition and structure) over time to changing environments (e.g., as driven by climate change) as in the geophysical approach. Moreover, our approach rests on an unproven and perhaps unprovable assumption that an index of ecological integrity can be measured that reflects the ecological functions necessary to confer ecological integrity to a site. Our approach assumes that by conserving relatively intact and resilient ecological settings as measured by an appropriate index, we can conserve most species and ecological processes. Moreover, by identifying the lands and waters most worthy of protection based on the highest relative ecological integrity, conservation organizations can target their limited dollars strategically. In this paper, we describe our ecosystem-based assessment of ecological integrity, which is encapsulated into an *index of ecological integrity* (*IEI*), and illustrate its application for conservation in the northeastern US.

Model development

Our approach is raster-based and can be applied at any spatial resolution over any landscape extent large enough to capture a sufficiently wide gradient of ecological settings and anthropogenic land use impacts. Here, we describe the method generically and demonstrate its application to a 30 m resolution raster over the extent of the 13 northeastern states (VA, WV, DE, MD, PA, NJ, NY, CT, RI, MA, NH, VT, ME) plus Washington DC (hereafter the Northeast). All modeling was done with custom APL programs (APL + Win 12, APLNow, LLC). Source code can be obtained from B. Compton. Figure 1 depicts a schematic outline of the analytical process described in this section.

Ecological settings and ecosystems

Central to our approach is the characterization of the biophysical setting of every cell. For this purpose, we derive a comprehensive but parsimonious suite of continuous "ecological settings" variables that characterize important abiotic and anthropogenic aspects of the environment (Table 1). Each settings variable is selected based on a distinct and well-documented influence on ecological systems. The only biotic attribute that we include is potential dominant life form (e.g., grassland, shrubland, forest). Otherwise, the ecological settings are agnostic to vegetation composition and structure, as in the geophysical stage approach. The exact list of variables and their data source can vary among applications depending on data availability and objectives. The setting variables are used in the calculation of the individual ecological integrity metrics and (optionally) in the calculation of the composite *IEI* described below.

We also assign each cell to a discrete ecosystem type, which can be based on any classification scheme that can be mapped (e.g., Online Appendix B). Ecosystems are used as an organizational framework for scaling the ecological integrity metrics described below. It is not necessary to assume discrete ecological systems, since an ecological gradient approach for scaling the metrics is also feasible (see below), but for ease of interpretation and consistency with other derived products, we have used discrete ecosystems in all of the conservation applications to date.

Ecological neighborhoods

Ecological neighborhoods (sensu Addicott et al. 1987) play an important role in the computation of the ecological integrity metrics described below, as in

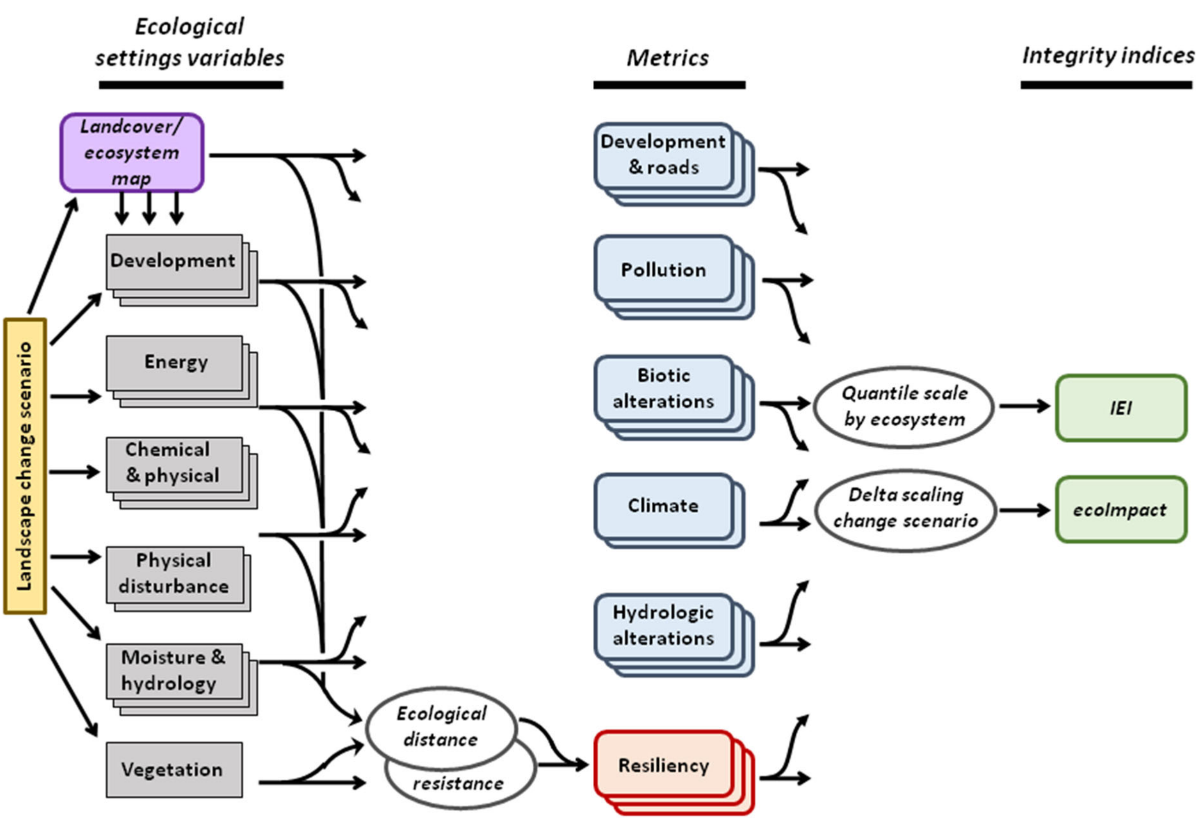

Fig. 1 Schematic outline of the workflow associated with deriving the *index of ecological integrity* (*IEI*) and the *index of ecological impact* (*ecoImpact*) as described in the text

Table 1 Weights (determined by expert teams) assigned to ecological settings variables (see Online Appendix A for links to detailed descriptions of each variable) in the ecological integrity assessment

	Resistance	Distance
Energy		
Incident solar radiation	0.1	1
Growing season degree-days	0.3	1
Minimum winter temperature	0.1	1
Heat index 35	0.1	1
Stream temperature	0.1	1
Chemical and physical substrate		
Water salinity	4	3
Substrate mobility	2	2
$CaCO_3$ content	0.1	1
Soil available water supply	0.05	0.5
Soil depth	0.05	0.5
Soil pH	0.05	0.5
Physical disturbance		
Wind exposure	0.1	1
Slope	1	1
Moisture and hydrology		
Wetness	4	8
Flow gradient	1	2
Flow volume	5	5
Tidal regime	2	2
Vegetation		
Dominant life form	3	8
Development		
Developed[a]	1	20
Hard development[a]	2	1000
Traffic[a]	40	0
Impervious[a]	5	0
Terrestrial barriers[a]	15	0
Aquatic barriers[b]	100	0

Resistance represents the weights assigned to the settings variables to determine resistance between the focal cell and each neighboring cell in the resistant kernels and watershed kernels used in the Connectedness and Aquatic connectedness metrics, respectively. Distance represents the weights to determine ecological distance between the focal cell and each neighboring cell for Similarity, Connectedness, and Aquatic Connectedness metrics. The settings variables are arbitrarily grouped into broad classes for organizational purposes

[a]Setting variable not used in Aquatic Connectedness

[b]Setting variable used only for Resistance in Aquatic Connectedness

other approaches (e.g., Theobold 2013; Anderson et al. 2014), but our particular implementation of neighborhoods are distinctive of our approach. We use non-linear kernels to specify how to weight the ecological neighborhood of a focal cell; i.e., to determine how much influence a neighboring cell has on the integrity of the focal cell. We use three different kinds of kernel estimators: (1) standard kernel estimator for the non-watershed-based metrics, (2) resistant kernel estimator for the connectedness metrics, and (3) watershed kernel estimator for the watershed-based metrics.

Standard kernel

The standard kernel produces a three-dimensional surface representing an estimate of the underlying probability distribution (or ecological neighborhood) centered on a focal cell (Silverman 1986). The standard kernel estimator begins by placing a standard kernel (e.g., Gaussian kernel) over a focal cell. In the standard Gaussian kernel, the "bandwidth" which controls the spread of the kernel is equal to one standard deviation and accounts for 39% of the kernel volume. The value of the kernel at each cell represents the weight of the cell, which decreases monotonically and nonlinearly from the focal cell according to the kernel function as the distance from the focal cell increases. Typically the kernel is scaled such that the weights sum to one across all cells. Lastly, the kernel weights are multiplied by the value of the ecological attribute under consideration (e.g., traffic intensity, nutrient loading, or percent impervious) and summed to produce a kernel-weighted average.

We can think of the standard kernel as an estimate of the ecological neighborhood of the focal cell, where the size and shape of the kernel represent how the strength of the ecological relationship varies (nonlinearly) with distance from the focal cell (Fig. 2a). The standard kernel estimator provides an estimate of the intensity of an ecological attribute within that ecological neighborhood; i.e., the kernel-weighted mean of the attribute. We use the standard kernel estimator, at various bandwidths (reflecting the width of the kernel), to estimate the intensity of point features (e.g., point sources of pollution), linear features (e.g., roads), and patches (e.g., developed land cover), including all non-watershed-based ecological integrity metrics with the exception of connectedness.

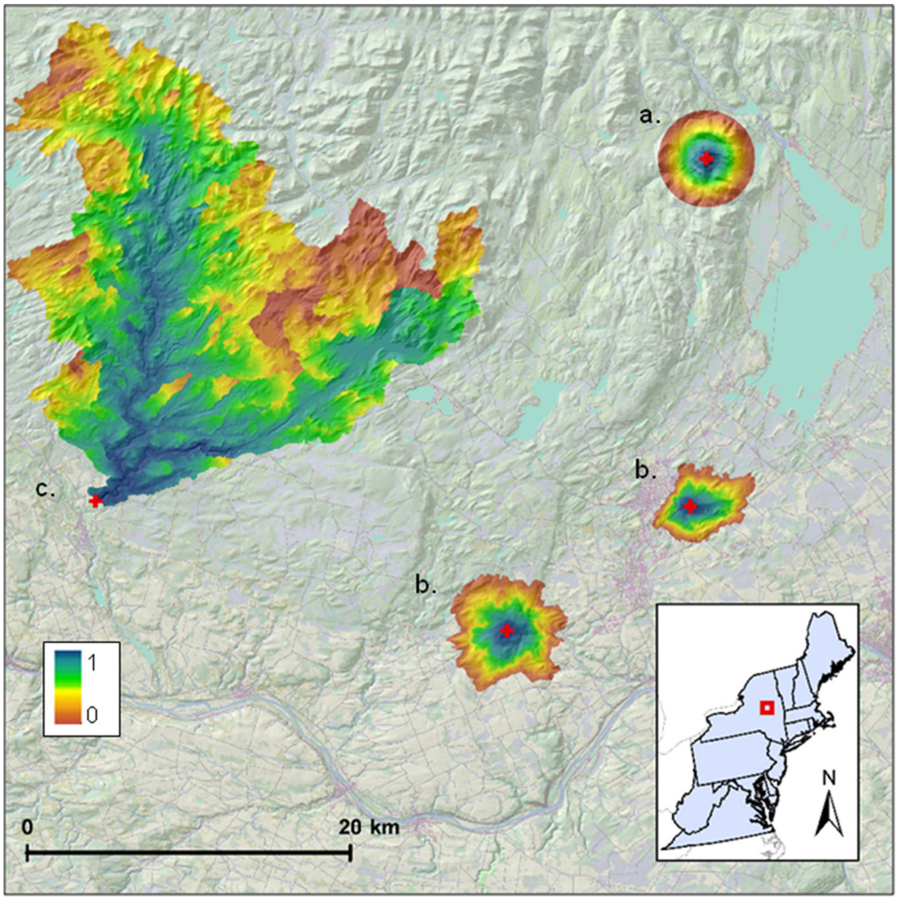

Fig. 2 Kernel estimators to estimate the ecological neighborhood of a focal cell (indicated by the red cross for each kernel) in an area west of Albany, New York: **a** standard Gaussian kernel around a focal cell in which the weight of the kernel at any cell is indicated by the color gradient and reflects the bandwidth (spread) of the kernel; **b** resistant Gaussian kernel around a focal cell in which the weight of the kernel at any cell is indicated by the color gradient and reflects bandwidth (spread) of the kernel as well as the resistance of the intervening landscape; and **c** watershed kernel in which the estimated relative time-of-flow from any cell within the watershed of the focal cell to the focal cell is indicated by the color gradient. Image is portrayed with hillshading

Resistant kernel

Like a standard kernel the resistant kernel is used to assign weights to a neighborhood around a focal cell with the critical difference being that the higher weight is now assigned to cells that are easier to get to (smaller cost-distances) instead of simply closer in Euclidian distance. Introduced by Compton et al. (2007), the resistant kernel is a hybrid between two existing approaches: the standard kernel estimator as described above and least-cost paths based on resistant surfaces. Resistant surfaces (also referred to as cost surfaces) are being increasingly used in landscape ecology to model ecological flows in heterogeneous landscapes (Zeller et al. 2012). In a patch mosaic, for example, a resistance value (or cost) is assigned to each patch type, typically representing a divisor of the expected rate of ecological flow (e.g., dispersing or migrating animals) through a patch type. In a least-cost path approach, the cost distance (or functional distance) between two points along any particular pathway is equal to the cumulative cost of moving through the associated cells. This least-cost path approach can be extended to a multidirectional approach that measures the functional distance (or least-cost distance) from a focal cell to every other cell in the landscape as a means of defining the accessible ecological neighborhood. These distances can then be converted to weights based on a Gaussian or other function such that higher weight is assigned to closer (in least-cost distance) cells.

In the resistant kernel algorithm, resistance values can be assigned any number of ways, but in this application we assign landscape resistance uniquely to each neighboring cell based on its “ecological distance” to the neighboring cell, where ecological distance is derived from the suite of ecological settings variables. Because resistance of neighboring cells is based on ecological distance to the focal cell, landscape resistance varies dynamically across the landscape; i.e., there is a unique landscape resistance surface for each focal cell. For each focal cell, first we calculate the weighted Euclidean distance between the focal cell and each neighboring cell in settings space (across all dimensions), where each settings variable is first range rescaled 0–1 and then multiplied by its assigned weight to reflect its importance in determining landscape resistance (Table 1), as follows:

$$d_n = \sqrt{\sum_{i=1}^{p} \left(w_i \left(x_{fi} - x_{ni}\right)\right)^2}$$

where d_n = Euclidean distance between the nth neighboring cell and the focal cell; $i = 1$ to p settings variables (dimensions); w_i = weight for the ith settings variable; x_{if} = value of the ith settings variable (scaled 0–1) at the focal cell; and x_{ni} = value of the ith settings variable at the nth neighboring cell. Next, we divide the result above by the maximum possible weighted Euclidean distance based on the non-anthropogenic (a.k.a. "natural") settings variables. Thus, if the focal cell and neighboring cell are both undeveloped and have identical values across all natural settings variables, the weighted Euclidean distance will always equal zero. On the other hand, if the two cells have maximally different values (i.e., a difference of one for each of the natural settings variables), the weighted Euclidean distance will always equal one. However, if the neighboring cell is developed, the weighted Euclidean distance can exceed one. Lastly, we convert weighted Euclidean distance to resistance by multiplying it by a constant and adding one to ensure that resistance is never less than one. The constant (which interacts with bandwidth) determines the theoretical maximum resistance between two undeveloped cells (i.e., when their weighted Euclidean distance is one), which we set to be 50 for the connectedness metric and 300 for the aquatic connectedness metrics described below. We selected the constants based on preliminary analyses in which we subjectively evaluated the behavior of the metric in discriminating among undeveloped and developed settings. By setting anthropogenic weights to be relatively high, the resistance (e.g., of a high-traffic expressway or a large dam) can become high enough to cause a neighboring developed cell to act as a complete barrier to spread in the resistant kernel. Consequently, rivers and other natural features can act as partial barriers to spread from focal cells with a high ecological distances (e.g., dry oak forests), but the maximum resistance between natural features is never more than two, while anthropogenic features such as highways can have higher resistances up to the maximum value determined by the constant.

A detailed description of the resistant kernel algorithm is given in Online Appendix C. Briefly, using the resistant surface described above, the resistant kernel computes the least cost distance to each neighboring cell (i.e., cumulative cost of spreading from the focal cell to the neighboring cell along the least cost path) and transforms these distances into probabilities based on the specified kernel, such that the probabilities (or weights) sum to one across all cells. The end result is a resistant kernel that depicts the functional ecological neighborhood of the focal cell (Fig. 2b). In essence, the standard kernel is an estimate of the fundamental ecological neighborhood and is appropriate when resistance to movement is minimal (e.g., highly vagile species), while the resistant kernel is an estimate of the realized ecological neighborhood when resistance to movement is nontrivial. The resistant kernel can also be thought of as representing a process of spread (e.g., dispersal) to or from the focal cell that combines the cost of moving through a heterogeneous and resistant neighborhood with the typically nonlinear cost of moving any distance away from the focal cell. In our ecological integrity assessment, we use the resistant kernel estimator in the terrestrial and aquatic connectedness metrics.

Watershed kernel

The standard kernel estimator may not be meaningful for aquatic communities where the ecological neighborhood is more likely to be the watershed area above the focal cell than a symmetrical area around the focal cell. Thus, for the watershed-based metrics, we use a watershed kernel estimator based on a time-of-flow model (Randhir et al. 2001) as described in detail in Online Appendix D. Briefly, the time-of-flow model estimates the time (t) it takes for a drop of water (or water-born materials such as pollutants) to reach the focal cell; it ranges from zero at the focal cell to some upper bound based on the size and characteristics of the watershed. We rescale t to range 0–1 by dividing t by the maximum observed value of t for the watershed of the focal cell and then taking the complement. In the resulting kernel, the weight ranges from 1 (maximum influence) at the focal cell to 0 (no influence) at the cell with the least influence (i.e., at the furthest edge of the watershed). In essence, kernel weights decrease monotonically as the distance upstream and upslope from the focal cell increases, but the weights decrease much faster across land than water so that the kernel typically extends much farther upstream than upslope. The resulting kernel can be viewed as a constrained watershed in which cells in the stream and closer to the focal cell have higher weight and cells in the upland and farther from the stream, especially on flat slopes with forest cover, have increasingly less weight (Fig. 2c).

Clearly, this simple time-of-flow model does not capture all the nuances of real landscapes that influence the actual time it takes for water to travel from any point in the watershed to the focal cell (e.g., soil characteristics that influence infiltration of precipitation and vegetation characteristics that influence water loss through evapotranspiration), but it nonetheless provides a much more meaningful way to weight the importance of neighboring cells than either the standard kernel estimator that does not account for flow or a uniform watershed kernel in which all cells in the watershed count equally.

Ecological integrity metrics

Our ecological integrity assessment involves computing a suite of metrics that characterize the ecological neighborhood of each focal cell based on one of the kernel estimators described above. Currently, our suite of metrics measure two important components of ecological integrity: intactness and resiliency.

Intactness refers to the freedom from human impairment (or anthropogenic stressors) and is measured using a broad suite of individual stressor metrics (Table 2) such that the greater the level of anthropogenic stress, the lower the estimated intactness. The stressor metrics are computed for all undeveloped cells, although some metrics apply only to certain ecosystems (e.g., watershed-based metrics apply only to aquatic and wetland systems). Each stressor metric measures the magnitude of the anthropogenic stressor within the ecological neighborhood of each cell and is uniquely scaled to the appropriate units for the metric. For example, the road traffic metric measures the intensity of road traffic (based on the estimated probability of an animal being hit by a vehicle while crossing a road given the estimated mean traffic rate) in the neighborhood surrounding the focal cell based on a standard logistic kernel (Fig. 3a). The value of each metric increases with increasing intensity of the stressor within the ecological neighborhood of the focal cell. Thus, the raw value of a stressor metric is inversely related to intactness and thus ecological integrity. The value of the metric at any location is generally independent of the particular ecological setting or ecosystem of the focal cell, as it depends primarily on the magnitude of the stressor emanating outward from the anthropogenic features of interest (e.g., roads). Thus, the stressor metrics are all interpretable in their raw-scale form; i.e., they do not need to be rescaled by ecological setting or ecosystem (as described below) to be meaningfully interpreted.

Each metric measures a different anthropogenic stressor and is intended to reflect a unique and well-documented relationship between a human activity and an ecological function. However, these stressor metrics are not statistically independent, since the same human activity can have multiple ecological effects. Consequently, these stressor metrics are viewed as a correlated set of metrics that collectively assess the impact of human activities on the intactness of the ecological setting or ecosystem.

Resiliency refers to the capacity to recover from disturbance and stress; more specifically, the amount of disturbance and stress a system can absorb and still remain within the same state or domain of attraction, i.e., resist permanent change in the function of the system (Holling 1973, 1996). In other words, as reviewed by Gunderson (2000), resiliency generally deals with the capacity to maintain characteristic ecological functions in the face of disturbance and stress. In contrast to intactness, resiliency is both a function of the local ecological setting, since some settings are naturally more resilient to stressors (e.g., a wetland isolated by resistant landscape features is less resilient to species loss than a well-connected wetland, because the latter has better opportunities for recolonization of constituent species), and the level of stress, since the greater the stress the less likely the system will be able to fully recover or maintain ecological functions. Moreover, the concept of resiliency applies to both the short-term or immediate capacity to recover from disturbance and the long-term capacity to sustain ecological functions in the presence of

Table 2 Intactness (a.k.a. stressor) and resiliency metrics included in the ecological integrity assessment for the northeastern United States (see Online Appendix E for links to detailed descriptions of each metric). Note, the final suite of metrics can vary among applications depending on available data. For example, several additional coastal metrics have been developed for the state of Massachusetts, including salt marsh ditching, coastal structures, beach pedestrians, beach ORVs, and boating intensity. The metrics are arbitrarily grouped into broad classes for organizational purposes

Metric group	Metric name	Description
Development and roads	Habitat loss	Intensity of habitat loss caused by all forms of development in the neighborhood surrounding the focal cell based on a standard Logistic kernel.
	Watershed habitat loss	Intensity of habitat loss caused by all forms of development in the watershed above the focal cell based on a watershed kernel.
	Road traffic	Intensity of road traffic (based on measured road traffic rates transformed into an estimated probability of an animal being hit by a vehicle while crossing the road given the mean traffic rate) in the neighborhood surrounding the focal cell based on a standard Logistic kernel.
	Mowing and plowing	Intensity of agriculture (as a surrogate for mowing/plowing rates) in the neighborhood surrounding the focal cell based on a standard Logistic kernel.
	Microclimate alterations	Magnitude of adverse induced (human-created) edge effects on the microclimate integrity of patch interiors.
Pollution	Watershed road salt	Intensity of road salt application in the watershed above an aquatic focal cell based on road class (as a surrogate for road salt application rates) and a watershed kernel.
	Watershed road sediment	Intensity of sediment production in the watershed above an aquatic focal cell based on road class (as a surrogate for road sediment production rates) and a watershed kernel.
	Watershed nutrient enrichment	Intensity of nutrient loading from non-point sources in the watershed above an aquatic focal cell based on land use class (primarily agriculture and residential land uses associated with fertilizer use, as a surrogate for nutrient loading rate) and a watershed kernel.
Biotic alterations	Domestic predators	Intensity of development associated with sources of domestic predators (e.g., cats) in the neighborhood surrounding the focal cell weighted by development class (as a surrogate for domestic predator abundance) and a standard Logistic kernel.
	Edge predators	Intensity of development associated with sources of edge mesopredators (e.g., raccoons, skunks, corvids, cowbirds; i.e., human commensals) in the neighborhood surrounding the focal cell weighted by development class (as a surrogate for edge predator abundance) and a standard Logistic kernel.
	Non-native invasive plants	Intensity of development associated with sources of non-native invasive plants in the neighborhood surrounding the focal cell weighted by development class (as a surrogate for non-native invasive plant abundance) and a standard Logistic kernel.
	Non-native invasive earthworms	Intensity of development associated with sources of non-native invasive earthworms in the neighborhood surrounding the focal cell weighted by development class (as a surrogate for non-native invasive earthworm abundance) and a standard Logistic kernel.
Climate	Climate stress	Magnitude of climate change stress at the focal cell based on the climate niche of the corresponding ecological system and the predicted change in climate between 2010 and 2080 (i.e., how much is the climate of the focal cell moving away from the climate niche envelope of the corresponding ecological system).
Hydrologic alterations	Watershed imperviousness	Intensity of impervious surface (as a surrogate for hydrological alteration) in the watershed above an aquatic focal cell based on imperviousness and a watershed kernel.
	Dam intensity	Intensity of dams (as a surrogate for hydrological alteration) in the watershed above an aquatic focal cell based on dam size and a watershed kernel.
	Sea level rise inundation	Probability of the focal cell being unable to adapt to predicted inundation by sea level rise, developed by USGS Woods Hole (Lentz et al. 2015).
	Tidal restrictions	Magnitude of hydrologic alteration to the focal cell due to tidal restrictions based on an estimate of the salt marsh loss ratio above each potential tidal restriction (road-stream and railroad-stream crossings).

Table 2 continued

Metric group	Metric name	Description
Resiliency	Similarity	Similarity between the ecological setting of the focal cell and its ecological neighborhood based on the weighted multivariate similarity computed across a variety of ecological settings variables (Table 1) and a standard Logistic kernel.
	Connectedness (connect)	Connectivity of the focal cell to its ecological neighborhood based on a resistant kernel (see text and Online Appendix C for details).
	Aquatic connectedness	Same as Connectedness except that it is constrained by the extent of aquatic ecosystems, such that the connectivity being assessed pertains to flows and disruption of flows (e.g., culverts and dams) within the aquatic network.

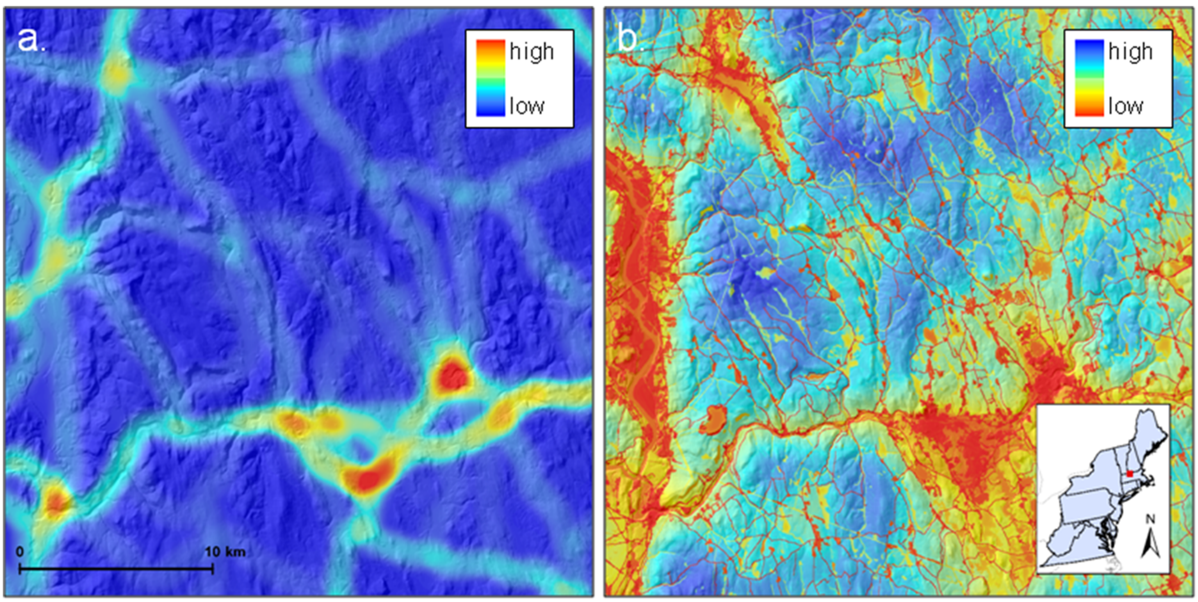

Fig. 3 **a** traffic (stressor) metric and **b** connectedness (resiliency) metric (scaled for the northeastern United States) for the North Quabbin region of western Massachusetts. See Table 2 for a brief description and Online Appendix E for a detail description of these two metrics. Note, the color legend is reversed in these two metrics so that the blue end of the gradient represents sites with greater ecological integrity (i.e., less traffic and greater connectedness in this case). Images are portrayed with hillshading

stress. The landscape attributes that confer short-term resiliency may not be the same as those that confer long-term resiliency, as discussed later. Given these considerations, resiliency is a complex, multi-faceted concept that cannot easily be measured with any single metric. For the applications presented in this paper we implemented a few different resiliency metrics (Table 2).

Like the stressor metrics, the resiliency metrics are computed for all undeveloped cells. In contrast to the stressor metrics, the value of each resiliency metric increases with increasing resiliency, so larger values connote greater integrity. Also in contrast to the stressor metrics, the value of the resiliency metric at any location is dependent on the particular ecological setting of the focal cell and its neighborhood. For example, the connectedness metric measures the functional connectivity of a focal cell to its ecological neighborhood (based on a resistant Gaussian kernel); more specifically, the capacity for organisms to move to and from the focal cell from neighboring cells with a similar ecological setting as the focal cell (Fig. 3b).

Consequently, connectedness is especially relevant for less vagile organisms where the resistance of the intervening landscape limits movement to and from the focal cell. Connectedness confers resiliency to a site since being connected to similar ecological settings should promote recovery of the constituent organisms following a local disturbance.

In contrast to the stressor metrics, the resiliency metrics are not particularly useful in their raw-scale form because they do not have interpretable units. Instead, they are best interpreted when rescaled by ecological setting or ecosystem (see below) so that what constitutes high resiliency for a small patch-forming ecological system such as a wetland need not be the same as for a matrix-forming system such as upland forest. Like the stressor metrics, each resiliency metric measures resiliency from a different perspective and is intended to reflect a unique and well-documented relationship between landscape context and ecological function, and resiliency metrics are correlated, yielding a set of metrics that collectively assess the capacity of a site to recover from or adapt to disturbance and stress.

Index of ecological integrity

The individual stressor and resiliency metrics can be used by themselves, but it is more practical to combine them into a composite index (*IEI*) for conservation applications.

Quantile-rescaling

Each of the raw stressor and resiliency metrics are scaled differently. Some are bounded 0–1 while others have no upper bound. Moreover, each of the metrics will have a unique empirical distribution for any particular landscape. In order to meaningfully combine these metrics into a composite index, therefore, it is necessary to rescale the raw metrics to put them on equal ground. Quantile-rescaling involves transforming the raw metrics into quantiles, such that the poorest cell gets a 0.01 and the best cell gets a 1. Quantile-rescaling facilitates the compositing of metrics by putting them all on the same scale with the same uniform distribution regardless of differences in raw units or distribution. Moreover, quantiles have an intuitive interpretation, because the quantile of a cell expresses the proportion of cells with a raw value less than or equal to the value of the focal cell. Thus, a 0.9 quantile is a cell that has a metric value that is greater than 90% of all the cells, and all the cells with > 0.9 quantile values comprise the best 10% within the analysis area. In light of these advantages, it is importance to recognize that quantile scaling means the ecological difference between say 0.5 and 0.6 is not necessarily the same as the ecological difference between say 0.8 and 0.9.

There are two fundamentally different ways to conduct quantile rescaling. In the first approach, which we refer to as "ecosystem-based rescaling," quantile-rescaling is done by discrete ecosystems. Ecosystem-based rescaling means that forests are compared to forests, emergent marshes are compared to emergent marshes, and so on. It doesn't make sense to compare the integrity of an average forest cell to that of an average wetland cell, because wetlands have been substantially more impacted by human activities such as development than forests, and they are inherently less-connected to other wetlands. Rescaling by ecosystem means that all the cells within an ecosystem are ranked against each other in order to determine the cells with the greatest relative integrity for each ecosystem. In the applications of *IEI* to date (see below) we have used this form of rescaling. In the second approach, which we refer to as "gradient-based rescaling," quantile-rescaling is done by comparing focal cells to similar cells based on multivariate distance in ecological setting space, which does not rely on discrete ecosystems. Comparative performance of these two alternative rescaling approaches remains an important subject for future research.

Ecological integrity models

The next step is to combine the quantile-rescaled metrics into the composite index. However, given the range of metrics (Table 2), it is reasonable to assume that some metrics are more relevant to some ecological settings or ecosystems than others. For example, the watershed-based stressor metrics and aquatic connectedness were designed specifically for aquatic and/or wetland communities. Moreover, it is reasonable to assume that the weights applied to the metrics should vary among ecological settings or ecosystems, since what stressors matter most, for example, to an emergent marsh may not be the same as for an upland boreal forest. Consequently, we employ ecosystem-specific ecological integrity models to weight the component metrics in the composite index (e.g., Online Appendix F). An ecological integrity model is simply a weighted (by expert teams, Online Appendix F) linear combination of metrics designated for each ecosystem, although for parsimony sake we generally designate a unique model for each ecological formation, which is a group of similar ecosystems (Online Appendix B).

Rescaling the final index

Lastly, we quantile-rescale the final composite index by ecosystem again to ensure the proper quantile interpretation. The final result is a raster that ranges 0–1. It is important to recognize that quantile-rescaling means that the results are dependent on the extent of the analysis area, because the quantiles rank cells relative to other cells within the analysis area (Fig. 4). The best of the Kennebec River watershed, for example, is not the same as the best of the state of Maine or the entire Northeast. Of course, dependence on landscape extent is true of any algorithm that compares a site to all other sites. Consequently, quantile-rescaling is done separately for each analysis unit of interest. Ultimately, the choice of extent for the analysis units is determined by the application objectives, but with consideration of the mapped heterogeneity. For example, our experience has shown us that when using the DSL ecosystem map, scaling by ecosystems at extents less than roughly a HUC6-level watershed can produce spurious results owing to the categorical mapping of ecosystems and the limited extent of some ecosystems. HUCs are a USGS system for hierarchically classifying nested watersheds, such that a HUC6-level watershed is comprised of two or more HUC8-level sub-watersheds.

Interpreting IEI

It is critical to recognize the relative nature of *IEI*; a value of 1 does not mean that a site has the maximum absolute ecological integrity (i.e., completely unaltered by human activity and perfectly resilient), only that it is the best of that ecological setting or ecosystem within the geographic extent of that particular analysis unit. In an absolute sense, the best within any particular geographic extent may still be degraded. Consequently, *IEI* is only useful as a comparative assessment tool. In addition, the final *IEI* has a nicely

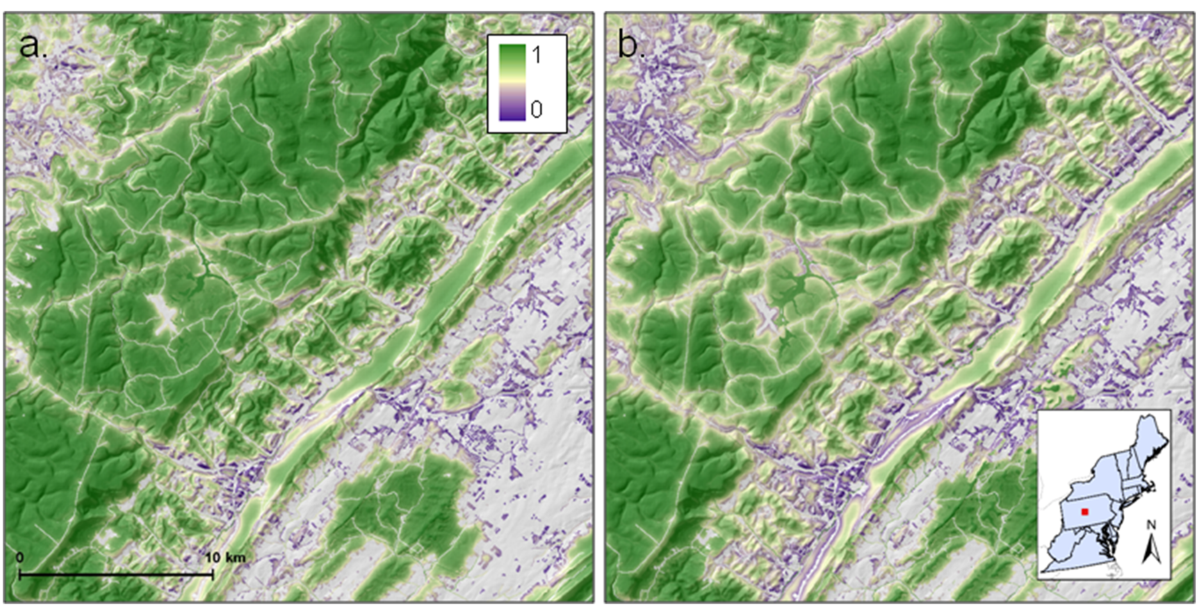

Fig. 4 *Index of ecological integrity* (*IEI*) scaled by **a** the entire northeastern United States and **b** by HUC6-level watersheds for an area northwest of State College, Pennsylvania. See the text for a description of *IEI* and Table 2 and Online Appendix E for descriptions of the constituent metrics. Larger values represent greater ecological integrity. Images are portrayed with hillshading

intuitive interpretation because the quantile of a cell expresses the proportion of cells with a raw value less than or equal to the value of the focal cell, thus a cell with an *IEI* of 0.9 is among the best 10% in its ecosystem within its geographic extent.

Index of ecological impact

IEI characterizes the integrity of sites relative to other sites in a similar ecological setting or ecosystem. Thus, it is a static measure of ecological integrity based on a snapshot of the landscape. It can be equally useful to assess the change in ecological integrity over time under a specific landscape change scenario (see Model Application). For this purpose, we developed the *index of ecological impact* (*ecoImpact*) to measure the change in *IEI* between the current and future timesteps relative to the current *IEI*; i.e., effectively delta *IEI* times current *IEI*. A site that experiences a major loss of *IEI* has a high predicted ecological impact; i.e., a loss of say 0.5 *IEI* units reflects a greater relative impact than a loss of 0.2 units. Moreover, the loss of 0.2 units from a site that has a current *IEI* of 0.9 is more consequential than the same absolute loss from a site that has a current *IEI* of 0.5. Thus, *ecoImpact* reflects not only the magnitude of *IEI* loss, but also where it matters most—sites with high initial integrity.

Delta-rescaling

The derivation of *ecoImpact* consists of rescaling the individual raw metrics, but using a different rescaling procedure than we used with *IEI*, which suffers from what we call the "Bill Gates" effect when used for scenario comparison. This occurs when the value of the raw metric is decreased at a high-valued site without changing the quantile. This is analogous to taking 10 billion dollars away from Bill Gates, yet he remains among the richest 0.1% of people in the world. Likewise, a small absolute change in a raw metric can, under certain circumstances, result in a large change in its quantile, even though the ecological difference is trivial. Therefore, the use of quantile-rescaling is not appropriate if we want to be sensitive to the absolute change in the integrity metrics. To address these issues, we developed delta-rescaling as an alternative to quantile-rescaling that is more meaningful when comparing landscapes.

Delta-rescaling is rather complicated in detail and thus is presented in full in Online Appendix G. Briefly, delta-rescaling involves computing the difference in the raw metric from its initial or baseline value rather than comparing it to the condition of ecologically similar cells or cells of the same ecosystem. These delta values are rescaled and combined in a weighted linear combination (as in *IEI*) and multiplied by the initial or baseline *IEI* to derive the final index (Fig. 5). The end result is that a cell with maximum initial *IEI* (1) that is completely degraded ($1 \rightarrow 0$) gets a value of -1, indicating the maximum possible ecological impact. Conversely, a cell that experiences no change in *IEI* gets a value of 0, indicating no ecological impact.

It is important to recognize the differences between *ecoImpact* and *IEI*. The former measures the change in *IEI* relative to the initial or baseline condition. Roughly speaking, *ecoImpact* compares each cell to itself—the change in integrity over time—whereas *IEI* compares each cell to other cells of the same ecological setting or ecosystem within the specified geographic extent. Also, *ecoImpact* is weighted by the current *IEI* of the cell, so that impact is greatest where it matters most—cells with high initial *IEI* that lose most or all of their value. Even though the units of *ecoImpact* do not have an intuitive interpretation, the absolute value of the index is meaningful for comparative purposes, and thus it can be summed across all cells in the landscape (or within a user-defined mask) to provide a useful numerical summary of the total ecological impact of alternative landscape change scenarios.

Model application

To demonstrate the application of *ecoImpact*, we quantified the loss of ecological integrity between 2010 and 2080 within the northeastern United States under two landscape change scenarios: (a) urban growth without additional land protection, and (b) same amount of urban growth but with strategic land protection based on a regional landscape conservation design (see www.naturesnetwork.org). For the first scenario only the existing secured lands representing ~ 18% of the landscape (and lands otherwise unsuitable for development) were restricted from future development. For the second scenario, 25% of

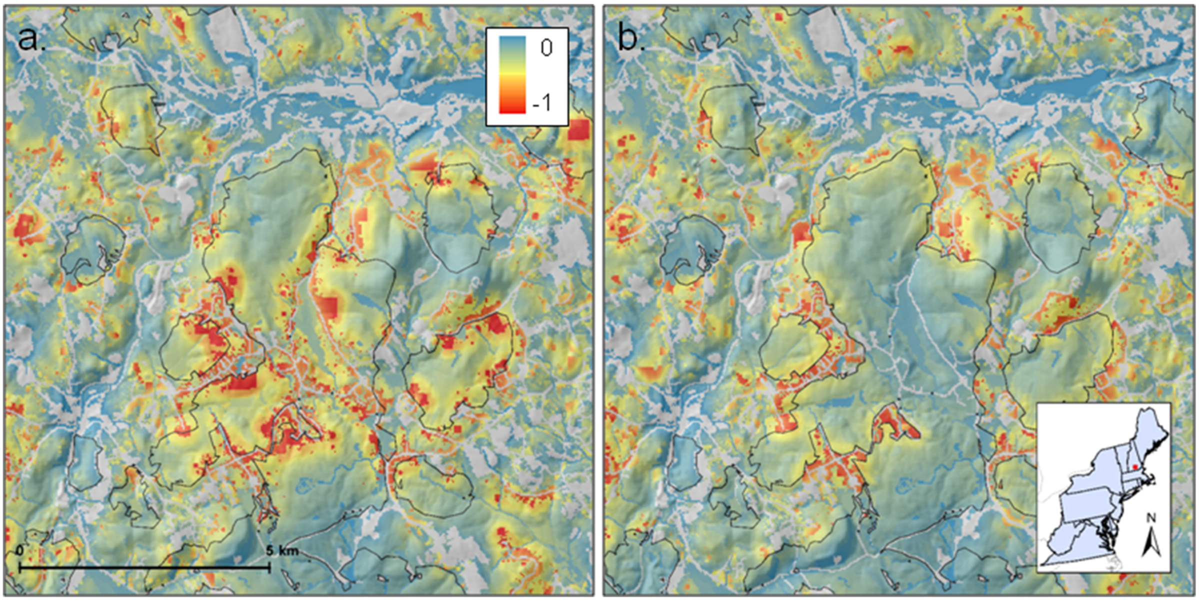

Fig. 5 *Index of ecological impact* (*ecoImpact*) representing the loss of ecological integrity between 2010 and 2080 under two landscape change scenarios: **a** urban growth without additional land protection, and **b** same amount of urban growth but with strategic land protection (delineated polygons) based on a regional landscape conservation design (see www.naturesnetwork.org), for an area west of Manchester, New Hampshire. *ecoImpact* ranges from 0 (no impact) to − 1 (maximum impact). The total impact (sum of *ecoImpact* across all cells, averaged across three stochastic simulation runs under each scenario) was 8.5% less under the landscape conservation design scenario. Note, the details of these two landscape change scenarios are not relevant to the demonstration of *ecoImpact* and thus have been omitted here. Images are portrayed with hillshading

the highest ecologically-valued lands and waters as well as any lands already secured (representing a total of ~ 34% of the landscape) or otherwise unsuitable for development, were protected from future development. For both scenarios, we simulated urban growth using the SPRAWL model that we developed in connection with the DSL project mentioned previously (McGarigal et al. 2018). The SPRAWL model allocates forecasted demand for new development within subregions (representing counties or census block statistical areas) to local application panes (5 km on a side in our application) based on their landscape context using a unique matching algorithm, such that the more historical development that occurred in the matched training windows (i.e., in a similar landscape context) the higher proportion of the future demand is assigned to the application pane. Subsequently, the demand in each pane is allocated among transition types (i.e., development classes) and then stochastically allocated to individual cells and patches based on suitability surfaces derived from logistic regression models unique to that landscape context. We conducted three replicate 70-year simulations of urban growth under each scenario and computed the average total impact (sum of *ecoImpact* across all cells) for each scenario. The total ecological impact was 8.5% less under the landscape conservation design scenario (Fig. 5). Consequently, even though the conservation design scenario restricted development from an additional 16% of the highest-valued locations, the reduced impact was only half that amount because there was still an abundance of moderate- to highly-valued lands that remained unprotected that suffered impacts from development.

Discussion

Coarse-filter ecological assessments are increasingly used by conservation organizations to evaluate ecological impacts and guide conservation planning, although there appears to be no consensus yet on a preferred approach (e.g., Andreasen et al. 2001; Parrish et al. 2003; Tierney et al. 2009; Beier et al.

2015). We developed an approach that has been used in several real-world applications (see below) that is distinctive in several ways.

First, our approach is based predominantly on geophysical settings (i.e., the geophysical stage) similar to approaches proposed by others (e.g., Anderson and Ferree 2010; Anderson et al. 2014; Beier et al. 2015), but modified to make limited use of the dominant biotic community as well. Specifically, we include the dominant potential life form of the vegetation in the broad suite of ecological settings variables that are used to define the biophysical setting of each cell, which affects ecological similarity and resistance as incorporated into a few of the ecological integrity metrics. In addition, we use mapped ecosystems to assign models (i.e., weights) for combining the individual integrity metrics into the composite *IEI* and *ecoImpact* indices, which has at least three advantages. First, it allows the results of the analysis to be easily combined with other products that adopt the same ecosystem classification. Second, it explicitly recognizes that ecological systems, which represent the co-dependency of the dominant biota and abiotic environment, are often a conservation target of interest, even while allowing the individual plant and animal species to vary among sites and over time. Lastly, it allows us to customize vulnerability to anthropogenic stressors among ecosystems, which can be incorporated directly into the metric weights that form the integrity models. Note, if distinct ecosystems are not deemed meaningful or reliably mapped, we have an alternative gradient-based approach that can be used.

Second, our approach embraces the concept of ecological integrity, but defined in a manner that makes it less subject to the criticisms often leveled against the use of ecological integrity (Brown and Williams 2016). In particular, our approach does not require the establishment of a reference condition or natural range of variation for each of the metrics as is customary for definitions of ecological integrity (Parrish et al. 2003), which we purport is exceedingly difficult or even impossible to do in most applications. Instead, we compare each cell to other cells in a similar ecological setting or ecosystem, or each cell to itself at a different point in time, to derive an index of relative integrity. Thus, our approach seeks to find the "best" places that are available today or that are likely to be impacted the least (or most depending on the application). In addition, while most approaches based on ecological integrity are heavily vegetation-centric in the constituent metrics (e.g., Wurtzebach and Schultz 2016), our approach relies very little on mapped vegetation patches and instead focuses on the anthropogenic stressors themselves (acting somewhat independently of the mapped vegetation) in the individual metrics. For example, in contrast to most approaches our approach is agnostic to the current vegetation structural stage on a site, which we view as a dynamic property of the ecosystem (at least within the bounds of the dominant life form of the vegetation) and thus not germane to the integrity of the site.

Third, our approach allows us to easily scale the results based on any geographic extent to facilitate assessments and conservation planning at multiple scales. For example, *IEI* can be quantile-scaled within watersheds to inform local watershed-based conservation planning, or within states to inform state agencies with conservation responsibilities, or at even broader scales to inform regional conservation organizations such as federal agencies and regional land trusts (Fig. 6).

Fourth, our approach uses a variety of sophisticated kernel estimators to provide an effective assessment of the ecological neighborhood affecting the ecological integrity of a cell (Fig. 2). The use of ecological neighborhoods is not unique to our approach; for example, Theobold (2013) used standard kernel density estimators to develop an index of ecological integrity at the 90 m resolution for the entire United States. All of our kernel estimators reflect nonlinear decreasing ecological influence as distance increases, which is one of the first principles of landscape ecology (Turner and Gardner 2015). For example, our watershed-based metrics which evaluate the integrity of aquatic systems use a watershed kernel that honors how terrain and land cover affect the movement of water and water-born pollutants to a site, which is clearly more appropriate than treating all locations in the watershed the same. Similarly, our connectedness metric uses a resistant kernel (Compton et al. 2007) to represent how organisms and ecological processes move across the landscape in response to environmental resistance (Zeller et al. 2012). We are unaware of other approaches that adopt these specific kinds of kernel estimators to evaluate ecological integrity, although our traversability metric (which is a version of connectedness), is used as a component of The

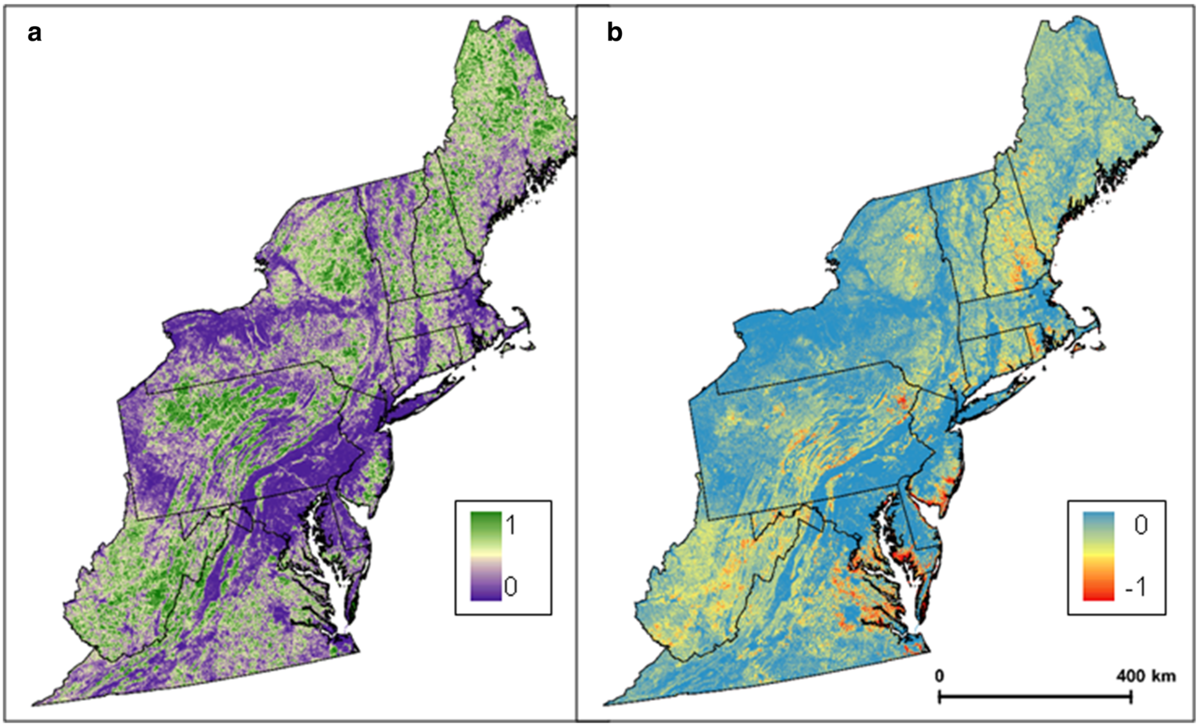

Fig. 6 *Index of ecological integrity* (*IEI*) scaled by the entire northeastern United States (**a**; larger values represent greater ecological integrity) and the corresponding *Index of ecological impact* (*ecoImpact*) representing the loss of ecological integrity between 2010 and 2080 under a baseline urban growth scenario without additional land protection (**b**, larger negative values represent greater ecological impact)

Nature Conservancy's (TNC) terrestrial resilience (Anderson and Ferree 2010).

Limitations

No approach is without limitations and ours is no exception. Among the many known limitations, a few are worth noting here. First, like all approaches, our suite of metrics is incomplete. There are anthropogenic stressors that we recognize as important but have not yet included due to the lack of reliable and regionally consistent high-resolution data (e.g., toxic pollutants, hydrological disruptions), and other metrics that adopt an especially crude estimate of the stressor for the same reasons (e.g., non-native invasive plants based solely on land cover within the ecological neighborhood rather than explicit models of occurrence for each of the important organisms). Of course, these metrics can be added and/or improved as data and knowledge become available.

Second, while our approach relies on objective measures of intactness and resiliency, it still has an important subjective component that can be considered either a strength or weakness (Beazley et al. 2010). Specifically, there are a number of model parameters that must be specified in order to compute the various ecological integrity metrics, including kernel bandwidths, weights for the ecological settings variables used in the resiliency metrics, and weights for the metrics used in the ecosystem-specific ecological integrity models to create *IEI* and *ecoImpact*. At present these model parameters are assigned by experts in the context of a specific application, as there is no easy or meaningful way to empirically derive these parameters. While this allows the assessment to be customized to each application, it comes at the cost of having to defend the chosen set of model parameters.

Third, our current measurement of resiliency is based on two metrics, similarity and connectedness (and its aquatic counterpart), which reflects a limited perspective on resiliency. In particular, what may confer short-term resiliency as measured by our two metrics may be antagonistic to what may confer long-term resiliency in the face of rapid environmental (e.g., climate) change. For example, short-term resiliency of a site may be a function of the amount and accessibility of similar environments in the neighborhood of the focal cell, since having larger and more connected local populations should facilitate population recovery of the constituent organisms (and thus ecosystem functions) following disturbance—which is the premise of our two resiliency metrics. However, long-term resiliency of a site may also be a function of the amount and accessibility of diverse environments in the neighborhood of the focal cell, since having a diverse assemblage of environments nearby increases the opportunities for different organisms to fill the ecological niche space as the environment (e.g., climate) changes over time—which is the premise of the metrics used in the geophysical stage approach proposed by others (e.g., Anderson and Ferree 2010; Beier and Brost 2010; Beier 2012; Beier et al. 2015). Consequently, while still unclear, it is possible that the factors driving short-term resiliency may differ from those driving long-term resiliency in the face of environmental change. Note, to account for this possibility, in the landscape conservation design applications referenced below we combined *IEI* with TNC's terrestrial resilience metric (Anderson and Ferree 2010), which prioritizes sites based on local geophysical diversity and connectivity, to establish priorities for conservation core areas.

Lastly, despite their increasing use, measures of ecological integrity are exceedingly difficult if not impossible to validate (but see McGarigal et al. 2013, which provides a partial validation of *IEI* based on extensive field data on a number of taxa) given the long-term nature of the predictions, which has been a major source of criticism (Brown and Williams 2016). We sought to reduce the need for formal validation of *IEI* by eliminating the need for a reference condition or natural range of variability and instead using quantile scaling to rate sites relative to each other. Indeed, *IEI* makes no assumptions about the absolute integrity of site, only that it is relatively more or less integral than another site. In this regard, each of the constituent metrics was chosen because of its clear and well-documented relationship with ecological functions that confer integrity to a site. For example, it is undisputed that increasing the intensity of roads and road traffic near a site will adversely affect critical ecological processes such as organism dispersal, watershed hydrology, and sedimentation of streams (Forman et al. 2003). *IEI* relies heavily on this well-established relationship between anthropogenic stressors and ecological integrity. Although the exact form and magnitude of the relationship is unknown; it may suffice to know that the relationship is monotonic.

Conservation applications

Our coarse-filter ecological integrity assessment has been applied to a wide variety of real-world conservation problems. Detailed information about each of these applications can be found at the DSL project website (McGarigal et al. 2017; www.umass.edu/landeco/research/dsl/dsl.html) or the UMassCAPS website (www.umasscaps.org).

- *Critical linkages* Working in partnership with the North Atlantic Aquatic Connectivity Collaborative (NAACC), we have used *IEI* and the aquatic connectedness metric to evaluate and prioritize dam removals and road-stream crossing (culvert) upgrades in the Northeast for their potential to restore aquatic connectivity.
- *Wetlands assessment, monitoring and regulation* Working in partnership with the MA Department of Environmental Protection (DEP), MA Office of Coastal Zone Management, and U.S. EPA, we have used *IEI* in a variety of contexts to develop cost-effective tools and techniques for assessment and monitoring of wetland and aquatic ecosystems in Massachusetts, including the development and validation of indices of biotic integrity for selected wetland and aquatic systems. In addition, IEI is being used by DEP in permitting activities affecting wetlands pursuant to the MA Wetlands Protection Act; specifically, projects occurring in the top 40% of wetlands based on IEI are subject to additional DEP review.
- *BioMap 2* Working in partnership with the MA Department of Fish & Game's Natural Heritage & Endangered Species Program and TNC's Massachusetts Program, we used *IEI* in the development of BioMap2 which serves as a guide for conservation decision making to preserve and restore biodiversity in Massachusetts; specifically, we used *IEI* to assist in the identification of forest cores, wetland cores, clusters of vernal pools and undeveloped landscape blocks with the highest

potential for maintaining ecological integrity over time.

- *Losing Ground* Working in partnership with Mass Audubon to prepare the 4th edition of the Losing Ground publications (DeNormandie and Corcoran 2009), we used *IEI* and *ecoImpact* to assess the change in ecological integrity between 1971 and 2005 in Massachusetts; specifically, to quantify the indirect impacts of development beyond its direct footprint.
- *South coast rail project* We used *IEI* and *ecoImpact* to assess the potential loss in ecological integrity of several alternative routes for the proposed South Coast Rail system in southeastern Massachusetts.
- *Connect the connecticut and nature's network* Working with a large partnership of organizations under the auspices of the North Atlantic Landscape Conservation Cooperative (NALCC), we used *IEI* in combination with several other data products to identify and prioritize a set of terrestrial and aquatic "core areas" as part of a landscape conservation design for the Connecticut River watershed (Connect the Connecticut, www.connecttheconnecticut.org) and for the entire Northeast (Nature's Network, www.naturesnetwork.org).

Conclusions

We suggest that the maintenance of ecological integrity is arguably the ultimate goal of ecological conservation. However, given the complexity of the ecological integrity concept (Gunderson 2000), the measurement of ecological integrity has remained a daunting challenge for scientists and conservation practitioners. We presented an *index of ecological integrity* (IEI) to evaluate the relative integrity among sites of the same or similar ecosystem that is derived from readily available spatial data on land use and land cover and that can be applied at any spatial resolution over any spatial extent (contingent upon data availability), and a corresponding *index of ecological impact* (*ecoImpact*) to assess changes in integrity over time. These two multi-metric indices emphasize the potential intactness (i.e., freedom from anthropogenic stressors) and resiliency (based on the ecological similarity and connectedness of the ecological neighborhood) of a site and make use of sophisticated kernels to represent meaningful ecological neighborhoods for each of the constituent metrics. While not without acknowledged limitations, these metrics have proven useful in several real-world conservation applications.

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References

Addicott JF, Aho JM, Antolin MF, Padilla DK, Richardson JS, Soluk DA (1987) Ecological neighborhoods: scaling environmental patterns. Oikos 49:340–346

Anderson M, Clark MG, Sheldon AO (2014) Estimating climate resilience for conservation across geophysical settings. Conserv Biol 28:959–970

Anderson M, Ferree C (2010) Conserving the stage: climate change and the geophysical underpinnings of species diversity. PLoS ONE 5:e11554

Andreasen JK, O'Neill RV, Noss R, Slosser NC (2001) Considerations for the development of a terrestrial index of ecological interity. Ecol Ind 1:21–35

Beazley KF, Baldwin ED, Reining C (2010) Integrating expert judgment into systematic ecoregional conservation planning. In: Trombulak S, Baldwin R (eds) Landscape-scale conservation planning. Springer, Dordrecht, pp 235–255

Beier P (2012) Conceptualizing and designing corridors for climate change. Ecol Restor 30:312–319

Beier P, Brost B (2010) Use of land facets to plan for climate change: conserving the arenas, not the actors. Conserv Biol 24:701–710

Beier P, Hunter ML, Anderson M (2015) Special section: conserving nature's stage. Conserv Biol 29:613–617

Belote RT, Dietz MS, Jenkins CN, McKinley PS, Irwin GH, Fullman TJ, Leppi JC, Aplet GH (2017) Wild, connected, and diverse: building a more resilient system of protected areas. Ecol Appl 27:1050–1056

Briers RA (2002) Incorporating connectivity into reserve selection procedures. Biol Cons 103:77–83

Brown ED, Williams BK (2016) Ecological integrity assessment as a metric of biodiversity: are we measuring what we say we are? Biodivers Conserv 25:1011–1035

Ceballos G, Ehrlich PR, Barnosky AD, Garcia A, Pringle RM, Palmer TM (2015) Accelerated modern human-induced

species losses: entering the sixth mass extinction. Sci Adv 1:1–5
Cerdeira JO, Gaston KJ, Pinto LS (2005) Connectivity in priority area selection for conservation. Environ Model Assess 10:183–192
Compton BW, McGarigal K, Cushman SA, Gamble LR (2007) A resistant-kernel model of connectivity for amphibians that breed in vernal pools. Conserv Biol 21:788–799
DeNormandie J, Corcoran C (2009) Losing ground beyond the footprint: patterns of development and their impact on the nature of Massachusetts. Fourth Edition of the Losing Ground Series, MassAudubon (http://www.massaudubon.org/content/download/8601/149722/file/LosingGround_print.pdf)
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. Island Press, Covelo, CA, Science and Solutions, p 504
Gunderson LH (2000) Ecological resilience—in theory and application. Annu Rev Ecol Syst 31:425–439
Haddad NM, Brudvig LA, Clobert J, Davies KF, Gonzalez A, Holt RD, Lovejoy TE, Sexton JO, Austin MP, Collins CD, Cook WM, Damschen EI, Ewers RM, Foster BL, Jenkins CN, King AJ, Laurance WF, Levey DJ, Margules CR, Melbourne BA, Nicholls AO, Orrock JL, Song D-X, Townshend JR (2015) Habitat fragmentation and its lasting impact on Earth's ecosystems. Sci Adv 1:e1500052
Holling CS (1973) Resilience and stability of ecological systems. Annu Rev Ecol Syst 4:1–23
Holling CS (1996) Engineering resilience versus ecological resilience. In: Schulze PC (ed) Engineering within ecological constraints. National Academy Press, Washington, D.C, USA
Hunter ML Jr, Jacobson GL, Webb T III (1988) Paleoecology and the coarse-filter approach to maintaining biological diversity. Conserv Biol 2:375–385
Lentz EE, Stippa SR, Thieler ER, Plant NG, Gesch DB, Horton RM (2015) Evaluating coastal landscape response to sea-level rise in the northeastern United States—approach and methods: U.S. Geological Survey Open-File Report 2014–1252, p 26. http://dx.doi.org/10.3133/ofr20141252 ISSN 2331–1258 (online)
Lerner J, Mackey J, Casey F (2007) What's in Noah's wallet? Land conservation spending in the United States. Bioscience 57:419–423
McGarigal K, Plunkett EB, Grand J, Compton BW, Portante T, Rolih K, Jackson SD (2013) Empirically derived indices of biotic integrity for forested wetlands, coastal salt marshes and wadable freshwaters streams in Massachusetts. Report to Massachusetts Department of Environmental Protection, September 15, 2013, p 249
McGarigal K, Compton BW, Plunkett EB, Deluca WV Grand J (2017) Designing sustainable landscapes project: documents and data products. https://scholarworks.umass.edu/designing_sustainable_landscapes/
McGarigal K, Plunkett EB, Willey L, Compton BW, DeLuca WV, Grand J (2018) Modelling urban growth in the northeastern United States: the SPRAWL model and the ecological impacts of urban growth. Ecol Model 177:178–190
Newbold T, Hudson LN, Hill SLL, Contu S, Lysenko I, Senior RA, Börger L, Bennett DJ, Choimes A, Collen B, Day J, De Palma A, Díaz S, Echeverria-Londoño S, Edgar MJ, Feldman A, Garon M, Harrison MLK, Alhusseini T, Ingram DJ, Itescu Y, Kattge J, Kemp V, Kirkpatrick L, Kleyer M, Correia DLP, Martin CD, Meiri S, Novosolov M, Pan Y, Phillips HRP, Purves DW, Robinson A, Simpson J, Tuck SL, Weiher E, White HJ, Ewers RM, Mace GM, Scharlemann JPW, Purvis A (2015) Global effects of land use on local terrestrial biodiversity. Nature 520:45–50
Noss R (1996) Ecosystems as conservation targets. Trends Ecol Evol 11:351
Ortega-Huerta MA, Peterson AT (2004) Modelling spatial patterns of biodiversity for conservation prioritization in North-eastern Mexico. Divers Distrib 10:39–54
Parrish JD, Braun DP, Unnassch RS (2003) Are we conserving what we say we are? Meas Ecol Integr Prot Areas 53:851–860
Pereira HM, Leadley PW, Proenca V, Alkemade R, Scharlemann JPW, Fernandez-Manjarres JF, Araujo MB, Balvanera P, Biggs R, Cheung WWL, Chini L, Cooper HD, Gilman EL, Guenette S, Hurtt GC, Huntington HP, Mace GM, Oberdorff T, Revenga C, Rodrigues P, Scholes RJ, Sumaila UR, Walpole M (2010) Scenarios for global biodiversity in the 21st century. Science 330:1496–1501
Pickett STA, Parker VT, Fiedler PL (1992) The new paradigm in ecology: implications for conservation above the species level. In: Fiedler PL, Jain SK (eds) Conservation biology: theory and practice of nature conservation and management. Chapman and Hall Press, New York, pp 65–88
Pimm SL, Russell GJ, Gittleman JL, Brooks TM (1995) The future of biodiversity. Science 269:347–350
Randhir TO, O'Connor R, Penner PR, Goodwin DW (2001) A watershed-based land prioritization model for water supply protection. For Ecol Manag 143:47–56
Sala OE, Chapin FC III, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Huber-Sanwald E, Huenneke LF, Jackson RB, Kinzig A, Leemans R, Lodge DM, Mooney HA, Oesterheld M, Poff NL, Sykes MT, Walker BH, Walker M, Wall DH (2000) Global biodiversity scenarios for the year 2100. Science 287:1770–1774
Sanderson EW, Jaiteh M, Levy MA, Redford KH, Wannebo AV, Woolmer G (2002) The human footprint and the last of the wild. Bioscience 52:891–904
Scott JM, Davis F, Csuti B, Noss R, Butterfield B, Groves C, Anderson H, Caicco S, D'Erchia F, Edwards TC Jr, Ulliman J, Wright RG (1993) GAP analysis: a geographic approach to protection of biological diversity. Wildl Monogr 123:1–41
Silverman BW (1986) Density estimation for statistics and data analysis. Chapman & Hall, London
Soulé ME, Terborgh J (eds) (1999) Continental conservation: scientific foundations of regional reserve networks. Island Press, Washington, DC
Theobald DM (2013) A general model to quantify ecological integrity for landscape assessments and US application. Landscape Ecol 28:1859–1874
Tierney GL, Faber-Langendoen D, Mitchell BR, Shriver WG, Gibbs JP (2009) Monitoring and evaluating the ecological integrity of forest ecosystems. Front Ecol Environ 7:308–316

Turner MG, Gardner RH (2015) Landscape ecology in theory and practice. Springer, New York, p 482

Venter O, Sanderson EW, Magrach A, Allan JR, BeherJ Jones KR, Possingham HP, Laurance WF, Wood P, Fekete BM, Levy MA, Watson JEM (2016) Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. Nat Commun 7:12558

Williams PH, Margules CR, Hilbert DW (2002) Data requirements and data sources for biodiversity priority area selection. J Biosci 27:327–338

Wurtzebach Z, Schultz C (2016) Measuring ecological integrity: history, practical applications, and research opportunities. Bioscience 66:446–457

Zeller KA, McGarigal K, Whiteley AR (2012) Estimating landscape resistance to movement: a review. Landscape Ecol 27:777–797