CHAPTER 2

FOREST ECONOMICS, NATURAL DISTURBANCES AND THE NEW ECOLOGY

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1. INTRODUCTION

The major thesis of this chapter is that the economic analysis of forest disturbances will be enhanced by linking economic and ecologic models. Although we only review a limited number of concepts drawn generally from mathematical and empirical ecology, the overarching theme we present is that ecological models of forest disturbance processes are complex and not particularly well-behaved from an economic perspective. We discover that standard concepts in the economists' tool kit, such as asymptotic equilibrium and convex production, may not adequately represent the dynamic behavior of forest disturbances. Consequently, other tools for economic analysis will be required.

This chapter proceeds by first sketching out the economic problems deriving from the peculiar temporal and spatial dynamics associated with forest disturbances (section 2). Then we provide a brief overview of select topics in ecological literature supporting the view that some important forest disturbances exhibit multiple- or non-equilibrial processes and that, additionally, stochastic factors induce high variation in the spatial pattern of disturbance production (section 3). These themes are illustrated by reviewing two models: (1) the classic spruce budworm model of pest outbreak, demonstrating how the interaction of slow and fast ecosystem variables cause multiple equilibria (section 4), and (2) a cellular automata model of forest fires, which demonstrates how the local interaction of stochastic processes can generate the emergence of unconventional spatial signatures at larger spatial scales (section 5). The chapter ends with a summary of the main points and some suggestions for future research (section 6).

2. ECONOMIC EQUILIBRIUM, NON-CONVEX PRODUCTION, AND SPATIAL SCALE

Since the early decades of the twentieth century, the concepts of equilibrium and comparative static analysis (the qualitative change in equilibrium conditions in

T. P. Holmes et al. (eds.), The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species, 15–32.

response to a change in a structural parameter) have been central in the development of neoclassical economic theory. Much credit for this development is due to Samuelson (1947) who emphasized that comparative static analysis needs to correspond with an underlying, asymptotic dynamic model. In the standard market model, for example, excess demand is usually thought to cause an increase in price until equilibrium is restored. This result can be found as the solution to an ordinary differential equation describing price dynamics, for which the root of the characteristic equation for the complementary function is negative (Chiang 1974, p. 472-473).[1] The resulting equilibrium is said to be asymptotically stable (Tu 1994, p. 33).

Of particular relevance to this chapter, Samuelson (1947) further recognized that some economic processes move rapidly relative to other, slow long run processes and that it is often convenient to treat slow processes (such as changes in the stock of capital) as fixed parameters while concentrating on the fast processes of economic interest (such as the level of investment, income, or employment). He goes on to note that due recognition needs to be given to the evolution of the slow variables in order to study the development of the economic system over time.[2]

In this chapter, we propose that some economically important forest disturbance processes, such as pest outbreaks and fires, result from the interaction of variables across fast and slow timescales, and that policy-relevant economic models need to recognize the impacts of long-term ecosystem dynamics on the fast behavior of economic variables. Because movement in a slow ecosystem variable (e.g., forest foliage, fuel accumulation) can induce a sudden, catastrophic eruption in a fast variable (e.g., area infested by pests, area burned) which is linked, in turn, to various economic variables (e.g., pest eradication costs, fire suppression costs, economic damages), simple comparative static analysis may provide uninformative predictions of changes in economic variables. This more complex situation arises when the root(s) of the characteristic equation describing system dynamics are non-negative, and the Implicit Function Theorem breaks down (Tu 1994,

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[1] It may be recalled that the general solution to a first-order differential equation is of the form $p(t) = Ae^{rt}$ where p (say, price) is a function of time (t) and r is the root of the characteristic equation of the complementary function describing the deviation of p(t) from asymptotic equilibrium. If $r < 0$, then p(t) will asymptotically converge to the particular integral describing equilibrium as $t \rightarrow \infty$.

[2] This decomposition into slow and fast variables was also suggested by Simon and Ando (1961) regarding the aggregation of variables in a dynamic macroeconomic system. They argued that aggregation could be accomplished by classifying the variables of an economic system into a small number of sectors. Because the dynamic interactions within a sector reach equilibrium relatively rapidly, an index representing the equilibrium condition for each sector could be established and then the slower interactions between sectors could be studied.

p. 241). Intuitively, the equilibrium path is not asymptotically stable and may suddenly jump to a different domain.[3]

A recent Symposium held by the Beijer Institute of Ecological Economics in Stockholm focused attention on the implications of discontinuities in ecosystem dynamics for economic analysis, and emphasized the importance of understanding Nature's non-convexities (Dasgupta and Mäler 2004).[4] One of the themes of the Symposium was that bifurcations in equilibrium paths, representing ecological thresholds, manifest across time and therefore require dynamic analysis. Non-convexities in ecosystem production due to discontinuities are consequential for economists because, under these conditions, a decentralized price system cannot reliably guide the economy to an optimal solution and other institutions are required for efficient resource allocation (Dasgupta and Mäler 2003).[5] Fortunately, when the economic planner is confronted with discontinuous ecosystem production, optimal economic programs can be evaluated using optimal control methods (Brock and Starrett 2003, Crépin 2003, Dasgupta and Mäler 2003, Mäler et al. 2003).

Although economists are generally familiar with dynamic processes operating over time, they are less familiar with dynamic processes operating over space. Spatial dynamics have been extensively studied by ecologists who have recognized that characteristic spatial patterns in complex adaptive systems can emerge purely from interactions at the local level (Levin 2002, Chave and Levin 2003, Hastings 2004, Pascual and Guichard 2005), and the use of statistical analysis for detecting complex patterns of spatial dynamics is an emerging discipline in ecology (Gumpertz et al. 2000, Turchin 2003, Liebhold et al. 2004).

Statistical models have been productively employed in the economic analysis of management interventions to control wildfires (Davis 1965, Ward et al. 2001, Prestemon et al. 2002, Bridge et al. 2005) by recognizing that, if wildfire occurrences converge to a statistical distribution, then interventions can be evaluated by identifying corresponding changes in the parameters of the statistical distribution. Some spatial patterns associated with forest disturbances are not well-behaved in

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[3] The case of the backward-bending supply curve provides a good example of an unstable equilibrium separating two stable equilibria. Small shifts in demand can cause catastrophic jumps in price and quantity (Clark 1976).

[4] A standard assumption of economic analysis is that production sets are convex, where a set is convex if the line joining any two points of the set is also entirely within the set. Non-convexities in forest production have been studied for the case of multiple local optimal solutions in a continuously differentiable multiple-use benefit maximization problem (Swallow et al. 1990) and for the case of multiple-use forest production with bifurcations occurring in the production possibility set (Crépin 2003).

[5] Standard comparative static analysis of forest protection programs that equate the marginal benefit of a management intervention with the marginal input cost may likewise provide inadequate guidance for optimal economic decisions if forest disturbance production is non-convex.

that they are scale invariant (i.e., they display self similar patterns across scales of measurement) as typified by power law relationships (Malamud et al. 1998, Chave and Levin 2003, Malamud et al. 2005). In such cases, innovative statistical methods are required to conduct economic analysis (chapter 4).

3. DISTURBANCE ECOLOGY AND THE LOSS OF BALANCE

The balance of nature paradigm has a long-standing tradition both in Western culture and in the development of ecological theory (Egerton 1973). A quasi-scientific foundation for the balance of nature perspective is found in the essay "The Oeconomy of Nature" (1749), written by the famous Swedish biologist Carl von Linné. In this article, Linneaus presents a view of nature that is divinely ordered and functions like a well-oiled machine (Worster 1994). This perspective was echoed throughout the 19th century, and can be found in the works of George Perkins Marsh (who authored the widely cited conservation classic *Man and Nature* in 1864) and Charles Darwin, both of whom accepted the view of nature as fundamentally orderly and maintaining a permanent structure (Wu and Loucks 1995).

More modern statements of the balance of nature paradigm are found in mathematical-ecological concepts such as equilibrium, stability, steady-state and homeostasis (De Angelis and Waterhouse 1987). Separation of the mathematically tractable concept(s) of equilibrium from the more vague notions of balance-of-nature has allowed ecologists to test equilibrium theories and models, at least in principle. However, even fundamental mathematical models of population equilibrium, such as density dependent regulation of population size, are often empirically untestable because the scale at which density dependence operates may be much broader than the scale at which observations are typically made (DeAngelis and Waterhouse 1987). Notably, when models of static ecosystem stability have been tested, they often fail (Wu and Loucks 1995).

Much interest in ecology has focused on thresholds and alternate stable states in ecosystems (May 1977). More than three decades ago, a critique of the equilibrium perspective of nature was advanced by Holling (1973) who argued that the classical equilibrium concept cannot account for the transient behavior observed in many ecological systems. As an alternative, he proposed a model based on the idea of resilience, which he defined as a measure of the ability of an ecosystem to absorb disturbance before flipping over to an alternative domain of attraction. In particular, Holling (1973) argued that random disturbances such as wildfires and pest outbreaks can drive ecosystems from one domain of attraction to another and he proposed that research should focus on locating the domain boundaries.

A second approach to thinking about ecosystem stability that does not rely on asymptotic equilibrium was provided by Botkin and Sobel (1975). By examining the fire history of the Boundary Waters Canoe Area (BWCA) in northern Minnesota as described by Heinselman (1973), they concluded that static stability was an inappropriate concept either for the analysis or management of fire-dependent ecosystems. They proposed a definition of stability based on θ-persistence which characterizes the bounds attained by ecosystem states (characteristics of interest such as biomass or population). In their view, the trajectory of an ecosystem is θ-persistent about state x_0 if $|x_0 - x_t| \leq \theta$ for all $t \geq 0$. Here, x_0 does not connote a state of equilibrium, but rather a state within the system. By emphasizing the bounds attained by ecosystem states, this perspective is consistent with natural variability concepts that are currently applied by resource managers to maintain biological diversity and understand human impacts on forests (Landres et al. 1999).

Along the trajectory of an θ-persistent ecosystem, various ecological states can be repeated, and thus represent recurrent states. Botkin and Sobel (1975) argue that management interventions should focus on maximizing the size of the state space that is recurrent and that minimizes the recurrence time of desirable states. They go on to argue that the satisfaction of these two conditions "is equivalent to ensuring the aesthetically desirable wilderness status—an ecosystem having maximal structural (species) diversity" (p. 636). We prefer to view this conjecture as a hypothesis and suggest that forest ecosystems in continual flux offer opportunities for economists to evaluate public preferences for dynamic, time-varying ecosystem characteristics.[6]

The shift away from a focus on asymptotic dynamics in ecology can also be found in Hastings (2004) who proposed that transient ecosystem dynamics may hold the key to long-term ecological understanding, where the term "transient" implies rapid changes in the state variable(s) of interest. An illuminating example of transient dynamics is the study of epidemics by Kermack and McKendrick (1927) who, employing a system of nonlinear differential equations, demonstrated that the outbreak and termination of an epidemic depends upon a particular set of infectivity, recovery, and death rates and a threshold population density.[7] The key to this approach was to focus attention on the time course of an epidemic and not on the asymptotic state (which is, of course, the state where the epidemic dies out and may occur where only a small proportion of the susceptible members of the population have been infected). Further, the timescale of an epidemic in humans is shorter than the average human lifespan, and it is this juxtaposition of timescales that has been identified as the essential element for understanding transient dynamics in ecosystems (Rinaldi and Muratori 1992, Carpenter and Turner 2001, Rinaldi and Scheffer 2001, Hastings 2004).

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[6] See chapter 10 for recent empirical evidence of post-wildfire wilderness demand.

[7] For an application of epidemiological methods to an invasive pathogen of trees, see Swinton and Gilligan (1996).

An alternative perspective argues that because ecosystems are open systems under the influence of stochastic processes, they are best characterized as nonequilibrium systems (DeAngelis et al. 1985, DeAngelis and Waterhouse 1987). This view is supported by historical evidence on wildfires and pest epidemics. For example, fire history data reconstructed from tree rings sampled in giant sequoia groves in the Sierra Nevada Mountains suggest that fire patterns are a nonequilibrial process synchronized by weather events (Swetnam 1993). This view is additionally supported by long-term fire history data from the Yellowstone sub-alpine ecosystem (Romme 1982). Stochastic meteorological phenomena have also been identified as key variables affecting outbreak dynamics for several forest insect pests (Peltonen et al. 2002).

The statistical analysis of forest disturbances has been enhanced by recent developments in phenomenological time series analysis that integrates deterministic nonlinear ecological models of population dynamics with stochastic variables due to exogenous factors. Berryman (1992) shows how to identify models for analyzing ecological time series using the autocorrelation and partial autocorrelation functions familiar to economists, and Berryman and Turchin (2001) later modified the standard time series model by introducing the partial rate correlation function. Turchin (2003) provides a detailed analysis of complex population dynamics and demonstrates that, for the economically important case of the Southern Pine Beetle, population fluctuations exhibit chaotic behavior.[8]

In sum, this review finds substantial evidence in the ecology literature that "the equilibrium view of ecological systems, which has always had a fair number of skeptics, now seems unsatisfactory to a large fraction, perhaps a majority, of ecologists" (DeAngelis and Waterhouse 1987, p.1). A pressing challenge for forest economists is to incorporate complex ecosystem dynamics into economic analyses of forest disturbances and, ultimately, to integrate economic analysis with decision-making (Pielke, Jr. and Conant 2003) and adaptive ecosystem management.

4. SLOW-FAST ECOSYSTEM PROCESSES: TEMPORAL DIMENSION

At an intuitive level, wildfires and biotic forest disturbances such as insect and disease outbreaks must rely to some degree upon the forest resource. This intuition has been formalized in ecological models by viewing forest disturbances as resulting from the interaction of variables across time scales. For example, the change in forest biomass during wildfires takes place on the scale of hours to months, while the growth of trees occurs on the scale of centuries. Models

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[8] For a general reference on the evidence for chaos in ecology, see the work of Hastings et al. (1993). Turchin and Taylor (1992) provide an accessible overview of complex dynamics in ecological time series.

designed to describe the evolution of a forest ecosystem over time in the presence of wildfire would have to simultaneously integrate the equations of motion for the slow and fast variables which, for practical purposes, is not possible. However, mathematicians have developed special methods for solving this type of problem, known as singular perturbation theory (Kokotovic 1984). In this section, we provide a simple example that demonstrates how singular perturbation methods can be used to characterize the temporal dynamics of an important forest pest, the spruce budworm, which causes severe mortality in boreal forests in eastern Canada and the northeastern United States on roughly 40 year cycles (Boulanger and Arseneault 2004).[9]

Simply stated, the singular perturbation method separates the dynamic variables into slow and fast categories which allow the fast and slow dynamics to be studied sequentially rather than simultaneously (Simon and Ando 1961, May 1977, Rinaldi and Muratori 1992, Rinaldi and Scheffer 2000). In the spruce budworm model, spruce budworm is a fast variable f(t) and forest foliage is a slow variable s(t):

$$\begin{aligned} \dot{f}(t) &= F(f(t), s(t)) \\ \dot{s}(t) &= \varepsilon S(f(t), s(t)) \end{aligned} \tag{2.1}$$

where the dot notation is used to represent the rate of change over time, and ε is a constant representing the ratio of the slow and fast time scales. For example, if forests grow on the scale of centuries and budworms grow on an annual scale, then $\varepsilon = 0.01$. Since the budworm dynamics occur much faster than forest growth, the quasi-equilibrium position for budworms can be evaluated by treating s(t) as a fixed parameter s(0):

$$\dot{f}(t) = F(f(t), s(0)) \tag{2.2}$$

which is equivalent to the singular case $\varepsilon = 0$.

Ludwig and others (1978) showed that budworm dynamics f(t) result from the interaction of the per capita rate of budworm growth and the per capita rate of budworm death, due to predation by birds. Avian predation is limited at low levels of budworm density because budworms are scarce and predators are not rewarded for specializing on that prey. At higher budworm levels, predation is limited by satiation—a relatively fixed population of birds can eat only a limited number of budworms. This behavior gives rise to a non-convex per capita death rate function (fig. 2.1). When the per capita budworm growth rate is greater (less) than the predation rate, budworm density increases (decreases). Thus, steady-

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[9] We note that the model we present is deterministic while recent research on forest pest dynamics emphasizes the importance of stochastic factors (Peltonen et al. 2002). The importance of the model is that it provides a simple demonstration of non-convex ecosystem production with multiple steady-states.

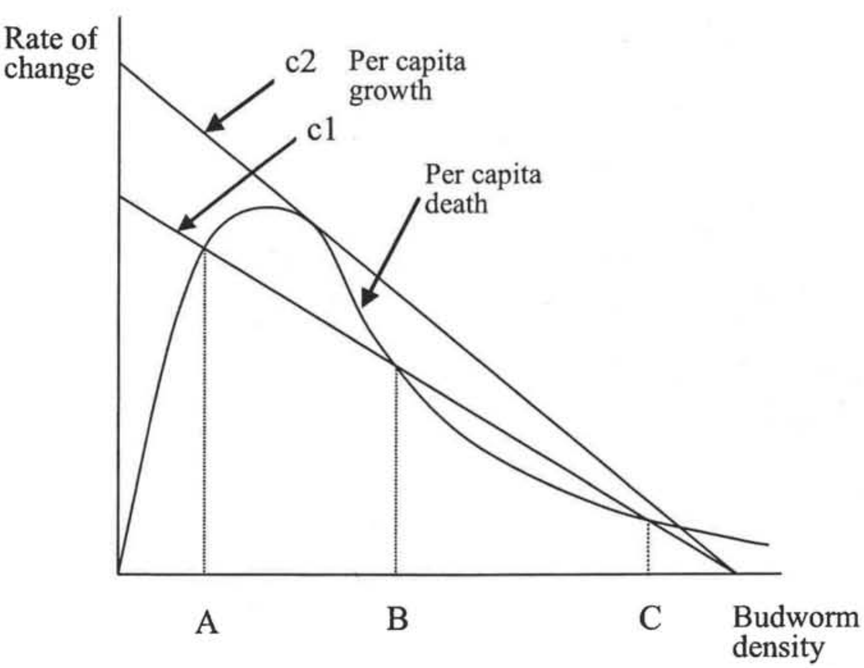

Figure 2.1. Spruce budworm dynamics demonstrating multiple steady states and catastrophic outbreak. Adapted from Ludwig, et al. (1978), with permission.

state positions for the budworm, holding forest growth constant, are found at the intersections of the per capita growth and predation curves. Considering an initial budworm growth curve (c1), three equilibrium points can be identified, for which two population levels are stable (A and C) and one is unstable (B).

The next step in singular perturbation analysis is to examine what happens to the equilibrium positions of the fast variable for any given value of the slow variable, $f^e(s)$. In the case of the spruce budworm, this can be represented by an upward rotation of the budworm growth function as the forest foliage parameter increases (fig. 2.1). Assume that budworm populations are initially at a low level (A). As forest foliage increases, the lower equilibrium converges with the unstable equilibrium. When these two equilibria become coincident (c2), budworm populations jump to the upper equilibrium and an outbreak is underway.

However, this is not the end of the story. Changing the time unit from 1 (for the fast variable) to 1/ε (for the slow variable), and substituting $f^e(s(t))$ for f(t), the dynamics of the slow variable are:

$$\dot{s}(t) = S[f^e(s(t)), s(t)]. \tag{2.3}$$

As forest foliage is consumed by budworms, the slow parameter (the amount of forest foliage) decreases and the budworm growth function rotates downwards.

At first, the unstable equilibrium re-appears and slowly moves towards the upper equilibrium. However, when forest foliage is at a low level, avian predation can again regulate the budworm population, and the population will crash. In figure 2.1, this occurs when the per capita budworm growth function lies nearly along the horizontal axis, and only the lower, stable equilibrium remains. As forest foliage regrows, the pattern is repeated and the cycle of forest growth followed by a rapid release of accumulated capital recurs.[10]

Although this model of ecosystem dynamics was presented in a heuristic fashion, it provides a qualitative illustration of the complexity of designing forest protection policies that maximize economic welfare.[11] Because the threshold for spruce budworm outbreak is not the same as the threshold for population collapse, the behavior of the system is history dependent (i.e., it exhibits hysteresis), and optimal policies depend upon the system memory. For example, historical evidence illustrates that forest-wide insecticide spraying in areas with high budworm densitites and imminent severe tree mortality can keep budworm populations in a perpetual outbreak condition (Ludwig et al. 1978). An alternative approach is to spray early when budworm egg masses are in isolated areas and at low densities (Stedinger 1984). Instead of focusing on the dynamics of the fast variable (budworms), alternative management strategies focus attention on managing the slow variable (trees) by harvesting live trees (Shah and Sharma 2001). Such a strategy may help prevent an outbreak, but once an outbreak is underway, vast amounts of timber would need to be harvested to cause a population collapse. In such a situation, the optimal policy may focus on salvaging dead and dying timber (Irland 1980). A complete economic analysis of the spruce budworm problem would thus need to evaluate the trade-offs between a suite of economic variables including spraying costs, public welfare impacts of increased use of insecticides, timber market impacts of pre-emptively harvesting green timber and timber salvage, and the non-market economic impacts of changes in forest health.

The slow-fast interaction leading to spruce budworm outbreaks suggests that management strategies may need to simultaneously address both pest and forest dynamics rather than focusing exclusively on the dynamic behavior of a single variable. This approach is evidenced in the recent paradigm shift in fire management (Dombeck et al. 2004). The long standing "10 a.m." policy that sought to control all wildfires by the morning after they were first detected focused on direct control of the fast variable (fire) to protect lives and property and ensure a predictable supply of timber. However, suppression or exclusion of the fast vari-

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[10] Technically, this ecological process is described as a cusp catastrophe because the dynamics can jump back and forth between states, and is therefore reversible. For the application of a cusp catastrophe to wildfires, see (Hesseln et al. 1998).

[11] Grimsrud and Huffaker (2006) demonstrate the complexity of finding the solution to an economic optimization problem that is subject to constraints incorporating slow-fast dynamics.

able (fire) can lead to a critical change in the slow variable, forest growth/fuel accumulation, resulting in larger and more intense fires (GAO 1998, GAO 1999, Stephens and Ruth 2005). Increased prescribed burning, wildland fire use, and mechanical fuel reduction programs are evidence of the resulting paradigm shift away from a policy of fire suppression and exclusion toward one that recognizes fire as a vital ecosystem process. Unfortunately, it is not yet known what effect fuel reduction efforts will have on wildfire dynamics or fire suppression costs. Until the linkages between these slow and fast ecosystem variables are understood, a full economic analysis of fire protection programs will be incomplete.

The long-term periodicity in the spruce budworm example provides another lesson. Data sets spanning decades or centuries may be required to understand slow-fast ecosystem dynamics (Holling and Gunderson 2002). Data that do not incorporate evidence of the feedback between fast and slow variables would likely yield misleading analyses and inadequate policy prescriptions.

Finally, we note that climate change might alter slow-fast ecosystem dynamics for some important forest disturbances (Dale et al. 2000, Logan et al. 2003). Westerling et al. (2006) identified a statistically significant change in the annual frequency of large (> 400 ha) western United States wildfires after 1987 that was correlated with mean March through August temperatures, suggesting that climatic thresholds may be important for fire dynamics. Others (Logan and Powell 2001, Logan et al. 2003) have suggested that global warming may be an important factor in widespread insect epidemics such as the recent Mountain Pine Beetle outbreak in British Columbia.

5. SLOW-FAST ECOSYSTEM PROCESSES: SPATIAL DIMENSION

In the previous section, we demonstrated how the interaction of slow and fast ecosystem variables can give rise to transient dynamics and rapid changes in ecosystem states. Our goal in this section is to show how the interaction of slow and fast variables can give rise to characteristic spatial patterns that are amenable to statistical analyses. Because the ecological literature on spatial spread and spatial pattern is extensive and succinct reviews are available elsewhere (Hastings 1996, Hastings et al. 2005), we are not compelled to review the entire span of this literature. Rather, we focus our attention on a recent innovation in spatial modeling, cellular automata, that utilizes Monte Carlo simulation to analyze spatial pattern. A more focused review of this literature reveals that some unconventional statistical distributions are associated with forest disturbances. Consequently, novel statistical methods may be required for economic analysis of interventions into these processes (chapter 4).

Cellular automata have been developed to model a variety of abiotic phenomena, including fire and wind damage in forests (Pascual and Guichard 2005). These models consist of a grid of cells on which discrete system dynamics unfold according to rules that specify the consequences of interactions between cells in a local neighborhood. Iteration of these models over many time steps simulates how characteristic patterns of disturbance can develop across forested landscapes, and these spatial patterns are characterized by spatial power laws (Malamud 1998). This spatial signature is not pre-determined by the specific rules governing local interactions. Rather, it is a self-emergent property resulting from many interactions across the entire system. Cellular automata Monte Carlo simulations generate simulated wildfire size distributions similar to those observed in fire data recorded in temperate and boreal forests (Ricotta et al. 1999, Cumming 2001, Song et al. 2001, Zhang et al. 2003, Malamud et al. 2005).

A cellular automaton uses a d-dimensional lattice with L^d regularly spaced cells to represent the spatial organization of the ecosystem. During the simulation, the value of each cell is updated in discrete steps according to deterministic or probabilistic rules, and rules governing cell behavior are applied equally to all cells. Thus, there is no local heterogeneity governing system behavior. Given a set of rules describing nearest neighbor interactions, the system is simulated over many time steps and the spatial pattern of disturbed areas is analyzed.

Drossel and Schwabl (1992) describe a prototypical forest fire model where each site (cell) is either empty, occupied by a living tree, or occupied by a burning tree. The system is updated in discrete steps using the following rules: (1) empty site → living tree with probability p, simulating regeneration that is well-mixed across the forest matrix; (2) living tree → burning tree with probability f, simulating an ignition source such as lightning; (3) living tree → burning tree if at least one immediate neighbor is burning, and (4) burning tree → empty site. Simulation of this model over many time steps results in a fire size-frequency density $f(\cdot)$ characterized by a power-law (Malamud et al. 1998, Malamud et al. 2005):

$$f(Area_i) = \alpha Area_i^{-\beta} \qquad (2.4)$$

where $Area_i$ is the area burned in normalized fire class i, and α and β are parameters.[12] As emphasized by Pascual and Guichard (2005), the power-law spatial pattern that results from many iterations of this model depends on a double separation of time scales. Fire spread is a fast variable, forest growth is a slow variable, and the rate of fire ignition (lightning strikes per unit area) is a very slow variable.

One convenient aspect of a power law is that a plot in log-log space results in a straight line. Figure 2.2 illustrates this result for the empirical size-frequency

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[12] Following Malamud et al. (2005), frequency density is defined as:

$$f(Area_i) = \frac{N_F}{\delta Area_i}$$

where N_F is the number of fires in a bin width of $\delta Area_i$, and bin widths increase with fire size.

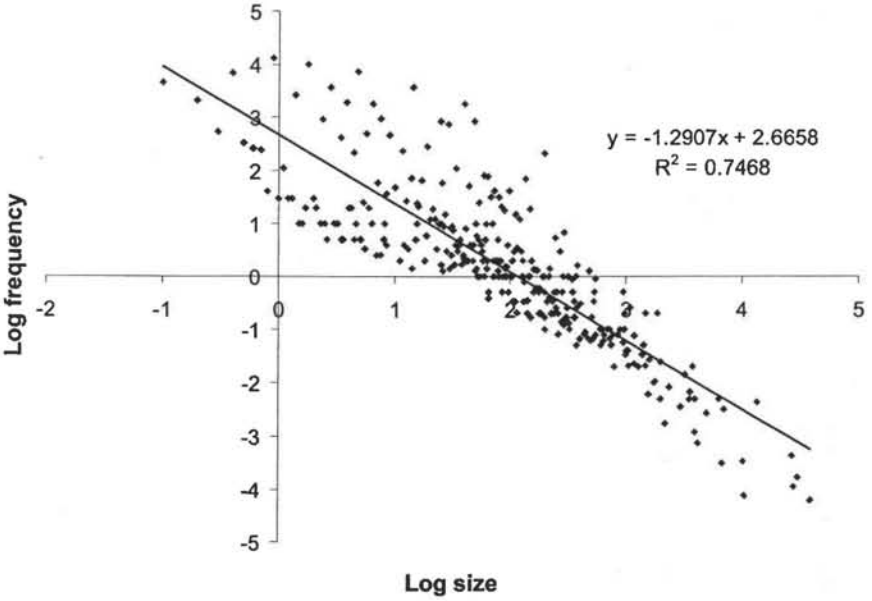

Figure 2.2. Frequency density for wildfires in Florida caused by lightning, showing power law behavior on a log-log scale.

distribution for lightning fires in Florida, U.S.A. A linear function fitted to the Florida data shows that a power law representation fits the data well across 4 orders of magnitude. The fitted function over-predicts fire frequency for fires exceeding about 5,000 acres, perhaps due to the fragmentation of forest fuels on the landscape (Ricotta et al. 2001).

Power law functions have heavy tails—most of the disturbance occurs in a small number of large events. Power laws are unconventional statistical distributions as they have infinite variance and may have an infinite mean. However, robust statistical procedures are available for analyzing spatial power law distributions (chapter 4). Power laws have also been used to describe the spread of plant pathogens (Shaw 1994), so their use in economic modeling of forest disturbance may become more common as their properties become more widely understood.

6. CONCLUSIONS

Over the past few decades, the view that nature is balanced and tends to return to a stable equilibrium following a natural disturbance has been challenged by alternative paradigms. Accompanying this change has been a shift in perspective regarding the role of forest disturbances such as wildfires, insect outbreaks, disease epidemics and storms. No longer are disturbances viewed as nuisance variables that temporarily perturb ecosystem equilibrium. Rather, disturbances are now generally regarded as key processes driving the temporal and spatial structure of landscapes. In this chapter we have highlighted how the interaction of slow and fast variables contributes to forest disturbance processes across temporal and spatial scales.

The literature we reviewed demonstrated that forest disturbance production functions represent the complex, transient behavior of ecosystems. Certain ecosystem processes such as wildfires, pest outbreaks and storms can be characterized as stochastic, nonlinear dynamic processes which induce a variety of temporal and spatial signatures including multiple steady-state cycles and non steady state dynamics. Given this evidence, we suggest that forest economists can utilize two general approaches to incorporate ecological models in the economic analysis of forest disturbances. First, ecosystem dynamics can be included in the specification of an economic welfare maximization problem. Notably, this bioeconomic approach to analysis has recently been applied to the economics of biological invasions (Sharov and Liebhold 1998, Leung et al. 2002, Olson and Roy 2003, Leung et al. 2005, Perrings 2005), and a call for the development of explicit bioeconometric analysis has been articulated (Smith 2006). Second, complex ecosystem dynamics can be summarized using statistical distributions. Taking advantage of the stochastic behavior of forest disturbance systems allows economists to investigate how statistical distributions shift in response to abiotic, biotic, and economic variables (Davis 1965, Prestemon et al. 2002, Mercer et al. 2007, chapters 3-5 of this book).

This chapter is necessarily incomplete and has not addressed some topics in ecology relevant to economic modeling of forest disturbances. These include the problem of aggregation across scales, the explicit spatial modeling of fires, insects, and pathogens in heterogeneous environments, and understanding the interactions among multiple forest disturbances. However, we hope that we have provided insight into the complexities associated with modeling forest disturbances and guidance into how ecological analysis can be incorporated into economic analysis. In sum, we think that economic analysis of forest disturbances will be improved by its congruence with ecological understanding and that, ultimately, joint economic-ecologic analysis will provide more relevant information for use in adaptive ecosystem management.

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