Landscape Ecol (2013) 28:1371–1385
DOI 10.1007/s10980-013-9888-7

RESEARCH ARTICLE

Ecosystem-level dynamics of soil-vegetation features, with implications for conserving a narrowly endemic reptile

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Received: 18 September 2012 / Accepted: 2 April 2013 / Published online: 17 April 2013

Abstract Narrow endemism presents challenges to species occurrence modeling particularly when the distribution of key local habitat features changes across space and time as a function of processes operating at larger scales. One need facing conservation in such settings is a better understanding of the biogeographic dynamics of the larger features that govern occurrence of critical local habitat. The Mescalero–Monahans shinnery sands region of western North America is a dynamic landscape where sand shinnery oak interacts with wind-driven sand to establish dune habitat. This ecosystem supports several narrowly endemic dune-dwelling species including the dunes sagebrush lizard. Using near-anniversary satellite and aerial imagery from 1986, 1998, and 2011, we integrated object-based image classification and statistical analysis to develop and validate a spatially explicit estimate of the sand shinnery oak ecosystem, including dynamics associated with its attrition and emergence, at high resolution throughout an 89,849-km^2 study area encompassing the range of the dunes sagebrush lizard. The spatial estimate of the distribution and extent of the sand shinnery oak soil-vegetation association validated reasonably well (overall accuracy = 0.79; sensitivity = 0.49; specificity = 0.91) and showed that the association declined 10.3 % in extent during the 25-year assessment window. The presence of sand shinnery oak, patch size, and patch isolation were dynamic across space and time; a regression model showed that smaller, isolated patches on the periphery of the system were more likely to be lost over time whereas larger, less isolated, and centrally distributed patches were more likely to persist or expand. This study details broadly applicable methods to accurately delineate landforms throughout large extents, and offers mapping tools specific to issues surrounding Mescalero–Monahans shinnery sands endemics that are readily amenable to testing, refinement, and application in efforts to focus sustainable landscape management including conservation of endemic species.

Keywords Dune-dwelling species · Dunes sagebrush lizard · Landscape context · Narrow endemics · Object-based image classification · Sand shinnery oak · Soil-vegetation dynamics · Sustainable landscape management

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Introduction

The southern high plains of western North America encompass a unique and dynamic landscape known as the Mescalero–Monahans shinnery sands ecosystem. In this system, eolian sand, or sand derived from wind-driven processes of erosion and deposition, interacts with sand shinnery oak (*Quercus havardii*), a drought-tolerant, clonal shrub that occurs in extensive stands, to form parabolic sand dunes throughout the sand shinnery oak plains (Muhs and Holliday 2001). Sand shinnery oak (semi-)stabilizes the dunes (Muhs and Holliday 2001); dunes are not present where the structural stability provided by sand shinnery oak does not occur. Within the dune system, wind activity establishes sand dune blow-outs, or bowl-shaped depressions largely devoid of vegetation. The dune fields and associated blow-outs exhibit a shifting dynamic (Fitzgerald et al. 1997) by which dunes emerge and recede across space and time as a function of historic landscape processes such as prevailing wind, sediment supply, and sand shinnery oak encroachment (Muhs and Holliday 2001), as well as contemporary processes such as landscape modification associated with human activity. The Mescalero–Monahans shinnery sands ecosystem, like dune systems in other parts of the world (Lamb et al. 2003), supports endemic species of conservation concern (see below). It is recognized that, given the dynamic nature of dune systems, conservation of sand dune endemics must look beyond the specific local habitat features that may be linked with species occurrence and focus broadly on the larger soil-vegetation association and the landscape processes that encompass the shifting dynamic of such features (Fitzgerald et al. 1997).

Seven lizard species occur throughout the dune fields and associated blow-outs in the Mescalero–Monahans shinnery sands ecosystem (Smolensky and Fitzgerald 2011). Additionally, at least 11 beetle and 3 grasshopper species are endemic to the system (Leavitt 2012). Among lizard species endemic to active sand dunes stabilized by sand shinnery oak within the Mescalero–Monahans shinnery sands ecosystem is the dunes sagebrush lizard (*Sceloporus arenicolus*; Degenhardt and Jones 1972; Fitzgerald et al. 1997; Fig. 1). The dunes sagebrush lizard has emerged as a focal species for conservation. It has the second-most restricted geographic distribution among North American lizards (Painter et al. 1999) and has received attention under the U.S. Endangered Species Act (USFWS 2010a, 2012). Conservation of other dune-dwelling endemics in this ecosystem ultimately is tied with conservation of the dunes sagebrush lizard. Throughout the world, "psammophilous" (sand-dwelling) lizards are characterized by endemism, convergent behavioral and morphological features across families (*i.e.*, burrowing behavior, toe fringes), and conservation concern (Lamb et al. 2003). Other examples include the federally threatened Coachella Valley fringe-toed lizard (*Uma inornata*) which has the most restricted distribution of all North American lizards (USFWS 2010b), and the sand dune lizard (*Liolaemus multimaculatus*) which is endemic to narrow portions of coastal Argentina (Kacoliris et al. 2009). Narrow endemism of the dunes sagebrush lizard coupled with the spatio-temporal dynamics of the specific local features to which its occurrence is tied (sand shinnery oak dune blow-outs) establish landscape process and context as guiding principles for its conservation (sensu Blevins and With 2011). The landscape context within which conservation intervention must be conceived and applied is the sand shinnery oak soil-vegetation association because key landforms comprising it, sand soil types and sand shinnery oak, constrain the shifting dynamic of sand shinnery oak dune blow-outs, thereby governing the spatio-temporal pattern of occurrence of the dunes sagebrush lizard. A need facing development of sustainable management strategies in the Mescalero–Monahans shinnery sands system is a better understanding of the landscape-level distribution and dynamics of the sand shinnery oak soil-vegetation association that determines occurrence of dune-dwelling endemics.

Image classification refers to the GIS-based process of converting spectral information in remotely sensed data to a finite set of classifications or themes that represent landscape features of interest. Remotely sensed data for image classification typically includes high-resolution imagery acquired by satellite or aircraft (Desclée et al. 2006; Stow et al. 2008). Image classification methods can be grouped into three categories: (1) visual interpretation, (2) pixel-based methods, and (3) object-based methods (Desclée et al. 2006). Visual interpretation relies on the analyst's experience to identify, interpret, delineate, and attribute features displayed in remotely sensed imagery. Visual interpretation can be highly accurate, but the

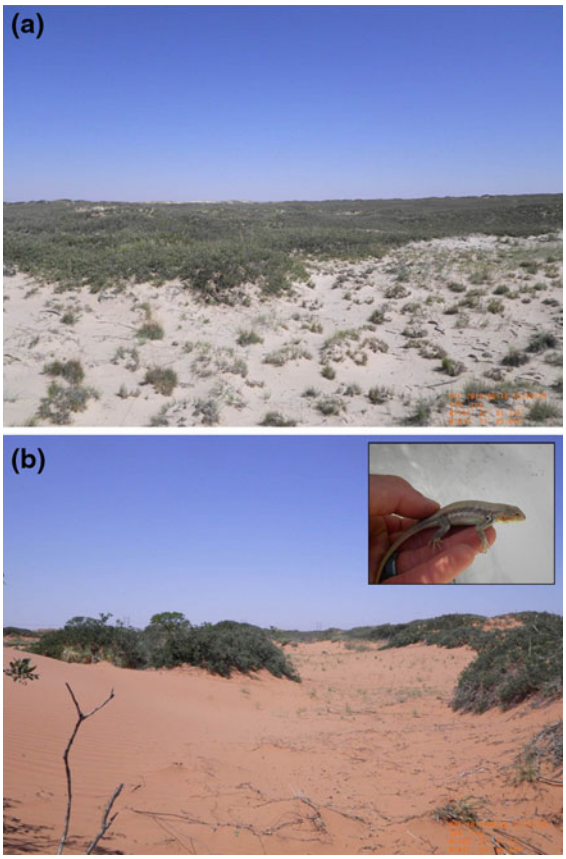

Fig. 1 The sand shinnery oak (*Quercus havardii*) soil-vegetation association (**a**) and an active sand dune stabilized by sand shinnery oak (**b**). The *inset* shows an adult female dunes sagebrush lizard (*Sceloporus arenicolus*). We developed spatial models of the sand shinnery oak soil-vegetation association (**a**) which encompasses preferred habitat of the dunes sagebrush lizard (**b**). Photos by N.P. Gould and D.J. Houchen

time required by the investigator to do the work can be cost-prohibitive at large spatial extents. Pixel-based methods assign all pixels in the image to particular classes or themes representing relevant landscape features. Pixel-based methods can also be accurate, but the practical utility of pixel-based methods is affected by landscape context. Specifically, pixel-based methods do not incorporate relationships among nearby pixels into the classification, spectrally similar features may be difficult to differentiate at the pixel level (i.e., mixed pixels), and there is often a mismatch between the size of the pixel and the spatial extent of relevant landscape features (Townshend et al. 2000; Desclée et al. 2006). Object-based methods classify images by grouping pixels into objects that capture contextual information among pixels and spatial attributes of the particular landscape feature. Object-based methods overcome many of the drawbacks associated with visual- and pixel-based methods (see Blaschke 2010). Object-based methods are more efficient and cost-effective than visual interpretation at large spatial extents. They typically provide better accuracy than pixel-based methods, and are more closely aligned with the spatial concept (Yan et al. 2006; Cleve et al. 2008; Myint et al. 2011).

Change detection is a specific application of image classification that aims to quantify how spatial attributes of classes or themes have changed through time. Change detection based on sequential high-resolution remotely sensed data has strong application in planning and managing landscapes for sustainability because it has the capacity to provide a spatially explicit assessment of the distribution, extent, and composition of important landscape features, and specifically how those features have changed through time (Walter 2004; Desclée et al. 2006; Madsen et al. 2011). Increasingly, change detection methods based on remotely sensed data are finding their way into conservation science as part of efforts to identify landscape features associated with biodiversity hotspots, the occurrence of special status species, or processes such as migration (sensu Stow et al. 2008; Maxwell et al. 2012). Applying an object-based approach (rather than visual- or pixel-based) in a conservation capacity is particularly appropriate when landscape change is manifested as multi-pixel objects, as are most human-related modifications, and when landscape contextual information is relevant in identifying target features.

This paper details application of an object-based image classification method for producing and validating a spatially explicit estimate of the sand shinnery oak soil-vegetation association throughout the range of a focal species, the dunes sagebrush lizard. Additionally, we integrated raster-based techniques in a GIS with statistical analysis to spatially depict landscape dynamics of the sand shinnery oak soil-vegetation association, and analyze factors thought to influence these dynamics. The sand shinnery oak soil-vegetation association constrains the past, present, and future distribution of the dunes sagebrush lizard and other endemic species (Leavitt 2012). Identifying this association, rather than delineating the present distribution of key local habitat features

(shinnery oak dune blow-outs), acknowledges the dynamic nature of dune field activity. Also, this approach better aligns applied spatial products with difficult-to-observe or latent processes that structure the occurrence of dune-dwelling endemics in the long-term such as annual resultant drift potential of wind-driven sand (Muhs and Holliday 2001) and patch occupancy dynamics. This assessment was based on near-anniversary remotely sensed data (imagery) from 1986, 1998, and 2011; a 25-year study window.

Study area

The study area was the 89,849-km^2 Monahan and Mescalero Sands region of western Texas and adjacent eastern New Mexico, USA. This area encompassed the entire distribution of the dunes sagebrush lizard (Fitzgerald et al. 2011). The study area occurred within a larger geologic formation known as the Permian Basin. Predominant land uses in the Basin included agriculture and development of energy resources. Agriculture mainly included production of peanuts, cotton, wheat, and livestock grazing. The Basin is an energy-rich area that produces >1 million barrels of oil per day, or about 17 % of U.S. annual oil production (UTPB 2012). The region was characterized by sand hills and dune blow-outs dominated by sand shinnery oak, honey mesquite (*Prosopis glandulosa*) and, to a lesser extent, sand sagebrush (*Artemisia filifolia*), yucca (*Yucca* spp.), grasses, and forbs (Peterson 1992).

Methods

Field data collection

In 2011, we visited 458 sample points randomly distributed throughout the study area at which we collected data on landscape attributes including species-level vegetation composition and density (Daubenmire 1959), the presence and type of human land use, and the presence of sand dunes, flats and dune blow-outs. Data were collected using Trimble Juno handheld GPS units (Trimble Navigation Ltd, Sunnyvale, CA) installed with ArcPad 10 (ESRI, Redlands, CA). Field data were partitioned for use in training of the object-based classifier ($n = 313$), and in final product validation ($n = 145$).

Training the object-based classifier, and soils-based refinement of the extent

Data from field sample points ($n = 313$) provided the basis for visual interpretation of high-resolution aerial imagery for manual delineation, or heads-up digitizing, of 242 training polygons that captured the sand shinnery oak soil-vegetation association. Training polygons "teach" object-based classifiers how to interpret remotely sensed imagery. We used National Agriculture Imagery Program (NAIP) 1-m Orthophotography county mosaic imagery for Texas (2010) and New Mexico (2011; http://gis.apfo.usda.gov/arcgis/services/) for training polygon development. To refine the extent throughout which the object-based classifier was implemented, we developed a mask based on soil type. The dunes sagebrush lizard occurs only throughout sand soil types. Using the Soil Survey Geographic Database (http://soils.usda.gov/survey/geography/ssurgo/), we refined the analysis extent to soil types in which the A horizon (top layer of soil) was sand-dominated (Fig. 2).

Object-based classification

We acquired cloud-free, near-anniversary (May–June) Landsat Thematic Mapper images (Landsat 5 TM; http://earthexplorer.usgs.gov) of the study area for the years 1986, 1998, and 2011. We used Feature Analyst 5.0 (Visual Learning Systems 2010) for image classification (Dzialak et al. 2011a, b; Madsen et al. 2011; Maxwell et al. 2012; Webb et al. 2012). Feature analyst uses hierarchical learning algorithms based on target feature characteristics such as color, size, shape, texture, and pattern to classify images by grouping pixels into objects that reflect contextual and spatial attributes of the particular landscape feature. We also acquired and incorporated a digital elevation model (DEM; http://seamless.usgs.gov/) into the classification process; elevation provides additional contextual information by which objects may be classified.

We conducted a supervised classification based on training polygons which delineated the sand shinnery oak soil-vegetation association (Fig. 2). Classification incorporated information from every pixel that fell within the mask based on soil type. The DEM and all seven spectral bands of Landsat 5 TM images (capturing visible, near-infrared, mid-infrared, and thermal wavelengths) were incorporated. Band three

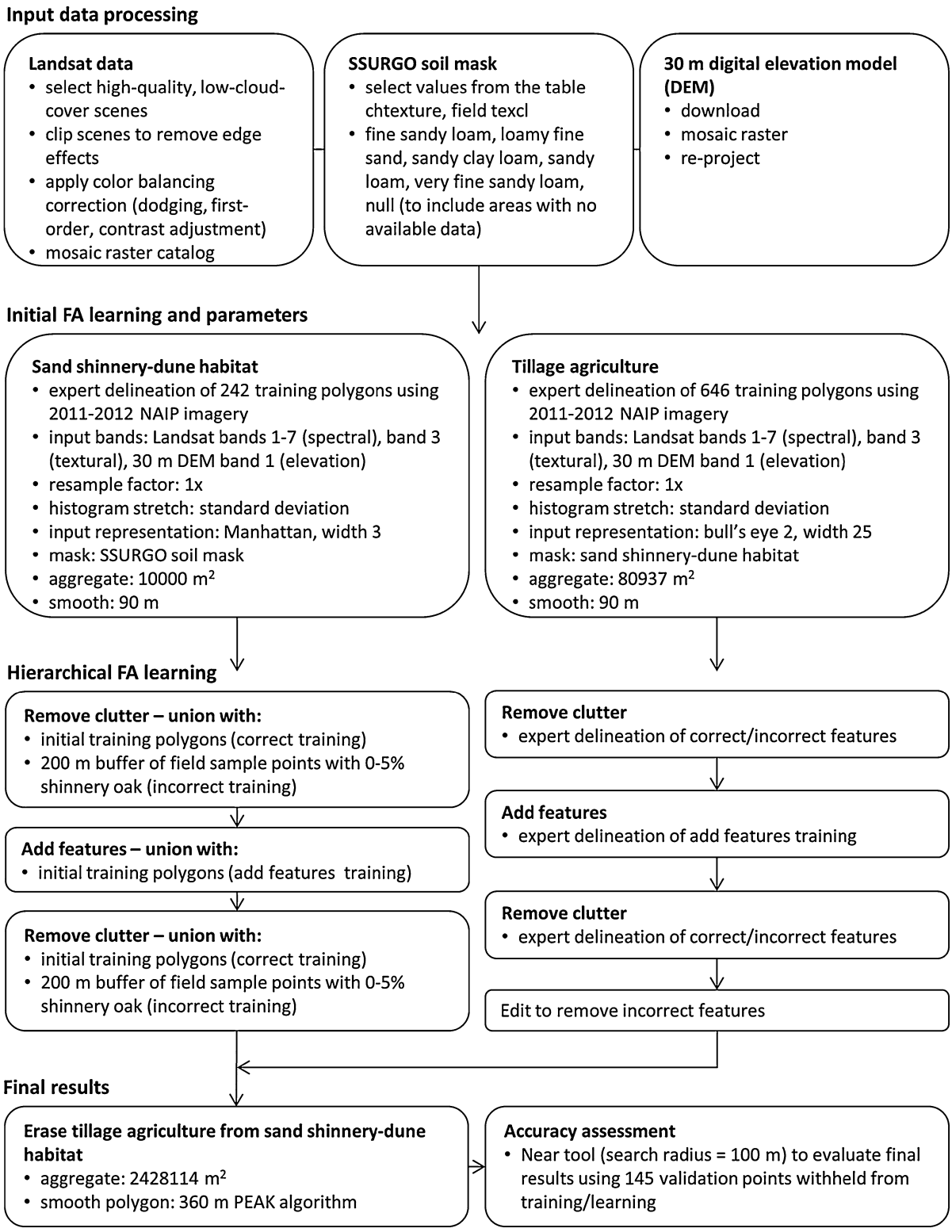

Fig. 2 Object-based image classification process flow

was re-incorporated singly into the analysis as a textural band. The output of the initial classification run, an estimate of the distribution and extent of the sand shinnery oak soil-vegetation association in 1986, 1998, and 2011, respectively, was visually inspected for systematic error. Inspection revealed systematic inclusion of tilled agricultural areas; specifically, irrigation pivots. Landforms such as tillage agriculture are considered unsuitable habitat (USFWS 2010a), and no evidence of the occurrence of dunes sagebrush lizards in such landforms appears in the literature.

To address systematic error, we heads-up digitized 646 irrigation pivots. We conducted a second supervised image classification based on these 646 training polygons depicting tillage agriculture. The output of the second classification run was an estimate of the distribution and extent of tillage agriculture in 1986, 1998, and 2011, respectively. This output was then applied as a mask by which all tillage agriculture was removed from the analysis extent. The final product of object-based image classification was an estimate of the distribution and extent of the sand shinnery oak soil-vegetation association in 1986, 1998, and 2011, respectively. A detailed representation of the process flow is provided (Fig. 2).

Map validation and spatio-temporal dynamics

To validate, we plotted 145 field sample points acquired within the sand shinnery oak soil-vegetation association on the newly generated object-based estimate of the sand shinnery oak soil-vegetation association for 2011. We developed a confusion matrix and tested agreement between validation locations and mapped features using metrics of overall accuracy, sensitivity, specificity, and the true skill statistic (Fielding and Bell 1997; Allouche et al. 2006). Overall accuracy is the proportion of correctly predicted locations. Sensitivity is the proportion of observed presences predicted as such; specificity is the proportion of observed absences predicted as such (Allouche et al. 2006). The true skill statistic, long known as Youden's index (Youden 1950), incorporates both sensitivity and specificity (sensitivity + specificity − 1) and ranges from −1 to 1 with 1 indicating a perfect score.

We integrated raster-based spatial applications in GIS and statistical modeling in SAS to explore factors associated with spatio-temporal dynamics of the sand shinnery oak soil-vegetation association (sensu Fitzgerald et al. 1997). We used Local\Combine and Reclassify tools in GIS to identify and depict locations characterized by loss (i.e., shrinkage or attrition), stability, emergence, or transience of the soil-vegetation association across the assessment window (1986–2011); the 2011 nominal reclassification bins of loss, stability, emergence, or transience comprised the response set in a multinomial regression model (Table 1). We addressed spatial autocorrelation in the response by including extra parameters, known as autocovariates, that capture spatial autocorrelation arising from processes related to ecology (i.e., conspecific attraction) or the analytical framework (i.e., size of the analytical unit relative to patch size; Dormann et al. 2007; Václavík et al. 2012). Typically, autocovariates are not intended for interpretation. In this analysis, spatial autocorrelation was an issue in two predominant ways. First, the response at a given cell (loss, stability, emergence, or transience) was strongly associated with values of neighboring cells (i.e., cells occurring within homogenous patches). Second, spatial autocorrelation was likely to be anisotropic, meaning that processes underpinning autocorrelation do not act the same way in all directions; prevailing wind relative to existing patches influences the geographic pattern of patch loss, emergence, or transience (Muhs and Holliday 2001). We developed two autocovariates to capture these respective sources of autocorrelation and included them in a model with five additional covariates depicting patch size, patch isolation, distance from the geographic center of the shinnery sands ecosystem, and Universal Transverse Mercator coordinates (easting and northing; Table 2). We converted the response raster to points wherein the value of each point was loss, stable, emergent, or transient, and we used Spatial Analyst\Extraction\Extract Values to Points to sample covariates (rasters). We estimated the model using the GLIMMIX procedure in SAS. We specified the conditional probability distribution of the data as multinomial and used a generalized logit (glogit) link function. We specified the response level "stable" as the reference level. We brought the results back into GIS using the following equation to spatially depict the general pattern of covariate influence on patch loss and emergence:

$$w(x) = \exp\left(\sum_{k=1}^{k} \beta_k x_k\right) \quad (1)$$

Table 1 Geographic information systems-based development of a nominal response set wherein the 2011 nominal reclassification was derived by combining pixel-based information on the presence or absence of the sand shinnery oak soil-vegetation association in 1986, 1998, and 2011, respectively

Sand shinnery oak soil-vegetation association comprising pixel				
1986	1998	2011	2011 Nominal reclassification	Number of pixels
No	No	No	Non-habitat	9,671,137
Yes	No	No	Loss	210,474
Yes	Yes	No	Loss	190,061
Yes	Yes	Yes	Stable	329,582
No	No	Yes	Emergent	166,152
No	Yes	Yes	Emergent	150,621
No	Yes	No	Transient	290,450
Yes	No	Yes	Transient	85,782

where $w(x)$ is an index of the relative probability of use as a function of covariates x_k ($k = 1 \ldots K$) with coefficients β estimated from conditional logistic regression.

Spatial prediction of loss was conducted within existing patches as defined by the 2011 estimate of the sand shinnery oak soil-vegetation association. Spatial prediction of emergence was conducted within the sand soils mask, as described above, excluding existing patches as defined by the 2011 estimate. All raster-based analysis and mapping was conducted at a resolution of 90 m.

Results

The 2011 map validated well with an overall accuracy of 0.79. Sensitivity was 0.49 indicating that error of omission was moderate. Specificity was 0.91 indicating that error of commission was minimal and that the model was strong in delineating non-sand shinnery oak areas. The true skill statistic, integrating sensitivity and specificity, was 0.40. Range-wide, there were 6,609.3 km^2 comprising the sand shinnery oak soil-vegetation association in 1986; 7,782.5 km^2 in 1998; and 5,930.4 km^2 in 2011 (Table 3; Fig. 3). The range-wide change in extent between 1986 and 2011 represents a 10.3 % decrease. It is notable that range- and state-wide extent increased between 1986 and 1998. Also notable is that, overall (1986–2011), there was a net decrease in extent in New Mexico, but a net increase in Texas (Table 3). Patch size mirrored trends in extent with a net decrease in patch size in New Mexico, a net increase in Texas, and an overall (1986–2011) decrease range-wide of 13.1 % (Table 3). Range-wide, patch isolation showed a net increase of 27.3 % during 1986-2011; however, increasing isolation in Texas was the driver of this trend with nearly no change in patch isolation in New Mexico (Table 3).

Spatial depiction of sand shinnery oak dynamics showed large extents characterized by stability throughout the C-shaped core of the distribution (Fig. 4). Reduction in extent was most apparent throughout western and northern portions of the distribution, whereas emergence was apparent to the east and throughout a large portion of the southern distribution in Texas. Transience was scattered throughout the assessment area (Fig. 4). The multinomial model revealed that loss of sand shinnery oak during 1986–2011 tended to occur throughout smaller, more isolated patches, and that were relatively distant from the geographic center of the system (Table 4). Emergence of new sand shinnery oak during that time tended to be associated with larger, less isolated existing patches that were relatively close to the geographic center of the system. The sand shinnery oak soil-vegetation association tended to be transient, or present inconsistently across time frames, among smaller, more isolated patches that were relatively close to the geographic center of the system (Table 4). Upon spatial depiction, geographic trends were apparent with loss of sand shinnery oak predicted to be more likely in northern and fringe portions of the distribution, and emergence showing a slight northeastern orientation and association with large existing patches in central portions of the system (Table 4; Fig. 5).

Discussion

For four decades, remotely sensed data have been used to monitor fundamental processes of landscape change (Foody et al. 2001). The past 10 years have seen rapid expansion in the application of image classification methods for land cover delineation (i.e., Tormos et al. 2012). Image analysis applied to landscape ecological questions, species conservation, or other sustainability problems has found prevalence more recently (Pasher

Table 2 Covariates calculated in a geographic information system (ArcMap 10) for inclusion in the autocovariate model of habitat change

Covariate	Description and development
Autocovariate 1	Capture spatial autocorrelation among neighboring grid cells. Using GIS (Spatial Analyst\Neighborhood\Focal Statistics), for each grid cell calculate the value that occurs most often among neighboring cells in a 3-cell × 3-cell window by specifying "majority" as the statistic type
Autocovariate 2	Capture anisotropic nature of habitat reduction and emergence across the landscape. This autocovariate was developed in GIS in three steps. First, a distance raster based on the 1986 estimate of habitat extent was calculated (Spatial Analyst\Distance\Euclidean Distance); the value of each cell was distance to the nearest cell that was comprised of habitat. Next, a direction raster based on the 1986 estimate of habitat extent was calculated (Spatial Analyst\Distance\Euclidean Direction); the value of each cell was the azimuth from the nearest cell that was comprised of habitat. To account for prevailing wind from the southwest (USFWS 2010), the direction raster was reclassified (Spatial Analyst\Reclass\Reclassify) such that cell values to the northeast of habitat patches received the highest value, with cell values progressively decreasing to the southwest. Then, we calculated a raster depicting exponential decay with distance using $\ln(d)\, e^{-d/100}$ where d is the cell value in the distance raster, $e \approx 2.718$ (base for natural logarithms), and 100 is a decay constant (Spatial Analyst\Map Algebra\Raster Calculator). Last, we multiplied the reclassified direction raster by the exponential decay raster producing a surface for which cell values were greatest near and to the northeast of habitat patches and lowest far and to the southwest of patches
Easting	Datum and projection were North American Datum of 1983 and Universal Transverse Mercator zone 13 north. In GIS, convert a generic raster to points (Conversion Tools\From Raster\Raster to Point), then add XY coordinates (Data Management Tools\Features\Add XY Coordinates). Convert points back to raster based on the X field (Conversion Tools\To Raster\Point to Raster). Cell values in the resulting surface are UTM east
Northing	Same as above, except use the Y field
Geographic center	Estimate the geographic center of the sand shinnery oak/dune-dominated system (Spatial Statistics Tools\Measuring Geographic Distributions\Mean center), then calculate a distance raster for which cell values are the distance from the geographic center. In SAS, natural log-transform the covariate (new = log (original + 0.1)) to model a decreasing magnitude of influence with increasing distance from that feature (adding 0.1 assures that a natural log transformation is not attempted on a cell with value =0)
Patch size	Raster-based surrogate for patch size estimated as the proportion of cells within a 50-km^2 moving window that is comprised of habitat based on the 1986 estimate. The size of the moving window was chosen as approximately twice the average patch size range-wide (Table 3). Low values indicate small patches encompassed by the moving window; high values indicate large patches encompassing the moving window (Spatial Analyst\Neighborhood\Focal Statistics specifying "sum" as the statistic type)
Patch isolation	Raster based surrogate for patch isolation estimated as the distance from the nearest habitat based on the 1986 habitat estimate. The resulting raster was inverted using Spatial Analyst\Map Algebra\Raster Calculator and the command ((input_raster–max-value) * −1) + min_value) resulting in more intuitive parameter estimates (*i.e.*, positively or negatively associated with isolation rather than with increasing distance values). As above, this covariate was natural log-transformed in SAS

A description of each covariate is provided in the right-hand column. All data (raster images) were calculated at a resolution of 90 m

et al. 2007; Barker and King 2012). The object-based approach we outlined provided a framework for integrating field data into the image classification process, conferring the capacity to develop expert-based rules for classification. As demonstrated in the sand shinnery oak system, this can enable reasonably accurate classification throughout large spatial extents wherein divergent landforms may exhibit spectral similarity across the geographic gradient (sensu Bock et al. 2005). The spatial extent need not be large, however, for the approach to have practical utility (Stow et al. 2008). The specific contribution of this work is that it offers an objectively derived delineation of soil-vegetation dynamics governing the occurrence of endemic species across an entire ecosystem (USFWS 2010a, 2012) that is readily amenable to replication, testing, refinement, and application in landscape planning. Specific applications may include targeting locations for reclamation, identifying areas important for connectivity, focusing stipulations on human activity, or isolating occurrence patterns of undesirable vegetation. We note that the spatial products we offer are not species distribution models *per se*. Rather, in keeping with the spirit of Fitzgerald

Table 3 Summary of the total extent, mean (SD) size of patches, and mean (SD) isolation (distance to the nearest patch) among patches of the sand shinnery oak soil-vegetation association

	Years		
	1986	1998	2011
Extent (km^2)			
Range-wide	6,609.3	7,782.5	5,930.4
New Mexico	5,150.2	5,180.5	3,927.5
Texas	1,459.1	2,602.0	2,002.9
Patch size (km^2)			
Range-wide	26.8 ± 110.0	26.3 ± 94.1	23.3 ± 71.3
New Mexico	34.3 ± 140.0	29.6 ± 115.4	26.9 ± 88.7
Texas	15.0 ± 28.6	21.5 ± 48.5	18.4 ± 36.3
Isolation (km)			
Range-wide	1.1 ± 2.3	1.2 ± 2.1	1.4 ± 3.3
New Mexico	1.2 ± 2.6	1.4 ± 2.4	1.2 ± 2.6
Texas	0.8 ± 1.2	0.8 ± 1.0	1.6 ± 4.1

We estimated 235, 281, and 247 patches range-wide in 1986, 1998, and 2011, respectively

et al. (1997), USFWS (2010a) wherein a static view of the distribution of dune-dwelling endemics is inappropriate, we depicted a soil-vegetation association that encompasses and constrains the spatio-temporal pattern of the specific local attributes, dune blow-outs and surrounding oak flats, with which the occurrence of species such as the dunes sagebrush lizard is strongly tied.

The geographic extent of the sand shinnery oak soil-vegetation association decreased 10.3 % between 1986 and 2011. This translates into a rate of 0.41 % annually. Patch size and total extent increased through time in portions of Texas but decreased in New Mexico. Patch isolation increased in Texas but remained stable in New Mexico. Prevailing wind and gradients in moisture and elevation establish an annual resultant drift potential in eastern and northeastern portions of the system (Muhs and Holliday 2001) which, in turn, influences the spatial distribution of sand shinnery oak as well as local features, such as dune blow-outs, nested hierarchically within the shinnery oak system. Long-term dynamics of the sand shinnery oak soil-vegetation association reflect ongoing ecological processes of wind, erosion, and sand shinnery oak encroachment; however, the predominant influence on the distribution and configuration of the association in the near-term is likely to be human activity (Leavitt and Fitzgerald 2010; Smolensky and Fitzgerald 2011). Human activity affects the spatial attributes of the association at the landscape-level primarily through influences on sand shinnery oak and soil properties (i.e., sediment supply). Shinnery oak is removed or suppressed for agriculture, livestock grazing, and infrastructure development (Peterson and Boyd 1998). While the decrease in the geographic extent of the sand shinnery oak soil-vegetation association reflects these influences, strong inference on the specific demographic effects of different human activities on endemics such as the dunes sagebrush lizard has yet to be developed (Painter et al. 1999; Smolensky and Fitzgerald 2011). Such inference is difficult in systems for which both ecological and human-related process driving changes in resource availability are dynamic. Prevailing wind, erosion, and sand shinnery oak encroachment will interact over time with anthropogenic processes such as landscape conversion for agriculture and subsequent reversion in some areas, infrastructure siting, and reclamation. Research in other human modified landscapes has shown that human activity can have a strong effect on ecological processes affecting population persistence (i.e., risk of mortality), but such activity may operate in fundamentally different directions depending on activity type. And, animal response to human activity can involve individual variation such that the effectiveness of conservation intervention based on average responses is diminished (Haggerty and Travis 2006; Berger 2007; Dzialak et al. 2011b).

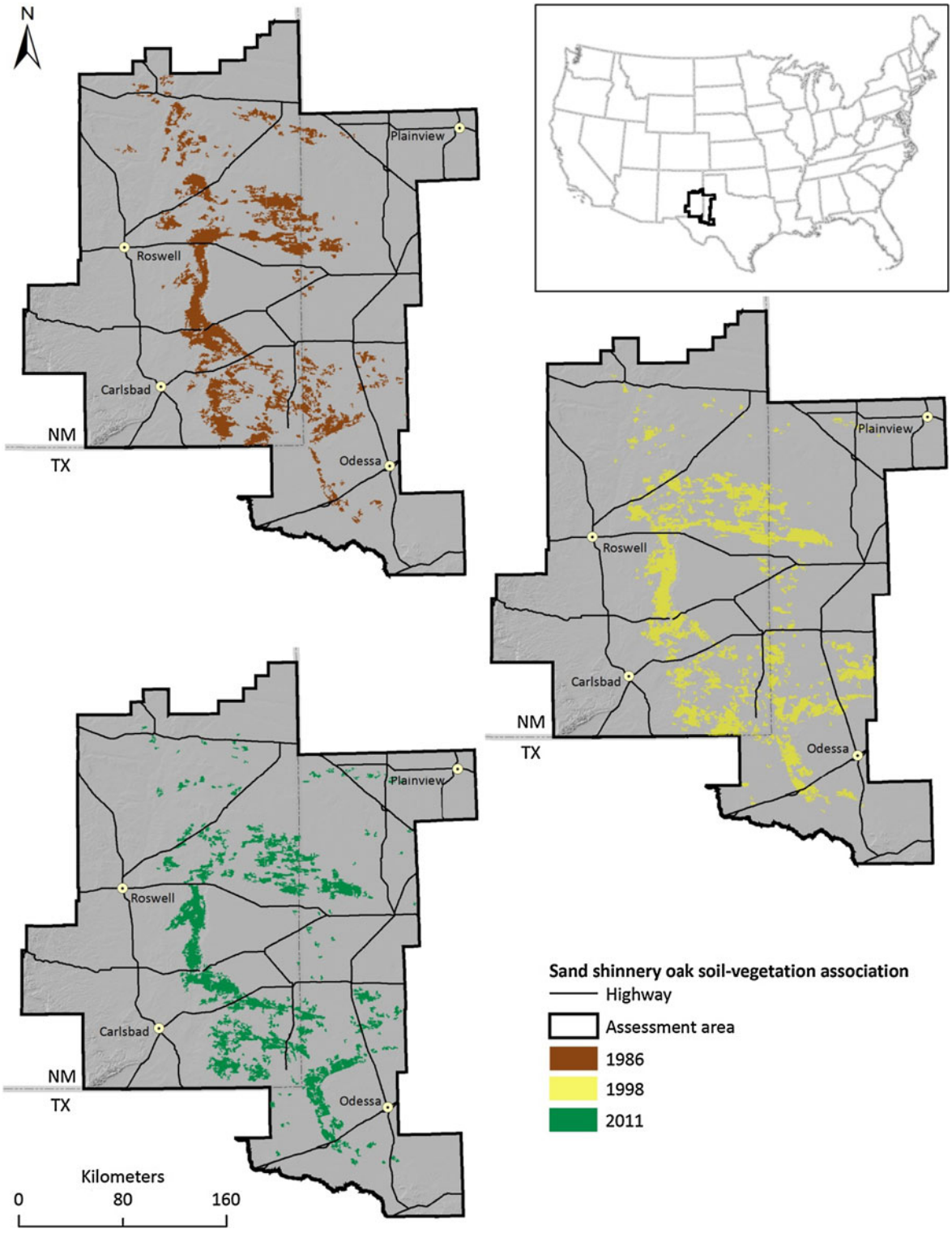

Fig. 3 Object-based assessment of the total extent of the sand shinnery oak soil-vegetation association in 1986 (6,609.3 km^2), 1998 (7,782.5 km^2), and 2011 (5,930.4 km^2)

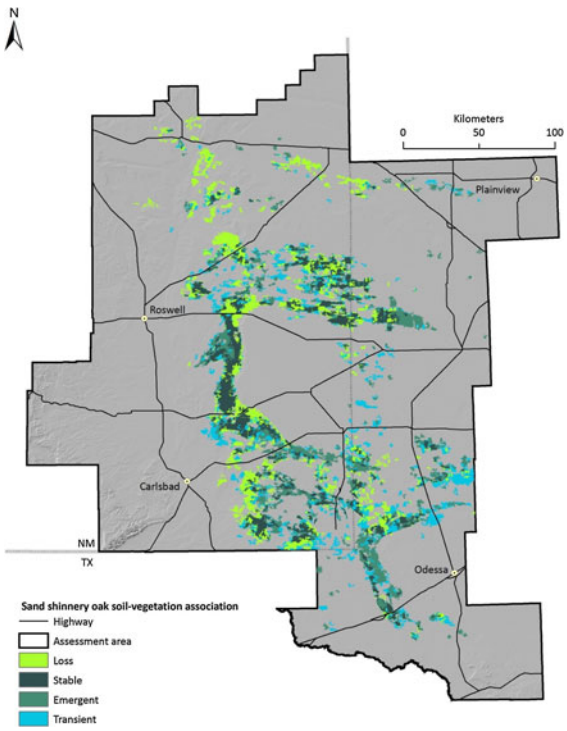

Fig. 4 Spatial and temporal dynamics of the sand shinnery oak soil-vegetation association including locations characterized by loss, stability, emergence, and transience across the 25-year assessment period (1986–2011)

We also note, relative to the interaction among landscape process, human activity, and dune-dwelling endemics, that sand shinnery oak occurs throughout privately—owned land in Texas, and throughout predominantly federally—managed land in New Mexico. Perhaps between-state differences in patch attributes partially reflect a more consolidated management approach throughout federal land in New Mexico versus locally varied land-use throughout private land in Texas. While speculative, the implication is that, given underlying geographic trends and the capacity of sand shinnery oak to regenerate and support dune establishment years after some types of treatment such as mechanical thinning and aerial application of herbicide (Pettit 1979; BLM 2011; USFWS 2012), the interplay between the more consolidated versus dispersed pattern of human activity in New Mexico and Texas, respectively, may establish a unique natural experiment in landscape management and species occurrence.

Sand shinnery oak has been lost in some areas, and likewise has emerged in other areas over the 25 years encompassed by the assessment. Losses were manifested largely as conversion for agriculture and infrastructure. Emergence reflected longer-term processes associated with prevailing wind, as well as changes in the location and extent of herbicide or mechanical treatment of sand shinnery oak (USFWS 2012). The specific ways in which the sand shinnery oak soil-vegetation association emerged and receded through time shed light on the observed model validation metrics. The model was highly specific (0.91) but only moderately sensitive (0.49). This means the model missed some sand shinnery oak, but was very good at predicting where sand shinnery oak did not occur. The model missed some sand shinnery oak probably because some areas were undergoing reversion to an oak-dominated landscape which, as a longer-term process, involved stages at which sand shinnery oak was similar spectrally to some non-oak areas. Areas converted to other land uses typically involved more distinct spectral, textural, and contextual signatures, thus the high proficiency at identifying

Table 4 Parameter estimates (β) and precision (SE) for the multinomial model of habitat loss, emergence, and transience

Parameter	β (SE) Loss	β (SE) Emergence	β (SE) Transience
Easting	−2.00E−5 (8.53E−6)	1.53E−4 (1.10E−6)	2.50E−5 (9.21E−6)
Easting (quadratic)	1.42E−7 (0.0)	1.18E−6 (0.0)	−2.00E−7 (0.0)
Northing	−3.10E−4 (2.70E−5)	−4.00E−4 (3.70E−5)	−5.40E−4 (2.90E−5)
Northing (quadratic)	4.26E−7 (0.0)	5.51E−7 (0.0)	7.34E−7 (0.0)
Geographic center	0.27 (0.07)	−0.70 (0.09)	−1.12 (0.07)
Patch size	−1.63 (0.05)	3.02 (0.08)	−0.91 (0.05)
Patch isolation	0.34 (0.04)	−1.78 (0.03)	1.18 (0.03)

Estimates represent the log-odds of a cell having the specified fate versus remaining stable as a function of covariates. Covariates are as in Table 1; $P < 0.001$ for all estimates

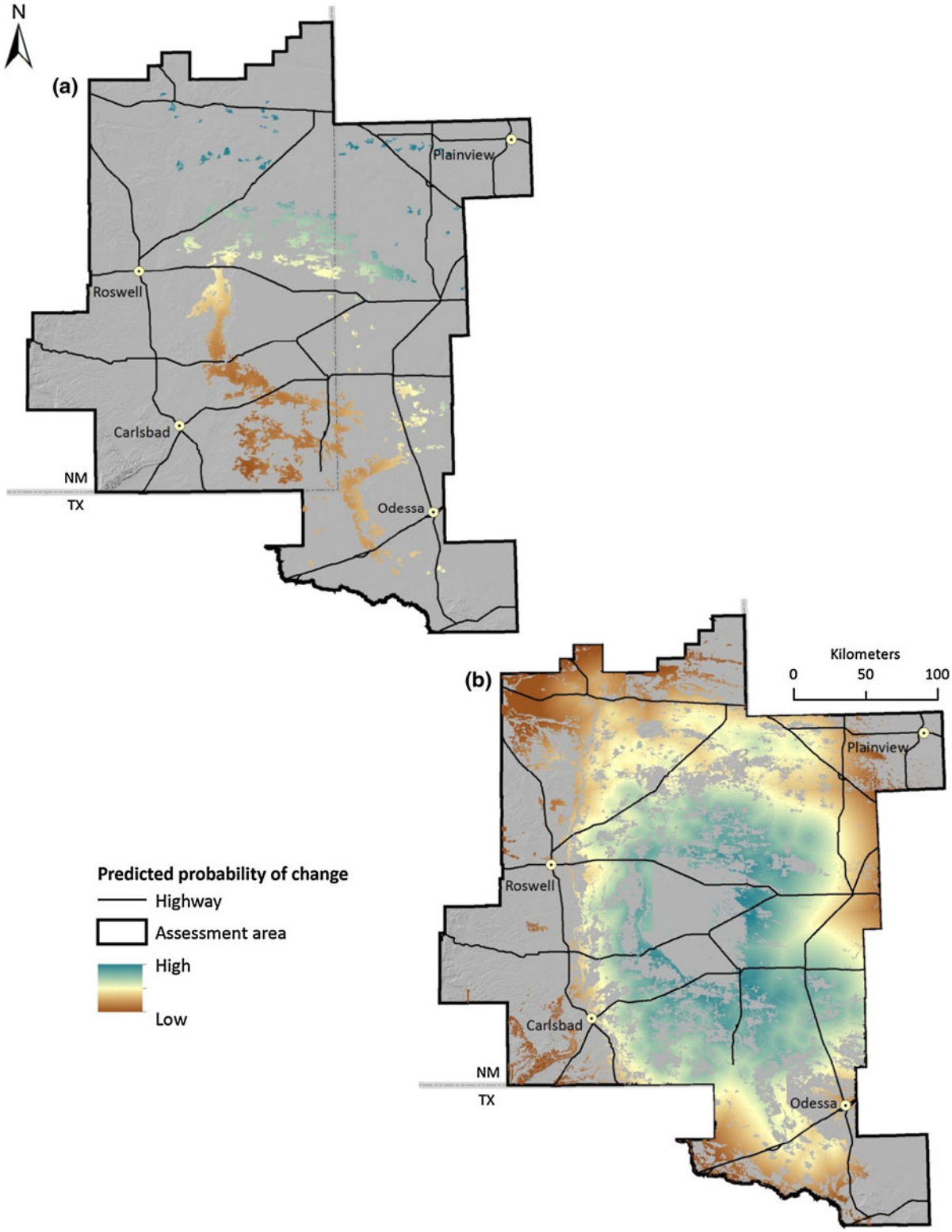

Fig. 5 Predicted loss (**a**) and emergence (**b**) of the sand shinnery oak soil-vegetation association based on results of the multinomial regression model

non-oak areas. Given that derived products of the object-based classification (i.e., Fig. 3), rather than spectral features of the imagery, were compared directly across the time series, it seems likely that the character of validation metrics (i.e., high specificity but only moderate sensitivity) was a function of the general approach applied in this ecosystem. In other words, we would expect validation to show high specificity but only moderate sensitivity, mediated by the subtleties of periodic variation in precipitation, regardless of image date. If this is indeed the case, in a comparison across any image dates, this approach would offer a robust assessment of sand shinnery oak loss via shorter-term processes of landscape conversion, yet offer an underestimate of the longer-term process of sand shinnery oak emergence. An implication of this is that, as of 2011, emergent habitat may be more extensive than this assessment indicates. Even if the location and spatial extent of longer-term processes associated with sand shinnery oak emergence varies across a time series, moderate sensitivity would be manageable, and the underestimate of emergence quantifiable, provided ongoing testing and refinement of the approach through time.

The multinomial model provided new information on difficult-to-observe processes affecting the spatio-temporal dynamics of the sand shinnery oak soil-vegetation such as patch size, isolation, and geographic gradient effects, which underpin latent processes associated with the occurrence of dune-dwelling species (Fitzgerald et al. 1997; USFWS 2010a). The model showed that, if a patch was small and isolated in 1986, it likely got smaller or was lost by 2011. If a patch was large, close to other patches, and centrally located 1986, it was likely to be larger in 2011. Landscape-level fragmentation in this system, then, would appear to have considerable potential to lead to patch isolation, shrinkage, and ultimately attrition. Patch contiguity is synonymous with long-term persistence or expansion (sensu Hanksi 1999). A relevant aim of future research would be to shed light on the interaction between human activity and the sand shinnery oak soil-vegetation association, and to link landscape-level changes in sand shinnery oak to population-level responses in the dunes sagebrush lizard (MacKenzie et al. 2002; Smolensky and Fitzgerald 2011). In the interim, one approach for conserving the shinnery oak system, given results of this assessment, would involve using the mapping tools developed herein to help guide, via spatial prioritization, implementation of programs (sensu Texas Comptroller of Public Accounts 2012) aimed at minimizing landscape-level fragmentation and retaining contiguity of existing patches. The 2011 map (Fig. 3) validated reasonably well and offers a reliable habitat management tool that is readily amenable to application in efforts to focus sustainable landscape planning. As GIS products (*i.e.*, raster data; Figs. 3, 4), the maps can be included in infrastructure siting, habitat avoidance, and reclamation processes by GIS users with agriculture, industry, the managing agencies, and other stakeholders.

Acknowledgments Pioneer Natural Resources Company funded this work. We thank C. Hedley, and two anonymous reviewers for guidance and helpful suggestions throughout this effort. This work was funded by a commercial source. Hayden-Wing Associates LLC provided in-kind contributions including materials associated with data collection and analysis such as GPS devices and statistical analysis software. Having received funding from these sources, our consultancy could reasonably be perceived as a financial competing interest.

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