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Modeling landscape condition for biodiversity assessment—Application in temperate North America

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A R T I C L E I N F O

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A B S T R A C T

Conservation decisions are well supported by predictive spatial models that indicate the relative ecological condition of a given place. The intent of this 90 m pixel landscape condition model is to use nationally available spatial data from the USA, Mexico, and Canada to express assumptions regarding the relative ecological effects of land uses on terrestrial natural communities and species. This approach emphasizes and updateable and transparent design which takes advantage of empirical biodiversity data from the USA to both calibrate and validate the model. Map layers depicting infrastructure, land use, and modified vegetation were each scored for site impact and distance decay, and then combined into one map surface. Field observations from Natural Heritage Programs, each scored for relative ecological condition (in categories A = excellent to D = poor), were used to calibrate distance decay parameters. Some 90,000 observations for at-risk species, invasive plant species, and natural communities were used for model validation. Statistically significant distinctions in ecological condition among validation samples were predicted by the resultant spatial model. Variation in landscape condition was then summarized by regional U.S. Landscape Conservation Cooperatives (LCCs) in terms of areas approximating A–D condition. Montane and desert LCCs scored on average much higher in area approximating "A" and "B" landscape condition, while LCCs with more substantial agricultural and urban footprints scored overwhelmingly within the "D" range of condition. Similar analyses illustrated range-wide scoring of landscape condition for major vegetation types across temperate North America.

1. Introduction

Ecological condition commonly refers to the state of the physical, chemical, and biological characteristics of natural ecosystems, and their interacting processes (Stoddard et al., 2006). Ecological condition is often equated with ecological integrity, which has been defined as the ability of an ecological system to support and maintain a community of organisms with the composition, diversity, and functional organization comparable to those of natural habitats within the region (Parrish et al., 2003). Many human land uses affect ecological condition, through vegetation removal or alteration, hydrologic alteration, and introduction of invasive species, resulting in stress to ecosystems. These human-induced stressors in turn fragment landscapes by disrupting species dispersal and other ecological processes that require contiguous natural conditions (Lindenmayer and Fischer, 2013). Therefore, if one seeks to understand ecological condition, one should consider condition both at local sites of interest and at broader spatial and temporal scales.

Since human land uses, such as built infrastructure for transportation, urban development, industry, agriculture and other vegetation alterations, are depicted in maps that are periodically updated (Turner et al., 2015), they can be used in spatial models to make inferences about the status and trends in human-induced stress and ecological condition of landscapes at regional to global scales (Sanderson et al., 2002; Theobald, 2013; Venter et al., 2016). Maps of this nature can be particularly helpful for identifying relatively unaltered landscape patches. These patches can be subsequently analyzed using a variety of fragmentation statistics aiming to quantify patch area, shape, isolation, and edge to area ratio (Nagendra et al., 2004). They can be used for screening ecological reference sites; i.e., a set of sites occurring in landscapes that vary from low to high landscape fragmentation (Comer and Faber-Langendoen, 2013). If they express a continuum of ecological condition, they could be overlain on ecosystem type distributions to indicate the relative extent and intensity of biotic disruption, as is desired for scoring range-wide at-risk status for natural communities or habitat types (Keith et al., 2013). If repeated over time, these maps can be used to understand overall trends in ecological

Abbreviations: LANDFIRE, Landscape Fire and Resource Management Planning Tools Project; US-EPA, U.S. Environmental Protection Agency; USGS, U.S. Geological Survey; ReGAP, Regional Gap Analysis Project part of USGS Gap Analysis Program

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Table 1
Date inputs and final parameters used for the NatureServe Landscape Condition Model. Site Impact Scores are derived from Brown and Vivas (2005) and NatureServe expert knowledge, Distance Decay values represent the mean value of Good-to-Excellent Ranked Element Occurrences*.

Data Theme	Data Sources			Site Impact Score	Impact Approaches Negligible (meters)
	USA	CAN	MEX		
Transportation					
Primary Highways with limited access (vector)	1	7		0.172	4500
Primary Highways without limited access (vector)	1	7	8	0.172	2700
Secondary and connecting roads (vector)	1	7	8	0.219	3000
Local, neighborhood and connecting roads (vector)	1	7		0.5	420
Minor and Dirt roads (vector)	1	7	8	0.7	3800
Urban and Industrial Development					
Mines (vector)	10			0.05	500
High Intensity Developed (raster)	2	7	9	0.058	3450
Transmission Lines (vector)	*	7	9	0.168	100
Oil and Gas Wells (vector)	*	7		0.168	500
Transmission and Utility Towers (vector)		7		0.168	500
Pipelines (vector)		7	9	0.168	200
Medium Intensity Development (raster)	2			0.25	2450
Open Space (raster)	2			0.308	900
Low Intensity Development (raster)	2			0.31	2400
Managed and Modified Land Cover					
Agriculture (raster)	3,4	5,6,7	5,6	0.3	2500
Introduced Upland grass & forb (raster)	3,4			0.5	2300
Introduced Wetland (raster)	3,4			0.626	2500
Pasture (raster)	3,4	5,6,7	5,6	0.723	1950
Managed Tree Plantations (raster)	3,4			0.842	1200
Recently Logged (raster)	3,4			0.9	1500

1-TIGER roads (https://www.census.gov/geo/maps-data/data/tiger.html); 2-USGS National Land Cover (http://www.mrlc.gov/nlcd2011.php); 3-USGS Gap land cover (http://gapanalysis.usgs.gov/); 4-NatureServe ecological systems and land cover (http://www.natureserve.org/conservation-tools/terrestrial-ecological-systems-united-states); 5-GlobCov global land cover (http://due.esrin.esa.int/page_globcover.php); 6-ChinaCov global land cover (http://glc30.tianditu.com/); 7-CanVec Canadian land cover (http://geogratis.gc.ca/api/en/nrcan-rncan/ess-sst/-/(urn:iso:series)canvec); 8-OpenStreetMap (https://www.openstreetmap.org/#map=5/51.500/-0.100); 9-CONABIO Mexican land cover (http://www.conabio.gob.mx/informacion/gis/?vns=gis_root/biodiv/monmang/manglegw); 10-USGS/MRDS mine location (http://mrdata.usgs.gov/mrds/)
*Proprietary data, available under license in USA; see www.NatureServe.org for more information.

condition of landscapes and the relative contributions of different land uses to landscape change (Griffith et al., 2003; Comer et al., 2013).

However, both conceptual and practical issues complicate development of these spatial models. Most studies documenting ecological effects of land use features on ecosystems are quite context-specific, aiming to document selected species responses to either habitat loss or fragmentation (Knick and Rotenberry, 1995; Gelbard and Belnap, 2003; Fischer and Lindenmayer, 2007; Reino et al., 2013); thus limiting their generalized applicability. This reflects in part a strong tendency among researchers to presume minimal interdependence among individual species in their responses to these factors (Didham et al., 2012).

As a result, some researchers have approached this problem by developing generalized spatial models with less context-specific inputs and applications in mind. That is, they use broad generalizations about the relative ecological effects of human land uses to then transparently construct the spatial model. Some then use field-based observations of land use effects to validate the model relative to their intended use. For example, Brown and Vivas (2005) scored 25 common land use classes along a continuum of estimates for energy input for their development and maintenance; from lowest-intensity "pine plantations" to highest-intensity "central business district (average 4 stories)." This scoring enabled development of a "Landscape Development Index" varying from 1.00 to 10.00 which was then translated as an area-weighted index to individual watersheds. Model results were evaluated using samples from field-based assessments of wetland function, but was not evaluated for its utility for predicting other aspects of ecological condition.

Theobald (2013) provided a generalized model of human modification for the conterminous USA using a series of "intensity" and "footprint" values. Intensity is the degree to which an activity at a location modifies a natural ecological system. Footprint is the aerial extent of the activity. Using a "fuzzy sum" algorithm, the combination of these values provides a (0.0–1.0) human modification score per raster cell. That is, as multiple stressors occur in a given raster cell, their combined values will always approach, but not exceed, 1.0. In that model, intensity values were taken directly from Brown and Vivas (2005) or from expert opinion, and applied to fourteen nationally-available map data sets for infrastructure and land use. The footprint was calculated for each of several hundred land cover classes derived from the U.S. National Gap Analysis land cover map. Through aerial photo interpretation of some 6000 random locations, the proportional overlap of each land use class with each land cover class was recorded. These combined intensity/footprint values were then applied to the regional distribution of each land cover class.

While the model was evaluated for its predictive power using the US-EPA Wadeable Streams Assessment database, a concern remains for the potential effect of applying footprint values to natural land cover classes that vary considerably in their natural extent and distribution; i.e., in a well-justified desire to incorporate empirical data into the model, this particular component of model design could cause distortions in the result, where natural land cover classes located far from sources of ecological stress are still scored for some level of human modification. This could occur where the spatial juxtaposition of land uses to a given natural land cover type is highly skewed. No specific evaluation of this issue was provided by Theobald (2013).

The spatial model discussed in this paper builds on this growing body of published methods for ecological effects assessment and spatial modeling to characterize relative ecological condition of landscapes (Andreasen et al., 2001; Sanderson et al., 2002; Hansen, et al., 2005; Leu et al., 2008; Woolmer et al., 2008; Theobald, 2013; Venter et al., 2016). The intent of this Landscape Condition Model (LCM) is to use nationally available, moderate to high-resolution spatial data from the USA, Mexico, and Canada to transparently express assumptions regarding the relative effects of land uses on a broad cross-section of terrestrial natural communities and species. Both empirical data and expert knowledge were used in stressor selection and in model parameterization. In contrast to other examples, this approach emphasizes an updateable and transparent model design which takes advantage of empirical biodiversity data from the conterminous USA to both calibrate and validate the model for its intended application. Variation in landscape condition of temperate North America was then summarized regionally and other potential applications are briefly described for consideration by conservation practitioners.

2. Materials and methods

Inputs for the LCM were obtained from readily available sources and are summarized below, followed by discussion of the theory underlying our model design. We then discuss data sets and methods used in model calibration and validation.

2.1. Model inputs

Table 1 summarizes the data sets and parameters for this model. Mapped information available for across temperate North America was compiled into 20 categories, organized by a) *Transportation,* b) *Urban and Industrial Development,* and c) *Managed and Modified Land Cover*.

No attempt was made to depict ecological stressors that act at regional scales, such as air pollutants, and climate change stress was not considered. Original data exist as a varying resolutions of vector data, or 30 m–270 m raster data and represent varying degrees of documented accuracy. Each data set used in the analysis represents the best available and no attempt was made by the authors to modify or correct original data.

Line data (buffered to 30 m) and polygon features were summarized to 30 m grids (see Table 1 for sources) Transportation features, derived from Tiger Line data (approx. 2010) for the U.S., depict roads of five distinct sizes (MTFCC Field). Transportation features in Mexico and Canada used data extracted from OpenStreetMap (Highway Field). These data provide a practical measure of human population centers and primary transportation networks that link those centers. While these road size classes do not directly indicate traffic volume along a given stretch of road, their engineering and construction aimed to support distinct levels of traffic volume. Therefore, inferences of expected traffic volume can be derived from these mapped classes, especially when applied on this sub-continental scale.

As a complement to Transportation features, Urban and Industrial Development includes industrial (e.g., mines, energy development) and built infrastructure across a range of densities, from high density urban and industrial zones, to suburban residential development and urban open spaces (golf courses, other parks for outdoor recreation). Urban footprints and attributes were obtained from individual country wide data sources (Table 1). For the U.S. data were derived from national land cover data through combined efforts of the inter-agency LANDFIRE, USGS ReGAP (approx. 2003), and National Land Cover Data (NLCD) (approx. 2010). Other data sets in this category included oil/gas wells and surface mining activity. The urban footprints for Canada and Mexico were are limited to only one category type and were treated as the High Density Urban category for this model.

The third category, Managed and Modified Land Cover, includes the gradient of land cover types that reflect vegetation-based land use stressors at varying intensities depending on data source (Table 1). Agriculture and pasture for Canada and Mexico used a combination of GlobCover (Bontemps et al., 2013), and GlobeLand30 (National Geomatics Center of China, 2014) to identify areas that map croplands in both models, those areas that are croplands in one layer, but not the other were assigned as pasture. U.S. national data from USGS ReGAP and LANDFIRE provide one consistent depiction of these varying land cover classes, from intensive (cultivated and/or irrigated) agriculture, vineyards and industrial tree plantations, recently logged areas, and areas dominated by introduced non-native vegetation in upland and wetland environments. For these latter classes, model users should presume varying degrees of accuracy and completeness in their original mapping, and map classes of introduced vegetation should likely only include areas where substantial and obvious infestation has occurred. These areas are concentrated in cold desert areas of the intermountain west where extensive cheatgrass (*Bromus tectorum*) infestations have been mapped in national mapping efforts. One can safely presume that the presence of introduced plant species, especially when at low densities, is not reliably represented by this model. Additionally, as has been identified elsewhere (Theobald, 2013), while "pasture" is mapped, there is currently no map reliably depicting effects from intense livestock grazing at regional or national scales for temperate North America.

2.2. Theory

A key assumption of this spatial model is that human land uses can interact with ecological processes in nature and result in ecosystem stress, and that with distance from these land uses, their effects tend to dissipate (Riitters and Wickham, 2003). Moreover, it is assumed that since ecological processes occur in nature at multiple spatial and temporal scales, the effects of human land uses are also manifested at multiple scales (Vitousek et al., 1997; Folke, 2006). While we recognize that analysis of spatial pattern (e.g., resulting from this spatial model) does not account for all relevant ecological processes, most ecological processes must be assessed indirectly, often through analysis of the spatial patterns they produce (Turner et al.,1989).

Ecological processes most directly addressed by our spatial model involve those linked to terrestrial landscape fragmentation, such as the disruption of species dispersal (especially for plants, invertebrates, and small vertebrates) or connectivity required to support disturbance regimes operating across local landscapes. Certain effects on ecological condition, such as alteration of natural fire or hydrologic regimes, or removal of top predators, are not addressed. As expressed in this spatial model, ecological condition acknowledges the critiques of fragmentation theory (Didham et al., 2012) that promote a more integrated view, assuming many interdependencies among species and fragmentation effects within natural communities. Fragmentation effects on one species may carry over to other species for which there are frequent interactions.

This model also adopts an approach to analysis that favors use of continuous surfaces as opposed to discrete patch mosaics (McGarigal et al., 2009). A patch mosaic approach remains quite justified for practical applications to natural resource management, such as with mapping discrete vegetation classes, to facilitate understanding of vegetation pattern. However, treatment of spatial heterogeneity as gradients likely better reflects actual fragmentation effects on vegetation, since patch mosaics impose internal homogeneity within each patch. Our approach leaves us with the option to combine a discrete classed vegetation map with our gradient surface of landscape condition to more realistically represent fragmentation effects.

These several theoretical perspectives suggest a degree of pragmatism in approaches to spatial modeling, where on the one hand, a) mechanistic models linking specific land use effects to specific biological responses tend to be overly simplistic, but that, b) models depicting a combination of common human-induced stressors, especially if designed in gradient surfaces, may explain much (albeit not all) about the ecological condition one might encounter on the ground.

2.3. Calculation

Building on this theoretical foundation and set of assumptions, this analysis uses the approach of combining the impact of condition at a site with a factor for distance decay to define a per pixel composite of overall landscape condition. Each input data layer (Table 1) is summarized to a 30 m grid and, where the land use feature occurs, given a **site impact score** that is greater than 0 and less than 1 (Table 1) reflecting presumed ecological stress or impact. These values were adapted here from those used by Brown and Vivas (2005) and further adapted by

Theobald, 2013. An alternative set of values could be used for a given application of this model approach, but for our purposes, these values suffice. Values close to 1.0 imply relatively little ecological impact from the land use feature. For example, a given pixel of 'recently logged' − historically cleared for timber, but recovering towards natural vegetation over recent decades, is given a 0.9 score for site impact as compared with irrigated agriculture (0.3) or high-density urban/industrial development (0.058). Certainly, there are some ecological values supported in these intensively used lands, but their condition is quite limited when compared with areas dominated by natural land cover.

For this model, the Euclidian distance for each input layer is calculated for the model extent with a distance extending away from each feature with and impact score < 1. The Euclidean distance was then rescaled using sigmoidal function (Krivoruchko and Butler, 2013):

$$f(d) = 1/(1 + \exp(-2*(d - d_s)/c))$$

*where d = *distance from the feature,* d_s = *distance intensity threshold,* c = *constant*

This represents a distance decay function, expressed as decreasing ecological impact with distance away from the mapped location of each feature as applied to the Euclidian Distance value described above.

Those features given a high decay score (d_s values approaching 1.0) result in a surface where the impact value dissipates within a relatively short distance. Those features given a low decay score (d values approaches d_s) create a surface where the per-pixel impact value dissipates more gradually with distance away from the impacting feature. Values for each layer will approach 1.0, symbolizing negligible impact, at the distance listed in the right-hand column of Table 1.

The combination of the two parameters is compounded in the formula:

$$f(d) = \prod_{1}^{n} \left(1/(1+\mathrm{EXP}(-2*(d-(d_s*0.5)/(d_s*0.25))))\right)^{(-0.25*\mathrm{LN(Si)}-8*10\text{-}16)}$$

*where d = *distance from the feature,* d_s = *distance intensity threshold,* S_i = *Site intensity threshold, Constants as a ratio (0.5, 0.25) are added to mark the midpoint and inflection points of the curves at ¼, ½, and ¾ points of the curve.*

The site impact value S_i is adapted as a modified power value and defines the y intercept of the function in which the closer the S_i get to 1 the less steep the decay function. Fig. 1 illustrates this effect using four of the model input layers, where S_i scores vary (0.05–0.723) and each to decay to negligible levels of impact at several distinct distances (500–3450 m). While in reality, this 30 m pixel model could appear on the graph as a stepped function, this illustration for values of 0–4000 m appears as a smooth line.

2.3.1. *Combining input layers*

9.7.2 The primary requirement of combining input layers for this model is our need for a 0.0–1.0 index, with the ability to compare regions which may have a different overall suite of stressors, but with a similar combination of site stressors, in either a spatial or temporal context. There were multiple sources of input layers for North America (Table 1). Some inputs such as "Local, neighborhood and connecting roads" were present in both the Canadian and U.S. sources, but not available for Mexico. Other types such as "Pipelines" are available for Canada and Mexico, but are considered proprietary in the U.S., and so they remain unavailable.

Similar spatial models to this model utilize two approaches for addressing overlapping stressors are commonly used for combining input layers. One model type uses a summation approach in which the impact score of each layer are (Halpern et al., 2008; Selkoe et al., 2009; Vorosmarty et al., 2010). Others merge stressors as a product in which the stressors are combined as multiples, or as ratios (Bogaert et al., 2002; Bogaert et al., 2005; Theobald, 2013). Similar to the Fuzzy Sum method (Bonham-Carter, 1984) we used a product based approach to minimize biases associated with the non-independence of spatial data. As such, we assume that the areas with multiple overlapping stressors have a higher degree of environmental stress than do areas with only one stressor (given the same site impact and distance effects). For example, at a pixel where there is "Secondary and connecting roads" adjacent to "Agriculture" the potential site impact would be equal to 0.0657 (*0.219 * 0.3*) in all regions, whereas in some regions with more detailed data the model might have an additional impact with the presence of "Local, neighborhood and connecting roads" and equal a pixel score of 0.0328 (*0.219 * 0.3 * 0.5*). An additive approach does not allow an easy comparison in the context of a 0.0–1.0 index where the final condition value would be predicated by the number of overall impacts within the broader landscape.

Given that this model is intended for applications at broader landscape (e.g., 100 km^2) areas and larger, the authors have confidence that scaling the 30 m pixel data to a 90 m pixel size was an adequate representation of model inputs. By querying a Table of Weights, per-pixel values for site impact apply to all pixels overlapping the individual pixel. Where more than one land-use feature type occurs in a given 90 m grid cell, the product score of all applicable features is applied to the grid cell (i.e., a multiplicative effect of **site impacts** − 0.05 and 0.9

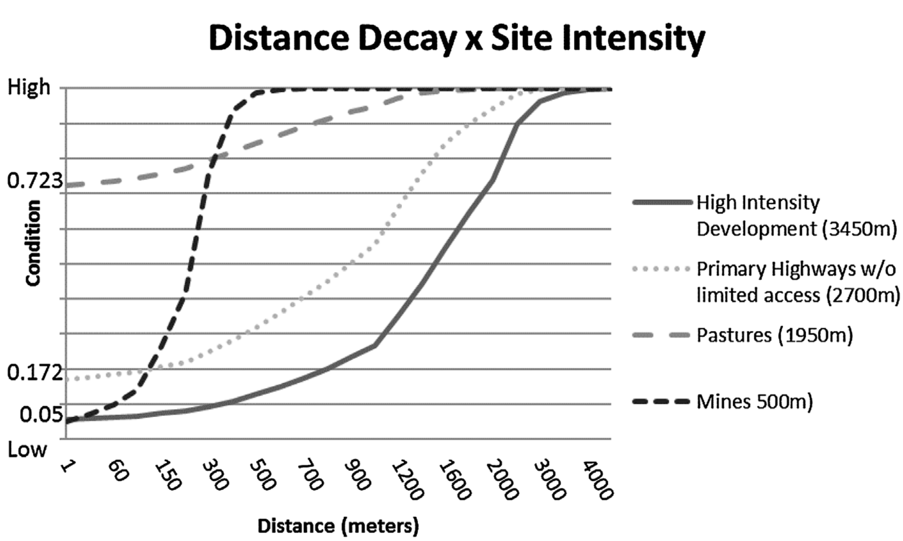

Fig. 1. Effect of site impact value (Si) on the slope of the distance decay function at 4 site intensities and variable rates of distance decay from 500 m (Mines) to 3450 m (High Intensity Development).

will equal 0.045). The distance decay formula utilizes per pixel Euclidian Distance and the Distance Decay formula to create a per-pixel 0.0–1.0 value for each land use feature layer.

2.3.2. Model calibration

In order to define where the distance decay (d_s) is null (i.e., approaching negligible ecological impact) for model calibration, field based estimates of ecological condition were gathered from Natural Heritage programs (NatureServe 2015). Since the 1970s, Natural Heritage programs have been conducting biodiversity inventories within each of the United States, and all data is summarized in a comprehensive national database (Stein et al., 2000). These inventories primarily aim to document the location and relative ecological condition for both at-risk species and representative natural community types. Each program employs botany, zoology, and community ecology experts from each jurisdiction. Systematic methods are used to document the surveyor, survey date, survey site, taxonomy, location, extent, and relative ecological condition of each "occurrence" of a given species or community type found on site.[1] While by no means complete, occurrence data provide several hundred thousand field-based observations of at-risk species and natural community types across temperate North America. Natural Heritage methods include criteria for expert evaluation ecological condition, considering occurrence size, condition, and landscape context.[2] Since a typical Natural Heritage field ecologists has observed other occurrences of a given species or community type, they are often well suited to apply criteria aiming to score ecological condition along a gradient from high to low. Additionally, some scoring results from expert workshops where multiple ecologists have reviewed field observations and agreed upon a relative score. The Element Occurrence Rank scores each occurrence along a 4-category scale from A–D. Occurrences with "A" and "B" ratings are considered of excellent or high ecological condition, respectively. The "C" rated occurrences are considered of fair condition, or with intermediate levels of degradation. Those occurrences scored as "D" are considered to be in poor ecological condition and are thought to be unlikely to persist without substantial management intervention.

A total of 56,709 occurrences of at-risk species, each having been observed since 1990 and scored as A-D for ecological condition, were used to calibrate distance decay values (D_s) for each input layer in the landscape condition model (Table 1). Occurrence data used in calibration represented 37 of the 48 conterminous United States. Aquatic species (fish and invertebrates), were not included in model calibration since the model aims to gauge upland and wetland ecological condition and does not factor in water pollution or diversion that could affect ecological condition of aquatic species.

The nearest distance between features from each model input layer (e.g., secondary and connecting roads) and each occurrence was calculated, and the results were plotted according to the A-D scores of the occurrences.

Fig. 2 depicts examples of the ranked distance relationship used to calibrate the landscape condition model for temperate North America. Mean plots (1-SD bars) depicting the relationship between the distance and scored occurrences were evaluated for statistical significance between A vs. B vs. C vs. D scores for all occurrences combined and for distinct taxonomic groups (mammals, birds, herptiles, invertebrates, plants). Two curves in Fig. 2 include the distance curves for agriculture and for low density urban development, with all species occurrence data combined. Two others curves in Fig. 2 indicate the relationships between local roads and plant occurrence, and between pastures and plant occurrences; respectively.

Statistically significant distinctions between B and C ranks were identified and the mean distance associated with B values was selected for use in the model of distance decay (D_s, Table 1). The mean distance of B rank was selected for its relatively high ecological condition, and we assume that, on average, they are located at a distance where effects of the land use feature approaches negligible levels.

2.3.3. Model validation

Following the model calibration and all model parameters were finalized, three independent sources of field-based measurements for ecological condition were used in model validation. By intersecting these geo-referenced observation data with the calibrated landscape condition model, the relative predictive performance of the model was evaluated.

A total of 14,362 Natural Heritage occurrences of at-risk species, all scored from A–D for ecological condition, were held aside from model calibration. Additionally, 38,723 of upland and wetland natural communities, all scored from A-C for ecological condition, were used as independent validation samples. Species occurrence data used in validation represented 37 states and community occurrences represented 30 states. All occurrences had been last observed since 1990. Since we cannot assume normal distributions of landscape condition scores relative to validation samples, a non-parametric Kruskal-Wallis statistic was generated to test for significant differences in landscape condition scores relative to occurrences ranked A, B, C, or D.

Second, 21,195 invasive annual grass, and 15,689 invasive forb field samples of vegetation sample plots, each including abundance of each plant species, were used for model validation. Vegetation plots samples were compiled nationwide to provide reference locations for vegetation mapping by the USA inter-agency LANDFIRE effort. Gathered sample data were evaluated by LANDFIRE to ensure that they a) were located with adequate precision for mapping with a 30 m grid resolution, b) reflected conditions from the past decade, and c) had sufficient floristic information to support their labeling to the LANDFIRE map legend. Therefore, sample plots tended to have information on plant species composition and relative abundance. For our purposes, the presence and relative abundance of invasive plants species, especially invasive annual grasses and forbs, were adequate for use in model evaluation. We expect to see increasing abundance of invasive plants with decreasing values from the landscape condition model. Sample plots with relative abundance values of invasive annual grasses were categorized into quartile classes, based on relative abundance of annual grasses; Quantile 1 (< = 1.5% cover), Quantile 2 (1.5–5%), Quantile 3 (5.1–15%), and Quantile 4 (15.1–100%). Invasive forbs categories were Quantile 1 (< = 1% cover), Quantile 2 (1–5%), Quantile 3 (5.1–20%), and Quantile 4 (20.1–100%). Validation sample plots, concentrated in the intermountain west states of the USA, were intersected with the calibrated landscape condition model, and a non-parametric Kruskal-Wallis was applied to test for significant differences in landscape condition scores relative to each quartile pair of abundance for invasive annual grasses and invasive forbs.

3. Results and discussion

3.1. Model validation

Table 2 provides a summary of validation results from Kruskal-Wallis tests for significant differences among occurrence ranks (A–D) or quantiles of invasive plant abundance relative to landscape condition values predicted by the spatial model.

Pairwise comparisons of occurrence ranks or invasive plant quantiles are summarized in each cell of the table, indicating TRUE for statistical significance (: '***' $p = 0.001$, '**' $p = 0.05$, '*'$p = 0.01$). These comparisons are summarized using different subsets of independent validation samples to indicate the degree to which the model could reliably predict condition relative to each group species, or community types. Sample size for each subset is included within each

[1] http://www.natureserve.org/conservation-tools/standards-methods/element-occurrence-data-standard.

[2] http://explorer.natureserve.org/eorankguide.htm.

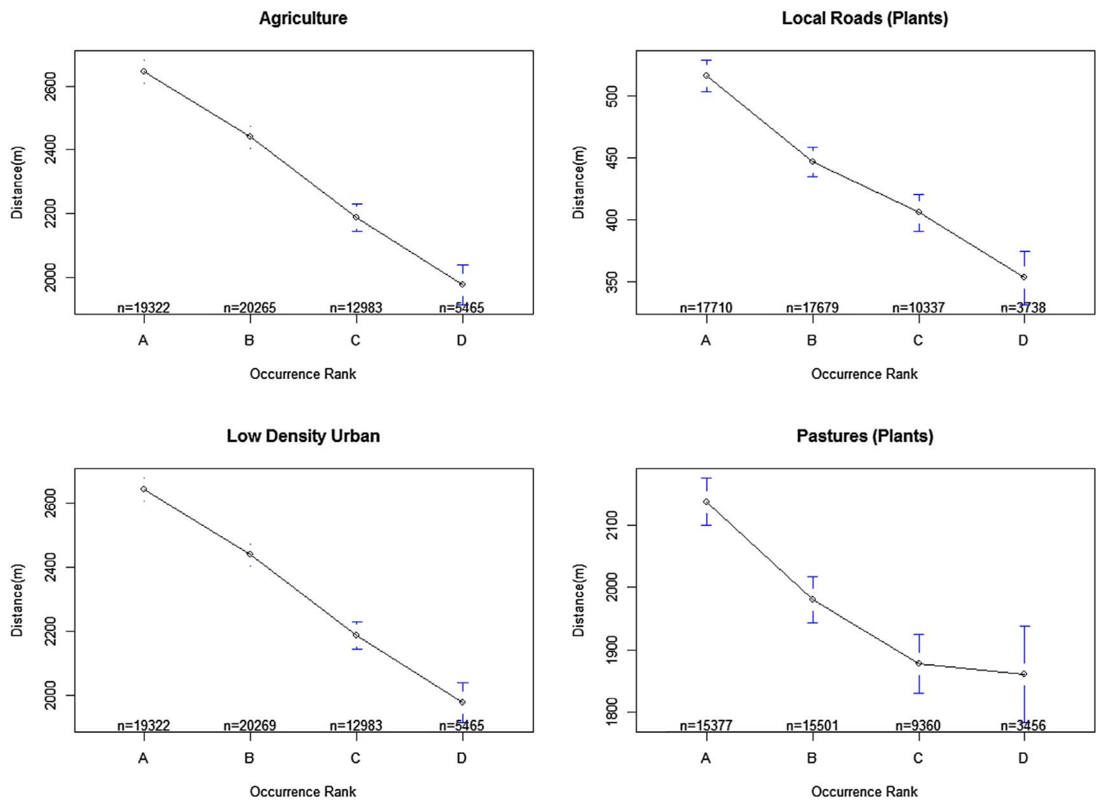

Fig. 2. Calibration of Distance Decay: Summary correspondence between Natural Heritage Occurrences Rank for condition as compared with distance from location of mapped features.

Table 2
Summary validation results by ranked groups. Values represent sample size followed by Kruskal-Wallis tests for significance. **Note LANDFIRE invasive plants grouped by quartiles.*

Element Occurrence and Invasive Species Rank Comparisons						
Species/Communities	A vs. B	A vs. C	A vs. D	B vs. C	B vs. D	C vs. D
All Species EOs (n = 14,262)	T***	T***	T***	T***	T***	T***
Amphibians/Reptiles (n = 1000)	F	F	T**	T**	T**	T**
Birds (n = 1500)	F	F	F	F	T**	T**
Terrestrial Invertebrates (n = 762)	T***	T***	T*	F	T*	T*
Mammals (n = 500)	F	F	F	F	F	F
Non-Vascular Plants (n = 500)	F	F	F	F	F	F
Plants (n = 10,000)	T***	T***	T***	T***	T***	T***
Wetland Communities (n = 9249)	T***	T***	NA	T***	NA	NA
Upland Communities (n = 29,362)	T***	T***	NA	T***	NA	NA
LANDFIRE − Invasive Plants	Q1 vs. Q2	Q1 vs. Q3	Q1 vs. Q4	Q2 vs. Q3	Q2 vs. Q4	Q3 vs. Q4
Invasive Annual Grass (n = 21,657)	T***	T***	T***	T***	T***	T***
Invasive-Forbs (n = 15,689)	T***	T***	T***	T***	T***	T***

Significance: '***' p = 0.001, '**' p = 0.05, '*'p = 0.01.

row of the table. Within Table 2, NA indicates circumstances where no D-ranked occurrences were available, so no tests for significant differences between occurrences with D-ranks vs. A–C ranks were possible.

Where all species occurrences are included together, differences between each occurrence rank are predicted with statistical significance, indicating that the landscape condition model may be able to differentiate landscapes that tend to support A vs. B. vs. C. vs. D occurrences of many at-risk species. This same result is repeated when considering plant occurrences. Sample sizes were much smaller for validation samples segmented into other subgroups of species. Results for terrestrial invertebrates show a decreasing trend between landscape condition score and occurrence rank, but the model appears to be less sensitive and is unable to distinguish A vs. B or B vs. C ranks, although C vs. D ranks were distinguished. For amphibians and reptiles, B vs. C and C vs. D ranks were distinguishable, but not A vs. B. With birds, C vs. D ranks were distinguished. No ranks could be reliably distinguished when using validation samples for mammals and for non-vascular plants. While interpretation of these results are complicated by small sample sizes, they generally reflect our expectation that this landscape condition model would be more sensitive and predictive for at-risk species groups that tend to occur in more local scales (e.g., plants) as compared with birds and mammals that tend to occupy larger areas and have more varied tolerances to a wider range of landscape stressors.

Analysis of validation samples for several thousand occurrences of natural communities, segmented into upland vs. wetland types and ranked A–C indicated statistically significant differences across all tested categories. Again, as indicated in Table 2, since no D ranked occurrences were available for validation, we could not determine whether or not C vs. D ranked occurrences of upland or wetland natural communities could be differentiated by landscape condition scores. On the whole, this result is quite encouraging in that a very common application of this form of landscape condition model is to provide an initial indication of quality and integrity for predominant upland and wetland natural communities across extensive regional landscapes.

Similar testing to distinguish predictive capabilities of the model for invasive annual grass and for invasive forbs indicated statistically significant distinctions in all but the first two quartile breaks (< 1.5% vs. 1.5–5%; and < 1% vs. 1–5%) for grasses and forbs, respectively. This suggests that, especially in the semi-arid intermountain western USA, trace levels of invasive grasses and forbs can appear to be ubiquitous across lower elevations, so distinguishing among low percentage classes is unlikely when using a spatial model of this nature. But conversely, where invasive plants are more abundant they are strongly tied to mapped infrastructure that shows strong correlations with land use

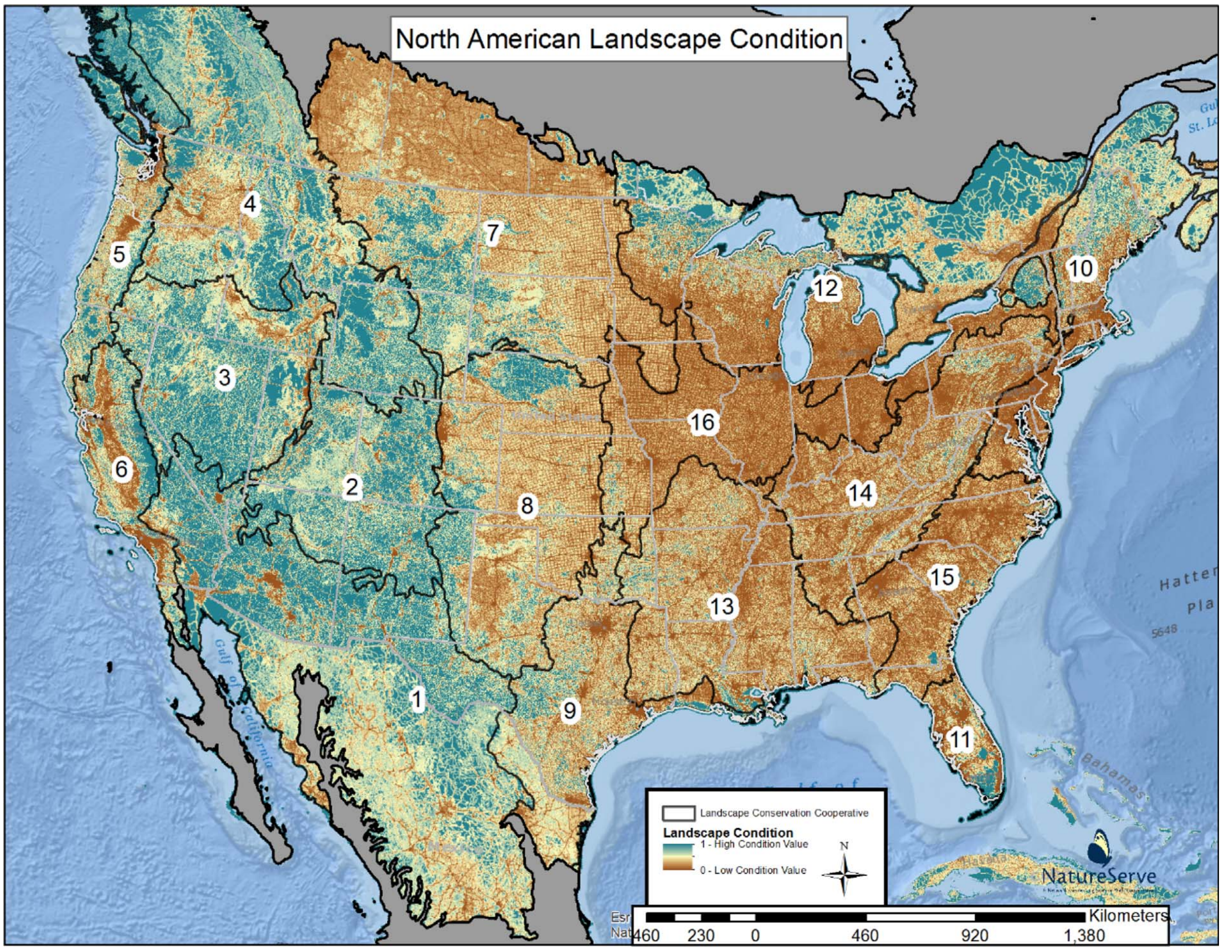

Fig. 3. Map of landscape condition with Landscape Conservation Cooperatives overlapping the conterminous Temperate North America.

history and the several common vectors for plant invasion (e.g., surface disturbance, intensive grazing, and seed transport with transportation tied to infrastructure).

3.2. Variation in landscape condition across LCCs

Landscape Conservation Cooperatives (LCCs) have become established across temperate North America as a mechanism for cross-jurisdiction collaboration in natural resource management and conservation. Included in Fig. 3 are boundaries of the 16 LCCs overlapping the conterminous USA.

Table 3 provides summary statistics for the landscape condition model within each LCC, including mean, standard deviation, median landscape condition and summarized ranked threshold. Using landscape condition thresholds derived from a 1 standard deviation range around the mean values associated with ranked (A–D) Natural Heritage occurrence data, the relative proportions of each LCC with landscape condition scores falling roughly within A-D ranked categories are included. In this instance, we used one standard deviation above the mean of the landscape condition value for the D occurrences to determine the C. vs. D threshold. For this analysis, the overall threshold value breaks are as follows; A-Rank > = 0.36, B-Rank > = 0.30, C-Rank > = 0.25, D-Rank < 0.25.

Striking patterns emerge where high proportions of each region fall at the extremes (i.e., most intact A-rankings vs. most impacted D-rankings) with much lower proportions falling within intermediate categories of B and C. LCCs throughout the west tend to include less intensively developed areas and so have higher average and median scores than those found across the east. The Desert, Southern Rockies, Great Basin, Great Northern, and North Pacific LCCs include extensive roadless areas, sparsely populated high mountains and desert, and relatively concentrated zones of agricultural and urban/industrial development; and as a result include much higher proportions scored in the A-Rank category. This contrasts with many LCCs in the east (e.g., South Atlantic) and across the Great Plains (e.g., Eastern Tallgrass Prairie and Big Rivers) where productive soils and extensive transportation infrastructure have resulted in much more fragmentation over several hundred years; and include 42.1%–93.7% of LCC land area in the D-ranked category.

3.3. Application to At-Risk status assessment

At-risk status assessments for biodiversity take many different forms. NatureServe methods factor together trends in the distribution, quality, and threat associated with species and natural communities in order to determine their relative status (Master et al., 2012). These methods parallel long-standing approaches for IUCN red listing of species (Mace et al., 2008) and more recently, for ecosystems (Keith et al., 2013). For the IUCN Red List of Ecosystems, a measurement of the proportional range wide extent of an ecosystem type that, within set timeframes, has been impacted by a) environmental degradation or b) disruption of biotic processes, gauge the relative risk of ecological collapse across the distribution of the type (Bland et al., 2016). While environmental degradation includes effects of physical alterations to

Table 3
Statistics for landscape condition summarized by Landscape Conservation Cooperative. *Note, for GIS processing purposes all values are represented as integers where the LCM x100.

LCC Number (see map)	LCC Name	Mean (x100)	Standard Dev. (x100)	Median (x100)	A-Rank (%)	B-Rank (%)	C-Rank (%)	D-Rank (%)
1	Desert	74.29	33.17	97	89.0%	1.5%	1.2%	8.3%
2	Southern Rockies	71.93	30.92	82	85.6%	2.6%	1.3%	10.5%
3	Great Basin	68.34	33.40	78	81.0%	2.5%	2.8%	13.7%
4	Great Northern	62.14	35.11	63	84.1%	2.1%	2.2%	11.6%
5	North Pacific	45.94	37.58	41	74.8%	2.1%	1.1%	22.0%
6	California	40.89	39.46	27	50.1%	2.5%	1.9%	45.5%
7	Plains and Prairie Potholes	35.15	33.78	23	30.8%	11.4%	11.6%	46.1%
8	Great Plains	32.90	33.10	20	32.8%	6.6%	6.5%	54.1%
9	Gulf Coast Prairie	32.36	33.49	17	45.3%	4.9%	3.8%	45.9%
10	North Atlantic	27.52	36.23	6	53.0%	2.6%	2.2%	42.1%
11	Peninsular Florida	26.34	35.23	7	27.6%	4.1%	3.0%	65.1%
12	Upper Midwest and Great Lakes	18.71	29.61	4	55.9%	1.7%	1.7%	40.6%
13	Gulf Coastal Plains and Ozarks	18.46	24.35	7	18.6%	4.2%	3.9%	73.3%
14	Appalachian	14.73	22.80	4	14.3%	3.3%	2.9%	79.5%
15	South Atlantic	11.51	19.59	3	9.8%	2.8%	2.6%	84.8%
16	Eastern Tallgrass Prairie and Big Rivers	7.49	12.92	3	3.3%	1.1%	1.8%	93.7%

geophysical settings, or effects of dynamic process alteration like fire or flooding regime, disruption of biotic processes may encompass many common effects of habitat fragmentation, such as disruption of species dispersal. In many instances, these effects may be inferred from spatial overlay of this landscape condition model. The D3 sub-criterion in IUCN approach suggests classifying disruption of biotic processes at three levels of severity, expressed in percentages (> 50%, > 70%, and > 90% ‘severity’ if applied to change since 1750) (Bland et al., 2016). Here we used landscape condition values that predicted C vs. D ranks occurrence scores from Natural Heritage inventories to approximate 50% and 90% severity measures, respectively.

Fig. 4 depicts results for one major vegetation type, North Central Interior Dry Mesic Oak Forest and Woodland (map source LANDFIRE.gov). In this region oak forests have been classified into several major types (Comer et al., 2003). This type covers over 42,000 km^2 where it dominates some of the more heavily populated portions of temperate North America. While there is considerable concern for ecological stressors to these woodlands, primarily from altered wildfire regimes, landscape conversion, and population pressures, the relative proportion of its distribution directly affected by landscape alteration is much more than for many other types in temperate North America. This is reflected by overlay scores with the landscape condition model, where more than 91% of the total extent of this type would score in D-ranked category (Rank Proportions: A = 4.3%; B = 4.4%; C = 0.75%, D = 90.5%). While other measures could suggest otherwise, based on this one measure of biotic disruption alone, this type would be categorized just over the threshold for “Critically Endangered” under the IUCN red list.

3.4. Considerations in model design and interpretation

This spatial modeling approach aims to utilize readily available data and knowledge to describe landscape conditions based upon a wide spectrum of stressors. Because no spatial model can account for all conditions one might encounter on the ground, this should be viewed as an initial indicator of those conditions; always subject to field verification and adaptation of the input parameters. More complex methods could be devised for combining spatial data layers than the ones depicted here, but our approach favored transparency, repeatability, and ease of application. Results of applying this modeling algorithm are more likely to vary based on the quality and quantity of input data layers (Table 1) than on model parameters. As noted above, the availability of certain data layers (e.g., a representation of grazing effects, certain invasive species, etc.), and the quality and completeness of such data, likely explain much about the relative predictive power of the spatial model. We anticipate that this same modeling approach could be applied at more local scales (e.g., states, ecoregions) with locally available data sets with increased predictive power.

Available data for model calibration and validation present another key challenge to application and refinement of this and related modeling approaches. In this instance, we have utilized two important sources of field-based biodiversity observations in the USA. We expect that calibration decisions we made with these data sets have sufficiently broad applicability to be considered for application elsewhere where equivalent field observation data are unavailable. However, we also acknowledge the limitations of these field observation data, as this application differs from the intended purpose for which the observations were originally collected.

Natural Heritage inventories are not directed towards a sampling of all species, but instead focus on a subset of species of conservation concern. So rather than the full spectrum of species occurring in a given region, model calibration was informed by species that tend to be most sensitive to human-induced alteration. Also, these data reflect an accumulation of field observations, the data are neither a census or a systematic sample of a given species or community type. While these reflect a systematic approach to documenting their location and condition, we presume that they also reflect the evolving perspectives of the field biologists and methods that have advanced since the 1990s. Additional factors are considered in occurrence ranking that may explain differences between predicted conditions and those encountered in the field. For example, some at-risk species may have been rated relatively high due to large sub-population size while landscape context has been compromised. This could be the case where population size is lagging indicator of condition, or their rating reflects viability requirements not addressed in the landscape condition model.

While this analysis focused solely on identifying threshold values for application across a continental scale as applied to the terrestrial biodiversity in Temperate North America, avenues for customizing of this model could consider region specific conditions, or variants based on major vegetation formations (Faber-Langendoen et al., 2014). For example, adjustments to distance decay parameters might be identified though analysis of subsets of Natural Heritage data spatially coincident with specific major ecosystem types, such as cool-temperate closed-canopy forests, or non-forested wetlands, across the eastern USA.

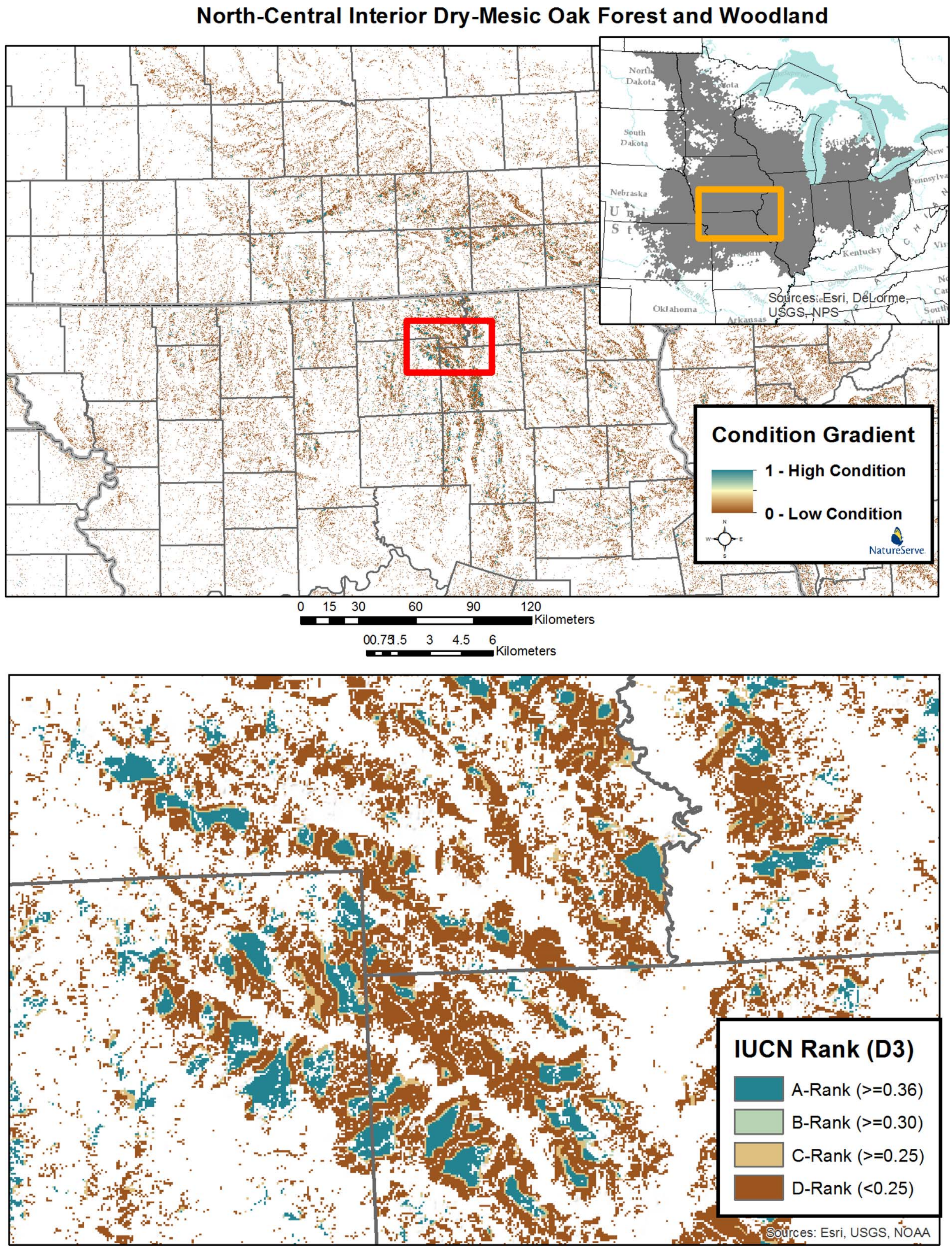

Fig. 4. Relative severity of biotic disruption across part of the distribution of North Central Interior Dry Mesic Oak Forest and Woodland. Maps depict the overall pattern of the land cover as intersected by the LCM score and categorization of LCM score to IUCN (D3) ranks.

4. Conclusions

Concerns exist in the application of threat models (Tulloch et al., 2015), where a threat model should not be used exclusively to determine conservation priorities. We fully agree, but an empirically-based analysis such as the Landscape Condition Model (LCM) offers a substantial contribution conservation priority-setting, in that it helps to identify locations along a gradient of condition that indicate the relative potential for successful conservation outcomes. The results for North Central Interior Dry Mesic Oak Forest and Woodland displayed in Fig. 4 illustrates one measure among several for documenting relative condition at a local site (Comer and Faber-Langendoen, 2013) or for rangewide conservation status of a given ecosystem type (Master et al., 2012, Bland et al., 2016). When used in conjunction with conservation planning software such as NatureServe Vista™[3]; or Marxan (Ball et al., 2009) the LCM can aid scenario-based planning processes by not only identifying areas of potential land-use impact, but can also provide a relative "cost surface" for site selection (Marxan) or for connectivity modeling with tools such as Circuitscape (McRae et al., 2008).

As part of a several comprehensive conservation planning efforts such as the Bureau of Land Management's Rapid Ecological Assessments (BLM REAs) (Comer et al., 2013), the LCM provided a crucial input for not only identifying where ecosystems and species are currently at risk. Additionally, the LCM was easily modified for future projections of landscape change using predictors such as Theobald (2010) prediction of landscape change from 1992 to 2030. Given that the LCM utilizes a product based summation, a simple subtractive analysis will identify where there is the greatest magnitude of change in the landscape.

The intent of the landscape condition model was to develop an easily modified, rapidly updateable approach that uses readily obtainable data that would not require specialized training for its use. With advancing knowledge and availability of new spatial data sets, users around the world may apply this modeling approach to characterize ecologically-relevant effects of land uses in a manner that may support both current status assessment and for monitoring change over time. As previously stated, this model is intended to be an easily implemented, and modified, tool. The tool has been developed as an ArcGIS V10.x Toolbox in Python scripting, and will be made available as a downloadable ToolBox via NatureServe's website.[4]

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