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Estimating Resilience Across Landscapes

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ABSTRACT

Although ecological managers typically focus on managing local or regional landscapes, they often have little ability to control or predict many of the large-scale, long-term processes that drive changes within these landscapes. This lack of control has led some ecologists to argue that ecological management should aim to produce ecosystems that are resilient to change and surprise. Unfortunately, ecological resilience is difficult to measure or estimate in the landscapes people manage. In this paper, I extend system dynamics approaches to resilience and estimate resilience using complex landscape simulation models. I use this approach to evaluate cross-scale edge, a novel empirical method for estimating resilience based on landscape pattern. Cross-scale edge provides relatively robust estimates of resilience, suggesting that, with some further development, it could be used as a management tool to provide rough and rapid estimates of areas of resilience and vulnerability within a

landscape.

KEY WORDS: alternative stable states, cross-scale edge, Eglin Air Force Base, longleaf pine, oak, probabilistic resilience, spatial resilience.

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INTRODUCTION

Although ecological management activities generally occur at local or regional scales, many ecological changes are driven by forces that operate at larger scales. The difficulty, and perhaps impossibility, of controlling or predicting these forces suggests that attempts to tightly control and regulate the dynamics of ecosystems frequently fail (Holling and Meffe 1996). These failures have led researchers to propose that ecological management should focus on maintaining or producing ecosystems that are likely to persist in a desired state despite shocks and surprises. This approach can be called "managing for resilience."

Resilience is the ability of a set of mutually reinforcing structures and processes to persist, rather than shifting to being organized around another set of processes and structures (Holling 1973, Peterson et al. 1998, Gunderson 2000). Alternate sets of mutually reinforcing ecological processes and structures, i.e., alternative stable states, have been described in a wide variety of ecosystems, including rangelands, shallow lakes, and coral reefs (Scheffer et al. 2001). For example, reefs can be dominated by either corals or algae. Transitions between these alternative stable states are influenced by changes in the extent of predation on algae by fish and sea urchins, changes in nutrient concentrations, and the availability of new areas for growth (Knowlton 1992). Consequently, variation in the density of algae eaters, eutrophication, and disturbance events that create new areas for recruitment can all influence shifts between coral- and algae-dominated states (Hughes 1994).

Advocates for managing the resilience of ecosystems argue that management should focus on increasing the resilience of desired ecological states while decreasing the resilience of unwanted ecological states (Gunderson and Holling 2002). Ecologists have analyzed ecosystems by searching for processes that build or erode the resilience of particular ecological states. However, managing for ecological resilience is complicated by the difficulty of predicting or estimating resilience (Carpenter et al. 2001).

The resilience of a specific ecological organization is measured by the amount of change that a system can experience before it is forced to reorganize. However, measuring resilience by altering an ecosystem until it reorganizes is inappropriate if ecological reorganization is costly or irreversible. Because ecological reorganization is what most ecological management is attempting to avoid, measuring resilience in this fashion is often impractical, which has led to attempts to estimate resilience.

The resilience of ecological systems has been investigated by the mathematical analysis of dynamical system models (Holling 1973, Ludwig et al. 1997, Carpenter et al. 1999). This approach uses bifurcation analysis to discover the stable states of a dynamical system model (Rinaldi and Scheffer 2000). These are the system states toward which the system moves over time. If alternative stable states exist, then the alternative state that a system moves toward depends on the current state of the system. However, a large disturbance can shift the organization of a system from one alternative state to another. Such a change has been defined as exceeding the resilience of the abandoned state (Holling 1973). The resilience of the model system can be calculated by discovering how much change is required to cause the system to shift from one attractor to another. This approach is described in more detail in Appendix 1.

Although the dynamical system approach is useful, it can be applied only to relatively simple models. However, ecological managers often do not have simple models of their systems. Methods of estimating resilience that do not depend on the construction of system models would greatly facilitate the application of resilience-based management. In this paper, I extend the system dynamic approach to resilience to estimate resilience in stochastic landscape models. This method, which I term "probabilistic resilience," allows landscape simulation models to be used to estimate resilience. I use it to test cross-scale edge, a new empirical method of resilience estimation that uses landscape pattern to estimate the resilience of sites within that landscape.

METHODS

To estimate the resilience of sites within a landscape, it is necessary to define a set of alternative stable states that could potentially exist across that landscape (e.g., savanna or forest), and then define a map of the landscape in terms of those alternative states. I estimate the resilience of such states across a landscape using probabilistic resilience and cross-scale edge. Below I describe these methods, the situation to which I applied them, and how I tested the estimates of resilience produced by cross-scale edge.

Probabilistic resilience

System dynamics approaches have previously been used to analyze resilience in models that consist of sets of continuously varying variables. I extended this approach to analyze resilience in models that are described in terms of transitions among discrete states. The behavior of a discrete state can be assessed in terms of the probabilities of leaving that state and remaining in that state. The probability that a state will persist is a measure of its resilience. If the probability that a state will persist is less than the probability that it will not, then it is vulnerable to change. By mapping these probabilities across space, the areas of vulnerability and resilience in a landscape can be estimated (Fig. 1).

This probabilistic approach to resilience differs from system dynamics approaches in that it does not attempt to analyze the underlying dynamics of a system (Appendix 1). Instead, it uses observed or simulated state transitions to estimate resilience. Observations of the results of implementing a management policy across a set of experimental plots could be used to estimate the probability of state transition. However, such experiments are difficult to conduct in real management situations because of confounding covariation among ecological and management processes across space. In these situations, simulation models are often used to better understand the possible dynamics of a system. Although the probabilities of state transition may be directly calculated in simple stochastic models such as Markov models (Usher 1992), most ecological models will require Monte Carlo simulation to estimate probabilities. Monte Carlo simulation consists of running the model from the same initial conditions multiple times and statistically describing the model's behavior (Appendix 2). In terms of probabilistic resilience, running a model multiple times can be used to estimate the likelihood of state change; probability error can also be estimated. The standard error of an estimated probability can be estimated from a binomial distribution, i.e., SE = sqrt (estimated probability * (1 - estimated probability)/*n*-1). A model can be run repeatedly until the standard error of an estimate of the probability of transition falls below the desired threshold (e.g., 10, 5, 1%). In this paper, models were run until the error in resilience estimates fell below 5%.

Cross-scale edge estimation of resilience

The distribution of vegetation across a landscape represents the combined effects of a multitude of social, biotic, and abiotic forces. Many ecological processes, such as tree cutting, seed dispersal and fire spread, vary spatially and interact with landscape patterns. Consequently, existing landscape patterns implicitly contain information about the processes that produced them. Therefore, it may be possible to estimate the future effects of these processes based on the current configuration of the landscape. Work done by Milne et al. (1996) to estimate the location of ecotones suggests a simple method for estimating landscape resilience. Ecotones divide systems structured by one set of mutually reinforcing processes from those structured by another. Ecotones result from changes in processes that vary across a landscape. Because ecotones are places that are poised between alternate ecological states, ecotones should be the first areas of a landscape to respond to changes in the processes structuring that landscape (Milne et al. 1996). In terms of resilience, an ecotone can be thought of as the edge that separates regions that are dominated by two alternative stable states. From this perspective, ecotones are areas of low resilience, where small changes can cause a site to shift from one state to another. Although the definition of regions that appear to be ecotones depends on the scale at which the landscape is examined, percolation theory (Stauffer and Aharony 1994) can be used to define ecotones in a way that is independent of the scale of observation.

Percolation theory describes how a landscape's connectivity undergoes an abrupt transition from unconnected to connected as the density of sites in the landscape is gradually increased. This transition occurs at a density that depends on the specific geometry of the connections among sites. On the type of two-dimensional matrix seen in Fig. 2, a site can be connected either to its four horizontal and vertical neighbors (the von Neumann neighborhood) or to its eight horizontal, diagonal, and vertical neighbors (the Moore neighborhood). The percolation threshold, which is the density of states at which states become aggregated into patches, is a density of 0.593 for the four-cell von Neumann neighborhood and 0.407 for the more connected eight-cell Moore neighborhood (Stauffer and Aharony 1994). Milne et al (1996) suggested that ecotones can be usefully defined by the areas whose density of sites falls in between these two types of edge (i.e., $0.407 < \text{density} < 0.593$). I used this approach to define sites that exist on the edge that separates two alternative states.

On any given landscape, the density of a state on that landscape depends on the spatial scale at which the landscape is being measured, because density is a measure that depends on area. Varying the size of the area being analyzed will change its density if the pattern varies across scale. For a particular scale (defined by the length L), it is possible to determine whether a specific site qualifies as an edge by looking at the density of sites within a window of area L^2. If the density of sites within this window is within the ecotone range (i.e., its density falls between 0.407 and 0.593), then the site can be considered to be an edge site (Fig. 3).

To apply this approach to a landscape, it is necessary to identify two alternative states that are distributed across the landscape and remap the landscape in terms of those two alternative states (e.g., forest and savanna). The edge between the two states identified defines an ecotone at each scale of observation. By moving the window across the landscape, the status of an entire landscape can be assessed, and, by varying L, it is possible to assess the location of edge at different spatial scales (Appendix 2).

Case study: Eglin Air Force Base, Florida

I compared the cross-scale edge method of estimating resilience to probabilistic estimates of resilience using a simulation model of northern Florida forest dynamics. I tested cross-scale edge using the landscapes produced by this model, because it allows the robustness of the predictions from cross-scale edge to be tested against a set of plausible landscape changes rather than against a single specific history. I used the model of northern Florida because it exhibits alternate stable states. Furthermore, because this model was developed to guide management of a regional landscape, it is representative of situations in which managers would want to assess resilience across a landscape. This landscape simulation model is similar to many other models of regional ecosystems (Sklar and Costanza 1991, Walters et al. 1992, Sklar et al. 2001). Below, I outline the ecology or northern Florida forests and the structure of the simulation model.

The forests of northeast Florida can exist in two alternative states: pyrogenic longleaf pine (*Pinus palustris*) savanna or mesic oak (*Quercus* spp.) forest. The transition between these alternative ecological organizations is regulated by fire. The ground vegetation in these forests burns frequently, and because longleaf pine and oak have quite different responses to and effects on fire, fire mediates the competitive relationships between these two vegetation types (Heyward 1939, Rebertus et al. 1989). In the case of longleaf pine, both young and mature longleaf pines can survive ground fires. Additionally, mature longleaf pines also shed needles that provide good fuel for ground fires. In contrast, young oaks are intolerant of fire, although mature oaks shed leaves that suppress the build-up of good fuel for ground fires. Thus, fire suppression in oak stands encourages the further growth of young oaks. Without fire, oaks grow up beneath longleaf pine and eventually replace it. However, regular fires suppress oak growth and allow longleaf pine to thrive, which in turn permits more fuel to accumulate in stands of pine and encourages more fires, thus further suppressing hardwoods and encouraging the growth of pine (Glitzenstein et al. 1995).

The simulation model was developed to analyze the ecological management of Eglin Air Force Base, which covers an area of about 1900 km^2 in northwestern Florida (Fig. 4). Eglin Air Force Base contains about 1500 km^2 of longleaf pine forest, the largest remaining area of an ecosystem type that formerly covered much of the southeast United States (University of Florida et al. 1993). During the past two centuries, human activities such as logging, agriculture, and fire suppression have reduced the area covered by longleaf pine forest to less than 5% of its former range. The land managers at Eglin Air Force Base wanted to expand the area and quality of the longleaf pine forest on the base (Hardesty et al. 2000).

The simulation model maintains a map of the forest vegetation on the central watersheds of Eglin Air Force Base, an area measuring approximately 25 km x 25 km. The model also includes a map of the time that has elapsed since a site last burned, which is indicative of the amount of available ground fuel. This landscape is represented as a matrix of sites, each of which is 60 m on edge. This resolution was chosen for two reasons. First, it is a reasonable scale on which to develop management alternatives because it displays enough heterogeneity for management without an overwhelming amount of detail (University of Florida et al. 1993). Second, tree size appears to have most of its variation at scales of less than 28 m (Platt and Rathburn 1993), making 60 m an ecologically reasonable scale to use when representing a portion of forest. The model operates at yearly time steps.

In the simulation model, fires are ignited every year. These fires can be either wildfires or prescribed fires ignited by managers who have decided to burn a particular area. The effectiveness of prescribed fire on a site within a burned area depends on the vegetation type and the amount of time that has elapsed since that site burned previously. Larger prescribed fires, which use aerial ignition, are more variable in their effects than smaller prescribed fires, which are ignited from the ground. Wildfires are ignited by lightning, and the way the fire spreads from the ignition point(s) depends on the time since the last fire and the vegetation type of the surrounding sites. For example, most burned areas contain remnant patches of unburnt vegetation, and the spread of fire can be impeded by roads and by older, less combustible vegetation. Vegetation change is controlled by a set of rules based on succession, fire frequency, and seed dispersal. Further details of this model are described elsewhere (Peterson 1999). An example of the type of landscape dynamics produced by the model is shown in Appendix 2.

Estimating resilience and comparison

To assess the resilience of this system, I defined longleaf pine-dominated savanna and hardwood-dominated mesic forest as two alternative states of the Eglin landscape (Fig. 5) and used cross-scale edge to estimate zones of vulnerability and resilience on the current landscape. I assumed that all edge sites were vulnerable to conversion to hardwoods. Cross-scale edge was calculated using window sizes that ranged from three to 51 cells, which is equivalent to scales of 180–3060 m. These sizes were chosen so that the window was always less than one-eighth of the total landscape size. The largest window size of one-eighth of the total area was chosen to be large, but not so large as to have significant edge effects, which I defined as less than one-fifth of the total area. These ranges were reasonable estimates of the spatial scale of forest fires and fire management at Eglin Air Force Base.

I applied the probabilitic approach to estimating the resilience of states across a landscape for three alternative management strategies over 50 yr. I compared the cross-scale edge estimates of resilience to the landscape change produced by these different management schemes, because, for cross-scale edge to provide a good estimate of resilience, its performance should be robust to variation in the forces modifying the ecosystem. These particular management alternatives were chosen because they represent a broad range of future conditions and they are actual management alternatives that have been considered by land managers at Eglin Air Force Base. Eglin's ecological managers chose the period of 50 yr as a reasonable duration to evaluate management policies, because trees mature over decades. Monte Carlo simulations were run until error in the classification of the landscape was less than 5%.

The three alternative management strategies considered were wildfire, rotation prescribed fire, and responsive prescribed fire. The wildfire management strategy simulates what would happen if fires were no longer suppressed at Eglin. The rotation and responsive burning strategies use prescribed fire to manage the Eglin landscape; both of them apply a given number of prescribed fires each year in a different pattern. Rotation burning is a common method of using prescribed fire in which a region is divided into units, each of which is burned at a given frequency. The responsive strategy burns areas that contain relatively high proportions of longleaf pine, rather than burning all areas at an equal frequency. By not burning areas that contain only small amounts of longleaf pine and are therefore difficult to burn, this strategy is able to burn areas containing large amounts of longleaf pine more frequently than with the rotation strategy. The details of these management strategies are available elsewhere (Peterson 1999).

Testing cross-scale edge predictions

The landscape resilience predicted by cross-scale edge was evaluated by comparing it with the probabilistic estimates of resilience obtained from the three different management strategies. The ability of cross-scale edge to estimate resilience is based on the proposition that landscape pattern embodies ecological driving forces; if these driving forces change, the ability of landscape pattern to predict future change will degrade. For example, if a region of old-growth forest is opened to helicopter logging, its disturbance regime will change, and sites that would have been resilient under the old regime may become vulnerable. However, even when ecological driving forces change, they will still be acting on the historical landscape, and, as a result, the areas of the landscape that are poised between alternative states can be expected to be more vulnerable to such changes.

The ecological forces produced by each of the three fire management strategies provide different degrees of continuity with past ecological processes. Because the current landscape has been produced by a regime of suppressed wildfire, the wildfire management strategy has the most continuity with the past. Both of the prescribed fire policies represent large departures from previous landscape dynamics. The rotation strategy burns the entire landscape, whereas the responsive strategy preferentially burns some areas while ignoring others. Both strategies apply fire to the landscape within management-defined burn areas; the responsive strategy applies fire more frequently to areas dominated by longleaf pine than to hardwood-dominated areas, whereas the rotation strategy applies the same frequency of fire to all areas.

I used three measures to evaluate the predictive success of cross-scale edge. The first measure was overall predictive success. This measure revealed how well the cross-scale edge method classified the observed future landscape. This calculation compared the future landscape to the predictions from cross-scale edge that sites classified as edge would convert to hardwood, that sites classified as hardwood would persist as hardwood, and that sites classified as longleaf pine would persist as longleaf pine. The second measure was how well the areas predicted by cross-scale edge were able to transition between states. Because edge sites are expected to remain or convert to hardwood, this measure is the proportion of future sites within the edge area that actually are hardwood. This measure assesses how much of the overall success of edge prediction is due to accurately segmenting the landscape into two states vs. predicting what happens in the edge itself. The third measure was how accurately cross-scale edge predicted the transition from longleaf pine to hardwood, which is the transition that managers are primarily concerned with predicting. From the perspective of managers, unpredicted change from pine- to hardwood-dominated forest is a negative surprise, whereas unpredicted change from hardwood to pine is a positive surprise. If managers wish to avoid negative surprises, then a technique that performs well according to this measure is valuable.

Along with an evaluation of cross-scale edge, I also evaluated the success of predictions at each individual scale (window size - *L*). I tested the prediction success of edge at each scale, as well the cumulative prediction success of each edge up to and including that scale, to determine how the predictive quality of cross-scale edge changed with the range of scales used. This approach allowed me to assess which components of cross-scale edge contributed the most to successful prediction in each case examined, and to determine whether, at least in the case of longleaf pine in northern Florida, the range of scales I had selected was adequate for predicting transitions among states.

RESULTS

Below, I present the results of my probabilistic and cross-scale edge estimations of resilience and compare the results of the simpler cross-scale method to the dynamics produced by simulation models.

Probabilistic resilience

The resilience of sites across the landscape varies greatly depending on the fire management strategy that it is likely to experience (Fig. 6). The wildfire management strategy maintains the large-scale pattern of the landscape but makes the edges of longleaf areas vulnerable to change. Wildfire tends to segment the landscape into large areas of resilient sites. Larger patches of pine are more resilient than smaller patches, and smaller patches are more vulnerable to changes around their edges. Isolated patches of hardwood within large patches of longleaf pine are also vulnerable. The rotation fire management strategy produces a landscape that is quite resilient compared to either the wildfire or the responsive fire management strategy. In addition, it produces a landscape in which sites in both the desired longleaf state and the unwanted hardwood state are resilient. Finally, the responsive strategy changes the landscape pattern significantly. It produces a landscape in which many hardwood sites are vulnerable to change but most longleaf pine sites are resilient. Because the responsive strategy chooses to burn some areas more frequently than others, areas of longleaf pine surrounded by or adjacent to large areas of hardwood are not burned and are vulnerable to conversion to hardwood. However, the increased burning of other regions makes most hardwood sites vulnerable to conversion to longleaf pine.

Cross-scale edge

The cross-scale edge calculated from the current Eglin landscape divides the landscape into areas that contain longleaf pine and hardwood as well as an edge area that exists between these two states. Many sites are edge sites at a few scales, whereas fewer sites are edge sites at many scales. The strongest cross-scale edges surround the largest patches of longleaf pine, whereas smaller patches exhibit edges at a narrower range of scales (Fig. 7).

The success of edge sites in predicting vulnerability to state change varies among the different fire strategies. Edge sites predict vulnerability best for wildfire, less well for rotation burning, and poorly for the responsive strategy (Fig. 8). In the wildfire case, cross-scale edge predicts much of the change from longleaf pine to hardwood. It overpredicts conversion in the larger patches of longleaf and misses the conversion of some small isolated patches of longleaf. In the rotation case, cross-scale edge predicts less well. Although substantial areas of longleaf and hardwood are accurately predicted to persist, there is unpredicted conversion of longleaf to hardwood within large longleaf patches. The edge areas are a mixed success, with just slightly better than half the edge being successfully predicted. Prediction in the responsive case is even worse. Despite success predicting longleaf and hardwood, there is substantial overprediction of edge transition to hardwood, with relatively few unpredicted transitions to hardwoods—even fewer than in the rotation case.

Examining the performance of cross-scale edge prediction at different scales reveals that, overall, cross-scale edge performs well. Prediction success is relatively constant across all scales (Fig. 9A), but cumulative prediction success gradually increases to a plateau that depends on the fire management strategy (Fig. 9D). The error rate for the responsive fire management is about three times greater than those of the other strategies (15 vs. 5%).

Although the success of edge at predicting the conversion of longleaf pine sites to hardwood declines with scale (Fig. 9B), this decline is steeper when considering edge at individual scales than it is for cross-scale edge (Fig. 9E). Edge is a much better predictor under a wildfire management strategy than in the other cases. Under the responsive fire management strategy, less than half of the hardwood conversion predicted by cross-scale edge occurs.

The success of cross-scale edge in predicting conversions of longleaf pine to hardwood is much better. Conversion is poorly predicted by edge at individual scales (Fig. 9C), and prediction success follows different patterns for each of the fire management strategies. However, the success of cross-scale edge increases for the range of scales considered to quite high levels (Fig. 9F). Cross-scale edge very successfully predicts the conversion of longleaf pine to hardwood under wildfire management (90%) and responsive fire management (85%). It is not as accurate for rotation fire management, although it does predict more than half of the transitions. The success of these predictions under wildfire management appears to plateau, whereas, in both the rotation and responsive cases, the accuracy of cross-scale edge continues to increase with increasing scale.

DISCUSSION

Probabilistic resilience provides a means of collapsing the results from an ensemble of simulation runs into a simple measure that indicates the resilience of sites across a landscape. However, the fair success of cross-scale edge in predicting state transitions suggests that simple empirical analysis of existing landscape patterns provides a rough equivalent of the results produced by complex models.

In general, cross-scale edge predicts resilience quite well. The strengths and weaknesses of this approach can clearly be seen in how accurately it performs at different scales among the three fire management strategies. These alternative strategies change the ecological forces that structure the landscape. The wildfire approach mainly increases the frequency of wildfire, whereas the rotation and responsive strategies change the spatial scale of fire to burn units. Within an area, the responsive strategy burns sections containing longleaf pine more frequently than sections dominated by hardwood. These changes in ecological drivers test the ability of cross-scale edge to predict landscape resilience across a reasonable range of alternatives. In general, cross-scale edge is robust to these changes, although its performance does vary.

Cross-scale edge worked best with the wildfire strategy. The errors were primarily false positives: cross-scale edge predicted changes where none actually occurred. Its success in prediction reached a plateau at intermediate scales at about 2000 m, after which the level of error increased. This suggests that, if the range of scales over which cross-scale edge was calculated were reduced, its prediction success could be increased. Cross-scale edge also failed to predict the degradation of some longleaf pine sites. For example, there were a number of sites in the lower left of the landscape that were predicted to persist but instead converted to hardwood from longleaf pine. These areas represented isolated longleaf sites. Cross-scale edge calculations treat these sites as edge, because an isolated site is not considered to be edge. Consequently, cross-scale edge predictions will sometimes fail to predict change for individual isolated sites.

Cross-scale edge worked less well with rotation fire management and responsive fire management. There are interesting differences between prediction success in these two cases and between these cases and the wildfire case. Although the large-scale pattern of prediction success and error across the landscape was similar for wildfire and rotation, they differed at the small scale. Furthermore, rotation had a much greater rate of failure to predict conversion; indeed, it had the highest failure rate of any of the strategies. This failure is due to the reduced impact of spatial pattern on fire dynamics. The rotation strategy tries to burn all sites at an equal frequency, rather than having fire determined by the vegetation itself. This causes change away from the edges between longleaf pine and hardwood states. This effect results in a lower success rate in predicting conversion from longleaf to hardwood.

Transitions between hardwood and longleaf pine were not predicted very well in the responsive strategy. Just as with the rotation strategy, prescribed fire instigated change away from the edge between hardwood and longleaf pine states, which produced large prediction errors. However, because this strategy preferentially burns areas that are dominated by longleaf, just as wildfire does, cross-scale edge performed fairly well when predicting the conversion of hardwood to longleaf, much better than it did in the rotation case.

Despite variation in its prediction success, cross-scale edge was a fairly robust estimator of the resilience of sites in the Eglin landscape. This suggests that cross-scale edge may be a useful tool that landscape managers can use to rapidly assess the resilience of sites within a landscape. However, cross-scale edge needs to be further developed in four areas to be useful to managers.

First, the method requires the definition of two alternative stable states. The definition of alternative states is often straightforward in a management situation: one is the state managers desire, and the other is everything else. However, I expect that, for cross-scale edge to work, the alternative states that are defined should be self-maintaining to some degree. Testing cross-scale edge in other, distinctly different ecosystems should help reveal some general procedures for and problems related to the definition of alternative stable states in a managed landscape.

Second, in the Eglin example, the sites influence their neighboring sites with regard to fire spread and seed dispersal. In particular, fire-inhibiting sites also inhibit fire in neighboring sites and vice versa. Although this effect provides positive reinforcement between similar neighboring sites in northern Florida, in other ecosystems there may be negative reinforcement between similar neighboring sites. For example, an ecological state that concentrates nutrients may impoverish neighboring sites, making it more difficult for them to obtain the necessary nutrients. I suspect that the cross-scale edge method will work only when there are positive interactions among mutually supporting neighboring sites in the same state. Exploring situations in which landscape patterns are structured by other processes should reveal whether or not this supposition is correct.

Third, in the Eglin case I predicted that all the edge sites were vulnerable to conversion to hardwood. Although this assumption was simple, other interpretations of edge sites are possible. The assumption for a particular case depends on the expectation of what will happen to vulnerable states. Examining what types of transitions are observed in edge sites in other systems should reveal if the behavior of edge sites follows simple general rules.

Fourth, in the Eglin example the temporal and spatial scales of the analysis were defined by management experience with the ecosystem. To apply cross-scale edge to another ecosystem, it would be necessary to define a range of appropriate spatial scales and a time horizon for analysis based on the dynamics of that particular ecosystem. I suspect that a range of spatial scales can be determined from estimates of the scales at which important processes operate. The time horizon should be defined by some management goal and will probably depend on the speed of transition between alternative states. How hard it is to make these estimations could be assessed by attempting to apply cross-scale edge to other landscapes.

CONCLUSIONS

Although ecological managers are increasingly being urged to manage ecological resilience rather than specific species, the lack of methods for estimating resilience in management situations makes it hard to adopt this type of approach. I have attempted to show how traditional approaches to analyzing resilience can be extended to the type of landscape simulation models that are often used to evaluate management alternatives. I also described a method called cross-scale edge, an alternative empirical approach for estimating resilience across a landscape.

Cross-scale edge is a simple measure of landscape resilience, because it does not require a detailed understanding of the ecological dynamics of a region. Unlike probabilistic resilience, which is calculated from many repetitions of a complex spatial model, cross-scale edge is calculated from a simple landscape map. Its simplicity makes the measure relatively easy to apply. For such a simple measure, it works well. It predicts change fairly accurately and is robust to broad alterations in the forces driving landscape change. This combination of simplicity and reasonable accuracy suggest that cross-scale edge may prove to be a practical tool in the management of actual landscapes. Its predictions can be used to shape and guide more sophisticated analyses of landscape change by suggesting which locations on a landscape are more likely to change and which are not. The fact that it is easy to use also suggests that this approach for estimating resilience across a landscape should be further developed and tested.

RESPONSES TO THIS ARTICLE

Responses to this article are invited. If accepted for publication, your response will be hyperlinked to the article. To submit a comment, follow this link. To read comments already accepted, follow this link.

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