Many of the hypotheses proposed to explain ecotones are based on an individualistic paradigm and are essentially static. While they include local feedbacks, they ignore the interactions between pattern and process across scales. These feedbacks in ecotones are nonlinear in nature and complicate the relations of pattern and process in vegetation, which, combined with observed fractal patterns, suggests a complexity science approach to investigate ecotone dynamics. A cellular automaton of alpine treeline, including nonlinear, local, positive, and negative feedbacks in tree establishment and mortality, as reported in field studies, is used as a model system. Fourier analysis of simulated alpine treelines shows fractal patterns across the treeline landscapes, which are created by patch development. The temporal evolution of the spatial pattern is also fractal. Landscape scale linear correlations between spatial pattern and the rate of advance of trees into tundra arise from localized nonlinear interactions. A tree-patch-landscape scale explanation of pattern–process interaction is proposed in which the endogenous feedbacks determine the spatial and temporal fractal properties of the ecotone. The simulated treeline advance exhibits self-organized complexity and may indicate a potential strategy for monitoring change.

Introduction

Ecotones, the transition zones between adjacent ecosystems (Risser 1995), are central to our understanding of the relations between spatial pattern and ecological fluxes across landscapes. Ecotones are primarily characterized by a change in species composition and/or form, which reveals the limit for a species range, at least locally, and can indicate how a species relates to the environment and other species (MacDonald et al. 2000c). Because of this limit, ecotones have been suggested to be sensitive indicators of global climate change (e.g., Hansen, di Castri, and Risser 1988; Kupfer and Cairns 1996). Among ecotones, treelines (here we use the term in the sense of the whole ecotone, one of several definitions; cf. Holtmeier...
2003) are the most studied and most treeline studies are those where forest borders grassland or tundra (rather than forest-shrubland/wetland/other boundaries). The contrast in physiognomy has led to a number of hypotheses of treeline formation, location, and pattern, but most lack the dynamics needed to explain how treelines are generated or evolve.

Current explanations of treeline focus on the relations of individual plants to their abiotic environment (Stevens and Fox 1991; Cairns and Malanson 1997) or include feedbacks wherein individuals alter the environment (e.g., Malanson 1997; Korner 1998; Smith et al. 2003) at local scale. Positive feedbacks, wherein trees improve the environment for trees, have been hypothesized as the basis for sharp ecotones (Wilson and Agnew 1992) and facilitation among trees (i.e., trees grow better with tree neighbors) in alpine treeline environments has been cited (Hattenschwiler and Smith 1999; Callaway et al. 2002). Feedbacks are not universal explanations of ecotones, however (Walker et al. 2003), and it remains unclear how feedbacks between pattern and process, a focal point of ecotone research (Wiens, Crawford, and Gosz 1985; Gosz 1993), can explain the dynamics of ecotone position and spatial pattern at the appropriate scale. More generally, Levin (1992) called for an understanding of patterns and their underlying mechanisms across scales and suggested that no single natural scale provides such understanding. To develop insights into ecotone dynamics we use theoretical simulations for alpine treeline ecotone to explain how local feedbacks between pattern and process can cross scales to create ecotone dynamics on landscapes. Our objective is to examine general relations between pattern and process, not to explain the dynamics of a particular place.

We use the alpine treeline ecotone as a model system because it exhibits a variety of spatial patterns and the role of feedbacks, while not well quantified, is well established; for example, Callaway (1998) reported facilitative effects at exposed treeline sites, resulting in aggregated patterns with higher growth rates. Patterns, which include abrupt change from trees to tundra, linear hedges, and moving patches of variable size and shape (Marr 1977; Holtmeier and Broll 1992; Allen and Walsh 1996), may be independent of the preexisting physical environment (Malanson, Xiao, and Alftine 2001; Malanson et al. 2002) and are often attributed to endogenous interactions of vegetation, wind, and snow instead (e.g., Daly and Shankman 1985; Walker et al. 1993; Hattenschwiler and Smith 1999; Walker, Billings, and deMolenaar 2001; Germino, Smith, and Resor 2002; Smith et al. 2003).

Endogenous factors include both negative and positive feedbacks. The primary negative feedback is shading and cooler soil temperatures that would inhibit tree growth by limiting the formation of tissue even if carbon is sufficient (Korner 1998; Hoch and Korner 2003). Positive feedbacks arise from structural protection from wind and intense radiation and from higher canopy temperatures due to lower albedo (Tranquillini 1979; Smith et al. 2003). The trapping of snow by larger plants is regarded as a key feedback (Hiemstra, Liston, and Reiners 2002; Smith et al. 2003;
Alftine and Malanson 2004). The role of snow changes across the ecotone, however (Hessl and Baker 1997; Callaway et al. 2002; Moir, Rochelle, and Schoettle 1999); with patches of meadow in forest, more snow may inhibit seedling establishment (e.g., Billings 1969; Rochefort and Peterson 1996), while at more windswept sites snow held by vegetation may provide an important source of water (Lloyd 1997) or may increase nutrient availability by maintaining higher winter soil temperatures (see Sturm et al. 2001 for the Arctic). We will focus on the advance of trees into exposed tundra as an example of the leading edge of an ecotone.

**Rationale**

Alpine treeline in Glacier National Park (GNP) advanced into tundra in the 19th century (Bekker 2005). We analyzed a 1999 airborne multispectral remote sensing image with 1 m spatial resolution for Lee Ridge, GNP, at the leading edge of a recent (1950–1980) treeline advance (Alftine, Malanson, and Fagre 2003). It was classified as tree or tundra (Fig. 1a). Patch sizes have a power-law distribution with an exponent of 0.83 (Fig. 1b), which shows a fractal spatial structure (a power-law distribution is self-similar) and is suggestive of a spatial process with a fractal temporal structure (Wootton 2001; Pascual et al. 2002). Such patterns are widely expected in nature. The low value of the exponent means there are few small patches of trees, and we expect single trees to have higher mortality due to the harsh alpine environment (Callaway 1998; Callaway et al. 2002). This empirical information suggests a modeling and analytical methodology based in complexity theory (e.g., Sole et al. 1999).

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**Figure 1.** Observed alpine treeline landscape and spatial structure. (a) Classified ADAR image of a treeline ecotone in Glacier National Park, MT. Gray area represents tundra; black area represents alpine trees. (b) Corresponding cumulative frequency distribution of patch sizes in (a) and the regression line for this distribution.
Complexity theory, an attempt to understand emergence, or how simple processes can combine to produce holistic systems (Phillips 2004), may help advance our understanding of ecotone processes and patterns (Malanson 1999). A related indicator, phase changes, has been observed and modeled for treelines bordering grasslands (Loehle, Li, and Sundell 1996; Milne et al. 1996; Li 2002). Self-organized complexity is a general umbrella for work that addresses commonly observed power-law distributions (Turcotte and Rundle 2002). Although self-organization has been defined in many ways (Phillips 1999), we follow systems dynamics usage to mean that although a system has a number of spatial and temporal degrees of freedom (the term “spatially extended dynamic system” is used), its dynamics can be simplified because they generate order, especially a fractal structure such as power-law distributions of important variables; that is, the degrees of freedom can be reduced to an attractor, usually of low dimension, without external tuning (Haken 1975; Bak, Tang, and Wiesenfeld 1988). Self-organizing complexity does not necessarily include evolution to criticality (e.g., Bak, Tang, and Wiesenfeld 1988; Fonstad and Marcus 2003).

Sole and Manrubia (1995) and Wootton (2001) used empirically calibrated cellular automata (CA) to show how landscape ecological patterns arise from local scale processes, and they analyzed power-law distributions of gaps (in tropical rainforest and in mussel patterns, respectively) across their landscapes (a CA is a spatially explicit simulation in which cells have states that are determined in large part by the states of their neighbors; e.g., Wolfram 1984). In geography, similar dynamic simulations incorporating nonlinear interaction have been used, mainly in urban systems and landscape studies (e.g., Allen 1982; Sheppard 1985; Phipps 1989; Straussfogel 1991), which showed complex system dynamics but did not examine the across-scale dynamics and the scaling relations underlying the phenomena. We took this approach further. We constructed a CA using two essential ecological processes driving alpine treeline advance: tree establishment and mortality. We captured the endogenous interaction between pattern and process in a local neighborhood with the assumption that interaction among trees beyond their local neighborhood is insignificant, and used it to simulate alpine treeline advance. We used landscape indicators to describe the treeline process and spatial pattern. We analyzed the dynamics at different scales through Fourier analysis and quantified the pattern–process dynamics using power-law distributions, which reveal the underlying scaling relations of treeline advance across a landscape. Using the model, we examined how nonlinear feedbacks across scales drive dynamics across the landscape. Finally, we developed an ecological narrative of how variable spatial patterns might be generated by a simple model.

**Methods**

We examined spatial and temporal structures using a CA of treeline. Noble (1993) similarly modeled treeline, but did not address dynamics of process–pattern rela-
tions. The cells change between two states, tundra and tree (the latter includes krummholz here), and these changes capture the dynamics of establishment and mortality. Seed rain and germination are subsumed in establishment. The grid of cells represents an alpine treeline landscape in a mountain slope with a linear environmental quality gradient. The CA model was run on a 100 x 1050 lattice representing a slope in the long dimension wherein the cells are nominally 1 m². All simulation runs started from a random distribution of trees in the lowest two rows, from which trees establish upslope. The initial condition of establishment probability is a slope from 0.05 to 0.0 over the bottom 300 rows of the lattice (nominally an ecotone of 300 m width). This 100 x 300 window moves upslope one cell every iteration, leaving lower cells with a base probability of 0.05. By computing the active ecotone within a large area, we eliminated the exogenous effect of topography and simulate unrestricted advance that would occur with a slow continuous amelioration of climate starting at time 0.

Feedbacks among neighboring trees modify establishment probability of tree in the focal cell positively and negatively. The positive feedback comes from facilitation among nearby trees through reduction of damaging environmental factors such as strong winter wind, cold night temperature, or improvement of environmental quality such as increasing water storage during the growing season and accumulating fallen foliage (Wilson and Agnew 1992; Callaway 1998; Callaway et al. 2002). The negative feedback can be created by a dense tree neighborhood where competition for environmental resources such as light, water, and nutrients dominates the interactions among trees or when shade lowers soil temperatures (e.g., Korner 1998) but it is canceled out by positive feedback here. The additional (to the initial slope of probability above) probability of establishment of a tree on a tundra cell is described as a logistic function that captures the combination of local positive feedback or facilitation and local negative feedback (Fig. 2a):

$$P_e = \frac{\alpha}{1 + \beta e^{-\gamma(x-x^2)}}$$

where \(x\) is the average size index of the local neighborhood which is the percentage of tree-occupied cells in a tree neighborhood; this average size index represents the density of the tree neighborhood. The positive feedback or facilitation exists when tree neighborhood is sparse and negative feedback appears when trees are densely located in the neighborhood; \(\alpha\) is a coefficient to adjust the magnitude of establishment probability and thus the strength of positive and negative feedbacks in establishment process and takes 0.5; \(\beta\) is a coefficient and takes 150 here; \(\gamma\) is a coefficient and takes 20; and the local neighborhood size is 5 x 5.

After establishment, the trees endure a harsh physical environment each year, and the mortality is especially high when the trees are very young. The protection by immediate neighboring trees becomes an important factor for survival of young trees. In this simulation, tree mortality is a function of tree age and the number of trees in its immediate neighborhood. Trees usually take 5–10 years to firmly
establish in alpine regions; if the tree age is less than or equal to 6 years; the probability of mortality is

\[
P_m = \frac{1}{C\sqrt{n}} \left( 1 - \frac{1}{1 + \lambda e^{-x}} \right)
\]  

(2)

Figure 2. (a) Tree establishment probability function; (b) tree mortality function.
where \( Z \) is the age of the tree, which reduces the mortality with growth of the tree; \( \lambda \) is a coefficient, here it takes 50. If the tree age is greater than 6 years, mortality is 0.02; if there is no tree in the neighborhood, \( P_m \) is equal to \( 1 - \left( \frac{1}{1+\lambda Z} \right) \). Figure 2b shows the decline of mortality with the tree growth used in this model, that is, the second part of equation (2). \( C \) is a parameter to adjust the strength of positive feedback in mortality, here it takes 3.0; \( n \) is the number of tree cells in the immediate neighborhood (3 \( \times \) 3) (seedlings are protected only by the immediate neighboring trees).

Every run simulates 747 annual iterations; cell states and tree ages are updated every iteration. The first 200 iterations are discarded to reduce the effects of initialization, for we initiate the simulation on a random landscape and let the landscape evolve into a relative stable stage in terms of its extent and growth rate that resembles the observed alpine treeline. We calculated means for 12 repetitions; we used a small number because the variance was very low.

To analyze the temporal evolution of the treeline landscape, especially the scaling property, the Fast Fourier Transforms is applied to the simulated time series to calculate the power spectrum of the time series. For a function of \( f(t) \), its Fourier transform is defined as

\[
F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-i\omega t} \, dt \tag{3}
\]

and the corresponding inverse Fourier transform is defined as

\[
f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} \, d\omega \tag{4}
\]

where \( i \) is the imaginary unity number, \( t \) is the time, and \( \omega \) is the range of angular frequencies.

When the Fourier transform is used for discrete series, the discrete Fourier transform is defined as

\[
F(k\Delta f) = \sum_{n=0}^{N-1} f(n\Delta t) e^{-i(2\pi n k \times n\Delta t)} \quad k = 0, 1, 2, \ldots, N - 1 \tag{5}
\]

where \( N \) is the number of discrete samples taken; \( T \) is the total sampling time; and \( \Delta t \) is time increment between samples, \( \Delta t = T/N \). Here we used Fast Fourier Transformation (FFT), which is a type of discrete Fourier transformation and requires the number of sampling points be a power of 2, and we chose 512 iterations. The value of 747 is the length of landscape (1050) minus the moving ecotone size of 300 and the 2 lines of initial random treelines plus 1.

After FFT, we used regression analysis of power spectrum obtained from FFT to examine the scaling properties. A linear regression model is used to find the relationship of log-normalized frequency and the power spectrum of the system dynamics using the least-square principle.
\[ \text{Log}(Y) = \alpha + \beta \text{Log}(X) \]  \hspace{1cm} (6)

where \(Y\) is the power spectrum of the time series, \(X\) is the frequency of the time series, \(\alpha\) is the intercept of the regression line, and \(\beta\) is the coefficient or scaling exponent. Power spectrum and frequency refer to the system time series. The standard way of determining the scaling exponent of the ‘‘1/f’’ type noise is

\[ F(S) = S^{-\tau} \]  \hspace{1cm} (7)

\(F\) is the frequency of patch size and \(S\) is the patch size. \(\tau\) is the scaling/critical exponent between them. If linear, it indicates that a power law relationship exists, and larger patches will persist longer in the landscape before being merged into continuous forest, which may indicate self-organization of trees at the landscape level.

We deliberately excluded the exogenous effects of climatic variability and topographic heterogeneity, because the purpose of this study is to reveal the endogenous dynamics that may shed light on the internal mechanism driving the alpine treeline landscape. Additional research can examine what impact of exogenous factors, such as climate and topographic heterogeneity, would exert. The model is not calibrated to produce specific patterns, but is for theoretical exploration. The coefficient values were chosen only to keep the rate of advance of the ecotone on the order of 1 m/year (cf. Bekker 2005)—that is, within the moving window. Sensitivity analyses show the results are robust with different coefficient values and different window sizes (3 \(\times\) 3, 5 \(\times\) 5, 7 \(\times\) 7, 9 \(\times\) 9), except that an extreme left skew of equation (1) produces no fractal spatial pattern.

**Analysis and results**

**Fractal analysis of dynamics**

We examined treeline advance dynamics in terms of its spatial process and pattern. We calculated two landscape scale indicators to investigate the spatial process of treeline advance. Landscape potential is the sum of the establishment probabilities of all unoccupied cells; this represents the cumulative effects of all trees on the slope; advance rate is the net gain of tree cells in every iteration. These indicators show fluctuations around long-term means of 159.9 (mean standard deviation of 1.44) and 97.2 (mean standard deviation of 0.59), respectively, at a variety of scales (e.g., Fig. 3a). The dynamics of landscape potential and advance rate are similar (Pearson’s correlation = 0.8438; \(P<0.001\)) except the latter has higher frequency noise. We applied Fourier analysis to the time series of landscape potential for 512 iterations. The power spectrum is obtained by squaring the amplitude spectrum calculated from FFT. The power-law exponent is calculated by regressing the log-normalized power spectrum on log-normalized frequency. The power spectrum of landscape potential reveals a temporal fractal scaling at a landscape scale with a mean critical exponent of 2.02 (standard deviation of 0.037). The result of Fourier analysis of landscape potential in one simulation is graphed in Fig. 3b. The regres-
sion result matches well with the power spectrum and indicates that a clear scaling property exists in the treeline advance process and treeline advance process is fractal. The changes of landscape potential display no characteristic scale, that is, tree establishment and mortality processes across the landscape fluctuate in a scale-free way. Next, we analyzed the evolution of spatial patterns across space. We used the characteristic exponent of frequency distribution of patch sizes in every iteration to represent spatial structure (Turcotte 1990) and its time series. This distribution is also characterized by power law, and so we calculated the power-law distribution of the patch sizes across the landscape for every iteration and we used it to represent the spatial structure of treeline landscape as we did for the remote sensing image. In this way, we constructed a time series of this value to represent the evolution of the spatial structure of the treeline landscape. The statistics of all simulation runs show the mean of this characteristic exponent of the power-law distribution is 0.697 with a standard deviation 0.005 (which indicates the consistency of the results from different simulation runs). Its power spectrum also displays temporal fractal scaling and the mean critical exponent of all simulation runs is 1.54 with a standard deviation of 0.179 (e.g., Fig. 3c). These results suggest that the temporal evolution of treeline spatial pattern is fractal (fractal dynamics; Sole and Manrubia 1995). So, the spatial structure of treeline landscape exhibits a temporal fractal fluctuation. These temporal fractal patterns for landscape potential and

Figure 3. Dynamics of the cellular automaton treeline model. (a) Landscape potential and advance rate starting from a random treeline structure. Upper line, time series of landscape potential; lower line, time series of advance rate. (b) Power spectrum of landscape potential and its regression line. (c) Power spectrum of the exponent of the frequency distribution of patch size and its regression line. (d) Time series of landscape potential and spatial structure evolution (after 200 transients are discarded); black, time series of landscape potential; gray, time series of exponent of power-law distribution of patch size; their values are normalized to [0.0, 1.0].
patch-size distribution are characteristic of scale-invariance, which suggests long-term temporal and spatial correlation across the treeline landscape.

**Correlation analysis of dynamics**

In order to search for the underlying mechanisms for such fractal scaling, we analyzed the relation between the time series of landscape potential and that of the exponent of frequency distribution of patch size (Fig. 3d). The exponent of frequency distribution of patch size is negatively correlated with landscape potential (Pearson’s correlation $= -0.3443; P<0.001$). When we lagged landscape potential by 5 years with respect to the exponent of the frequency distribution of patch size, the coefficient reaches $-0.4186$, suggesting that spatial structure may change ahead of landscape potential and exert a positive impact on it. Lower exponents represent the existence of large tree patches; this state, which has a higher fractal dimension, corresponds to higher potential for treeline advance (Figs. 4a and b). At these times more tundra cells are on the edge of, but not surrounded by, forest and so are most likely to change. This high fractal dimension of the treeline landscape

![Figure 4](image)

**Figure 4.** Snapshots of two distinct fractal states and evolution of spatial structure. Gray area represents tundra and black area represents alpine trees. (a) Snapshot of high fractal state (iteration 414 in Fig. 2d); (b) snapshot of low fractal state (iteration 213 in Fig. 2d).
may be an indicator of the vulnerability of tundra to invading trees, which may be instrumental to raise the landscape potential and thus the advance into tundra. The rules in our model only specify the nonlinear positive and negative feedbacks between pattern and process at a local scale, but these local interactions create significant correlation between pattern and process (fractal pattern and potential or advance rate) at a landscape level. This linear correlation emerges from the dispersed, localized interactions. Furthermore, large fluctuations show that the ecotone varies between high and low fractal patterns (inverse to the exponent of the power-law slope) (Fig. 3d). These large fluctuations signal a significant change of states of treeline advance similar to a second order phase transition and thus have an important impact on landscape potential and advance rates based on the correlation analysis.

Discussion
A complexity narrative explanation

Our simple model demonstrates that local endogenous, nonlinear interactions (the effects of trees on neighboring cells) can produce landscape-scale order. Landscape dynamics (rates of advance) are fractal (i.e., they have a power-law distribution and so are self-similar), and the spatial patterns (size distribution of patches) are also fractal. The local interactions create long-term, landscape-scale linear correlations (between advance and potential). These results suggest that multiscale pattern–process interaction is the key to treeline advance and the self-organizing behaviors exhibited in this system. Based on analyses of the dynamics and similarities between the simulations and a range of observed spatial patterns (e.g., Allen and Walsh 1996), we could conclude that the endogenous dynamics of alpine treeline are a process of self-organized complexity (Turcotte and Rundle 2002). Rather than stopping at this point and hypothesizing a process alone, we go on to identify a pattern–process mechanism.

We see feedbacks between pattern and process at multiple scales as the explanation. When new tree patches form or existing patches expand, localized pattern–process interactions are established across the landscape. Smith et al. (2003) explained how the spatial pattern of trees determines the distribution of environmental resources and stresses. The pattern increases biotic and abiotic environmental heterogeneity; resource-rich sites ameliorate the harsh alpine conditions and facilitate tree establishment and reduce mortality. These interactions cause fluctuations at small and medium scales at most times; trees affect their immediate neighborhood through relatively simple, although nonlinear effects. As the number of trees increases, large patches develop, the open space between them and between the patches and the contiguous forest becomes small, and negative feedback (i.e., cooler soil temperatures) reduces the effect of positive feedback. Occasionally, the interactions coherently create connectivity at the landscape scale in a synchronized coalescence of patches. When large patches merge into each other
and/or into contiguous forest, a second-order phase transition (i.e., the transition is smooth rather than dramatic) between high and low fractal states is triggered to produce large changes across the landscape, which collapse the spatial variability of the environment (through feedbacks, not through exogenous forces) and extend connectivity of trees across the landscape.

These endogenous fractal dynamics can be explained in three hierarchical scales. At the local scale, interaction between pattern and process in individual tree establishment and mortality drive the dynamics. At the landscape scale, the system dynamics of treeline advance are maintained by feedbacks between process and pattern that have spatial and temporal fractal scaling properties. Between them is a middle scale of patch dynamics, best captured by the inverse cascade model (Turcotte et al. 1999) that connects the local and global scales through the growth and coalescence of tree patches. Using a forest fire CA (a percolation model in which sites are removed by spreading fires), Turcotte et al. (1999) introduced the inverse cascade model, in which trees coalesced in patches to form a fractal landscape. The inverse cascade builds clusters of trees that are eventually destroyed by coalescence. The result is a 1/\textit{f}-type power-law distribution of clusters. The processes provide a better explanation of the dynamics for percolation models that exhibit self-organized criticality, and the criticality is not constrained to a small region.

We do see spatial patterns of alpine timberline in GNP that appear to correspond to the processes that the simulation reveals. In particular we do see small islands of tree species developing from initial establishment events (Resler, Butler, and Malanson 2005), the development of linear forms that later coalesce (Bekker 2005), and the eventual envelopment of these patterns by forest. These conclusions might apply to other cases where endogenous processes have been used to explain nonrandom patterns of vegetation (e.g., Watts 1947; Billings 1969; Valentin, d’Herbès, and Poesen 1999; Rietkerk et al. 2002).

That a significant linear correlation between landscape pattern and process emerges from dispersed, nonlinear, localized interactions may explain why many seemingly linear relations are found in a complex world with so many nonlinear processes. Perhaps linear correlations at a large scale do not necessarily indicate linearity in ecosystems, but instead indicate an emergent property as a result of collective nonlinear interactions at smaller scales as suggested by Levin (1992, 1999). Thus a limited predictive power can emerge in a spatially extended nonlinear dynamic system through cross-scale self-organization. Considering multiple scales of explanation, at a metascale, spatial structure can be generated endogenously; at a phenomenological scale, the dynamic exaggeration of fine-scale processes that are not adequately observed (e.g., seedling establishment and microtopography; Resler, Butler, and Malanson 2005) produces divergence or self-organization; and at a process scale, the ecological interactions, here those among trees, are those represented in the simulation.
Implications for ecotones as indicators of climatic change

Our results show that a variety of spatial patterns and advance rates are generated without variable external forcing. The exogenous forces of continued climatic variability and underlying topographic and soil variability would complicate the endogenous dynamics. By focusing on the latter, we are able to examine the emergent properties that theoretically should be common to ecotones. On one hand, this suggests that a relatively large change in ecotone position at one period does not necessarily indicate a correspondingly large climatic change. An ecotone may be far from equilibrium, and its change (or lack thereof; cf. Butler, Malanson, and Cairns 1994; Klasner and Fagre 2002) at any one time may only exhibit the non-linearity in its advance driven by endogenous dynamics; as suggested by Payette et al. (1989) for Arctic treeline, the spatial pattern when climate begins to change may affect how an ecotone will respond. So, the conventional monitoring measures based on advance rates (e.g., Hughes 2000; Walther et al. 2002) are questionable indicators in active ecotones without careful examination. On the other hand, given the nature of internal scaling properties produced by such endogenous dynamics, sudden changes in an ecotones temporal and spatial fractal scaling properties may indicate response to abnormal external forcing. This simulation suggests that monitoring responses to climate change using alpine ecosystems requires taking into account the fundamental characteristics of the ecosystem dynamics that show variability over time. In theory, scaling properties, such as a power-law slope, might be helpful to design potential indicators of responses to climatic change, but we still must acknowledge that topographic and climatic variability may overwhelm any such signal at some ecotones. For now, we can only say that timberlines are not useful indicators of climate change because any dynamics may be endogenous and/or a delayed response to past change, and a lack of spatial response at alpine timberline is not necessarily indicative of a lack of change in driving variables.

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