

2018

# Designing Sustainable Landscapes: Modeling Ecological Integrity

Kevin McGarigal

*University of Massachusetts Amherst*

Brad Compton

*University of Massachusetts Amherst*

Ethan Plunkett

*University of Massachusetts Amherst*

Bill DeLuca

*University of Massachusetts Amherst*

Joanna Grand

*University of Massachusetts Amherst*

Follow this and additional works at: [https://scholarworks.umass.edu/  
designing\\_sustainable\\_landscapes\\_techdocs](https://scholarworks.umass.edu/designing_sustainable_landscapes_techdocs)

---

McGarigal, Kevin; Compton, Brad; Plunkett, Ethan; DeLuca, Bill; and Grand, Joanna, "Designing Sustainable Landscapes: Modeling Ecological Integrity" (2018). *Designing Sustainable Landscapes Project Technical Documents*. 8.

Retrieved from [https://scholarworks.umass.edu/designing\\_sustainable\\_landscapes\\_techdocs/8](https://scholarworks.umass.edu/designing_sustainable_landscapes_techdocs/8)

This Article is brought to you for free and open access by the The Designing Sustainable Landscapes (DSL) Project at ScholarWorks@UMass Amherst. It has been accepted for inclusion in Designing Sustainable Landscapes Project Technical Documents by an authorized administrator of ScholarWorks@UMass Amherst. For more information, please contact [scholarworks@library.umass.edu](mailto:scholarworks@library.umass.edu).

# Designing Sustainable Landscapes: Modeling Ecological Integrity

## *A project of the University of Massachusetts Landscape Ecology Lab*

### *Principals:*

- Kevin McGarigal, Professor
- Bradley Compton, Research Associate
- Ethan Plunkett, Research Associate
- Bill DeLuca, Research Associate
- Joanna Grand, Research Associate

### *With support from:*

- North Atlantic Landscape Conservation Cooperative (US Fish and Wildlife Service, Northeast Region)
- Northeast Climate Science Center (USGS)
- University of Massachusetts, Amherst



***Report date: 20 April 2018***

### *Reference:*

McGarigal K, Compton BW, Plunkett EB, DeLuca WV, and Grand J. 2018. Designing sustainable landscapes: modeling ecological integrity. Report to the North Atlantic Conservation Cooperative, US Fish and Wildlife Service, Northeast Region.

## Table of Contents

1	Problem Statement.....	3
2	Solution Statement.....	3
3	Key Features .....	4
4	Detailed Description of Process .....	7
4.1	Kernel weighting.....	8
4.1.1	Standard kernels.....	8
4.1.2	Time-of-flow kernels .....	9
4.1.3	Resistant kernels .....	12
4.2	Intactness.....	16
4.3	Resiliency .....	22
4.3.1	Similarity .....	24
4.3.2	Connectedness.....	25
4.3.3	Ecosystem diversity .....	29
4.3.4	Adaptive capacity.....	31
4.4	Index of ecological integrity (IEI) .....	32
4.4.1	Quantile-rescaling .....	33
4.4.2	Ecological integrity models .....	34
4.4.3	Rescaling the final index .....	34
4.4.4	How to interpret <i>IEI</i> .....	35
4.5	Index of Ecological Impact (Impact).....	40
4.5.1	Delta-rescaling.....	40
4.5.2	Ecological integrity models .....	42
4.5.3	Computing the final index.....	42
4.5.4	How to interpret the index of ecological impact.....	43
5	Alternatives Considered and Rejected.....	44
6	Major Implementation Constraints .....	46
7	Major Risks and Dependencies.....	46
8	Literature Cited .....	46
	Appendix A. Hierarchical classification of formations and ecological systems .....	48
	Appendix B. Ecological settings variables .....	54
	Appendix C. Detailed description of the resistant kernel algorithm .....	59
	Appendix D. Ecological Integrity Products .....	62

## **1 Problem Statement**

Our primary mission as conservationists and public stewards of fish and wildlife resources is to ensure the conservation of biological diversity. Thus, our primary over-arching goal is to maintain well-distributed viable populations of all native species and the ecosystem processes they perform and depend on, and the Strategic Habitat Conservation (SHC) approach was developed for the purpose of achieving this goal, but it does not specify how. Because the entirety of biodiversity is vastly complex and effectively unknowable, and thus unmeasurable, the conservation of biodiversity is plagued by having an admirable ultimate goal but one that is incredibly vague, impractical and open to myriad interpretations. Most contemporary approaches focus almost entirely on individual species' habitat needs. However, it is widely recognized that species-based approaches are insufficient, and perhaps also inefficient, as a means for conserving biodiversity. There are simply too many species to manage for individually. Moreover, it has not been shown that a small subset of species can adequately represent a larger suite of species let alone all of biodiversity (e.g., Cushman et al. 2010). Further, species-based approaches tend to focus on vertebrate organisms and ignore the vast array of invertebrates and micro-organisms. More recently, approaches have emphasized the conservation of the geophysical or ecological stage as a coarse filter, under the assumption that if the stage is conserved the players (i.e., organisms) will be able to meet their specific needs and perform their essential ecosystem functions and shift in distribution and abundance over time. Consequently, under the auspices of the Designing Sustainable Landscapes (DSL) project (McGarigal et al 2017), we decided to combine a coarse-filter ecosystem-based approach with the traditional species-based approach.

In this document, we describe the basis for our ecosystem-based approach in the context of the landscape change, assessment and design (LCAD) model. More specifically, here we describe our ecosystem-based assessment of ecological integrity, which serves as a coarse-filter for identifying conservation core areas in the context of landscape conservation design, and we describe our ecosystem-based assessment of local and regional connectivity, which serves as the basis for identifying conservation focus areas important to the maintenance and/or restoration of local and regional connectivity, in a separate document.

## **2 Solution Statement**

The coarse-filter, ecosystem-based approach, as we define it, is an overarching approach for the conservation of biodiversity and not of individual species per se. In this context, the premise of the ecosystem-based approach is as follows:

- 1) Maintaining the integrity of ecosystems and the landscape will ensure that important ecological functions persist (to benefit the natural world and humans).
- 2) Protecting ecosystems as a coarse filter is an efficient and thus practical means of protecting the bulk of biodiversity, including most species, but especially the hidden biodiversity that can't easily be conserved on its own.
- 3) The coarse filter alone is probably not sufficient to conserve all species since some species have special life history requirements, such as the juxtaposition of specific environments, that can easily "fall through the cracks" of the coarse filter, and thus a

fine filter to capture those biodiversity elements that are not captured by the coarse filter is needed.

Given this premise, the coarse-filter ecosystem-based approach depends on a clear definition of the approach, which we provide in the following section.

### **3 Key Features**

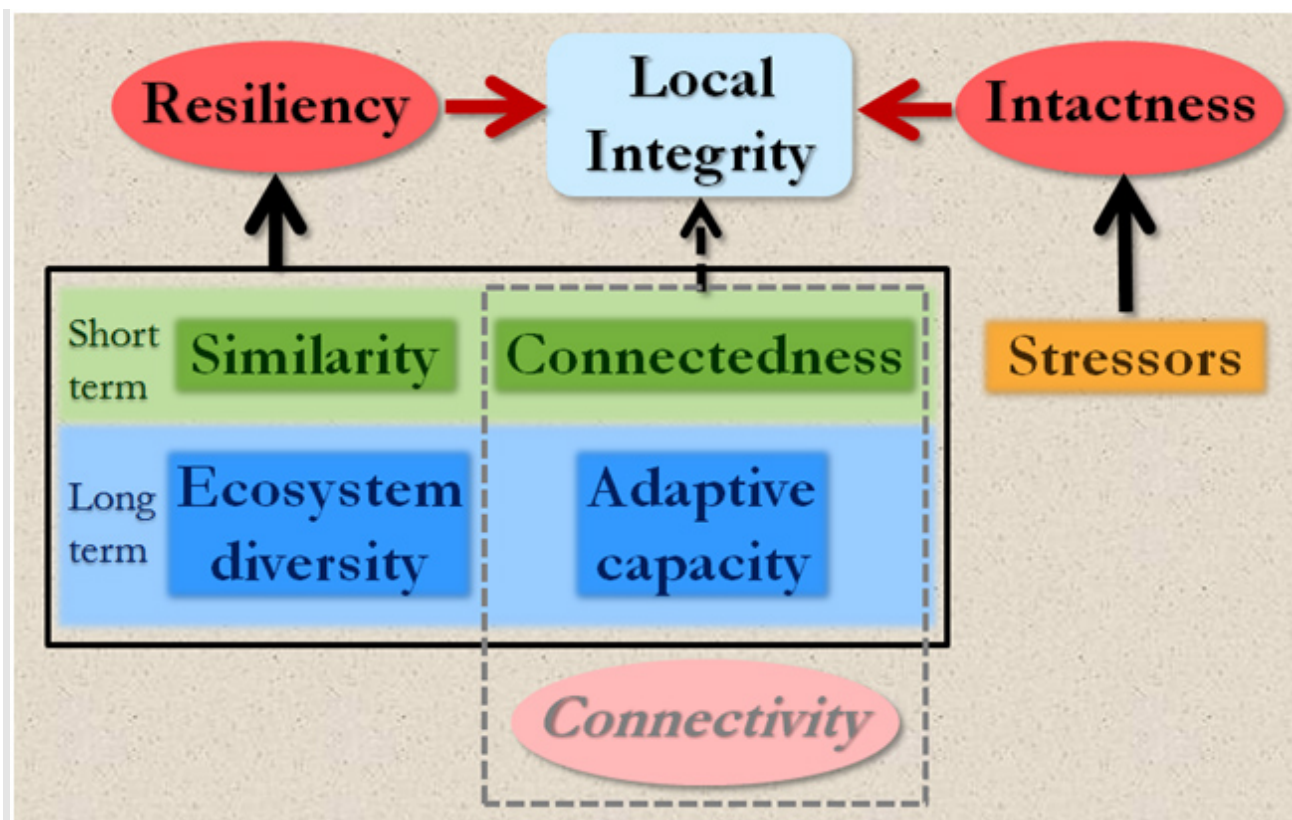
Our coarse-filter, ecosystem-based assessment is distinctive in the following ways:

- 1) *Multivariate assessment of ecological integrity.*—our ecosystem-based assessment consists of several distinct and important attributes of landscape ecological integrity, each of which is quantified using one or more spatial and/or non-spatial metrics.
- 2) *Unique and distinctive environments.*—our ecosystem-based approach is based on unique and distinctive environments rather than distinctive habitat for individual species.
- 3) *Ecological assessment can be done at any geographic extent.*—our ecosystem-based results can be scaled and summarized at any geographic extent or hierarchy of extents to accommodate planning needs at multiple scales.
- 4) *Spatially comprehensive assessment.*—every location (cell) in the landscape is assessed and contributes to the overall landscape assessment. It is not sample-based or restricted to particular sites where certain data exist (e.g., as if often the case when based on Heritage occurrences).

There are two other important over-arching considerations to our coarse-filter, ecosystem-based assessment:

- 1) *Ecological systems.*—our coarse filter is based on a suite of ecological systems (or simply, ecosystems), which we treat as distinct ecological entities that can be mapped and assessed. Note, it is not necessary to assume discrete ecological systems, since an ecological gradient approach is also feasible, but for practical reasons and for consistency with established practices, we have opted to treat ecological systems as discrete entities for purposes of applying the coarse filter. Importantly, the use of a relatively small number of distinct ecological systems offers us an efficient and practical approach for implementing the coarse-filter approach.
- 2) *Ecological integrity.*—our coarse filter is based on the concept of landscape ecological integrity, which we define as the ability of an area to sustain ecological functions over the long term; in particular, the ability to support biodiversity and the ecosystem processes necessary to sustain biodiversity over the long term. Note, this definition of ecological integrity emphasizes the maintenance of ecological functions over the long term, rather than the maintenance of a static composition and structure, and thus accommodates the modification or adaptation of systems (in terms of composition and structure) over time to changing environments (e.g., as driven by climate change).

Based on this definition, there are three major components of ecological integrity; i.e., measurable attributes that confer ecological integrity either to the landscape as a whole or to the site (cell) and thus, by extension, to the landscape as a whole (**Fig. 1**).



**Figure 1.** Conceptual diagram of the components of ecological integrity.

- 1) *Intactness*.—refers to the freedom from human impairment (anthropogenic stressors); it is an intrinsic attribute of a site (cell) that contributes to the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Intactness is measured using a broad suite of stressor metrics (see below).
- 2) *Resiliency*.—refers to the capacity to recover from or adapt to disturbance and stress; more specifically, it refers to the amount of disturbance and stress a system can absorb and still remain within the same state or domain of attraction (e.g., resistance to permanent change in the function of the system) (Holling 1973, 1996). Resiliency is a complex, multi-faceted concept that cannot easily be measured with any single metric. Consequently, we have conceived of the following suite of metrics for measuring resiliency from different perspectives, although we have not yet implemented all of these metrics (see below).
  - a) *Similarity* — refers to the ecological similarity of the neighborhood of a focal cell and reflects the capacity for organisms to move into the focal cell from neighboring cells with a similar ecological setting as the focal cell; it is relevant for highly vagile organisms where the intervening landscape is not limiting movement to the focal cell.
  - b) *Connectedness* — refers to the ecological similarity and accessibility of the neighborhood of a focal cell and reflects the capacity for organisms to move into the focal cell from other neighboring cells with a similar ecological setting as the

focal cell; it is relevant for movement-limited organisms where impediments to movement are important. Connectedness differs from similarity in that it explicitly considers local connectivity; i.e., the ability of organisms to get to the focal cell.

- c) *Ecosystem diversity (or diversity for short)* — refers to the variety and abundance of ecological settings in the neighborhood of a focal cell and reflects the opportunities for organisms to move between the focal cell and neighboring cells with different ecological settings than the focal cell. Like similarity, diversity is especially relevant for highly vagile organisms where the intervening landscape is not limiting movement to the focal cell (at least over the long term), since connectivity between the neighboring cells and the focal cell is not considered. However, in contrast to similarity, diversity is relevant primarily from a long-term perspective on resiliency.
  - d) *Adaptive capacity* — refers to the accessibility of diverse ecological settings in the neighborhood of a focal cell and reflects the opportunities for organisms to move between the focal cell and neighboring cells with different ecological settings than the focal cell. Like connectedness, adaptive capacity is especially relevant for movement-limited organisms where impediments to movements are important (even over the long term), since connectivity between the neighboring cells and the focal cell is explicitly considered. However, in contrast to connectedness, adaptive capacity is relevant primarily from a long-term perspective on resiliency.
- 3) *Connectivity*.— refers to the propensity to facilitate or impede ecological flows (including individuals) across the landscape. Connectivity it is a complex, multi-faceted concept that can be considered from several different perspectives and at different scales, and thus connectivity can be measured in many different ways. Connectivity is incorporated into the connectedness and adaptive capacity metrics (above); however, connectivity can also be measured directly and more generally without regard to resiliency per se using a suite of metrics that operate at different scales. In this regard, we measure a suite of connectivity metrics for the purpose of informing landscape design; specifically, to assess and prioritize sites for their importance in conducting flows within and among designated core areas. In addition, we evaluate restoration opportunities associated with restoring or improving connectivity by upgrading culverts (i.e., road-stream crossings), removing dams, and building terrestrial wildlife passage structures across roadways independent of the designated core areas created as part of the landscape design. Due to the complexity and varied set of connectivity assessments, we describe our connectivity assessment in a separate document (see technical document on Connectivity, McGarigal et al 2017).

Our ecological integrity assessment involves quantifying the attributes described above, which consists of a combination of spatial and non-spatial results, as described below. Spatial results include grids depicting the individual metrics as well as a couple of composite local indices, including the *Index of Ecological Integrity (IEI)*, which is a weighted combination of the intactness and resiliency metrics (as described below), and the *Index of Ecological Impact (Impact)*, which is the measure of the reduction in *IEI* due to future development, and both of these are useful for visually depicting the consequences of alternative landscape change scenarios and for choosing sites for conservation action (e.g., protection) in the context of landscape design. Non-spatial results include numerical

summary statistics for some of the ecological integrity attributes described above for each ecological system or for the landscape as a whole, and these are useful for quantitatively summarizing and comparing among scenarios. The ecological integrity assessment is done at select timesteps of the simulation, and summarized for the entire run and across stochastic runs for each scenario. The ecological integrity assessment is useful as a means of comparing scenarios with regards to achieving biodiversity conservation, and it is also useful as a basis for landscape design.

## **4 Detailed Description of Process**

Our ecological integrity assessment involves computing a suite of metrics representing the components of ecological integrity described previously; specifically, intactness and resiliency. In the calculation of these metrics there are several important considerations:

- 1) *Cell-level metrics.*—most of the metrics are computed at the cell level; i.e., they measure ecological integrity of the local site (cell) and logically produce a grid. However, in some cases the cell-level metrics can also be aggregated into a non-spatial summary statistic to characterize individual ecological systems or the entire ecological mosaic at the landscape level.
- 2) *Static versus dynamic metrics.*—most of the metrics are computed for a static snapshot of the landscape (i.e., they measure the condition of the landscape at a single point in time), while adaptive capacity is computed for a dynamic landscape trajectory (i.e., time series of landscapes) and incorporates the change in ecological settings over time.
- 3) *Quantile scaling.*—many of the raw metrics need to be rescaled for practical interpretation across ecological settings and for combining them into composite indices of ecological integrity. For this purpose, we use *quantile-scaling* to compute metrics for a single timestep, typically by ecological system, as described below. Briefly, quantile-rescaling puts all the metrics on the same 0-1 scale with a uniform distribution of values, with the same general interpretation (0=worse case, 1=best case), and when rescaled by ecological system over some spatial extent it accounts for the differences among ecological system, so that each ecological system is compared only to other places classified as the same ecological system within the specified extent. Also, in order to combine metrics into composite indices of ecological integrity, we apply ecological integrity models indexed by ecological system (as described below) so that the individual metrics are combined in weighted linear combinations specific to each ecological system.
- 4) *Delta scaling.*—quantile-rescaling is subject to what we refer to as the "Bill Gates" effect, whereby the degradation of the very best lands may degrade the raw metric value, but not the quantile. This happens because a reduction in the intactness of the very best site by say 50% may still result in it being the "best" of the available, and thus still have a quantile of 1. Likewise, even a very small absolute change in a raw metric, that may represent a trivial ecological change, can nonetheless result in a large change in its quantile. To deal with these undesirable effects, we employ a *delta-scaling* method when comparing ecological integrity across timesteps or among landscape



change scenarios, whereby we compute the change in the raw metric from the designated baseline scenario, as described below.

Importantly, the choice of metrics: spatial versus non-spatial, cell-level versus landscape-level, static versus dynamic, and quantile-scaled or delta-scaled depends entirely on the specific application. Thus, the metrics described essentially represent a "toolbox", whereby any combination of tools can be used depending on the objectives of the application and availability of data.

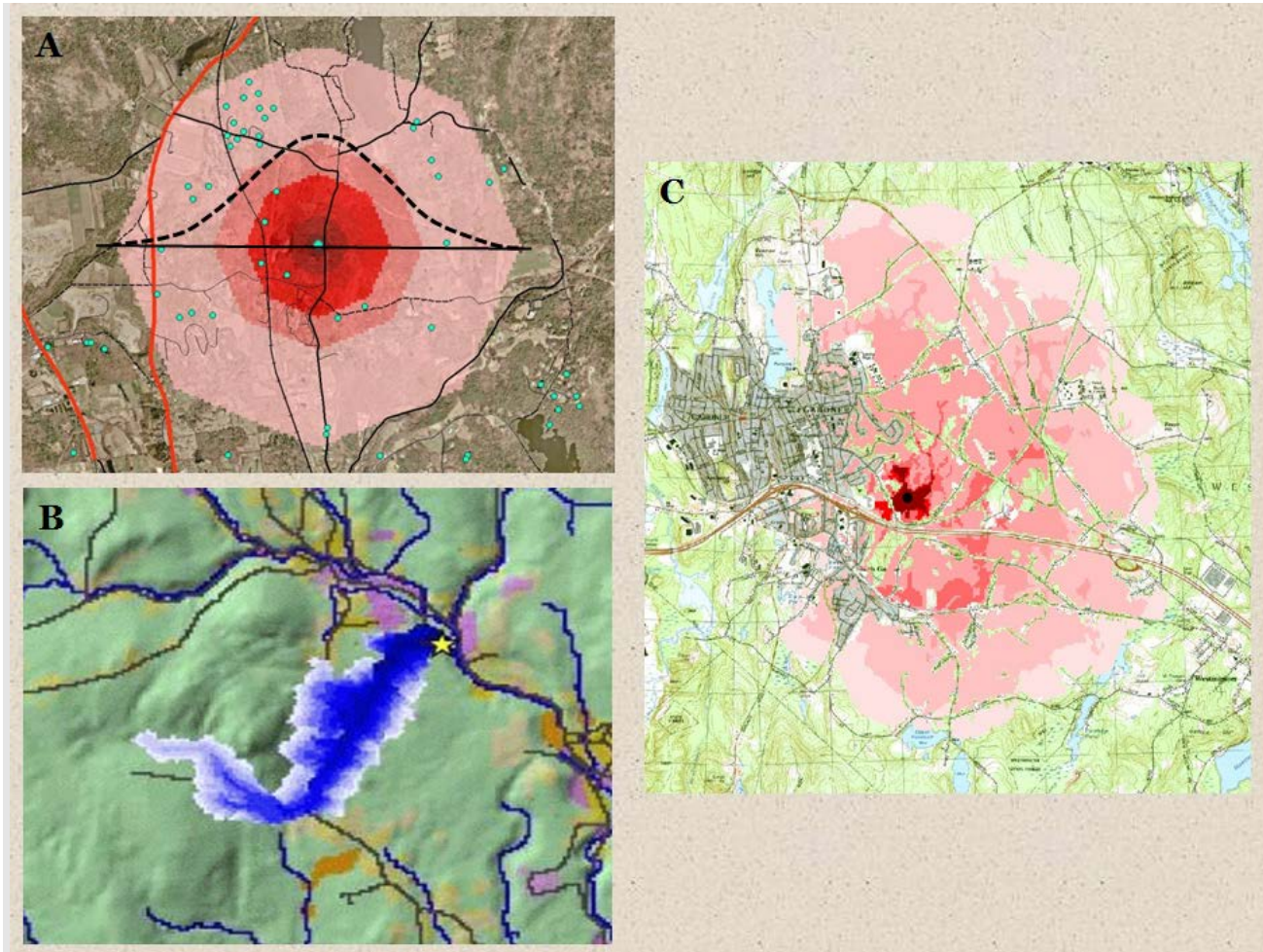
### **4.1 Kernel weighting**

Kernel estimators play an important role in the computation of the ecological integrity metrics and thus warrant special attention here. We use kernels to specify how to weight the ecological neighborhood around a focal cell; i.e., to determine how much influence a neighboring cell has on the integrity of the focal cell. We employ three different kinds of kernel estimators: 1) standard Gaussian kernel estimator (Silverman 1986) for the non-watershed-based metrics, 2) time-of-flow kernel estimator based on a time-of-flow model (Randhir et al. 2001) for the watershed-based metrics, and 3) resistant kernel estimator (Compton et al. 2007) for the connectedness metrics.

#### **4.1.1 Standard kernels**

The *standard kernel estimator*, given two-dimensional data (e.g., x,y points), produces a three-dimensional surface representing an estimate of the underlying probability distribution by summing across bivariate curves centered on each sample point. The standard kernel estimator begins by placing a standard kernel (in our case, a Gaussian kernel) over each sample point or ecological attribute of interest. 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. Typically, the kernel is scaled to have a volume of one, but it can be adjusted to reflect differential weighting of sample points based on the magnitude of the ecological attribute. For example, the kernel volume might be scaled proportionate to the intensity of traffic on each road segment, the nutrient loadings for each land cover type, or the percent impervious surface at each location.

We can think of the standard kernel as estimating the ecological neighborhood of the sample point, where the size (width and volume) and shape of the kernel represent how the strength of the ecological relationship varies with distance from the sample point (**Fig. 2a**). The sum of all the kernels across all sample points is a surface that represents the intensity of the ecological attribute in the ecological neighborhood of any location. Alternatively, we can think of the standard kernel as representing the ecological neighborhood of a focal cell, for which we want to estimate the intensity of some ecological attribute within that neighborhood. In this case, the height of the kernel represents the weight to be applied to each cell when computing the intensity of the attribute; think of it as simply the kernel-weighted mean of the attribute. These two conceptualizations are equivalent mathematically. Standard kernels can be used to estimate intensity for point features (e.g., point sources of pollution), linear features (e.g., roads), patches (e.g., developed land cover), and even continuous surfaces (e.g., imperviousness). The key is that the standard kernel allows one to estimate the intensity of some ecological attribute of interest that incorporates some ecological knowledge about the size and shape of the ecological



**Figure 2.** Bivariate kernel estimators to estimate the ecological neighborhood of a focal cell: (A) standard Gaussian bivariate kernel around a focal cell (blue center point) in which the height of the kernel at any cell is indicated by the color intensity and reflects the bandwidth (spread) of the kernel; (B) time-of-flow kernel in which the estimated relative time-of-flow from any cell to the focal cell (yellow star) within the watershed of the focal cell is indicated by the color intensity; and (C) resistant Gaussian kernel around a focal cell (black center point) in which the height of the kernel at any cell is indicated by the color intensity and reflects bandwidth (spread) of the kernel as well as the resistance of the intervening landscape.

neighborhood. In our ecological integrity assessment, we use the standard kernel estimator in all non-watershed-based stressor and resiliency metrics (see below).

#### **4.1.2 Time-of-flow kernels**

The standard kernel estimator may not be that 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 stressor metrics (see below), we use a *time-of-flow kernel estimator* based on a time-of-flow model (Randhir et al. 2001). In this case, for any given focal aquatic cell we determine its

watershed based on the flow grid by identifying all the cells that eventually flow to that cell based on the digital elevation model. For each cell within the watershed of the focal cell, we compute the time-of-flow based on the model derived by Randhir et al. (2001), but modified it slightly for use in the LCAD model, as follows:

- If cell is in a stream channel, use revised Manning's equation:

$$t = \frac{LN}{1.49R_h^{\frac{2}{3}}\sqrt{S}}$$

- else, use the Kinematic Wave equation:

$$t = \frac{0.933 \times (LN)^{0.6}}{(CI)^{0.4} \times S^{0.3}}$$

Where:

- $t$  = time-of-flow
- $L$  = cell width (cell size x 1.4 for diagonal flow)
- $N$  = roughness coefficient (based on land use)
- $C$  = runoff coefficient (based on land use)
- $S$  = slope
- $I$  = rainfall intensity, inches/hour
- $R_h$  = hydraulic radius (= cross-sectional area of flow / wetted perimeter)

In the "revised" Manning's equation, 1.49 is  $k/N$ , where  $k$  is a unit-conversion constant, and  $N$  is the roughness constant for the stream channel. The roughness and runoff coefficients ( $N$  and  $C$ ) are parameterized uniquely for each land cover type, or ecological formation (groups of related ecological systems) in our case (**Table 1**). Rainfall intensity can be estimated for each location by interpolation of meteorological data or simply assigned the average for the project area (e.g., 2 in/h for the Ware River watershed in Massachusetts).

Hydraulic radius ( $R_h$ ) can be approximated by the stream depth (because the wetted perimeter can be approximated by stream width), but because streams all have a very short time of flow compared to everything else and we have no legitimate way of estimating stream depth, we set  $R_h$  to a constant of 1 m.

The time-of-flow model estimates the time ( $t$ ) it takes for a drop of water (or 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 from 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 zero 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 increases from the focal cell, but the weights decrease much faster across land than water so that the kernel typically extends much farther

**Table 1.** Roughness and runoff coefficients used in the time-of-flow kernel based on the model derived by Randhir et al. (2001). Coefficients are given by ecological formation or

## **DSL Project Component: Modeling ecological integrity**

ecosystem (see **Appendix A**) and were based on coefficients used in Randhir et al. (2001), obtained from the author, and cross-walked to our land cover types. Ecosystem = n/a pertains to formations that contain only a single ecosystem. Time-of-flow is used to weight the influence of each cell in the watershed above a focal cell in the watershed-based stressor metrics (**Table 3**).

<b>Formation</b>	<b>Ecosystem</b>	<b>Roughness</b>	<b>Runoff</b>
Alpine	n/a	0.1	0.45
Cliff & Rock	All	0.02	0.4
Grassland & Shrubland	All	0.1	0.45
Coastal Scrub-Herb	All	0.1	0.45
Boreal Upland Forest	All	0.6	0.4
Northeastern Upland Forest	All	0.6	0.4
Northeastern Wetland	All	0.1	0.4
Peatland	All	0.1	0.4
Stream (headwater/creek)	All	0.02	n/a
Stream (small)	All	0.02	n/a
Stream (medium)	All	0.02	n/a
Stream (large)	All	0.02	n/a
Lentic	All	0.02	n/a
Freshwater Tidal Riverine	All	0.02	n/a
Estuarine Intertidal	All	0.06	0.4
Marine Intertidal	All	0.02	0.4
Agriculture	Cultivated crops	0.2	0.5
	Pasture/hay	0.4	0.45
Developed	Abandoned train	0.02	0.6
	Active train	0.02	0.6
	Culvert/bridge	0.02	0.6
	Dam	0.02	0.6
	Developed- high intensity	0.02	0.5
	Developed- medium intensity	0.04	0.5
	Developed- low intensity	0.06	0.5
	Developed- open space	0.1	0.3
	Local road	0.02	0.6
Motorway	0.02	0.6	

Primary road	0.02	0.6
Secondary road	0.02	0.6
Tertiary road	0.02	0.6
Track	0.02	0.6
Barren land	0.08	0.45

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 a lot of weight and cells in the upland and farther from the stream, especially on flat slopes with forest cover, have less weight (**Fig. 2b**).

Clearly, this simple time-of-flow model does not capture the many 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 the standard kernel estimator.

### 4.1.3 Resistant kernels

The *resistant kernel estimator*, introduced by Compton et al. (2007), 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, replacing the binary habitat/nonhabitat classifications of island biogeography and classic metapopulation models with a more nuanced approach that represents variation in habitat quality (e.g., Ricketts 2001). 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. For example, a forest-dependent organism might have a high rate of flow (and thus low resistance) through forest, but a low rate of flow (and thus high resistance) through high-intensity development. In this case, the cost assigned to each patch type in the resistant surface may represent the willingness of the organism to cross the patch type, the physiological cost of moving through the patch type, the reduction in survival for the organism moving through the patch type, or an integration of all these factors. Empirical data on costs are often lacking (and thus expert opinion is often used), but can be derived from a variety of data sources, including detection, movement (e.g., capture/recapture, telemetry) and/or genetic data for the organism (or process) under consideration (Zeller et al. 2012). Traditional least-cost path analysis finds the shortest functional distance between two points based on the resistant surface. 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. Least-cost path analysis finds the path with the least total cost. 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, or from every cell (treated as a focal cell) to every other cell. In this sense, the multi-directional approach (from all cells to all

cells) represents the most synoptic approach available for measuring functional connectivity.

In the resistant kernel algorithm, we assign landscape resistance uniquely for each focal cell based on the ecological distance from it to each neighboring cell. We measure ecological distance using a number of ecological settings variables (**Table 2**). These settings variables describe abiotic, vegetative, and anthropogenic aspects of the landscape, including, for example, growing season degree days, soil pH, wetness, vegetative structure, imperviousness, and traffic rate. Each of these settings variables has a value for each 30 m cell; together, they describe all the important ecological aspects of each cell, to the extent possible with existing GIS data.

Because resistance is based on ecological similarity, landscape resistance depends on the ecological setting of each cell; thus, there is a unique landscape resistance grid for each cell in the landscape. For each focal cell, we calculate ecological distance by taking the weighted Euclidean distance between the focal cell's location in settings space and the location of each other cell in the neighborhood in settings space (across all dimensions), where each settings variable is weighted to reflect its importance in determining landscape resistance (**Table 2**). Each settings variable is already standardized to be on the same 0-1 scale. The weighted Euclidean distance between cells is computed as follows:

$$\sqrt{\sum_{i=1}^p w_i (x_i^f - x_i^n)^2}$$

where  $i = 1-p$  settings variables (dimensions),  $w_i$  = weight for the  $i^{th}$  settings variable (scaled such that the maximum possible distance among non-anthropogenic settings variables is 1),  $x_i^f$  = value of the  $i^{th}$  settings variable at the focal cell, and  $x_i^n$  = value of the  $i^{th}$  settings variable at the  $n^{th}$  neighboring cell. Thus, if the focal cell and neighboring cell have identical values across all ecological 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 1 for each of the variables), the weighted Euclidean distance will always equal one.

A detailed description of the resistant kernel algorithm is given in **Appendix C**. Briefly, in the resistant kernel estimator, the complement of least-cost distance (a.k.a. functional proximity) to each cell from the focal cell is multiplied by a weight reflecting the shape and width of the standard kernel. Consequently, given the typical shape of a standard kernel (e.g., Gaussian), the functional proximity distance is one at the focal cell and asymptotically approaches zero after roughly three standard deviations from the focal cell, but its shape depends on the resistance of the neighboring cells. The end result is a resistant kernel that depicts the functional ecological neighborhood of the focal cell (**Fig. 2c**).

**DSL Project Component: Modeling ecological integrity**

**Table 2.** Ecological settings variables (see **Appendix B** for a brief description of each variable) and information on how they're used in the ecological integrity assessment. Ecological settings variables are used to determine resistance ("R" in the metric columns) for Connectedness and Aquatic connectedness metrics, and to determine ecological distance ("D" in the metric columns) for Connectedness, Aquatic Connectedness, and Similarity metrics. Settings variables are combined using the weights listed below for resistance and distance. Weights for both resistance and distance were determined by expert teams. Settings variables are mixed for water bodies according to the Mixing column.

<b>Ecological settings variable</b>	<b>Resistance</b>	<b>Distance</b>	<b>Similarity</b>	<b>Connectedness</b>	<b>Aquatic Connectedness</b>	<b>Mixing<sup>1</sup></b>
<i>Temperature</i>						
Growing season degree-days	0.3	1	D	RD	RD	
Minimum winter temperature	0.1	1	D	RD	RD	
Heat Index 35	0.1	1	D	RD	RD	
Stream temperature	0.1	1	D	RD	RD	
<i>Solar energy</i>						
Incident solar radiation	0.1	1	D	RD	RD	
<i>Chemical &amp; physical substrate</i>						
Water salinity	4	3	D	RD	RD	
Substrate mobility	2	2	D	RD	RD	
CaCO3 content	0.1	1	D	RD	RD	inflows
Soil available water supply	0.05	0.5	D	RD	RD	
Soil depth	0.05	0.5	D	RD	RD	
Soil pH	0.05	0.5	D	RD	RD	
<i>Physical disturbance</i>						
Wind exposure	0.1	1	D	RD	RD	
Slope	1	1	D	RD	RD	
<i>Moisture</i>						

<b>Ecological settings variable</b>	<b>Resistance</b>	<b>Distance</b>	<b>Similarity</b>	<b>Connectedness</b>	<b>Aquatic Connectedness</b>	<b>Mixing<sup>1</sup></b>
<i>Hydrology</i> Wetness	4	8	D	RD	RD	pond sumlogs
Flow gradient	1	2	D	RD	RD	
Flow volume	5	5	D	RD	RD	
Tidal regime	2	2	D	RD	RD	
<i>Vegetation</i> Dominant life form	3	8	D	RD	RD	
<i>Development</i> Developed	1	20	D	RD	---	
Hard development	2	1000	D	RD	---	
Gibbs traffic rate	40	0	D	RD	---	
Impervious	5	0	D	RD	---	
Terrestrial barriers	15	0	D	RD	---	
Aquatic barriers	100	0	-	---	R-	

<sup>1</sup> Settings variables may be mixed for water bodies and wetlands in several different ways:  
inflows: all cells in a water body or wetland get the sum of inflowing values  
sumlogs: the same as inflows for log-scaled variables  
pond: all cells in a water body or wetland get the mean of all non-missing values

In essence, the standard kernel is an estimate of the fundamental ecological neighborhood and is appropriate when resistant to movement is irrelevant (e.g., highly vagile species), while the resistant kernel is an estimate of the realized ecological neighborhood when resistance to movement is relevant. The resistant kernel can also be thought of as representing a process of spread (e.g., dispersal) outward from the focal cell, that combines the cost of moving through a heterogeneous 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 connectedness metrics (both the terrestrial and aquatic versions, see below).



## **4.2 Intactness**

The stressor metrics deal with the concept of intactness, which refers to the freedom from human impairment (anthropogenic stressors); the greater the level of anthropogenic stress, the lower the intactness. Intactness is measured using a broad suite of individual stressor metrics (**Table 3**). The stressor metrics are computed for all undeveloped cells, although some metrics apply only to certain ecological systems (e.g., watershed-based metrics apply only to aquatic and wetland systems) and may only be selected for application to some ecological systems (see ecological integrity models below). Each stressor metric measures the magnitude of human stressor impacts at each cell based on its kernel-weighted neighborhood context and is uniquely scaled in the appropriate units for the metric.

In general, 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 the intactness metric is inversely related to ecological integrity. In addition, the value of the metric at any location is generally independent of the particular ecological system of the focal cell, as it depends primarily on the magnitude of the stressor emanating outward from the anthropogenic features of interest. Thus, the stressor metrics are all interpretable in their raw-scale form; i.e., they do not need to be rescaled by ecological system (see below) to be meaningfully interpreted.

Each metric measures a different anthropogenic stressor and is intended to reflect a unique 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 should be viewed as a multi-collinear or correlated set of metrics that collectively assess the impact of human activities on the intactness of the ecological setting. In addition, this suite of stressor metrics is not comprehensive, because it is limited to anthropogenic stressors for which suitable spatial data exist. For example, while toxic chemicals are an important stressor on ecological systems, we lack sufficient spatial data to measure this stressor comprehensively.

Intactness is an intrinsic attribute of a site (cell) that contributes to the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Consequently, intactness is something that we measure at the cell level. Each stressor metric assigns a value to each cell, as appropriate, and thus returns a grid depicting the spatial variation in the stressor across the project area for each timestep of each landscape change simulation (e.g., **Fig. 3**). Intactness is a critical component of local ecological integrity and the individual stressor metrics can be used by themselves (in their raw-scale form) or be rescaled by ecological system (see below) and combined with the resiliency metrics to provide a composite local index of ecological integrity, as described below. The specific suite of stressor metrics applied in any particular application will depend on available spatial data and objectives.

**Table 3.** Intactness (a.k.a. stressor) and resiliency metrics included in the ecological integrity assessment in the Landscape Change, Assessment and Design (LCAD) model. Note, the final suite of metrics was based on available data. A suite of additional coastal metrics (shown in gray) were developed for the state of Massachusetts, but their application to the entire Northeast will depend on additional intensive data development not yet available for the entire Northeast. Abbreviations used for grid names are given in parentheses after the metric name, and the metrics are arbitrarily grouped into broad classes for organizational purposes. A detailed description of each metric is under development.

<b>Metric group</b>	<b>Metric name (grid name)</b>	<b>Description</b>
Development and Roads	Habitat loss (habloss)	Measures the intensity of habitat loss caused by all forms of development in the neighborhood surrounding the focal cell based on a standard Gaussian kernel. Habitat loss has myriad effects, both direct and indirect, on the ecological integrity of the focal cell and in many ways subsumes the individual effects targeted by many of the other metrics. In particular, the loss of habitat in the neighborhood of the focal cell affects the occurrence and abundance of many organisms via their minimum area requirements.
	Watershed habitat loss (whabloss)	Measures the intensity of habitat loss caused by all forms of development in the watershed above the focal cell based on a time-of-flow kernel. Similar to habitat loss, watershed habitat loss has myriad effects, both direct and indirect, on ecological integrity and is perhaps more pertinent for aquatic and wetland systems where the ecological neighborhoods are more watershed based than circular.
	Road traffic (traffic)	Measures the intensity of road traffic (based on measured road traffic rates) in the neighborhood surrounding the focal cell based on a standard Gaussian kernel. Road traffic is a direct source of animal mortality and a source of chemical and noise pollution.
	Mowing & plowing (mowplow)	Measures the intensity of agriculture (as a surrogate for mowing/plowing rates) in the neighborhood surrounding the focal cell based on a standard Gaussian kernel. Mowing and plowing are a direct source of animal mortality, especially for slow-moving terrestrial species such as turtles.
	Microclimate alterations (edges)	Measures the adverse effects of induced (human-created) edges on the microclimate integrity of patch interiors. The microclimate edge effects metric is based

		<p>on the “worst” edge effect among all adverse edges in the neighborhood surrounding the focal cell, where each adverse edge is evaluated using a “depth-of-edge” function in which the “effect” is scaled using a standard Gaussian kernel. Microclimate alterations along induced edges alter the physical environment for native plant and animal communities and exacerbate natural disturbance rates (e.g., windthrow) that together alter vegetation composition, structure and function.</p>
Pollution	Watershed road salt (salt)	<p>Measures the 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 time-of-flow kernel. Road salt alters the chemistry of adjacent ecological systems and thus alters the suitability of the environment for native plant and animal communities, and is especially relevant to palustrine and lacustrine ecosystems.</p>
	Watershed road sediment (sediment)	<p>Measures the 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 time-of-flow kernel. Road sediment and the pollutants carried by sediments alter the physical and chemical environment of adjacent ecological systems and thus the suitability of the environment for native plant and animal communities, and is especially relevant to palustrine, lacustrine and riverine ecosystems.</p>
	Watershed nutrient enrichment (nutrients)	<p>Measures the 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 time-of-flow kernel. Nutrient enrichment, especially nitrogen and phosphorus derived from fertilizers, alters the chemistry of adjacent ecological systems and thus the suitability of the environment for native plant and animal communities, and can have an important influence on the trophic status of aquatic and wetland ecosystems.</p>
Biotic Alterations	Domestic predators (cats)	<p>Measures the 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 Gaussian kernel. Domestic predators, especially domestic cats, are a direct source</p>

		of animal mortality, especially for small birds, mammals and herpetofauna.
	Edge predators (edgepred)	Measures the 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 Gaussian kernel. Edge predators are a direct source of animal mortality, most notably for songbirds, and their populations are enhanced by induced (human-created) edges.
	Non-native invasive plants (badplants)	Measures the 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 Gaussian kernel. Non-native invasive plants can substantially alter the physical and chemical environment and thus the suitability of the environment for native plant and animal communities.
	Non-native invasive earthworms (worms)	Measures the 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 Gaussian kernel. Non-native earthworms alter the physical and chemical environment and thus the suitability of the environment for native plant and animal communities, and effect myriad ecological processes (e.g., nutrient cycles, decomposition), with the most notable impacts on the native flora understory of many forests.
Climate	Climate stress (climate)	Measures the 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 (i.e., how much is the climate of the focal cell moving away from the climate niche envelope of the corresponding ecological system). Climate is a major attribute of the physical environment and a principal determinant of plant and animal distribution.
Hydrologic Alterations	Watershed imperviousness (imperv)	Measures the intensity of impervious surface (as a surrogate for hydrological alteration) in the watershed above an aquatic focal cell based on imperviousness and

		<p>a time-of-flow kernel. Watershed imperviousness, by disrupting infiltration rates, has a major impact on watershed hydrology, which is a major determinant of the composition, structure and function of many aquatic ecosystems.</p>
	Dam intensity (dams)	<p>Measures the intensity of dams (as a surrogate for hydrological alteration) in the watershed above an aquatic focal cell based on dam size and a time-of-flow kernel. Dam intensity, by disrupting flows and impounding water, has a major impact on watershed hydrology, which is a major determinant of the composition, structure and function of many aquatic ecosystems.</p>
	Sea level rise inundation (searise)	<p>Measures the 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. Whether a site gets inundated by salt water permanently due to sea level rise or intermittently via storm surges associated with sea level rise clearly determines whether an ecosystem can persist at a site and thus its ability to support a characteristic plant and animal community.</p>
Coastal Metrics	Tidal restrictions (tr)	<p>Measures the magnitude of <i>hydrologic</i> alteration to the focal cell due to tidal restrictions based on the estimated tidal hydroperiod (ecological setting variable) and magnitude of tidal restriction (on the upstream side of a restriction).</p>
	Salt marsh ditching (ditches)	<p>Measures the magnitude of temporal loss of open water habitat (i.e., loss of open water habitat during mid to low tides) around the focal cell due to ditching based on a standard Gaussian kernel.</p>
	Coastal structures	<p>Measures the proximity of the focal cell (applied only to certain cover types; e.g., beaches, intertidal flats) to up-gradient manmade jetty/groin based the nearest up-gradient jetty/groin and a standard Gaussian kernel.</p>
	Beach pedestrians (beachped)	<p>Measures the intensity of beach pedestrian traffic at the focal cell (applied to beach settings only) based on land cover, public beaches and beach parking lots and a standard Gaussian kernel.</p>
	Beach ORVs (beachorv)	<p>Measures the intensity of beach ORV traffic in the neighborhood surrounding the focal cell (applied to beach settings only) based on mapped ORV beaches and a standard Gaussian kernel.</p>

	Boating intensity (boats)	Measures the intensity of boat traffic disturbance at the focal cell based on a standard kernel applied to mapped boat traffic.
Resiliency	Similarity (sim)	Measures the amount of similarity between the ecological setting at the focal cell and those of neighboring cells, weighted by a logistic function of distance. Similarity is based on the ecological distance between the focal cell and each neighboring cell, where ecological distance is a multivariate distance across all ecological setting variables. Similarity is an important determinant of a site's resiliency or ability to recover from disturbance and stress, since it determines whether organisms from nearby similar ecological systems are available to recolonize the site or rescue declining populations, and it is especially relevant for highly vagile species in which movement among sites is not easily impeded (e.g., for many birds).
	Connectedness (connect)	Measures the disruption of habitat connectivity caused by all forms of development between each focal cell and surrounding cells. A hypothetical organism in a highly connected cell can reach a large area with minimal crossing of "hostile" cells. This metric uses a least-cost path algorithm to determine the area that can be reached from each focal cell. The focal cell gets a "bank account," which represents the distance a hypothetical organism could move through the undeveloped landscape. Each cell is assigned a travel cost, based on a resistance matrix, as a function of its ecological similarity to the focal cell. The algorithm then creates a least-cost hull around the focal cell, representing the maximum distance that can be moved from the cell until the "bank account" is depleted. Connectedness uses the ecological distances times a multiplier to come up with resistances values. Connectedness, as a measure of local connectivity, is an important determinant of a site's resiliency or ability to recover from disturbance and stress, since it determines whether organisms from nearby similar ecological systems can recolonize the site or rescue declining populations, and it is especially relevant for less vagile species in which movement among sites is more easily impeded by unfavorable environments (e.g., many amphibians and reptiles).
	Aquatic connectedness	Aquatic connectedness is identical to connectedness except that it is constrained by the extent of aquatic

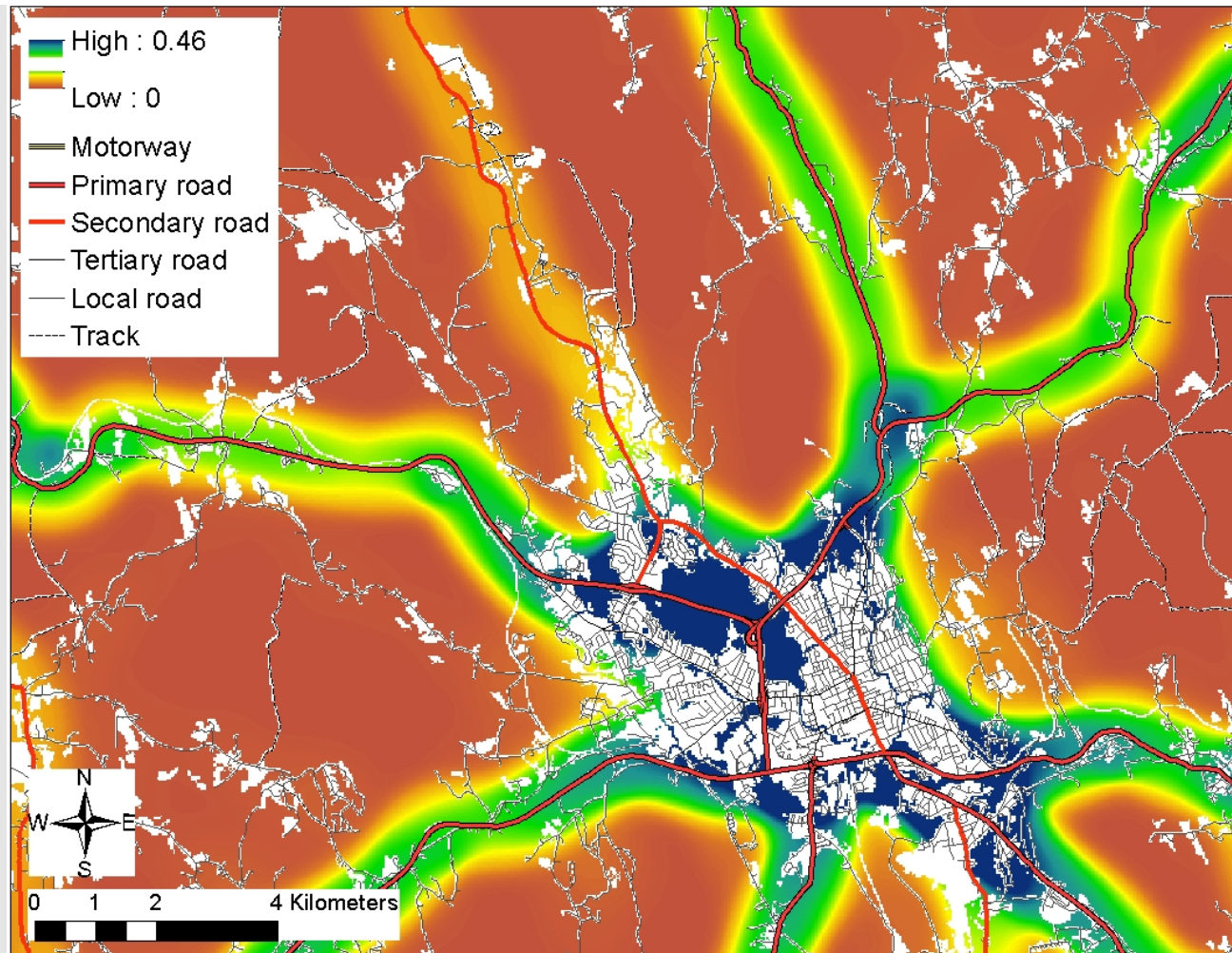
(aqconnect) ecosystems, such that the connectivity being assessed pertains to flows within the aquatic network. Impediments to movement of aquatic organisms, such as culverts and dams, are especially relevant for aquatic connectedness but may be less important or unimportant for terrestrial connectivity. Aquatic connectivity, like terrestrial connectivity, is essential to the resiliency of aquatic communities and is often a principal determinant of the distribution and viability of many aquatic species.

### **4.3 Resiliency**

The resiliency metrics deal with the capacity to recover from disturbance and stress; more specifically, they deal with the amount of disturbance and stress a system can absorb and still remain within the same state or domain of attraction (e.g., resistance to permanent change in the function of the system) (Holling 1973, 1996). In other words, resiliency metrics deal with the capacity to maintain characteristic ecological functions.

Resiliency is both a function of the local ecological setting, since some settings are naturally more resilient to disturbance and stress (e.g., an isolated wetland 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 anthropogenic stress, since the greater the stressor 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 stress, and the landscape attributes that confer short-term resiliency may not be the same as those that confer long-term resiliency. For example, short-term resiliency of a site may be a function of the amount and accessibility of similar ecological settings 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, whereas long-term resiliency of a site may be a function of the amount and accessibility of diverse ecological settings in the neighborhood of the focal cell, since having a diverse assemblage of species nearby increases the opportunities for different organisms to fill the ecological niche space as the environment changes over time. Lastly, resiliency is both an intrinsic attribute of a site based on its neighborhood context and a collective property of the landscape as a whole.

Given the above, it is evident that resiliency is a complex, multi-faceted concept that cannot easily be measured with any single metric. Consequently, we have conceived of a suite of metrics for measuring resiliency from different perspectives, although we have not yet implemented all of these metrics (see below). Importantly, no one metric fully captures the entirety of the resiliency concept and, in fact, some of the metrics may actually be antagonistic (i.e., act in opposite directions). For example, what might confer short-term resiliency as measured by the similarity and connectedness metrics (see below) may be opposite of what might confer long-term resiliency as measured by the ecosystem diversity and adaptive capacity metrics (see below). Despite representing different perspectives, the



**Figure 3.** Illustration of the traffic metric, which is one of the intactness (aka stressor) metrics. The numeric value shown here is the raw traffic metric in which the areas shown in blue depict relatively high traffic rates (or low intactness) whereas the areas shown in red depict relatively low traffic rates (or high intactness); areas mapped as development and roads are not evaluated; development is depicted in white, whereas the roads are depicted by road class.

resiliency metrics are not statistically independent and thus they should be viewed as a multi-collinear or correlated set of metrics that collectively assess the capacity of a site to recover from or adapt to disturbance and stress.

Like the stressor metrics, the resiliency metrics are computed for all undeveloped cells, although they may only be selected for application to some ecological systems (see ecological integrity models below). Each resiliency metric measures the capacity of each site (cell) to recover from or adapt to disturbance and stress over either the short or long-term based on its kernel-weighted neighborhood context. In contrast to the stressor metrics, however, the value of each resiliency metric increases with increasing resiliency, so larger values connote greater integrity. In addition, in contrast to the stressor metrics, the value of the resiliency metric at any location is dependent on the particular ecological system or



setting of the focal cell, since that determines the ecological similarity or dissimilarity of the neighborhood. Thus, the resiliency metrics are not particularly useful in their raw-scale form. Instead, they are best interpreted when rescaled by ecological system (see below) so that what constitutes high resiliency for a small patch-forming ecological systems (e.g., wetland) need not be the same as for a matrix-forming system (e.g., Northeastern upland forest).

Like intactness, resiliency is an intrinsic attribute of a site (cell) that contributes to the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Consequently, resiliency is something that we measure at the cell level. Each resiliency metric assigns a value to each cell and thus returns a grid depicting the spatial variation in resiliency across the project area for each timestep of each landscape change simulation. Resiliency is a critical component of local ecological integrity and the individual resiliency metrics can be used by themselves (typically after rescaling by ecological system, see below) or be combined with the intactness metrics to provide a composite local index of ecological integrity, as described below. The specific set of resiliency metrics applied in any particular application will depend on available spatial data and objectives.

### **4.3.1 Similarity**

Similarity refers to the ecological similarity of the neighborhood of a focal cell and reflects the capacity for organisms to move into the focal cell from neighboring cells with a similar ecological setting as the focal cell; it is relevant for highly vagile organisms where the intervening landscape is not limiting movement to the focal cell. Similarity confers resiliency to a site in the short-term, since a similar ecological neighborhood should support larger populations of the constituent organisms and thus provide greater capacity for recolonizations following a local disturbance.

The raw-scaled similarity metric is computed as the complement of the volume of a *standard* Gaussian kernel derived for every undeveloped cell, where the kernel is multiplied by the ecological distance to the focal cell, briefly as follows:

- 1) for each undeveloped focal cell, build a standard Gaussian kernel (700 m bandwidth) with a volume of 1;
- 2) multiply the kernel value at every cell by the ecological distance to the focal cell (see below);
- 3) sum the resulting values across cells — the result is automatically scaled 0-1; and
- 4) take the complement.

In step 2 above, the ecological distance between the focal cell and each neighboring cell is based on weighted Euclidean distance in multivariate ecological setting space as described earlier for resistant kernels. In step 4 above, taking the complement of dissimilarity converts it to similarity, such that larger values reflect greater similarity.

As defined above, the similarity metric measures the ecological similarity of the neighborhood of the focal cell, where ecological similarity is based on the suite of ecological settings variables and distance is weighted by a standard Gaussian kernel. A focal cell surrounded by homogeneous ecological conditions would have a similarity score of one,

whereas, for example, a focal cell surrounded by a sea of development would have a similarity score of zero. Note, as with all resiliency metrics, increasing values of similarity imply increasing ecological integrity, and the value of the metric at any location is totally dependent on the particular ecological setting of the focal cell.

Similarity is an intrinsic attribute of a site (cell) that contributes to the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Consequently, similarity is something that we measure at the cell level. The similarity metric assigns a value to each undeveloped cell and thus returns a grid depicting the spatial variation in similarity across the project area for each timestep of each landscape change simulation (**Fig. 4**). Similarity is an important component of local ecological integrity and the metric can be used by itself (typically after rescaling by ecological system, see below) or be combined with the stressor metrics and other resiliency metrics to provide a composite local index of ecological integrity, as described below.

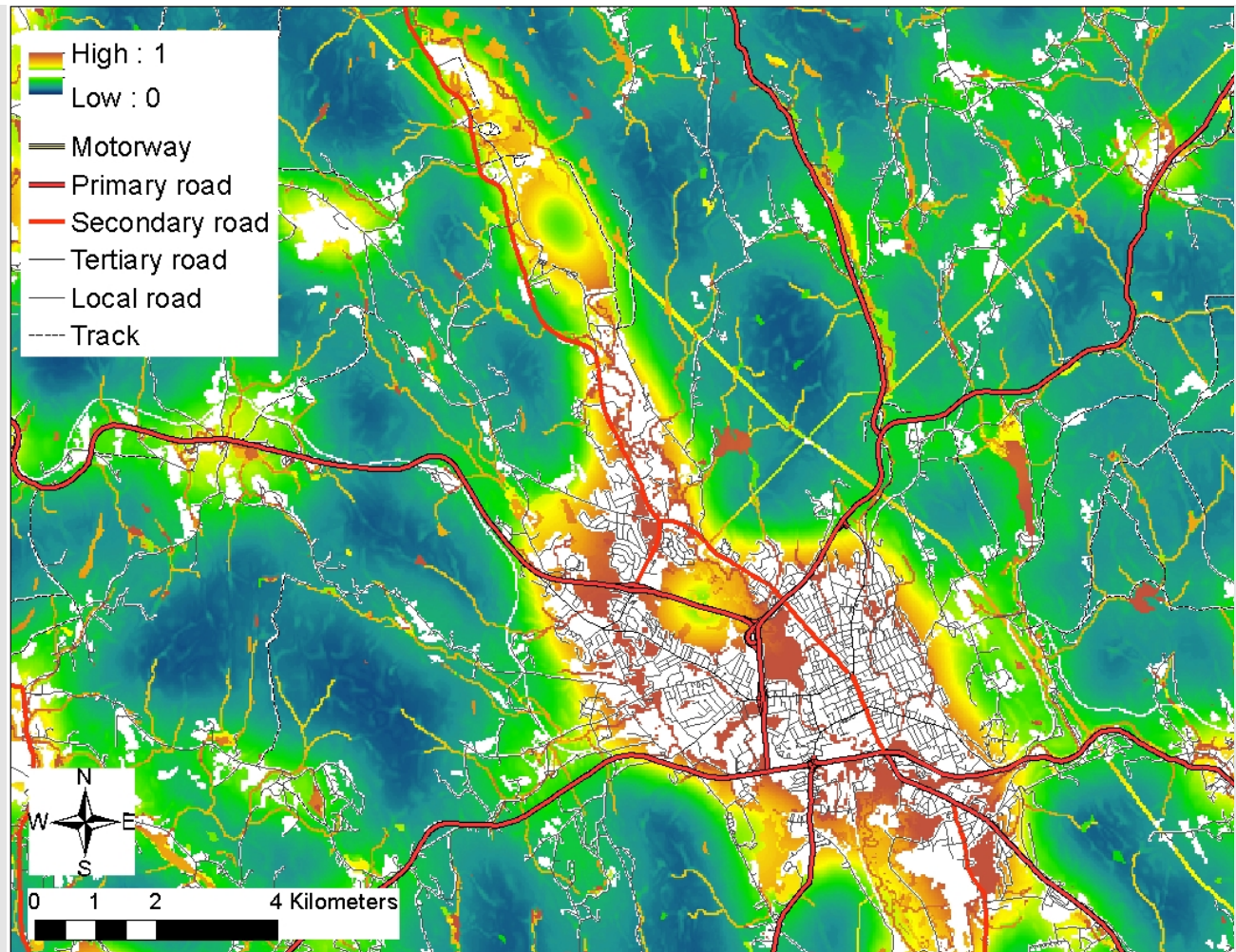
### **4.3.2 Connectedness**

Connectedness refers to the connectivity (see technical document on Connectivity, McGarigal et al 2017) for a detailed description of connectivity) of a focal cell to its ecological neighborhood or, more specifically, the capacity for organisms to move into the focal cell from neighboring cells with a similar ecological setting as the focal cell; it is relevant for less vagile organisms where the resistance of the intervening landscape limits movement to the focal cell. For example, to what extent can organisms from similar ecological settings in the surrounding landscape disperse to that location? If the cell is unable to receive many dispersers, it is said to be highly isolated and have low connectedness, and vice versa. Connectedness differs from similarity in that it explicitly considers local connectivity; i.e., the ability of organisms to get to the focal cell. Otherwise, connectedness is like similarity in that it confers resiliency to a site in the short-term, since being connected to similar ecological settings should promote recovery of the constituent organisms following a local disturbance.

There are two versions of the connectedness metric: 1) connectedness, and 2) aquatic connectedness. The former metric can be applied to any cell regardless of ecological system or setting; the latter is reserved for aquatic settings only, as described below.

The raw-scaled connectedness metric is computed as the overlap at the focal cell of *resistant* Gaussian kernels derived for every neighboring undeveloped cell, where each kernel is multiplied by the ecological similarity to the focal cell, briefly as follows:

- 1) for each undeveloped focal cell, build a resistant Gaussian kernel (2 km bandwidth, extending out to a maximum distance of 4 km)(see below) for all neighboring cells;
- 2) multiply each kernel value at the focal cell by the ecological similarity between the neighboring cell from which the kernel was built and the focal cell (see below);
- 3) sum the resulting values across kernels; and
- 4) divide by the maximum value in step 3 for a nonresistant (i.e., resistance = 1 everywhere) and homogeneous ecologically similar neighborhood.

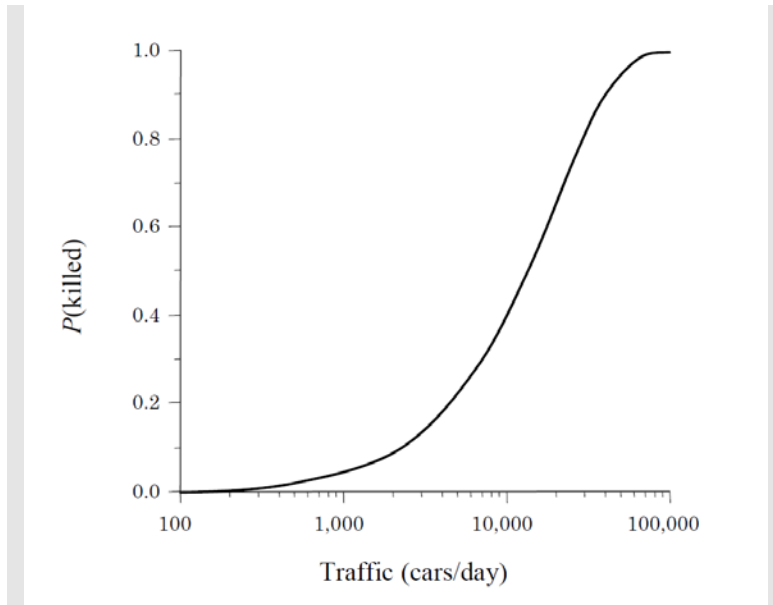


**Figure 4.** Illustration of the similarity metric, which is one of the resiliency metrics. The numeric value shown here is actually the complement of the raw similarity metric (i.e., dissimilarity) in which the areas shown in blue depict relatively high similarity (or high resiliency) whereas the areas shown in red depict relatively low similarity (or low resiliency); areas mapped as development and roads are not evaluated; development is depicted in white, whereas the roads are depicted by road class.

Conceptually, the connectedness metric is similar to the similarity metric (see above) except that a resistant kernel is used (to account for connectivity) instead of a standard kernel in step 1 above. Specifically, in step 1 the resistance between the focal cell and each neighboring cell is based on weighted Euclidean distance in multivariate ecological setting space. The weighted Euclidean distance between cells is computed as defined above for similarity, except that the resistance weights for the settings variables are different (**Table 2**). The resulting distances (scaled 0-1) are multiplied by a factor (50 in this case) and added to 1 so that the final resistances vary from 1 (minimum resistance for two cells with identical ecological settings) to 50 (maximum resistance for two maximally dissimilar cells).

Note that the variable weights used for computing resistance in step 1 differ from those used to compute ecological similarity in step 2 (**Table 2**). In particular, resistance incorporates road traffic rate and terrestrial barriers (see document on terrestrial barriers for details, McGarigal et al 2017) as impediments to ecological flows, with the following important considerations:

- 1) Traffic rates for roads and railways are assigned from a custom algorithm based on raw road traffic data from TrafficMetrix (MPSI), predicted future increases in traffic based on development, and the transformation of raw traffic into probability of road-crossing mortality based on the Gibbs model (Gibbs and Shriver 2002) (**Fig. 5**).
- 2) Dams generally have traffic rates of zero. However, dams that have a road that runs along their surfaces will have non-zero traffic rates.
- 3) To assign terrestrial barrier scores for road-stream crossings, we created a scoring algorithm using data collected by the [North Atlantic Aquatic Connectivity Collaborative \(NAACC\)](#) and its predecessor, the Stream Continuity Project. We included the following variables in the scoring algorithm: height, width, openness (cross-sectional area divided by structure length), substrate and span (an approximation of constriction ratio). We developed a statistical model to predict terrestrial barrier scores for crossings that had not been assessed in the field.
- 4) Dams have a terrestrial barrier score of zero unless a road goes over the dam, in which case it gets the road's terrestrial barrier score.
- 5) An expert team assigned terrestrial barrier scores for all other road cells based on road size class.



**Figure 5.** Relationship between traffic rate and probability of mortality based on the Gibbs model (Gibbs and Shriver 2002).

In step 2 above, note that we are using similarity here instead of its complement, distance. The ecological similarity between each neighboring cell and the focal cell is based on weighted Euclidean distance in multivariate ecological setting space, as before, but the final similarity value is the complement of the weighted Euclidean distance, such that a score of 1 represents maximum similarity and a score of 0 represents maximum dissimilarity.

Ecological flows modeled for connectedness are allowed to flow overland and diagonally from cell to cell. As a result, resistant kernels can wrap around highly resistant cells or patches of cells. This makes sense for organisms that move terrestrially because flows can

go around a building, parking lot or subdivision. However, for aquatic organism passage this is a problem because what would otherwise be considered severe barriers (e.g., dams, bad culverts) are easily circumvented. We created aquatic connectedness to get around this problem. The raw-scaled aquatic connectedness metric is computed much like connectedness but with a few important differences:

First, aquatic connectedness is constrained to move only along the centerlines of streams, rivers, water bodies and wetlands. While the aquatic connectedness algorithm is applied to stream centerline cells only, we expand the results to all off-centerline cells as follows. For off-centerline lotic cells we take the nearest neighbor centerline value for aquatic connectedness. For all water bodies (i.e., lentic) and wetlands, we use "pond" mixing, in which all cells in the patch get the mean of the centerline cell values.

Second, in aquatic connectedness we use a 5 km bandwidth extending out to a maximum search distance of 7.5 km for the resistant kernel in step 1 above.

Lastly, aquatic connectedness includes one settings variable not used by connectedness (aquatic barriers) and ignores four settings variables used by connectedness (terrestrial barriers, traffic, imperviousness, and developed) (**Table 2**). This allows aquatic connectedness to respond to the effects of culverts, bridges, and dams on aquatic passability, rather than the effects of roads that may pass overhead. Aquatic barrier scores are computed with the following important considerations (see technical document on aquatic barriers for details, McGarigal et al 2017):

- 1) Aquatic barrier scores for dams are a function of dam height.
- 2) To assign aquatic barrier scores for road-stream crossings we used an assessment protocol and scoring system developed by NAACC and its predecessor, the Stream Continuity Project. The protocols were developed for implementation by trained volunteers or technicians and rely on information that can be readily collected in the field without surveying equipment or extensive site work. The Collaborative also created an algorithm for scoring crossing structures according to the degree of obstruction they pose to aquatic organisms (i.e., passability) based on field-measured variables. The current aquatic barrier scores are based on the algorithm developed in 2010. We used scores based on the November 10, 2015 scoring algorithm for a set of 12,133 crossings after considerable filtering of the original crossings database to ensure correspondence with our derived road-stream crossings to create a statistical model to predict aquatic barrier scores for those crossings that had not been assessed in the field.

As defined above, the connectedness (and aquatic connectedness) metric measures the ecological similarity and accessibility of the neighborhood of the focal cell, where ecological similarity is based on the suite of ecological settings variables and accessibility is based on a resistant Gaussian kernel. A focal cell surrounded by homogeneous identical ecological conditions would have a connectedness score of 1, whereas, for example, a focal cell surrounded by a sea of development would have a connectedness score of 0. Note, as with all resiliency metrics, increasing values of connectedness imply increasing ecological integrity, and the value of the metric at any location is totally dependent on the particular ecological setting of the focal cell.

Connectedness is an intrinsic attribute of a site (cell) that contributes to the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Consequently, connectedness is something that we measure at the cell level. The connectedness metric assigns a value to each undeveloped cell and thus returns a grid depicting the spatial variation in connectedness across the project area for each timestep of each landscape change simulation (**Fig. 6**). Connectedness is an important component of local ecological integrity and the metric can be used by itself (typically after rescaling by ecological system, see below) or be combined with the stressor metrics and other resiliency metrics to provide a composite local index of ecological integrity, as described below.

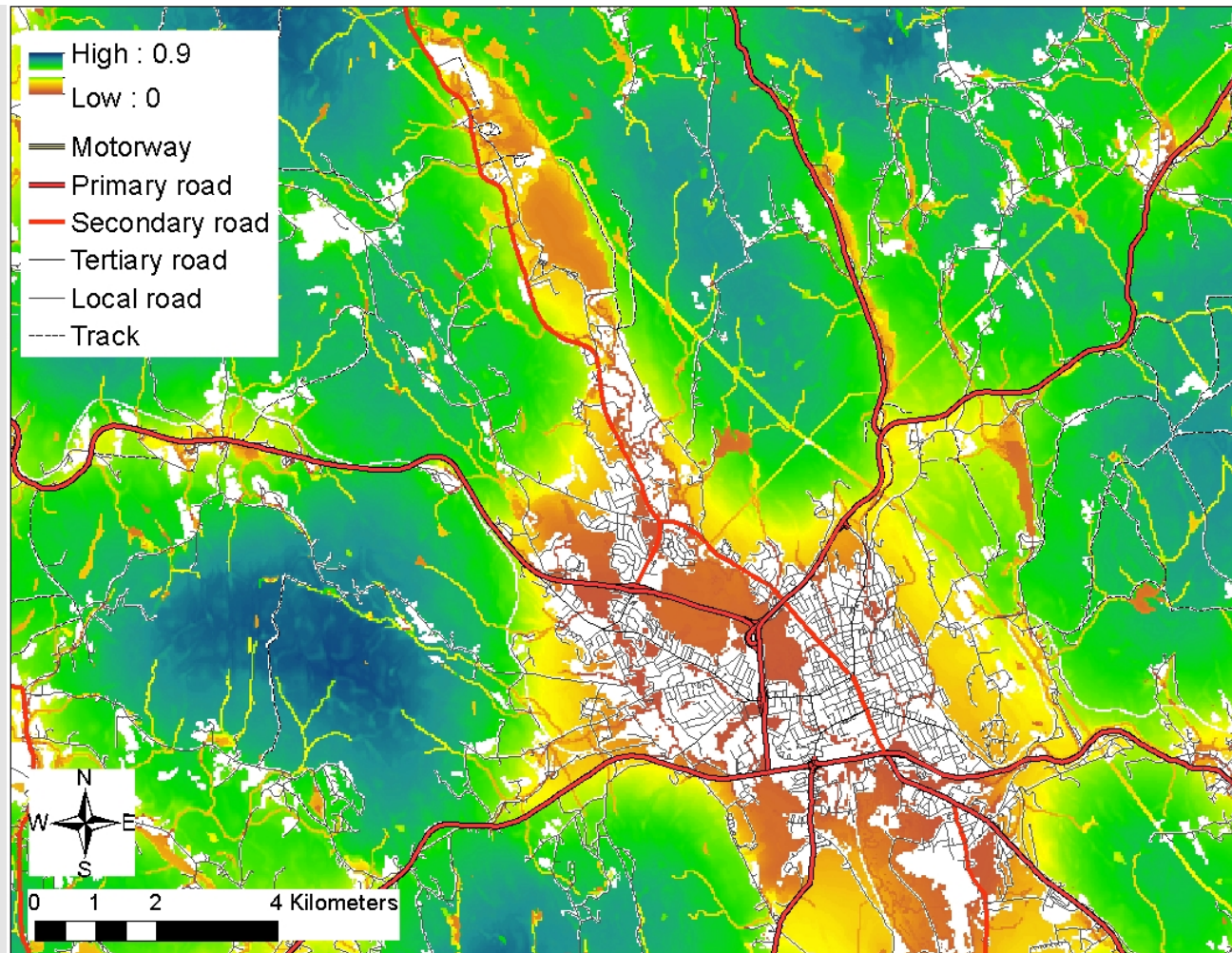
### **4.3.3 Ecosystem diversity**

Ecosystem diversity (or "diversity" for short) refers to the variety and abundance of ecological settings in the neighborhood of a focal cell and reflects the magnitude of opportunities for organisms to move between the focal cell and neighboring cells with different ecological settings than the focal cell in order to adapt to changing environmental conditions (e.g., changing climate). Like similarity, diversity is especially relevant for highly vagile organisms where the intervening landscape is not limiting movement to or from the focal cell (at least over the long term), since connectivity between the neighboring cells and the focal cell is not explicitly considered. However, in contrast to similarity, diversity is relevant primarily from a long-term perspective on resiliency. In general, local diversity reflects the capacity of a site (and the constituent organisms) to adapt to a changing environment (e.g., as driven by climate change) over the long term by having opportunities to find a variety of different environments nearby, some of which may become more favorable to individual organisms over time as environmental conditions change.

Note, diversity is antagonistic to similarity (as defined above) in the short-term, because a diverse neighborhood will have lower similarity to the focal cell. However, diversity may provide more resiliency than similarity over the long-term by providing diverse opportunities for adaptation by allowing organisms opportunities to move to new sites that offer favorable environments as the local environment changes. Thus, similarity addresses resiliency more from a shorter-term perspective, whereas diversity addresses resiliency more from a longer-term perspective.

The raw-scaled diversity metric is currently under development. However, as currently conceived it will be computed as the *standard* Gaussian kernel-weighted generalized variance for every undeveloped cell, where the generalized variance is computed as the determinant of the variance-covariance matrix and is a measure of the multi-dimensional scatter of points, briefly as follows:

- 1) for each undeveloped focal cell, build a data matrix in which each row represents a neighboring cell within a fixed geographic distance of the focal cell (defined as three times the specified bandwidth of the standard Gaussian kernel) and each column represents one of the ecological settings variables;
- 2) multiply each column by the corresponding specified weight for the ecological settings variable;



**Figure 6.** Illustration of the connectedness metric, which is one of the resiliency metrics. The numeric value shown here is the raw connectedness metric in which the areas shown in blue depict relatively high connectedness (or high resiliency) whereas the areas shown in red depict relatively low connectedness (or low resiliency); areas mapped as development and roads are not evaluated; development is depicted in white, whereas the roads are depicted by road class.

- 3) weight each neighboring cell (row) by its standard Gaussian kernel value (2 km bandwidth extending out to a maximum distance of 4km); and
- 4) compute the determinant of the weighted variance-covariance matrix (note, this is the multivariate equivalent of sample variance).

In step 3 above, the standard Gaussian kernel weights each neighboring cell based on its geographic distance to the focal cell, such that cells closer to the focal cell contribute more to the generalized variance and weights decrease nonlinearly with increasing distance and asymptotically approach 0 at three standard deviations from the focal cell.

As defined above, the diversity metric measures the ecological diversity of the neighborhood of the focal cell, where ecological diversity is based on the suite of ecological

settings variables and distance is weighted by a standard Gaussian kernel. A focal cell surrounded by homogeneous ecological conditions would have a diversity score of 0, whereas, for example, a focal cell surrounded by a diversity of ecological settings would have a larger (unbounded) score. Note, in contrast to the stressor metrics, increasing values of diversity imply increasing long-term resiliency and thus ecological integrity. However, like the stressor metrics, the value of the metric at any location is not dependent on the particular ecological setting of the focal cell but rather on the ecological diversity of its neighborhood.

Diversity is an intrinsic attribute of the neighborhood of a site (cell) that contributes to the long-term resiliency and thus the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Consequently, diversity is something that we measure at the cell level. The diversity metric assigns a value to each cell and thus returns a grid depicting the spatial variation in diversity across the project area for each timestep of each landscape change simulation. Diversity is an important component of local ecological integrity from the perspective of long-term resiliency and the metric can be used by itself or be combined with the stressor metrics and other resiliency metrics to provide a composite local index of ecological integrity, as described below.

#### **4.3.4 Adaptive capacity**

Adaptive capacity refers to the capacity to adapt to a changing environment (e.g., as driven by climate change), and like diversity above, it encompasses the ability of an ecosystem subject to stress to reorganize and renew itself and how much it expresses a capacity for learning and adaptation (Carpenter et al. 2001, Elmqvist et al. 2003). Like connectedness, adaptive capacity reflects the accessibility of ecologically similar locations in the neighborhood of the focal cell, but here the resistance and similarity of neighboring cells is based on the future environmental conditions rather than the current. As such, adaptive capacity is the long-term equivalent of connectedness and is relevant for assessing local connectivity in a changing environment. Thus, adaptive capacity reflects the potential for adaptation via movement to and from a site in order to track similar ecological conditions as they change over time (i.e., across all timesteps) under non-equilibrium dynamics. Like connectedness, adaptive capacity is especially relevant for movement-limited organisms where impediments to movements are important (even over the long term), since connectivity between the neighboring cells and the focal cell is explicitly considered. However, in contrast to connectedness, adaptive capacity is relevant primarily from a long-term perspective on resiliency, as described above for diversity.

The raw-scaled adaptive capacity metric is currently under development. However, as currently conceived it will be computed as follows:

- 1) for each undeveloped cell, compute the volume of a *resistant* Gaussian kernel built for the focal cell multiplied by the complement of the ecological distance (i.e., ecological similarity) between the focal cell and each neighboring cell, but where resistance and ecological distance, which are based on the weighted Euclidean distance in multivariate ecological setting space (as described above), are based on the future ecological conditions at the receiving cell compared to the conditions at the focal cell at timestep 0 (note, this measures outflow from the focal cell; i.e., can stuff in the focal cell get to places in the future with a similar ecological setting as the focal cell today);



- 2) at the focal cell, compute the sum across ecological distance-weighted *resistant* Gaussian kernels built for every neighboring cell, where ecological distance and resistance are based on the current ecological conditions at the source neighboring cell compared to the conditions at the focal cell in the future (note, this measures inflow from to the focal cell from the neighboring cells; i.e., can stuff in the neighboring cells got to the focal cell in the future with a similar ecological setting as the neighboring cell today); and
- 3) sum the values of #1 and #2 at the focal cell.

As defined above, the adaptive capacity metric measures the capacity for organisms at the focal cell to move outward and track favorable environments over time and for organisms to move into the focal cell from other cells that had similar initial settings as the current focal cell. A focal cell well connected to an abiotic gradient would have a relative large adaptive capacity score and, for example, a focal cell surrounded by homogeneous abiotic conditions or severe anthropogenic barriers to movement would have a relative low adaptive capacity score. Like diversity, increasing values of adaptive capacity imply increasing long-term resiliency and thus ecological integrity. However, in contrast to the diversity metric, the value of the metric at any location is dependent on the particular ecological setting of the focal cell, and thus the adaptive capacity metric is probably most meaningful when scaled by ecological system (see below). Note, this metric is only appropriate for applications involving explicit landscape change scenarios because it depends on having the ecological conditions (i.e., ecological settings variables) at both current and future timesteps.

Adaptive capacity is an intrinsic attribute of the neighborhood of a site (cell) that contributes to the long-term resiliency and thus the ecological integrity of the site itself and thus, by extension, confers ecological integrity to the landscape as a whole. Consequently, adaptive capacity is something that we measure at the cell level. The adaptive capacity metric assigns a value to each cell and thus returns a grid depicting the spatial variation in adaptive capacity across the project area for each timestep of each landscape change simulation. Adaptive capacity is an important component of local ecological integrity from the perspective of long-term resiliency and the metric can be used by itself (typically after rescaling by ecological system, see below) or be combined with the stressor metrics and other resiliency metrics to provide a composite local index of ecological integrity, as described below.

#### **4.4 Index of ecological integrity (IEI)**

Intactness and resiliency represent local attributes that confer ecological integrity to the cell itself and thus, by extension, to the landscape as a whole. A site (cell) that is intact (i.e., unimpaired by anthropogenic stressors) and in a setting that promotes resiliency (i.e., short- and long-term capacity to recover from or adapt to changing environmental conditions driven by human land use and climate change) has high ecological integrity (i.e., the capacity to maintain ecological functions). Consequently, we combine the intactness and resiliency metrics into a single composite *Index of Ecological Integrity (IEI)* that is useful for comparing the ecological impacts of alternative landscape change scenarios and for prioritizing sites for conservation action in the context of landscape conservation design.

The derivation of *IEI* consists of rescaling the individual raw metrics, combining the metrics into the composite index, and rescaling the final index optionally within specified geographic extents (e.g., state, ecoregion, watersheds). Each of these steps are described in the following sections.

### **4.4.1 Quantile-rescaling**

Recall that each of the raw intactness and resiliency metrics are scaled differently. Some are bounded 0-1 (e.g., similarity), while others have no upper bound. Moreover, each of the metrics will have a unique empirical distribution for any particular landscape. In order to combine the metrics into a composite index, it is therefore necessary to rescale the raw metrics to put them on equal grounds.

*Quantile-rescaling* involves transforming the raw metrics into quantiles, such that the poorest cell gets a 0 and the best cell gets a 1. Quantile-rescaling facilitates interpretation and 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.

There are two fundamentally different ways to conduct quantile rescaling. In the first approach, which we refer to as "community-based rescaling", quantile-rescaling is done by some form of categorical landscape stratification such as land cover types or ecological systems. Community-based rescaling means that forests are compared to forests and 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 than forests. Rescaling by ecological system means that all the cells within an ecological system are ranked against each other in order to determine the cells with the greatest relative integrity for each ecological system. In the LCAD model we currently employ this form of quantile-rescaling by ecological system.

In the second approach, which we refer to as "gradient-based rescaling", quantile-rescaling is done without requiring a categorical landscape stratification such as ecological systems, but instead rescales cells based on their ranking among cells that are nearby in multivariate ecological settings space. In this gradient-based quantile-rescaling, each cell is compared to other ecologically similar cells without regard to any a priori mapping of ecological systems. Gradient rescaling is intended to downplay the importance of classified land cover maps (which is often the source of great inconsistency and arbitrariness) and instead rely on the multivariate ecological settings database to discern the continuous ecological differences between locations. This method of rescaling has been implemented in LCAD but is currently not being used because we have reasonably well-defined and mapped ecological systems and an NALCC directive to use ecological systems as a template for the modeling. Thus, we are employing community-based rescaling, whereby the raw metrics are quantile-rescaled within each ecological system.

#### **4.4.2 Ecological integrity models**

After quantile-rescaling by community (i.e., ecological system in this case), the metrics are all on the same scale (0-1) and have identical uniform distributions within each community. The next step is to combine the rescaled metrics into a composite index. However, given the range of metrics (**Table 3**), it is reasonable to assume that some metrics are more important than others to the overall ecological integrity of the cell and thus should be assigned more weight. Indeed, the watershed-based stressor metrics and aquatic connectedness were designed specifically for application to aquatic and/or wetland communities. Moreover, it is reasonable to assume that the weights applied to the metrics might vary among community types, 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 community-specific ecological integrity models to weight the component metrics in the composite index (**Table 4**). A community model is simply a weighted linear combination of metrics designated (by expert teams) for each ecological community (i.e., ecological system in this case). For parsimony sake, we designate a unique ecological integrity model for each ecological formation, which is a group of similar ecological systems (**Appendix A**). Note, the models given by formation in **table 4** are applied to each of the nested ecological systems within each formation as given in **Appendix A**.

#### **4.4.3 Rescaling the final index**

After combining the rescaled-metrics in a weighted linear combination, to maintain the quantile-scaling by community, we quantile-rescale the composite index by community again to ensure the proper quantile interpretation. The final result is a grid that ranges 0-1.

It is important to recognize that quantile-rescaling (whether it is by community or not, and whether it is for the individual metrics or the composite index) 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. Therefore, quantile-rescaling must be done separately for each analysis area. The best of the Northeast is not the same as the best of the Connecticut River watershed or the state of Maryland. Consequently, the analysis area used for the quantile-rescaling must be explicit. Note, the analysis area used for the quantile-rescaling may be larger than the focal area of interest. For example, let's say that we wanted to evaluate the integrity of cells within the Connecticut River watershed. We might nonetheless rescale cells based on the entire Northeast, and merely clip the results to the Connecticut River watershed. In this case, the range of values within the Connecticut River watershed may not range from 0-1 because the relatively best locations may fall outside of the watershed.

In the LCAD model, we quantile-rescale *IEI* not only by ecological system but also by state, ecoregion, HUC6 watershed and the entire Northeast region by default, but any geographic extents can be used. However, experience has shown us that scaling by ecological system at extents less than the full region is subject to producing occasional spurious results. For example, when scaling by ecological system and state, the quantile-rescaled *IEI* values can vary abruptly along ecosystem boundaries even within a single forest patch, owing entirely to the categorical mapping of the systems. This effect is more pronounced at finer spatial extents; therefore, we are reluctant to quantile-rescale *IEI* below the level of state or HUC6 watershed. By default, we produce the following five quantile-scaled versions of *IEI*:

1. Scaled by ecosystem within the Northeast region
2. Scaled by ecosystem within each state
3. Scaled by ecosystem within each ecoregion
4. Scaled by ecosystem within each HUC6 level watershed

In the LCAD model, we compute each of the scaled versions of *IEI* for the initial (2010) landscape condition as well as the future landscape condition in 2080 averaged across replicate landscape change simulations for each user-defined landscape change scenario.

#### **4.4.4 How to interpret *IEI***

As described above, *IEI* is a composite index derived from the individual intactness and resiliency metrics (**Table 3**); it is a synoptic measure of local ecological integrity and represents the principal result of our coarse-filter ecological assessment.

In contrast to the individual component metrics, *IEI* is quantile-scaled by ecological system within various geographic extents (Northeast Region, state, ecoregion and HUC6 watershed). Briefly, as described in the previous sections, the individual raw metrics are first quantile-scaled by ecological system across the analysis extent (e.g., Northeast region), then combined in a weighted linear function specific to each ecological system (or at least specific to groups of similar ecological systems as designated by formations, **Table 4**), and then the composite *IEI* is again quantile-scaled by ecological system within each geographic extent to produce the final *IEI*. The end result is that within the extent considered the poorest cell within an ecological system gets a 0 and the best cell within that system gets a 1. Thus, forests are compared to forests and emergent marshes are compared to emergent marshes, and so on, within the corresponding geographic extent. As discussed previously, 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 than forests. Rescaling by ecological system means that all the cells within an ecological system are ranked against each other in order to determine the cells with the greatest relative integrity for each ecological system. Similarly, it may not be that meaningful to compare the integrity of an average forest cell in Maine to that of a cell in, say, Maryland, if you are responsible for finding the best forest in Maine to conserve. Therefore, *IEI* is scaled not only by ecological system but also by various geographic extents, including the entire Northeast region, state, ecoregion and HUC6 watershed.

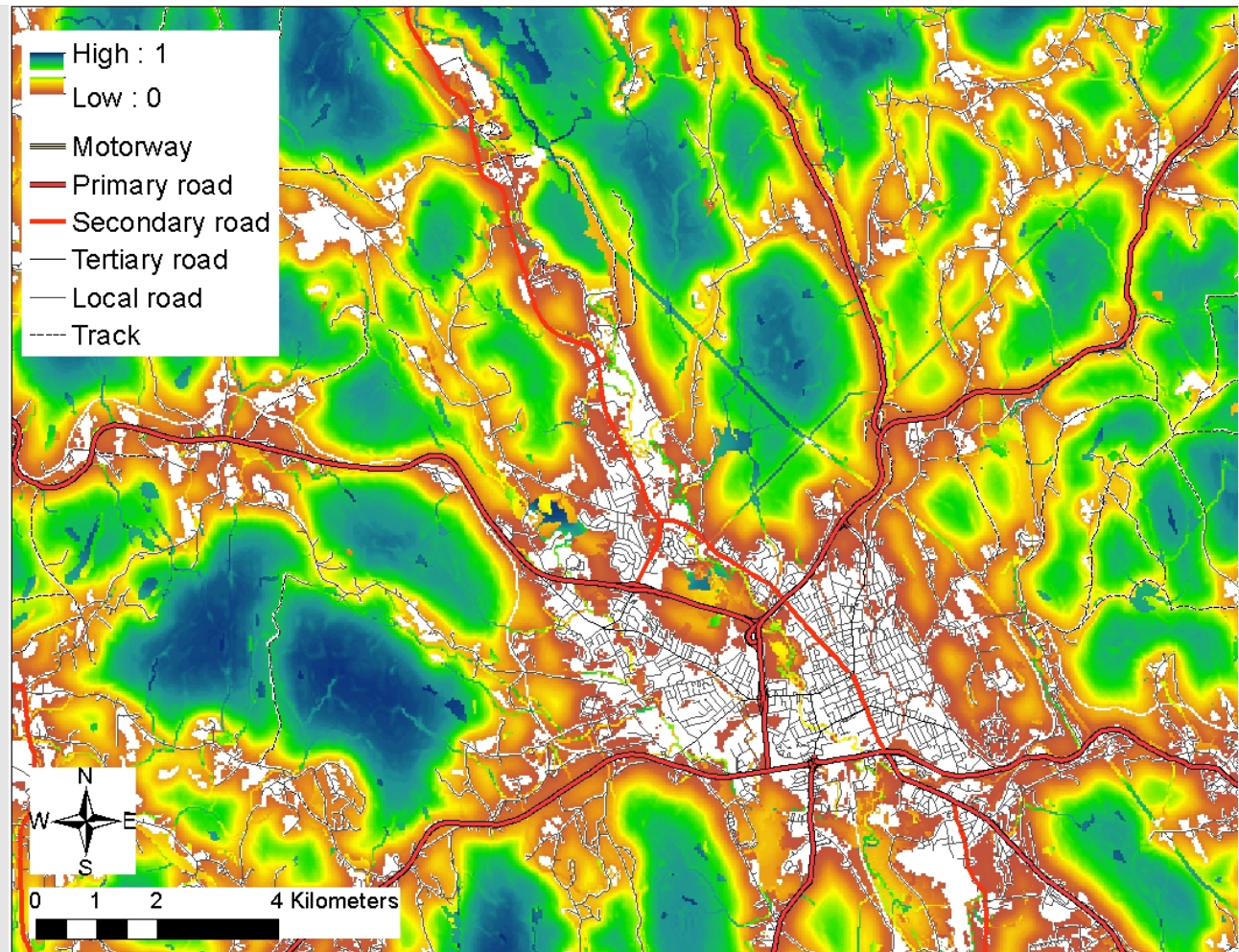
**DSL Project Component: Modeling ecological integrity**

**Table 4.** Integrity (intactness and resiliency) metrics included in the Impact index and the *Index of Ecological Integrity (IEI)* and their weights by ecological formation (groups of similar ecological systems, **Appendix A**) in the Landscape Change, Assessment and Design (LCAD) model. Note, the weights are relative and reflect the relative importance of each metric to the composite *Impact* and *IEI* indices for each formation and they sum to ~100% for each ecological formation. See Table 1 for a description of each metric. Note, climate and searise metrics are only used for computing future *IEI* and *Impact*.

Ecological formation	habloss	whabloss	traffic	mowplow	edges	salt	sediment	nutrients	cats	edgepred	badplants	worms	imperv	damint	sim	connect	aqconnect	climate	searise	tidal restrictions
Alpine	0.0	0.0	5.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.3	0.0	0.0	0.0	7.1	7.1	0.0	25.1	50.0	0.0
Cliff & Rock	6.9	0.0	3.3	0.0	0.0	0.0	0.0	0.0	4.4	3.1	6.5	0.0	0.0	0.0	9.5	10.9	0.0	5.0	50.0	0.0
Grassland & Shrubland	9.0	0.0	4.5	0.0	0.0	0.0	0.0	0.0	2.2	4.5	4.5	2.2	0.0	0.0	6.7	11.2	0.0	5.0	50.0	0.0
Coastal Scrub-Herb	7.4	0.0	4.1	0.0	0.0	0.0	0.0	0.0	3.9	4.5	3.6	0.0	0.0	0.0	10.0	11.3	0.0	4.9	50.0	0.0
Boreal Low Elevation Forest	4.5	0.0	4.5	0.0	2.2	0.0	0.0	0.0	2.2	4.5	4.5	4.5	0.0	0.0	6.7	11.2	0.0	5.0	50.0	0.0
Boreal Montane Forest	3.5	0.0	3.5	0.0	1.7	0.0	0.0	0.0	1.7	3.5	3.5	3.5	0.0	0.0	5.2	8.7	0.0	15.0	50.0	0.0
Northeastern Upland Forest	4.5	0.0	4.5	0.0	2.2	0.0	0.0	0.0	2.2	4.5	4.5	4.5	0.0	0.0	6.7	11.2	0.0	5.0	50.0	0.0
Northeastern Wetland	4.1	4.2	4.1	2.0	0.9	2.0	2.0	2.0	0.0	2.0	2.0	0.9	1.0	0.0	4.1	7.3	1.4	4.5	50.0	4.6
Peatland	4.7	4.7	2.3	2.3	0.0	4.7	2.3	4.7	0.0	2.3	0.0	0.0	2.3	0.0	4.7	9.5	0.0	5.0	50.0	0.0
Stream (headwater/creek)	2.4	4.8	2.4	2.4	2.4	0.0	2.4	2.4	0.0	2.4	0.0	0.0	4.8	7.3	0.0	4.8	7.3	0.0	50.0	4.1

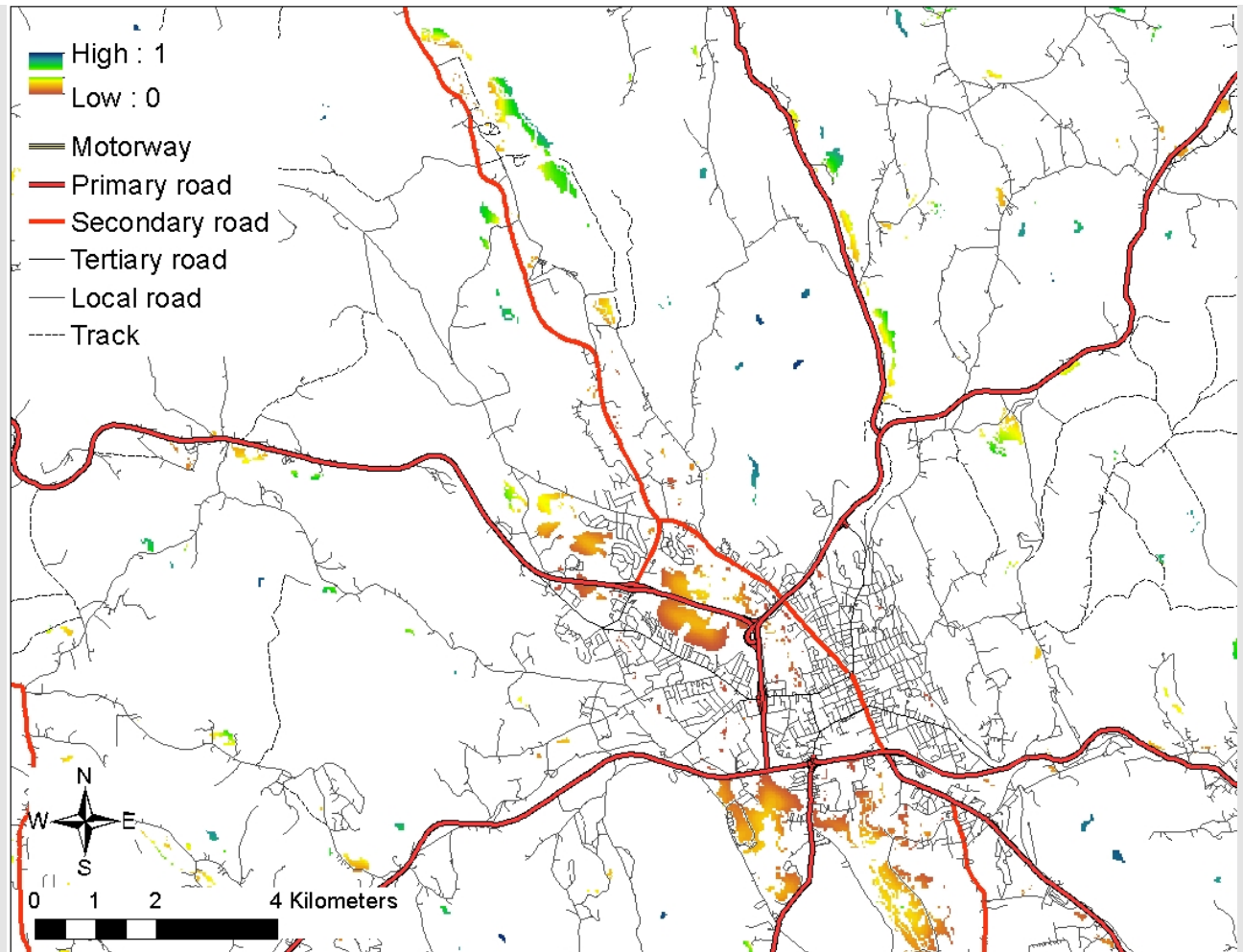
**DSL Project Component: Modeling ecological integrity**

Stream (small)	2.4	4.8	2.4	2.4	2.4	0.0	2.4	2.4	0.0	2.4	0.0	0.0	4.8	7.3	0.0	2.4	9.7	0.0	50.0	4.1
Stream (medium)	2.5	5.1	2.5	2.5	0.0	0.0	2.5	2.5	0.0	2.5	0.0	0.0	5.1	7.7	0.0	2.5	10.3	0.0	50.0	4.1
Stream (large)	2.5	7.7	2.5	2.5	0.0	0.0	2.5	2.5	0.0	2.5	0.0	0.0	5.1	5.1	0.0	2.5	10.3	0.0	50.0	4.1
Lake	2.6	10.6	2.6	2.6	0.0	2.6	2.6	5.2	0.0	2.6	0.0	0.0	2.6	0.0	5.2	5.2	5.2	0.0	50.0	0.0
Pond	2.6	10.6	5.2	2.6	0.0	2.6	2.6	5.2	0.0	2.6	0.0	0.0	2.6	0.0	5.2	7.8	0.0	0.0	50.0	0.0
Freshwater Tidal Riverine	2.5	7.7	2.5	2.5	0.0	0.0	2.5	2.5	0.0	2.5	0.0	0.0	5.1	5.1	0.0	2.5	10.3	0.0	50.0	4.1
Estuarine Intertidal	8.3	0.0	2.4	0.8	0.0	0.0	0.0	0.0	1.6	2.7	0.0	0.0	0.0	0.0	11.4	13.1	0.0	4.5	50.0	4.9
Marine Intertidal	7.2	0.0	0.9	0.0	0.0	0.0	0.0	0.0	2.6	4.2	0.0	0.0	0.0	0.0	14.0	13.2	0.0	4.7	50.0	2.8



**Figure 7.** Index of Ecological Integrity (IEI) metric in 2010 scaled by ecosystem across the Northeast region. Note, developed lands are not assessed and are shown in white.

It is critically important 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), only that it is the best of that ecological system within the corresponding geographic extent. In an absolute sense, the best within any particular geographic extent may still be pretty impacted. Consequently, *IEI* is best used as a comparative index to compare one site to another. To compare the same site to itself over time, however, we must use a different scaling scheme, as discussed below for the index of ecological impact. In addition, the final *IEI* has a nicely 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 a value of 0.9 has a value that is greater than or equal to 90% of all the cells, and all the cells with  $>0.9$  values comprise the best 10% across ecological systems within the corresponding geographic extent. For these reasons, the *IEI* maps are best interpreted in conjunction with the DSLland map, since the latter depicts the land cover classes (i.e., ecological systems) by which the quantile-scaling was conducted.



**Figure 8.** Index of Ecological Integrity (IEI) metric in 2010 scaled by ecosystem across the Northeast region, shown here with a mask to reveal only the Northern Swamp ecosystem; all other ecosystems and developed lands are shown in white, although road classes are depicted separately.

**Figure 7** depicts an example of the *IEI* map in 2010 scaled by ecosystem across the entire Northeast region for a random location. Note that values for undeveloped cells range from near 0 (minimum integrity) to 1 (maximum integrity) over the full extent of the study area, and this is true separately for each ecological system; developed cells are not assessed for *IEI* and are represented as Nodata. Because *IEI* is based on quantile scaling, it can easily be thresholded to show the top x% of the landscape. For example, we could slice **figure 7** at 0.8 and show only the top 20% of the landscape in terms of *IEI* (roughly corresponding to areas in blue). Importantly, these "top 20%" areas are distributed across all ecosystems in proportion to their abundance in this landscape. Thus, 30% of the top 20% is composed of northern hardwood and conifer forest, since this ecosystem comprises roughly 30% of the Northeast region.

Given the previous discussion, when viewing the *IEI* map it is important to recognize that the eye naturally will be drawn to the areas of high integrity associated with the dominant



ecosystem(s). For example, if 90% of the landscape is composed of a particular forest type, then 90% of the *IEI* greater than some threshold, say 0.8, will be composed of that forest type due to the quantile-scaling by community. In the area depicted in **figure 7**, there is a preponderance of forest; therefore, the high-integrity streams and wetlands, for example, are easily "lost" or overwhelmed by the preponderance of high-integrity forest. Indeed, the problem is not restricted to aquatic and wetland ecosystems. Given the many different "flavors" of forest that exist at the ecosystem level, the patterns of variation in particular forested ecosystem types is also swamped by the pattern of the dominant forest ecosystem type. Consequently, it is often useful to mask all but the focal ecological system(s) of interest. For example, in **figure 8**, the *IEI* for only the "Northern Swamp" ecosystem is displayed for a random location in the Northeast and reveals the integrity gradient for this ecosystem without being overwhelmed by the integrity of the dominant systems.

## **4.5 Index of Ecological Impact (Impact)**

As described above, *IEI* can be computed for any timestep of the landscape change model and it reflects the intactness and resiliency of a site based on the conditions existing at that timestep. Thus, we can compute *IEI* for the initial (2010) landscape condition or for the future condition in, say, 2080. Whereas *IEI* is in effect a static measure of the ecological integrity of a site at any point in time, the *Index of Ecological Impact (Impact)* essentially measures 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 of the simulated landscape changes; a loss of say 0.5 *IEI* units reflects a greater relative impact than a loss of 0.2 *IEI* units. Moreover, the loss of 0.5 units from a site that has a current *IEI* of say 0.9 is much more important than the same absolute loss from a site that has a current *IEI* of 0.5. Thus, *Impact* reflects not only the magnitude of loss of *IEI*, but also where it matters most — sites with high initial integrity.

The derivation of *Impact* consists of rescaling the individual raw metrics, but using a different rescaling procedure than used with *IEI*, then combining the metrics into the composite index, and then computing the final index. Each of these steps are described in the following sections.

### **4.5.1 Delta-rescaling**

The embedded use of quantile-rescaling in *IEI* suffers from the "Bill Gates" effect when used for scenario comparison. The "Bill Gates" effect occurs when the value of the raw metric is decreased in a cell but it remains the highest valued cell -- the quantile is unchanged. This is analogous to taking millions of dollars away from Bill Gates and yet he remains the richest man around. 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 any 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 among scenarios (or timesteps of a single scenario).

Delta-rescaling is rather complicated in detail. Briefly, delta-rescaling involves computing the difference in the metric from its baseline value at timestep 0 (2010). Thus, delta-rescaling does not involve comparing the condition of a cell to ecologically similar cells of

the same ecological system, but rather comparing the condition of a cell to itself under the baseline (timestep 0) condition. These delta-rescaled metrics can then be combined in a weighted linear combination to form a composite delta ecological integrity index, and this composite index can be multiplied by the ecological integrity index (*IEI*) of the cell under the baseline scenario to derive an "impact" index (*Impact*), as described below.

Unfortunately, since the raw metrics are on different scales,

we can't simply compute the delta between the current and future timesteps, since the raw deltas would also be on different scales. But in order to combine the metrics into a composite index they must be put on the same or similar scale. A simple solution would be to range rescale each raw metric so that it ranges 0-1. However, range rescaling is very sensitive to extreme values and most of the raw metrics have positively or right-skewed distributions containing relatively few very large values. To address this issue we instead use a rather complicated rescaling procedure, as follows:

- 1) For each raw stressor metric at the fullest geographic extent, we find its 90<sup>th</sup> quantile benchmark and apply a logistic transformation such that this benchmark ends up with a score of 0.95, as follows:

$$rescaled.metric = \left( \frac{1}{e^{(-raw.metric/s)} + 1} \right) * 2 - 1$$

$$s = \frac{-benchmark}{\ln(2/1.95 - 1)}$$

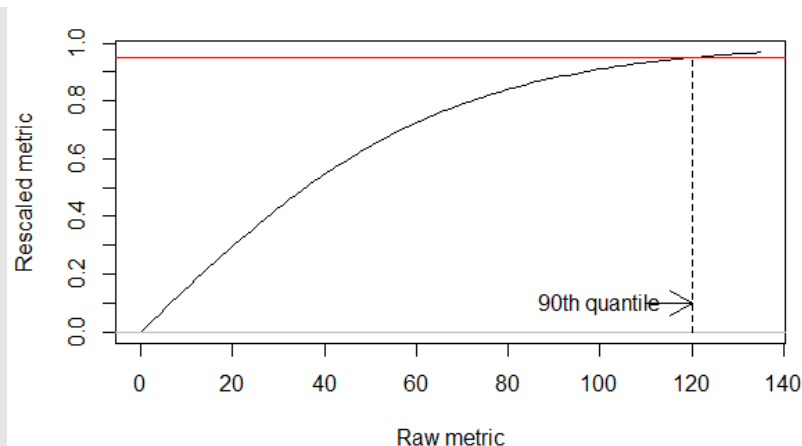
The end result is that each rescaled stressor metric ranges from 0~1 (**Fig. 9**).

- 2) For the aquatic connectedness (*aqconnect*) metric, we compute the maximum value of *aqconnect* (*aqcmax*) for each cell by running it without the anthropogenic settings variables (i.e., as if there were no road-stream crossings and dams), find the 95<sup>th</sup> quantile of *aqcmax*, and rescale the metric as follows:

$$rescaled.aqconnect = \frac{0.95}{quantile(aqcmax, 0.95)}$$

The end result is that rescaled *aqconnect* ranges from 0 ~ 1.

- 3) For the connectedness and similarity metrics, which scale naturally from 0~1 (for a highly similar and connected neighborhood), we keep them in their raw scale form.



**Figure 9.** Logistic transformation of a raw metric scaled 0-135 with a 90<sup>th</sup> quantile of 120 as used in delta-rescaling. The rescaled metric ranges from 0~1 with a value of 0.95 for the 90<sup>th</sup> quantile.

After rescaling each of the integrity metrics, we compute the difference (or delta) between the baseline (2010) value and the future timestep (e.g., 2080) value. These delta-rescaled metrics have a theoretical range of -1 to 1. A value of -1 indicates the maximum potential loss of *IEI* (e.g., a cell with the maximum *IEI* gets developed), whereas a value of +1 indicates the maximum potential increase in *IEI* (e.g., a developed cell is restored to the maximum *IEI*). These delta-rescaled metrics are combined into a composite index as described next.

### **4.5.2 Ecological integrity models**

After delta-rescaling, the metrics are all on approximately the same scale. The next step is to combine the delta-rescaled metrics into a composite index. However, given the range of metrics (**Table 3**), it is reasonable to assume that some metrics are more important than others to the overall ecological integrity of the cell and thus should be assigned more weight. Indeed, the watershed-based stressor metrics and aquatic connectedness were designed specifically for application to aquatic and/or wetland communities. Moreover, it is reasonable to assume that the weights applied to the metrics might vary among community types, since what stressors matter most, for example, to an emergent marsh may not be the same as an upland boreal forest. Consequently, as with *IEI*, we employ community-specific ecological integrity models to weight the component metrics in the composite index (**Table 4**). A community model is simply a weighted linear combination of metrics designated (by expert teams) for each ecological community (i.e., ecological system in this case). For parsimony sake, we designate a unique ecological integrity model for each ecological formation, which is a group of similar ecological systems (**Appendix A**). Note, the models given by formation in **table 4** are applied to each of the nested ecological systems within each formation as given in **Appendix A**.

### **4.5.3 Computing the final index**

After combining the delta-rescaled metrics in a weighted linear combination, we multiply the value by the baseline value of *IEI* (the value in 2010 in this case). In this manner, roughly speaking the index is designed to reflect the percentage change in *IEI* (as estimated via delta-rescaling) where it matters most — areas with high initial *IEI*. For example, the ecological impact is relatively greater (and thus more important) for a cell with a delta score of -0.4 and an initial *IEI* of 1 compared to a cell with the same delta score but an initial *IEI* of 0.5. The final index has a theoretical range of -1 (when a cell with initial *IEI*=1 gets developed) to +0.25 (when a cell with initial *IEI*=0.5 gets restored to the maximum *IEI*), but in practice it will rarely approach the upper limit and only infrequently will it even be > 0 (denoting an improvement in *IEI*).

In addition, because *IEI* is scaled by community (e.g., ecological system in this case) and geographic extent, as described above, *Impact* also varies depending on which scaled version of *IEI* is used for the baseline condition. Thus, in the LCAD model, by default we produce four different scaled versions (see above) of *Impact* based on 2080 and averaged across replicate landscape change simulations for each user-defined landscape change scenario.

#### **4.5.4 How to interpret the index of ecological impact**

As described above, *Impact* is a composite index derived from the individual intactness and resiliency metrics (**Table 3**); it is a synoptic measure of the predicted local ecological impact of landscape change and represents the principal result of our coarse-filter assessment of the ecological impact of the forecast landscape changes.

In contrast to *IEI*, *Impact* is delta-scaled to reflect the percentage loss of *IEI* from cells of high initial *IEI* largely independent of their ecological system or the geographic extent of the analysis. Briefly, as described in the previous sections, the individual raw metrics are first delta-rescaled, then combined in a weighted linear function specific to each ecological system (or at least specific to groups of similar ecological systems as designated by formations, **Table 4**), and then multiplied by the baseline *IEI* in 2010 to produce the final *Impact* index for each landscape change simulation. To produce a single product, we average the results across replicate landscape change simulations to capture the stochastic realization of simulated landscape changes. The end result is that a cell with maximum initial *IEI* (1) that loses all of its *IEI* (1→0) in each replicate landscape change simulation gets a value of -1, indicating the maximum possible ecological impact. Conversely, a cell that experienced no change in *IEI* in any of the replicate simulations would get a value of 0, indicating no ecological impact. Lastly, a cell that experienced a gain in *IEI* in any of the replicate simulations would get a positive value that has an upper limit of 0.25, although in practice positive values are rare and typically very small.

It is important to recognize the relative nature of *Impact* and how it differs from *IEI*. Whereas *IEI* is always relative to the ecological system of a cell and the geographic extent of the scaling, the *Impact* of a cell is always relative to itself (regardless of ecosystem or landscape extent) under the baseline condition (2010). The *Impact* of a cell reflects how much the integrity of the cell (as measured by *IEI*) decreases as a result of the forecasted landscape changes relative to the initial or baseline *IEI* of the cell. Thus, *Impact* compares a cell to itself — the change in integrity over time — whereas *IEI* compares a cell to other cells of the same ecological system within the specified geographic extent. While this interpretation is roughly correct, it is not entirely so. *Impact* involves multiplying the weighted linear combination of delta-rescaled metrics by the current or baseline *IEI*. Therefore, technically speaking the ecological system of the cell and the geographic extent of the analysis have an effect on the final computed value, but the role of community membership and geographic extent is relatively minor compared to *IEI*. Because of the relative nature of *Impact*, it can be used as a comparative index to compare one site to another or to compare the same site to itself under different landscape change scenarios.

**Figure 10** depicts an example of the *Impact* map in 2010 for the Kennebec River watershed in Maine averaged across several landscape change simulations reflecting uncertainty in climate change and urban growth. Note that values for cells developed in 2010 (the baseline condition) are always 0 because we do not measure *IEI* for developed cells. For all other undeveloped cells, the values range from -0.69 (maximum observed impact or loss of ecological integrity) to 0.02 (maximum observed increase in ecological integrity). Note, unlike *IEI*, *Impact* is not quantile scaled (although it could be), so in its raw form it cannot be thresholded to show the most impacted x% of the landscape.

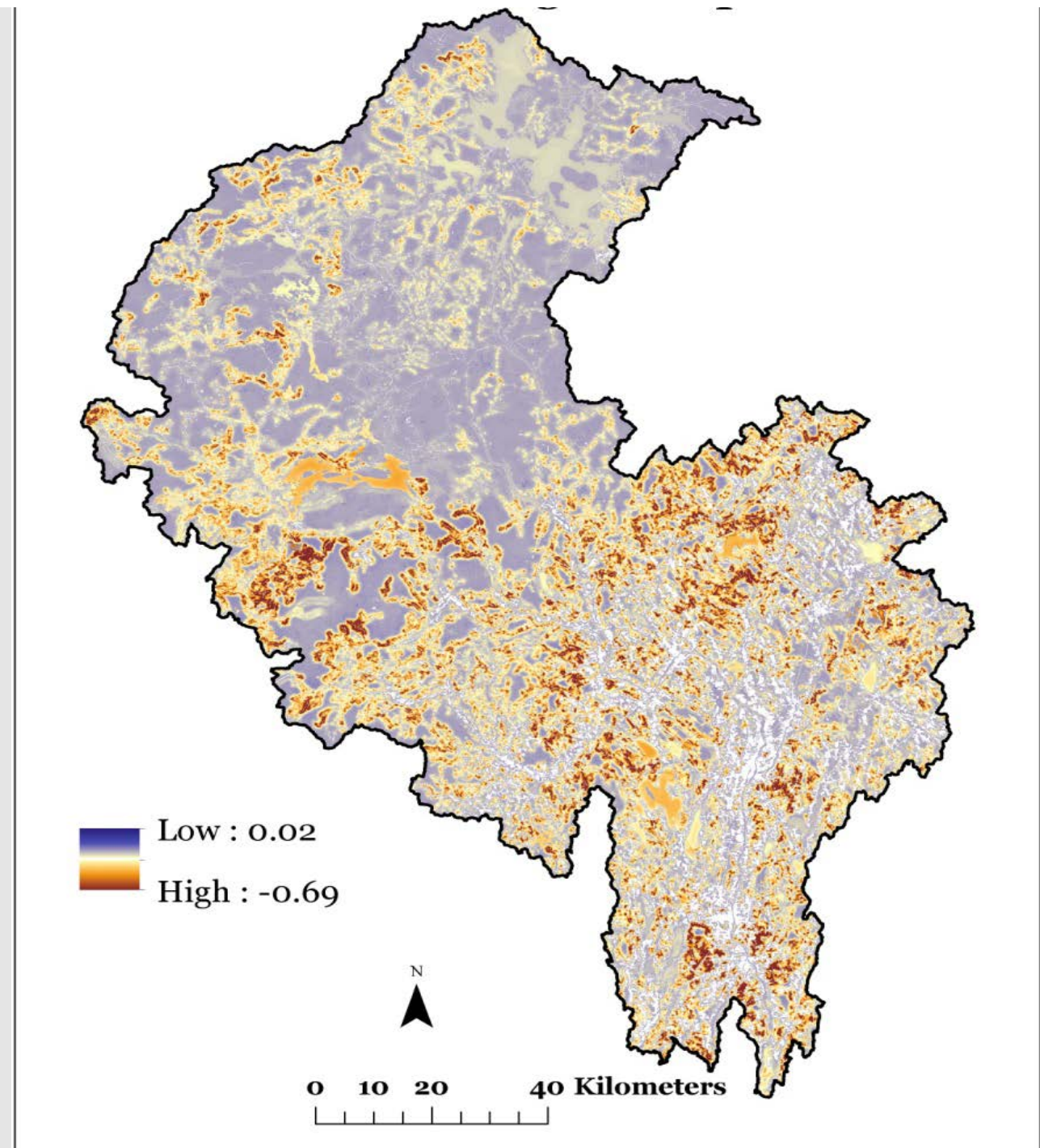
## **5 Alternatives Considered and Rejected**

We did not seriously consider any alternatives to the overall coarse-filter ecosystem-based approach based on landscape ecological integrity. However, we did consider many options for measuring the individual components of landscape ecological integrity and limited our assessment to those components for which we had regionally consistent and relatively reliable spatial data. In addition, we did consider complementing our coarse filter with a complementary fine filter intended to protect the unique and important environments that might fall through the cracks of the coarse filter, but due to limitations on time and resources available, we opted to forgo implementing the fine filter. However, there are two important considerations to developing a fine filter:

First, the fine filter should be complementary and subsequent to the coarse filter. More specifically, the fine filter should target those biodiversity elements that are not going to be protected by the coarse filter alone. Moreover, the fine filter should be applied after or subsequent to the coarse filter in order to "catch" the things that fall through the cracks of the coarse filter.

Second, the fine filter should not be equivalent to representative (a.k.a. surrogate) species for two reasons. First, representative species are more often than not selected to represent a suite of species associated with particular ecological systems, which is the function of the coarse filter, not the fine filter. Second, the fine filter need not be based on individual species at all, since there are other ways to define unique and important environments that may fall through the cracks of the coarse filter. There is nothing inherently wrong with using individual species as the fine filter, but given the intent of the fine filter, we believe that it is more robust to simply identify and protect the suite of unique environments that are not captured by the coarse filter (e.g., vegetation seral stages, juxtaposition of ecosystems or vegetation conditions) without using representative species. In this manner, the coarse and fine filters truly complement each other and function together to conserve general biodiversity. Note, the role of species in the fine filter would be to help think about and define the unique environments that should serve as the fine filter, but the fine filter model should be for the unique environments and not specific species. In other words, the emphasis should be on the unique environment, not on the individual species. In this context, species spanning all taxa (not just conservation priority species) should be identified and associated with each fine filter, but merely to provide examples of the types of species that rely on each unique environment.

Perhaps the most important alternative considered but not implemented here is the "gradient-based rescaling" option for *IEI*. Recall that *IEI* uses quantile-rescaling within some specified geographic extent, but it can be done using either community-based or gradient-based approaches. Community-based quantile rescaling, the approach used here, is based on a categorical classification and mapping of the landscape into community types — ecological systems in this application. All classifications, such as the one used in this project, are fraught with numerous problematic issues owing to the subjectivity of the classification (i.e., there are myriad alternative classification systems) and the arbitrariness of mapping a continuous environment into discrete and categorically different patches. The end result is hard boundaries that are more often than not artificial and that propagate themselves through all derivatives of the landcover map such as the ecological integrity



**Figure 10.** Index of Ecological Impact (*Impact*) metric in 2080 for the Kennebec River watershed in Maine averaged across replicate landscape change simulations. Large negative values indicate areas of high predicted ecological impact of the forecasted landscape changes and represent places with high current ecological integrity (i.e., high *IEI* in 2010) and relatively large predicted loss of ecological integrity over time. Note, this figure is based on earlier phase 1 landscape change simulations.

assessment and species landscape capability modeling. There is a viable alternative to community-based rescaling that we refer to as gradient-based rescaling. The latter is done without requiring a categorical landscape stratification such as ecological systems, but instead rescales cells based on their ranking among cells that are nearby in multivariate ecological settings space. In this gradient-based quantile-rescaling, each cell is compared to other ecologically similar cells without regard to any a priori mapping of ecological systems. Gradient rescaling is intended to downplay the importance of classified land cover maps and instead rely on the multivariate ecological settings database to discern the continuous ecological differences between locations. This method of rescaling has been implemented in LCAD but is currently not being used because we have reasonably well-defined and mapped ecological systems familiar to the partners and an NALCC directive to use ecological systems as a template for the modeling. Thus, we are employing community rescaling, whereby the raw metrics are quantile-rescaled within each ecological system.

## **6 Major Implementation Constraints**

The major implementation constraint is time. We have the tools and the know-how to implement all of the metrics described in this document, but have not had the time or directive to prioritize implementing the remaining undeveloped metrics: coastal stressor metrics, ecosystem diversity and adaptive capacity.

## **7 Major Risks and Dependencies**

The major risk is not being able to implement the full suite of metrics in this project and thus end up with an incomplete ecological integrity assessment. A few of the stressor metrics have dependencies on specific spatial data layers that are not readily available for the Northeast. For example, most of the coastal metrics (which we developed in Massachusetts) require specific spatial data layers that are not currently available for the entire Northeast.

## **8 Literature Cited**

- Carpenter SR, B Walker, JM Anderies, and N Abel. 2001. From metaphor to measurement: Resilience of what to what? *Ecosystems* 4:765–81.
- Compton, B.W., K. McGarigal, S.A. Cushman, and L.R. Gamble. 2007. A resistant-kernel model of connectivity for amphibians that breed in vernal pools. *Conservation Biology* 21(3):788-799.
- Cushman SA, KS McKelvey, BR Noon, and K McGarigal. 2010. Use of abundance of one species as a surrogate for abundance of others. *Conservation Biology* 24: 830-840.
- Elmqvist T, C Folke, M Nystrom, G Peterson, J Bengtsson, B Walker, and J Norberg. 2003. Response diversity, ecosystem change, and resilience. *Front Ecol Environ* 1: 488–94.
- Holling CS. 1973. Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics* 4:1–23.

- Holling CS. 1996. Engineering resilience versus ecological resilience. In P. C. Schulze, editor. *Engineering within ecological constraints*. National Academy Press, Washington, D.C., USA.
- Lentz EE, SR Stippa, ER Thieler, NG Plant, DB Gesch, and RM Horton. 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, 26 p., <http://dx.doi.org/10.3133/ofr20141252> ISSN 2331–1258 (online).
- McGarigal K, Compton BW, Plunkett EB, DeLuca WV, and Grand J. 2017. Designing sustainable landscapes products, including technical documentation and data products. [https://scholarworks.umass.edu/designing\\_sustainable\\_landscapes/](https://scholarworks.umass.edu/designing_sustainable_landscapes/)
- Randhir TO, RO O'Connor, PR Penner, and DW Goodwin. 2001. A watershed-based land prioritization model for water supply protection. *Forest Ecology and Management* 143:47-56.
- Silverman, BW. 1986. *Density estimation for statistics and data analysis*. Chapman & Hall, London.



## Appendix A. Hierarchical classification of formations and ecological systems

Cross-walk between ecological "formation" as referenced in **tables 1 and 4** and "ecological system" in the Landscape Change, Assessment and Design (LCAD) model. Note, each ecological system is mapped separately with regards to ecological integrity based on the model specified by formation (**Table 4**). The formations are used for practical purposes to group the ecological systems into broader classes for purposes of weighting the individual integrity metrics in the calculation of the *Index of Ecological Integrity (IEI)* and the *Index of Ecological Impact* and to assign roughness and runoff coefficients in the time-of-flow kernels (**Table 1**). See TNC documentation for a description of the ecological systems.

<b>Formation</b>	<b>Ecosystem</b>
Alpine	Acadian-Appalachian Alpine Tundra
Boreal Upland Forest	Acadian Low Elevation Spruce-Fir-Hardwood Forest
Boreal Upland Forest	Acadian Sub-boreal Spruce Flat
Boreal Upland Forest	Acadian-Appalachian Montane Spruce-Fir-Hardwood Forest
Boreal Upland Forest	Central and Southern Appalachian Spruce-Fir Forest
Cliff & Rock	Acidic Cliff and Talus
Cliff & Rock	Calcareous Cliff and Talus
Cliff & Rock	Circumneutral Cliff and Talus
Coastal Scrub-Herb	Atlantic Coastal Plain Beach and Dune
Coastal Scrub-Herb	Atlantic Coastal Plain Beach and Dune
Coastal Scrub-Herb	Great Lakes Dune and Swale
Coastal Scrub-Herb	North Atlantic Coastal Plain Heathland and Grassland
Grassland & Shrubland	Acidic Rocky Outcrop
Grassland & Shrubland	Appalachian Shale Barrens
Grassland & Shrubland	Calcareous Rocky Outcrop
Grassland & Shrubland	Central Appalachian Alkaline Glade and Woodland
Grassland & Shrubland	Eastern Serpentine Woodland
Grassland & Shrubland	Great Lakes Alvar
Grassland & Shrubland	Shrubland & grassland (NLCD 52/71)
Grassland & Shrubland	Mafic Glade and Barrens
Grassland & Shrubland	Southern Appalachian Grass and Shrub Bald
Grassland & Shrubland	Southern Ridge and Valley Calcareous Glade and Woodland
Northeastern Upland Forest	Allegheny-Cumberland Dry Oak Forest and Woodland

<b>Formation</b>	<b>Ecosystem</b>
Northeastern Upland Forest	Appalachian (Hemlock)-Northern Hardwood Forest
Northeastern Upland Forest	Central and Southern Appalachian Montane Oak Forest
Northeastern Upland Forest	Central Appalachian Dry Oak-Pine Forest
Northeastern Upland Forest	Central Appalachian Pine-Oak Rocky Woodland
Northeastern Upland Forest	Central Atlantic Coastal Plain Maritime Forest
Northeastern Upland Forest	Glacial Marine & Lake Mesic Clayplain Forest
Northeastern Upland Forest	Laurentian-Acadian Northern Hardwood Forest
Northeastern Upland Forest	Laurentian-Acadian Northern Pine-(Oak) Forest
Northeastern Upland Forest	Laurentian-Acadian Pine-Hemlock-Hardwood Forest
Northeastern Upland Forest	Laurentian-Acadian Red Oak-Northern Hardwood Forest
Northeastern Upland Forest	North Atlantic Coastal Plain Hardwood Forest
Northeastern Upland Forest	North Atlantic Coastal Plain Maritime Forest
Northeastern Upland Forest	North Atlantic Coastal Plain Pitch Pine Barrens
Northeastern Upland Forest	North-Central Interior Beech-Maple Forest
Northeastern Upland Forest	Northeastern Coastal and Interior Pine-Oak Forest
Northeastern Upland Forest	Northeastern Interior Dry-Mesic Oak Forest
Northeastern Upland Forest	Northeastern Interior Pine Barrens
Northeastern Upland Forest	Piedmont Hardpan Woodland and Forest
Northeastern Upland Forest	Pine plantation / Horticultural pines
Northeastern Upland Forest	South-Central Interior Mesophytic Forest
Northeastern Upland Forest	Southern and Central Appalachian Cove Forest
Northeastern Upland Forest	Southern Appalachian Low Elevation Pine Forest
Northeastern Upland Forest	Southern Appalachian Montane Pine Forest and Woodland
Northeastern Upland Forest	Southern Appalachian Northern Hardwood Forest
Northeastern Upland Forest	Southern Appalachian Oak Forest
Northeastern Upland Forest	Southern Atlantic Coastal Plain Mesic Hardwood Forest
Northeastern Upland Forest	Southern Atlantic Coastal Plain Upland Longleaf Pine Woodland
Northeastern Upland Forest	Southern Piedmont Dry Oak-Pine Forest
Northeastern Upland Forest	Southern Piedmont Mesic Forest
Northeastern Upland Forest	Southern Ridge and Valley / Cumberland Dry Calcareous Forest

**DSL Project Component: Modeling ecological integrity**

<b>Formation</b>	<b>Ecosystem</b>
Northeastern Wetland	Atlantic Coastal Plain Blackwater/Brownwater Stream Floodplain Forest
Northeastern Wetland	Central Appalachian Stream and Riparian
Northeastern Wetland	Central Atlantic Coastal Plain Non-riverine Swamp and Wet Hardwood Forest
Northeastern Wetland	Central Interior Highlands and Appalachian Sinkhole and Depression Pond
Northeastern Wetland	Glacial Marine & Lake Wet Clayplain Forest
Northeastern Wetland	High Allegheny Headwater Wetland
Northeastern Wetland	Laurentian-Acadian Alkaline Conifer-Hardwood Swamp
Northeastern Wetland	Laurentian-Acadian Freshwater Marsh
Northeastern Wetland	Laurentian-Acadian Large River Floodplain
Northeastern Wetland	Laurentian-Acadian Wet Meadow-Shrub Swamp
Northeastern Wetland	North Atlantic Coastal Plain Basin Peat Swamp
Northeastern Wetland	North Atlantic Coastal Plain Basin Swamp and Wet Hardwood Forest
Northeastern Wetland	North Atlantic Coastal Plain Pitch Pine Lowland
Northeastern Wetland	North Atlantic Coastal Plain Stream and River
Northeastern Wetland	North Atlantic Coastal Plain Tidal Swamp
Northeastern Wetland	North-Central Appalachian Acidic Swamp
Northeastern Wetland	North-Central Appalachian Large River Floodplain
Northeastern Wetland	North-Central Interior and Appalachian Rich Swamp
Northeastern Wetland	North-Central Interior Large River Floodplain
Northeastern Wetland	North-Central Interior Wet Flatwoods
Northeastern Wetland	Northern Appalachian-Acadian Conifer-Hardwood Acidic Swamp
Northeastern Wetland	Piedmont Upland Depression Swamp
Northeastern Wetland	Piedmont-Coastal Plain Freshwater Marsh
Northeastern Wetland	Piedmont-Coastal Plain Large River Floodplain
Northeastern Wetland	Piedmont-Coastal Plain Shrub Swamp
Northeastern Wetland	Ruderal Shrub Swamp
Northeastern Wetland	Southern Atlantic Coastal Plain Tidal Wooded Swamp
Northeastern Wetland	Southern Piedmont Lake Floodplain Forest
Northeastern Wetland	Southern Piedmont Small Floodplain and Riparian Forest

**DSL Project Component: Modeling ecological integrity**

<b>Formation</b>	<b>Ecosystem</b>
Peatland	Acadian Maritime Bog
Peatland	Atlantic Coastal Plain Northern Bog
Peatland	Atlantic Coastal Plain Peatland Pocosin and Canebrake
Peatland	Boreal-Laurentian Bog
Peatland	Boreal-Laurentian-Acadian Fen
Peatland	North-Central Interior and Appalachian Acidic Peatland
Lentic	Great Lakes
Lentic	Lentic
Lentic	Very Cold Lake
Lentic	Cold Lake
Lentic	Cold Pond
Lentic	Cool Eutrophic Lake
Lentic	Cool Oligo-Mesotrophic Lake
Lentic	Cool Eutrophic Pond
Lentic	Cool Oligo-Mesotrophic Pond
Lentic	Warm Eutrophic Lake
Lentic	Warm Oligo-Mesotrophic Lake
Lentic	Warm Eutrophic Pond
Lentic	Warm Oligo-Mesotrophic Pond
Lentic	Small Pond
Lotic	Lotic
Stream (headwater/creek)	Stream (headwater/creek) cold high
Stream (headwater/creek)	Stream (headwater/creek) cold moderate
Stream (headwater/creek)	Stream (headwater/creek) cold low
Stream (headwater/creek)	Stream (headwater/creek) cool high
Stream (headwater/creek)	Stream (headwater/creek) cool moderate
Stream (headwater/creek)	Stream (headwater/creek) cool low
Stream (headwater/creek)	Stream (headwater/creek) warm high
Stream (headwater/creek)	Stream (headwater/creek) warm moderate
Stream (headwater/creek)	Stream (headwater/creek) warm low
Stream (small)	Stream (small) cold moderate
Stream (small)	Stream (small) cold low
Stream (small)	Stream (small) cool moderate

<b>Formation</b>	<b>Ecosystem</b>
Stream (small)	Stream (small) cool low
Stream (small)	Stream (small) warm moderate
Stream (small)	Stream (small) warm low
Stream (medium)	Stream (medium) cold
Stream (medium)	Stream (medium) cool
Stream (medium)	Stream (medium) warm
Stream (large)	Stream (large) cool
Stream (large)	Stream (large) warm
Stream (tidal)	Freshwater Tidal Riverine
Estuarine Intertidal	Estuarine Subtidal Sheltered
Estuarine Intertidal	Estuarine Intertidal Aquatic Bed
Estuarine Intertidal	Estuarine Intertidal Emergent
Estuarine Intertidal	Estuarine Intertidal Forested
Estuarine Intertidal	Estuarine Intertidal Reef
Estuarine Intertidal	Estuarine Intertidal Rocky Shore
Estuarine Intertidal	Estuarine Intertidal Scrub Shrub
Estuarine Intertidal	Estuarine Intertidal Unconsolidated Shore
Estuarine Subtidal	Estuarine Subtidal Aquatic Bed
Estuarine Subtidal	Estuarine Subtidal Unconsolidated Bottom
Marine Intertidal	Marine Intertidal Aquatic Bed
Marine Intertidal	Marine Intertidal Rocky Shore
Marine Intertidal	Marine Intertidal Unconsolidated Shore
Marine Subtidal	Marine Subtidal Aquatic Bed
Marine Subtidal	Marine Subtidal Unconsolidated Bottom
Agriculture	Cultivated crops
Agriculture	Pasture/hay
Developed	Abandoned train
Developed	Active train
Developed	Barren land
Developed	Culvert/bridge
Developed	Dam
Developed	Developed- high intensity
Developed	Developed- medium intensity
Developed	Developed- low intensity

***DSL Project Component: Modeling ecological integrity***

<b>Formation</b>	<b>Ecosystem</b>
Developed	Developed- open space
Developed	Motorway
Developed	Primary road
Developed	Secondary road
Developed	Tertiary road
Developed	Local road
Developed	Track

## Appendix B. Ecological settings variables

Ecological settings variables included in the LCAD model for the Northeast region. Note, the exact list of variables and the source of data could vary among applications depending on data availability and objectives. Ecological setting variables include a variety biophysical site descriptors that are used in the calculation of the individual ecological integrity metrics and/or in the calculation of the final rescaled index of ecological integrity. Settings variables are arbitrarily grouped into broad attribute classes for organizational purposes.

<b>Biophysical attribute</b>	<b>Setting variable (grid name)</b>	<b>Description/Units/Range</b>
<i>Temperature</i>	Growing season degree-days	Growing season degree days is a heuristic tool for predicting vegetation growth; calculated by taking the sum of the daily average temperatures above a threshold $T_{base}$ (10 °C) and where temperatures above an upper threshold $T_{max}$ (30 °C) are excluded. <u>Units:</u> number of degrees Celsius <u>Range:</u> 0 - unbounded
	Minimum winter temperature	Minimum air temperature (°C) reached in the winter (in January) sets the northern range limit for many plants and animals. <u>Units:</u> degrees Celsius <u>Range:</u> unbounded
	Heat index 35	Heat stress days is heuristic tool for predicting where heat stress may limit the geographic range and/or demographic performance for many plants and animals; calculated by taking the sum of the daily average temperatures above the critical air temperature (35°C) . <u>Units:</u> number of degrees Celsius <u>Range:</u> 0 - unbounded
	Stream temperature	Mean annual water temperature (°C) is an important determinant of habitat conditions for many aquatic species. <u>Units:</u> classes: cold=1, transitional cool=2, transitional warm=3, and warm=4 <u>Range:</u> n/a
<i>Solar energy</i>	Incident solar radiation	Solar radiation is a principal determinant of plant growth; calculated based on slope, aspect,

<b>Biophysical attribute</b>	<b>Setting variable (grid name)</b>	<b>Description/Units/Range</b>
		<p>topographical shading and latitude.</p> <p><u>Units:</u> none</p> <p><u>Range:</u> unbounded</p>
<i>Chemical and physical substrate</i>	Water salinity	<p>Salinity measures the salt content of water in aquatic settings, which is an important determinant of the ecological community in coastal ecosystems. Currently, we are using a measure derived from mapped salt marsh until an improved data source can be developed.</p> <p><u>Units:</u> ppt (rescaled 0-1)</p> <p><u>Range:</u> 0 - 1</p>
	Substrate mobility	<p>Substrate mobility measures the <i>realized</i> mobility of the physical substrate, due to both substrate composition (i.e., sand) and exposure to forces (wind and water) that transport material, which is an important attribute of certain dynamic systems (e.g., coastal dune systems).</p> <p><u>Units:</u> ordinal</p> <p><u>Range:</u> 0 (stable) - 10 (highly mobile)</p>
	CaCO <sub>3</sub> content	<p>Calcium content of the soil and water influences buffering capacity (and hence susceptibility to acidification) among other things; calculated based on the composition of the soil and underlying bedrock at the focal cell for terrestrial and within the watershed for aquatic.</p> <p><u>Units:</u> %</p> <p><u>Range:</u> 0 - 100</p>
	Soil available water supply	<p>Soil available water supply (AWS), representing the total volume of water (cm) that should be available to plants when the soil, inclusive of rock fragments, is at field capacity, is a principal determinant of plant growth. AWS is calculated as the available water capacity times the thickness of each soil horizon to a specified depth (25 cm).</p> <p><u>Units:</u> cm</p>



<b>Biophysical attribute</b>	<b>Stetting variable (grid name)</b>	<b>Description/Units/Range</b>
	Soil depth	<p><u>Range:</u> 0 - unbounded</p> <p>Soil depth (cm) to impervious layer affects communities primarily because shallow soils (usually on steep slopes or ridgetops) limit deep-rooted plants.</p> <p><u>Units:</u> cm</p>
	Soil pH	<p><u>Range:</u> 0 - 201</p> <p>Soil pH within top 30 cm measures acidity, which affects nutrient uptake by plants.</p> <p><u>Units:</u> ordinal</p> <p><u>Range:</u> 0 - 14</p>
<i>Physical disturbance</i>	Wind exposure	<p>Wind exposure measures exposure to sustained high winds, which can be an important determinant of plant community development under extreme conditions (e.g., Krumholtz vegetation on mountaintops); calculated based on the mean sustained wind speeds at 50 m above ground level using a 200 m resolution model developed for wind energy purposes.</p> <p><u>Units:</u> meters/second</p> <p><u>Range:</u> 0 - unbounded</p>
	Slope	<p>Steep slopes measures the propensity for gravity-induced physical disturbance (e.g., talus slopes), which can limit plant development.</p> <p><u>Units:</u> %</p> <p><u>Range:</u> 0 - unbounded</p>
<i>Moisture &amp; hydrology</i>	Topographic wetness	<p>Soil moisture, measured by a topographic wetness index, is a principal determinant of plant growth.</p> <p><u>Units:</u> none</p> <p><u>Range:</u> unbounded</p>
	Flow gradient	<p>Gradient (percent slope) of a stream determines water velocity (and hence influences geomorphic processes) is a principal determinant of lotic communities, often</p>

<b>Biophysical attribute</b>	<b>Setting variable (grid name)</b>	<b>Description/Units/Range</b>
		<p>approximated by categories such as pool, riffle, run, cascade.</p> <p><u>Units:</u> Percent slope</p> <p><u>Range:</u> 0 (flat) - unbounded</p>
	Flow volume	<p>Flow volume, measured as the flow accumulation, which is a function of watershed size (and precipitation), is a principal determinant of riverine communities.</p> <p><u>Units:</u> none</p> <p><u>Range:</u> 0 (non-flowing systems) - unbounded</p>
	Tidal regime	<p>In coastal areas, tidal regime is determined by the frequency, period and depth of tidal flooding, which is a principal determinant of estuarine communities; varies from permanently inundated, to frequently inundated deeply for long periods by daily tides, to infrequently inundated to varying depths by biweekly spring tides, to rarely inundated to shallow depths by episodic storm surges, to never inundated.</p> <p><u>Units:</u> probability</p> <p><u>Range:</u> 0 (upland/inland beyond the reach of storm surges) - 1 (maximum tidal influence)</p>
<i>Vegetation</i>	Potential dominant life form	<p>Vegetation structure measures the height of the dominant plant life form (e.g., barren, herbaceous, shrub, tree), which is a principal attribute of ecological communities.</p> <p><u>Units:</u> ordinal</p> <p><u>Range:</u> 1 (unvegetated) - 10 (closed canopy forest)</p>
<i>Anthropogenic</i>	Developed	<p>Developed is an indicator of development of any intensity, useful for discriminating between undeveloped lands that can take on a non-zero integrity value and developed lands that by default have zero integrity.</p> <p><u>Units:</u> none</p>

Biophysical attribute	Setting variable (grid name)	Description/Units/Range
	Hard developed	<p><u>Range:</u> 0=undeveloped, 1=developed</p> <p>Developed is an indicator of hard development useful for discriminating between hard (impervious) and soft (pervious) development.</p> <p><u>Units:</u> none</p>
	Gibbs traffic rate	<p><u>Range:</u> 0=undeveloped or all pervious development, 1=impervious development</p> <p>Traffic rate measures the average number of vehicles per day on roads and railways and is transformed to represent the probability of an animal crossing a road and being hit given the traffic rate (see Gibbs and Shriver 2002, Conservation Biology 16:1647-1652), which is an important determinant of landscape connectivity for mobile organisms.</p> <p><u>Units:</u> none</p> <p><u>Range:</u> 0 - 1</p>
	Imperviousness	<p>Impervious measures the percentage of the ground surface area that is impervious to water infiltration, which is an indicator of intensive development and thus an important determinant of ecological communities.</p> <p><u>Units:</u> %</p> <p><u>Range:</u> 0 - 100</p>
	Terrestrial	<p>Terrestrial barriers measures the degree to which railroads and culverts may physically impede movement of terrestrial organisms.</p> <p><u>Units:</u> none</p> <p><u>Range:</u> 0 (no impediment) - 5 (complete barrier) assigned by expert team</p>
	Aquatic barriers	<p>Aquatic barriers measures the degree to which culverts and dams impede upstream and downstream movement of aquatic organisms.</p> <p><u>Units:</u> none</p> <p><u>Range:</u> 0 (no impediment) - 1 (complete barrier)</p>

## **Appendix C. Detailed description of the resistant kernel algorithm**

The resistant kernel is derived as follows (**Fig. C1**):

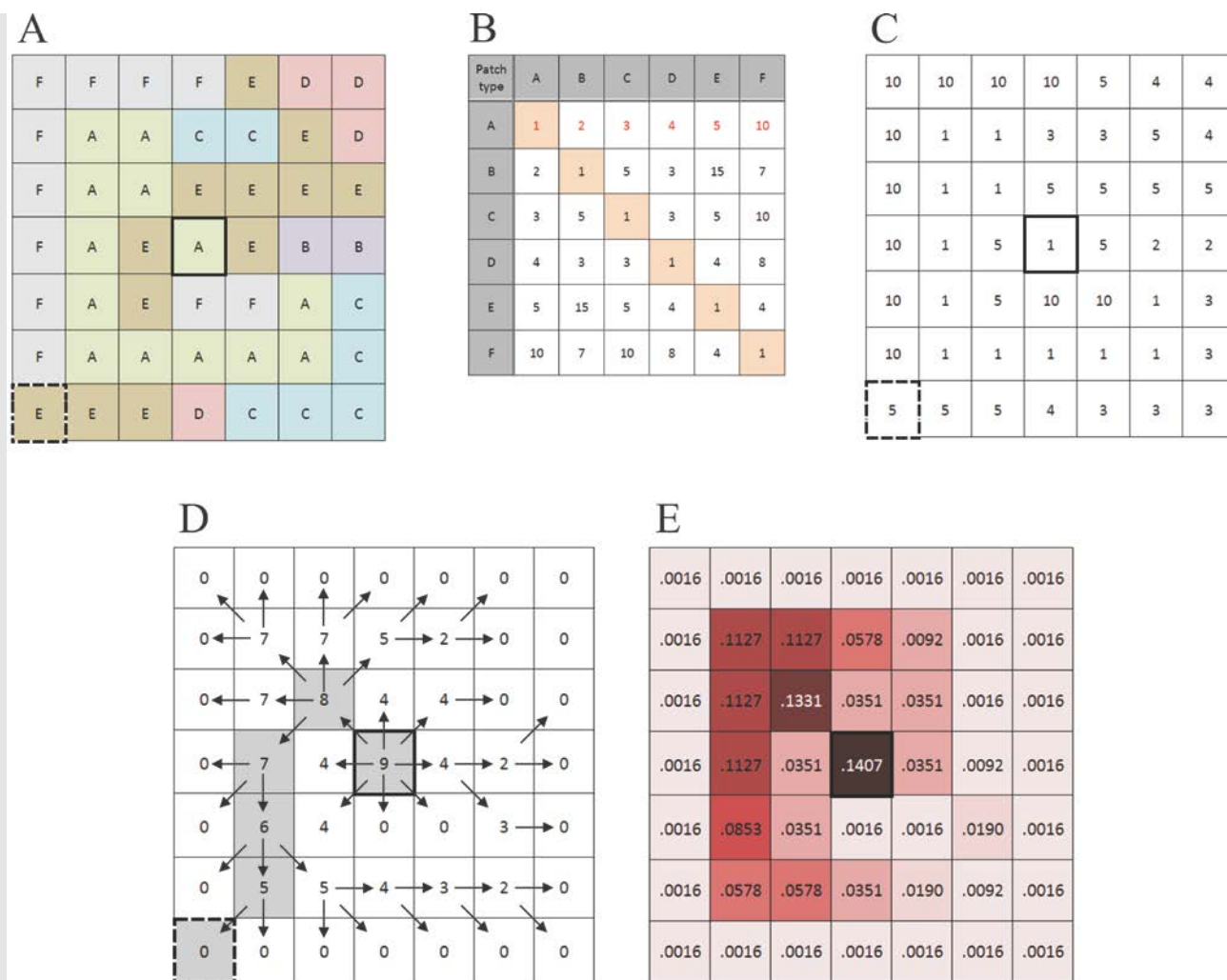
**Step 1.**—The first step is to derive a cost surface for the neighborhood surrounding a focal cell, and there are two different cases:

1. In the first case, the cost surface is derived from a single categorical grid (e.g., landcover types; **Fig. D1-A**). In this case, we assign a cost to each landcover type. Note, the cost matrix (**Fig. D1-B**) represents the relative cost of moving through each patch type from an initial patch type, and it need not be symmetrical. For example, the cost matrix in figure B1-B is read as follows. The row heading represents the "from" patch type, and the column heading represents the "to" patch type. Thus, the first row of the matrix is read as follows: from a focal cell of patch type A, the cost of moving through a cell of the same patch type (A) is one (the minimum cost); the cost of moving through a cell of patch type B is two (i.e., two times more costly than moving through a cell of patch type A); the cost of moving through a cell of patch type C is three (i.e., three times more costly than A), and so on. The costs are user-defined and can take on any values, as long as the minimum cost (and the cost of moving through a cell of the same patch type) is one. Thus, the diagonal elements of the matrix are always set to one, but the off-diagonals can take on any value greater than one. For a focal cell, we generate a resistant (or cost) surface by assigning the relevant cost to each cell based on the cost matrix (**Fig. D1-C**). For example, the focal cell in **figure D1-C** is of patch type A, so the costs assigned to each cell are based on the information in the first row of the cost matrix corresponding to "from" patch type A. Note, the resistant surface will change depending the patch type of the focal cell.
2. In the second case, the cost surface is derived from one or more continuous grids (e.g., representing continuous ecological variables). In this case, we compute the Euclidean distance in ecological space between the focal cell and each neighboring cell. Note, Euclidean distance is easily computed for a single continuous variable as the absolute value of the difference between cell values, but this is easily extended to multivariate ecological distance for two or more variables. In this case, the variables are standardized (e.g., z-scores) and (optionally) weighted before computing the Euclidean distance. Next, we convert the Euclidean distance to cost based a user-specified transformation function. For example, we might range rescale Euclidean distance by stretching or shrinking it to fit the desired cost range (e.g., 1-20). Alternatively, we might apply a nonlinear transformation such as a logistic function or power function. Thus, for a focal cell, we generate a resistant (or cost) surface by assigning the transformed Euclidean distance to each neighboring cell. Note, as in the first case described above, the resistant surface will change depending the ecological setting of the focal cell.

It is important to recognize the dynamic cost surface approach described above, whereby the resistant surface will change depending the landcover type (case 1) or ecological setting (case 2) of the focal cell.

**Step 2.**—The second step is to assign to the focal cell a “bank account” based on the width of the user-specified standard kernel, and spread outward to adjacent cells iteratively, depleting the bank account at each step by the minimum cost of spreading to each cell (**Fig. C1-D**). For illustrative purposes, let's say that the grid cell size in **figure C1-A** is 10 m and we wish to create a resistant Gaussian kernel with a bandwidth  $h$  (equal to one standard deviation) of 30 m (three cells). Further, let's say that we want the Gaussian kernel to extend outward to no more three standard deviations ( $3h$ ; 90 m or nine cells), since beyond that distance the landscape has only a trivial influence on the focal cell. Given these parameters, we start with a bank account of nine, since at the minimum cost of one of moving through a single cell, the kernel will extend outward nine cells. Starting with a bank account of nine in the focal cell, if we move to an adjacent cell of patch type F (cost of 10, **Fig. C1-B**), we reduce the bank account by ten and assign a balance of zero (since negative accounts are not allowed) to that cell. This means that we use up our entire bank account if we attempt to move through a cell of patch type F and can spread no further from that cell. On the other hand, if we move to an adjacent cell of patch type A (cost of one; **Fig. C1-B**), we reduce the bank account by one and assign a balance of eight to that cell. For simplicity in this illustration, diagonal paths are treated the same as orthogonal paths; in the model diagonal costs are multiplied by the square root of 2. Note, an artifact of weighting the diagonal neighbors in this manner and using a cellular automata approach (in which distance is measured in a zig-zag like manner instead of straight line) is an octagonal shaped standard kernel. This process is repeated iteratively, spreading outward in turn from each visited cell, each time finding the least cost of getting to that cell from any of its neighbors, until the balance reaches zero. This produces a functional proximity surface representing the proximity of every cell to the focal cell within a threshold proximity distance. Note the difference between functional proximity and least cost path distance. Functional proximity decreases as you move away from the focal cell, whereas least-cost path distance increases – they are complementary measures of distance. In addition, note that the proximity surface has embedded within it the least cost path to each cell.

**Step 3.**—The last step is to multiply the cell values in the proximity surface by weights derived from the specified kernel function. This actually involves three steps. First, based on the specified kernel function, transform the proximity values into number of bandwidths from the focal cell. For example, for a Gaussian kernel, transform the proximity values into number of standard deviation units from the focal cell, such that in our example, a proximity value of nine (focal cell) is equal to zero and a proximity value of zero (cells at the periphery of the kernel) is equal to three. Second, based on the specified kernel function, compute the probability density for the value derived above. For example, for a Gaussian kernel, compute the probability density for each value based on a normal distribution with a mean of zero and standard deviation of one. Third, divide these values by a constant equal to the sum of the values above for a standard kernel (or resistant kernel in a non-resistant landscape). Note, the constant above ensures that the volume of a standard kernel (or resistant kernel in a non-resistant landscape) is equal to one. The resulting surface is the resistant kernel and its volume is always less than or equal to one (**Fig. C1-E**).



**Figure C-1.** Illustration of the resistant kernel algorithm as applied to a focal cell (outlined in bold in the center of the image). (A) categorical landcover map in which each landcover type is represented by a unique letter. (B) matrix of ecological resistance values for each pairwise combination of landcover types, in which the landcover of the focal cell is given by the row and the columns represent the resistance values to move from the focal cell landcover type through each of the other landcover types; note the diagonals are 1 which is the minimum resistance. (C) the original grid or raster landcover map translated into a resistance surface relative to the landcover of the focal cell derived by applying the corresponding values from the matrix shown in B. (D) functional proximity distance surface representing the functional distance between each cell and the focal cell in the center, derived by starting with a "bank account" of 10 units in the focal cell and spreading outward, discounting the value at each step by the resistance shown in C; the arrows indicate the "least cost path" spread. (E) the final resistant kernel surface derived by a Gaussian transformation of the surface in D (see text for details).

## **Appendix D. Ecological Integrity Products**

The following products are derived and distributed for the ecological integrity assessment for the Northeast region. See the DSL website for links to each of these products.

### Individual Integrity Metrics (raw scale 2010):

These are the raw-scale individual ecological integrity metrics that have not been quantile-rescaled by community and geographic extent computed for the baseline landscape condition in 2010; these are the component metrics for the 2010 *Index of Ecological Integrity (IEI)* index and 2010 *Index of Ecological Impact (Impact)* index below. Note, the raw-scale individual metrics are also computed for future timesteps under each landscape change simulation but are not stored for distribution. See **Table 3** in the main body of the document for a description of each metric.

- Aquatic connectedness
- Connectedness
- Dam intensity
- Domestic predators
- Edge predators
- Edges
- Habitat loss
- Impervious
- Invasive plants
- Invasive worms
- Mowing and plowing
- Nutrients
- Salt
- Sediment
- Similarity
- Tidal restrictions
- Traffic
- Watershed habitat loss

### Index of Ecological Integrity (IEI) Metrics:

These are the *IEI* metrics for the baseline landscape condition in 2010 and future landscape conditions in 2080 reflecting uncertainty in climate change and urban growth under a baseline development scenario involving no additional land protection. *IEI* is available in several scaled versions by ecological system for various geographic tiling schemes: Northeast, states, ecoregions and HUC6 watersheds. Note, *IEI* should be viewed in combination with the landcover map (DSLland) at the corresponding level (ecological system) and geographic tiling scheme.

#### Landcover map:

- DSLland (note, this grid has an attribute table that allows you to display it at the ecosystem or formation level)

Geographic tiling schemes: (note, these are all shape files)

- Northeast
- States
- Ecoregions
- HUC8 watersheds

Current 2010:

- *IEI* scaled by ecosystem and Northeast
- *IEI* scaled by ecosystem and state
- *IEI* scaled by ecosystem and ecoregion
- *IEI* scaled by ecosystem and HUC6 watershed

Future 2080:

- *IEI* scaled by ecosystem and Northeast
- *IEI* scaled by ecosystem and state
- *IEI* scaled by ecosystem and ecoregion
- *IEI* scaled by ecosystem and HUC6 watershed

*Index of Ecological Impact (Impact) Metrics:*

These are the *Impact* metrics for the future landscape conditions in 2080 reflecting uncertainty in climate change and urban growth under a baseline development scenario involving no additional land protection. *Impact* is available in several versions depending on which scaled version of *IEI* was used for the current condition (see text for details).

Future 2080: (note, these are averaged across landscape change simulations)

- *Impact* (derived from *IEI* scaled by ecosystem and Northeast)
- *Impact* (derived from *IEI* scaled by ecosystem and state)
- *Impact* (derived from *IEI* scaled by ecosystem and ecoregion)
- *Impact* (derived from *IEI* scaled by ecosystem and HUC6 watershed)