Chapter 3
Native Fire Regimes and Landscape Resilience

Max A. Moritz, Paul F. Hessburg, and Nicholas A. Povak

3.1 Introduction

First introduced by Holling (1973), the term "resilience" has been used widely in the ecological literature, but it is not always defined and is rarely quantified. Holling suggested that ecological resilience is the amount of disturbance that an ecosystem could withstand without changing self-organized processes and structures. His description suggests that resilience may be: (1) represented by an observable set of properties; (2) defined by measures of degree; and (3) related to system states and their (in)tolerance to reshaping, and that some properties of resilience may be quantifiable. We also see the idea of *fire resilience* in the literature (e.g., MacGillivray and Grime 1995; He and Mladenoff 1999; Díaz-Delgado et al. 2002; Brown et al. 2004; Pausas et al. 2004), but this term has different meanings in diverse contexts.

Despite disparate interpretations of resilience in the existing literature and of the role that fire may play, many agree that there is important linkage between naturally functioning fire regimes, the vegetation and terrain that fires move through, and the climate and weather that promote a fire ecology. This linkage manifests itself in fire-related plant traits (Bond and van Wilgen 1996), changes to landscape patterns, processes, and ecosystem functioning when fire is suppressed (Agee 1993; Hessburg et al. 2005), and potentially large changes as plant invaders alter native fire regimes and plant community structure (D'Antonio and Vitousek 1992).

One of the key challenges in defining properties of fire resilient landscapes is identifying mechanisms through which fire influences and reinforces landscape structure and functionality. What we observe on any single landscape is inevitably a mixture of both ecological interaction and adaptive response (Herrera 1992), providing only one snapshot in time and space. By choosing a relevant scale of

M.A. Moritz (✉)
Department of Environmental Science Policy and Management, Division of Ecosystem Sciences, University of California Berkeley, Berkeley, CA 94720-001, USA
e-mail: mmoritz@berkeley.edu

D. McKenzie et al. (eds.), *The Landscape Ecology of Fire*, Ecological Studies 213,
DOI 10.1007/978-94-007-0301-8_3,

observation and similar biophysical settings, however, one may characterize a breadth of ecological structure and organization that is a function of interactions between species and processes operating within that scale (Peterson et al. 1998). Ultimately, positive and negative interactions between organisms, tradeoffs between exogenous and endogenous controls, and feedbacks between biotic and abiotic variables must all influence the patterns of vegetation within an ecosystem and the fire regime they co-create (Moritz et al. 2005).

The goal of this chapter is to examine mechanisms that might contribute to resilience in fire-prone ecosystems and their persistence in the face of ongoing natural disturbances and environmental variation. Our emphasis is on landscape patterns and processes, as opposed to finer spatial scales relevant to the fire ecology of a given species or patch. Because fire size distributions have been increasingly important to descriptions and explanations of ecosystem organization and structure, we examine datasets and examples from several different fire environments to look for consistent patterns among them. This was important to us because disturbances like fire have the greatest potential to restructure landscapes. Likewise, along with other factors, the living and dead structure of the landscape after fires provides endogenous feedback to future fire event and fire severity patterns (*sensu* Peterson 2002).

In particular, power law statistics have been used to characterize fire-event size distributions and what may control them, so we will examine the theories and methods related to this approach. Given that pattern and scale continue to present some of the most complex and interesting questions in ecology (Levin 1992), our intent is to shed new light on interactions between fire and its drivers at different scales. Without a better idea of how fire and ecosystem resilience are intertwined, their management and conservation may be impossible, as human influences and climatic changes continue to unfold.

3.2 Landscape Resilience

In order for an ecological system to persist and continue functioning in an environment with stochastic influences, it must be able to recover or rebound after disturbance. Intuitively, this is what many of us think of when the term resilience is used. Landscape resilience would thus apply to ecological persistence or a sort of metastability (*sensu* Wu and Loucks 1995) and continued functioning at a meso-scale, above that of vegetation patches and below that of physiographic province. Regardless of scale, a "ball-in-cup" model with one or more basins of attraction is often employed as a metaphor. This qualitative notion is somewhat vague, however, and there has been a profusion of literature and much confusion over terminology (e.g., Grimm and Wissel 1997) about what resilience actually means.

We introduce resilience concepts that are covered extensively in the edited volume of Gunderson and Holling (2002), due largely to members of the Resilience Alliance (*http://www.resiliencealliance.org*). In their parlance, there is *engineering resilience*, which focuses on system stability and the capacity to resist movement

away from an equilibrium state, as well as the speed with which it can return to equilibrium. On the other hand, *ecosystem resilience* highlights non-equilibrium conditions and the ability of a system to absorb disturbance, changing and reorganizing to maintain structure and functionality over time. Holling and Gunderson (2002) draw a distinct contrast between engineering resilience (i.e., emphasizing efficiency, control, constancy, predictability) and ecosystem resilience (i.e., emphasizing persistence, adaptation, variability, unpredictability), although aspects of both would appear necessary for resilience in the face of ongoing fire events.

To consider landscape resilience, it is useful to scale these two concepts. Engineering resilience seems to emerge most clearly at relatively fine scales of space and time, under relatively more homogeneous conditions that arise from local, deterministic, and mostly bottom-up or endogenous controls. In contrast, ecosystem resilience emerges at meso- and broader scales, arising from a mix of bottom-up, top-down, and stochastic influences. *Cross-scale resilience*, a third concept put forth by Peterson et al. (1998), emphasizes the distribution of functional diversity within and across scales to allow, for example, regeneration after disturbances such as wildfire. To paraphrase Peterson et al. (1998), we will suggest that although most patterns and processes interact within system levels, there is also a certain amount of cross-talk or "leakage" between levels. This is especially true where processes and patterns reach their upper and lower bounds, or process domains, and where bounding is fuzzy or porous in nature. Wu and Loucks (1995) referred to this as loose vertical coupling: strongly coupled interconnections of patterns and processes within an observed level of organization, but cross-scale connections from the context (bottom-up) and constraint (top-down) levels in the fuzzy transition zones between levels. We illustrate an example of this later in the chapter.

Although processes and patterns at different scales are said to self-organize (Kauffman 1993), the origin and structure of relevant feedbacks and forcing factors are seldom quantified. How do these feedbacks and factors relate to landscape resilience? We know that species interactions with their local environments, disturbance regimes, and other ecological processes can lead to species sorting, structuring of communities, and ecological patterns of conditions to support them over moderate time scales (e.g., centuries to millennia, Moritz et al. 2005). However, species persistence and ecological functioning must also accommodate infrequent extreme events that may overwhelm bottom-up controls and any self-reinforcing feedbacks that may have developed in conjunction with more moderate disturbances. How ecosystems recover and continue functioning across the full distribution of events in a naturally functioning fire regime is therefore a key to landscape resilience.

3.3 Fire Regime Characterization

The fire regime (Gill 1975; Romme 1980) is a simplifying construct used throughout this book, so only a few of the relevant features are covered here. A conceptual framework for depicting controls on fire at different scales is presented in Fig. 3.1,

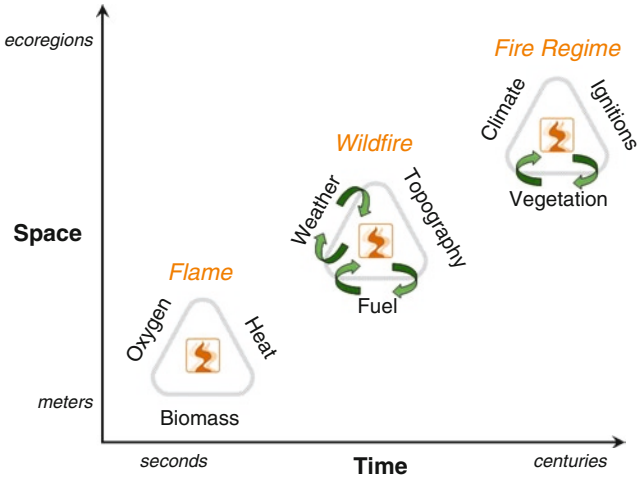


Fig. 3.1 Controls on fire at different scales of space and time. This framework adds a fire regime triangle (*upper right*) to the traditional triangles used to characterize combustion (*lower left*) and the fire environment (*middle*). Mechanisms most relevant to landscape resilience would tend to be operating at and in between the scales of wildfire and a fire regime. *Arrows* represent feedbacks between fire and the forces controlling fire at different scales

which combines the traditional "fire triangles" for combustion and wildfire with one for fire regime controls at the broadest scales. This framework was introduced in Moritz (1999) and developed in subsequent work (Davis and Moritz 2001; Moritz et al. 2005; Krawchuk et al. 2009; Parisien and Moritz 2009). Others, notably Martin and Sapsis (1992) and Bond and van Wilgen (1996), have also identified similar fire regime controls.

An excellent source for more general background on disturbance regimes is the edited volume of Pickett and White (1985). Despite the ongoing relevance of this early synthesis, there has been relatively little theoretical progress in disturbance ecology over the last 25 years. There have certainly been advances in understanding of individual ecological disturbances, such as fires, avalanches, debris flows, and floods, and a significant literature documents these insights. On the whole, however, still lacking are a general conceptual framework and body of quantitative methods that form the basis of disturbance ecology as a thriving research field in its own right (White and Jentsch 2001).

Because fire is a naturally recurring process, it can be statistically characterized by how often it occurs, when it occurs, the extent of area burned, and burn intensity. For example, one might be interested in the mean return interval of fire, some measure of interval variance, or the best fitting statistical distribution that describes the probabilities of all possible return intervals. An applied use of fire return interval distributions is to transform them into a measure of the "hazard of burning" (Johnson and Gutsell 1994). This hazard measure is used to quantify the degree to which fire probabilities change with time since the last fire (e.g., due to plant age or size effects, species composition, fuel density, or accumulation). This analytical

approach originates largely in the forestry literature, but it has also been applied to the fire regime of chaparral shrublands across southern California (Moritz et al. 2004). Censored observations of fire return intervals (i.e., open-ended intervals that were at least age X when burned) are common in many fire datasets, and they can alter statistical outcomes and interpretations substantially (Polakow and Dunne 1999, 2001). Although return intervals are only one fire regime property, their characterization is an active area of research (Moritz et al. 2009).

Other fire regime parameters include fireline intensity (a measure of heat energy released), fire season (time of year), and fire size (area burned). Similar to fire interval data, the mean, variation, and statistical distributions of other fire regime parameters are often of interest. Note that all of these parameters refer to characteristics of fire itself, as opposed to the ecological effect of fire. The net ecological impact of fire—fire severity—is a function of several different fire regime parameters in an unlimited variety of combinations, and it may not manifest itself in vegetation or soils until well after a fire. In addition, ecological structure and function in one ecosystem may be highly sensitive to specific fire regime parameters, but much less to others (Romme et al. 1998). An ecologically severe fire in chaparral, for example, would be one that occurs soon after a preceding event (i.e., short fire interval), eliminating many of the native dominant species that require a decade or two to become sexually mature and contribute seeds to a soil seedbank (Zedler et al. 1983). An ecologically severe fire in a ponderosa pine forest might be one that occurs after a long fire-free interval, burning at a higher intensity than the dominant trees can survive (Agee 1993; Swetnam and Betancourt 1998).

In terms of the area affected, many fire regimes are dominated by the largest events (e.g., Strauss et al. 1989; Moritz 1997) and are sometimes said to have "heavy-tailed" fire size distributions (e.g., Malamud et al. 1998). These descriptive terms have statistical definitions, and their relevance in analysis of power law relations is discussed later in this chapter. Whether the largest fires are unusual and severe ecological events, however, depends on the ecosystem in question. Similar to the fire interval examples previously given, ecological resilience after a large fire hinges on how well species and communities inhabiting an ecosystem can regenerate, reorganize, and persist in the face of fires of varying size. The notion that there should be some natural range of variation for a fire regime has therefore become central to the management of fire-prone landscapes (Hessburg et al. 1999a; Landres et al. 1999; Swetnam et al. 1999). Later in this chapter, we discuss possible origins of that natural range of variation and why it is intuitive to think in these terms.

3.4 Fire Regime Variation and Resilience

One may aim to define the "native" fire regime of an ecosystem by quantifying variation in fire characteristics and connectivity of natural landscape states (e.g., before modern human activities) over some defined climatic period. This approach has been the basis of ecosystem management efforts (e.g., Hessburg et al. 1999a;

Landres et al. 1999) and large government agency projects, such as LANDFIRE (Schmidt et al. 2002) and the Interior Columbia River Basin Project (Hann et al. 1997). Quantifying native fire regimes for use in forest management is also the basis for "emulation forestry" (Perera and Buse 2004, and chapters therein). Ideally, all fire regime parameters described above would be factored into this approach, because each can be ecologically meaningful. The parameter emphasized most frequently tends to be fire return interval, which is often assumed to produce an associated fire intensity. This is a widely held assumption for many fire-prone ecosystems. However, longer fire free intervals do not always result in higher fire intensities. Likewise, short fire return intervals do not always result in lower fire intensities. Examples include ecosystems in which extreme fire weather events (a top-down influence) can overwhelm constraints that time since the last fire, recovery pathway, and fuel accumulation might otherwise pose (bottom-up influences). This tradeoff in controls applies for many chaparral shrublands of southern California (Moritz 2003) and a variety of coniferous crown fire dominated ecosystems (Turner and Romme 1994). There are also examples of ecosystems in which rarely burned stands display a decreasing probability of intense fire, such as the forests of the western Klamath Mountains in California described by Odion et al. (2004, 2009).

In addition to paying more attention to some parameters than others, use of the historical range of variation (HRV) in native fire regimes also requires that a particular period of relevant climate be chosen as a reference (e.g., Landres et al. 1999; Swetnam et al. 1999). Therefore, one can arrive at different estimates for a given parameter, simply by considering different periods. For example, restricting the temporal baseline to the Little Ice Age (~1,400–1,850) could give quite different estimates than if the Medieval Warm Period (~800–1,300) were included. Several reference periods, however, can be highly informative about the dynamics and interplay between the climate, land, and biotic systems, and that is the primary utility of historical ecology.

Rather than being a single snapshot of conditions in space and time, we suggest that the HRV should represent the broad envelope of realizations that can occur in a given landscape, considering a particular climate reference period. When the climate system changes, the envelope of realizations drifts to include new conditions, but is not likely re-invented. This is due to the potent effect of the historical ecology, which is the system memory; i.e., prior influences can determine, to a large but incomplete extent, future landscape or ecosystem trajectories, and the effects can last for centuries (Peterson et al. 1998; Peterson 2002). A thought experiment for estimating the HRV of any landscape is to consider the range of conditions that would occur were we able to rewind time in a particular climatic period a 1,000 times or more, all else being equal (Hessburg et al. 1999a, b; Nonaka and Spies 2005). In this light, the HRV is an emergent property of landscapes and ecosystems (Peterson 2002), derived from the same exogenous and endogenous forcing factors that shape their resilience. Any future range of variation (FRV) is then a consequence of the prior HRV, plus changes in exogenous and endogenous forcings, and the resulting range of conditions.

A related alternative approach is to identify a bounded range of fire regime variation, regardless of what the past has demonstrated, within which long-term persistence of ecosystem structure and function might be possible. As opposed to a focus on a central-tendency measure of mean fire return interval, the emphasis here is on avoiding ecological thresholds. This would seem to be at the heart of fire resilience, but it presupposes knowledge of the thresholds to avoid, the manner and rate of ecosystem shifting once thresholds are exceeded, and which fire regime parameters are most ecologically influential (Romme et al. 1998). Such knowledge is seldom available. Another unknown is whether thresholds themselves shift in a dynamic climatic future and how species, communities, and processes might respond. So, while conceptually important, a focus on thresholds may offer limited guidance (e.g., only for certain species) until much more is learned about ecosystem dynamics in general.

In the face of climatic change, discussion has also emerged about reinforcing ecological resilience (Millar et al. 2007; Moritz and Stephens 2008), as opposed to recreating or restoring more natural disturbance regimes. This is largely due to uncertainty in whether the last few centuries can indicate how ecosystems will respond to climates of future decades and the fire regimes that may accompany them. Even so, it is not time to toss away the historical range of variation concept or historical ecology. Understanding the mechanisms that have to date controlled landscape resilience is of central importance, and a marriage of the aforementioned ideas seems warranted.

3.5 Fences and Corridors

Landscape resilience in stochastic environments must involve a variety of species and processes at different scales, some of which are redundant and others that are overlapping, such that reorganization and persistence of ecological function are possible after disturbances (Peterson et al. 1998). In the case of fire, there must also be mechanisms that generate "fences and corridors" on the landscape—the patchiness of conditions that retard or facilitate progress of combustion—that fire has to negotiate at any given time. We propose that fire's fences and corridors, both metaphorically and in reality, are a key to landscape resilience.

In a completely homogeneous (and hypothetical) landscape, an extreme situation would be that all biomass burns every year, and at all scales, assuming the infrequent ignition at some locations. For all but a few species, this lack of fences and corridors for fire would clearly be intolerable to their persistence. It is heterogeneity across the landscape that allows for patchiness in space and time, for vegetation as well as fire, and thus persistence of diverse ecosystems. Even after very large and stand-replacing fires like those of Yellowstone in 1988, heterogeneity at the landscape scale is seen as key to resilience and regeneration (Schoennagel et al. 2008). Landscape heterogeneity, variation in fire regimes, and patchiness in fire effects all contribute to landscape pattern complexity and different types of refugia for post-fire regeneration.

Areas that are less likely to burn (fences) and more flammable swaths of landscape (corridors) influence fire patterns and are due to both biotic and abiotic factors. Some landscape patterns that either constrain or facilitate the spread of fire will be relatively static, while others will change with the seasons, and with time since the last fire. Certain climatic trends (e.g., protracted drought) and extreme fire weather episodes (e.g., hot, dry, and strong winds) can also temporarily reduce constraint on fire spread across the landscape. Over long enough time scales, feedbacks that occur between vegetation and fire eventually lead to vegetation patterns that are tolerant of – and often adapted to – the fire regime that exists there. Since these feedbacks are partially responsible for the frequencies and types of fires that are characteristic of a given region, they also reinforce the network of fences and corridors in a given ecosystem.

It seems self-evident that landscape heterogeneity should affect the rates and patterns of biomass consumption by fire. But does this heterogeneity have inherent structure? Is there any reason to suspect that the size distributions of fires should somehow be similar across ecosystems that have different inherent rates of primary productivity or types of topographic complexity? If so, this would imply that the ensemble of fences and corridors characteristic of one ecosystem can produce fire patterns that are somehow comparable to those from another ecosystem.

3.6 Fire Size Distributions and Power Laws

Theory and observation hold that certain systems exhibit self-organizing properties (Turcotte 1999). Under a broad range of conditions, event size distributions of landslides, earthquakes, floods, and some argue, forest fires exhibit this behavior (e.g., Malamud et al. 1998; Turcotte and Malamud 2004). Event-size distributions are described using a power-law relation (Pareto I distribution), which implies scale-invariance of event frequency-size distributions, and system self-reinforcement.

Power laws have been found in many fire size distributions (e.g., Malamud et al. 1998, 2004; Song et al. 2001; Carlson and Doyle 2002; Reed and McKelvey 2002; Moritz et al. 2005; Boer et al. 2008), although there is substantial disagreement about what this shared characteristic signifies. A distribution may include very large and unlikely events—the signature of being "heavy-tailed"—but this does not necessarily mean it displays a power law relation. Specifically, a fire size distribution is said to fit a power law relation with slope α if the probability P of a fire of size (l) is given by:

$$P(l) \approx l^{-\alpha} \tag{3.1}$$

Using a cumulative form of the data (e.g. rank-ordered by size, or the cumulative distribution function, CDF) avoids having to choose bin widths and other potentially subjective decisions related to model fitting (Malamud et al. 1998). A constant must be added to Eq. 3.1 to normalize units of P such that values range from 0 to 1 in

the cumulative probability distribution. Plots of data are typically shown after log-log transforming both axes, so that the slope α provides a linear fit to the data. Moreover, a distribution of fire sizes may be heavy-tailed and not be purely power law in a log-log plot, if the probability does not decrease in a linear fashion as fire size increases over the entire range of the distribution. As we will show later, several closely related statistical distributions have heavy tails and do not show a linear fit at either end of the CDF, yet they display robust power law behavior across a middle range of fire sizes. In the simplest form, purely power law relations are synonymous with the single parameter Pareto I (P1) model (Newman 2005).

Because fire size distributions have exhibited power-law behavior, despite very different geographic locations and vegetation types, some have seen this as evidence of a common mechanism, and of self-organization (e.g., Malamud et al. 1998, 2004; Ricotta et al. 1999; Song et al. 2001). Observation of power law characteristics over a broad range of spatial scales has led to descriptions of these relations as scale-invariant; that is, relations apparently exist regardless of the scale of observation.

3.7 Theories on the Origin of Power Laws

One body of theory, called self-organized criticality (SOC), argues that such system behavior is a function of purely endogenous controls (Bak 1996; Turcotte 1999). This has been shown, for example, in simple sand pile and forest fire simulation models, which exhibit scale-invariance of event frequency-size distributions and apparent system self-reinforcement. Criticality is said to be driven by distinct events (e.g., landslides, fires, earthquakes). Above a "critical" threshold, rates of endogenous processes produce cascades of events and a range of event sizes fitting a power law (P1) distribution (Turcotte 1999; Turcotte and Malamud 2004; Malamud and Turcotte 2006).

When one examines the simulation logic behind the SOC fire model, it is clear that these experiments must reveal chiefly endogenous controls, due to the simulation approach and the modeling rules driving critical events (e.g., fuel regrowth rates). At the other end of the spectrum, one can imagine a system in which event-size distributions are completely driven by exogenous factors. In the case of wildfires, for example, Boer et al. (2008) have argued that the frequency of wind events is the sole structuring mechanism of several fire size distributions they examined. While their comparison of wind severity distributions and fire size distributions is compelling, the analysis itself required the specification of a vegetation-related parameter – an endogenous factor – to match the power law exponents of wind and fire events.

Given the many interactions across different scales that ultimately produce a fire regime (Fig. 3.1), it is almost inconceivable that a full range of fire sizes could be controlled by a single exogenous or endogenous factor. Indeed, Reed and McKelvey (2002) have shown that fire size distributions in different regions fit power laws

under certain circumstances and that multiple influences should be involved. Across a range of fire sizes, the importance of factors driving fire spread is approximately equal to that of factors causing fires to go out (i.e., mathematically, a balanced extinguishment : growth ratio).

The findings of Reed and McKelvey (2002) imply a type of meta-stability, which may have profound implications if generally true. First, they confirm that both fences (extinguishment) and corridors (growth) are involved in structuring fire size distributions, implying a variety of endogenous and exogenous factors at play. Furthermore, this suggests an ongoing tradeoff in the influence of constraints vs. drivers of fire spread, from which *we should actually expect power law distributions of fire sizes to emerge*. Marked deviations from a power law distribution could thus indicate ecosystems in which forces facilitating the process of combustion are consistently overwhelming those constraining it (or vice versa). Such a skewed dynamic might reflect ecosystems going through a major transition (e.g., due to climate change) or the possibly loss of inherent resilience mechanisms. Although it is not obvious what the power law slope should be for a robust and functioning ecosystem, nor over how many orders of magnitude this should be observed, the findings of Reed and McKelvey (2002) suggest the importance of structured networks of fences and corridors on fire-prone landscapes, as well as an expectation for power law distributions in fire sizes.

The idea that there are multiple inherent constraints on fire size and that ecosystems become somewhat "tuned" to the local fire regime is central to the concept of Highly Optimized Tolerance (HOT) in fire-prone ecosystems (Carlson and Doyle 2002; Moritz et al. 2005). HOT also provides an explanation for the slopes of observed power laws. HOT is a conceptual framework for studying organization and structure in complex systems, and the clearest examples come from biology and engineering, where adaptation and control theory have direct application (Carlson and Doyle 1999, 2000; Doyle and Carlson 2000; Zhou and Carlson 2000; Robert et al. 2001; Zhou et al. 2002). The HOT framework is based on the assumption that complex systems of interacting components must be robust to environmental variation within some characteristic range. Otherwise complex systems would not be able to persist and function in fluctuating and uncertain environments. Being more finely tuned to a narrow spectrum of conditions – even if increasing performance or efficiency under these conditions – will ultimately make a system more susceptible to failure in circumstances outside the narrow range of variation. This tradeoff is at the heart of what it means to be "robust yet fragile" in the HOT framework (Carlson and Doyle 2002), and it may offer substantial insight into landscape resilience. Notably, there are also direct parallels between the concept of HRV in fire regimes and the degree of environmental variation to which complex systems must be resilient.

In addition to providing theory for how tradeoffs and feedbacks operate in complex systems, HOT also employs an analytical framework for optimizing these tradeoffs under uncertainty, and solutions relate directly to the dimensionality of the problem (Carlson and Doyle 2002). In the case of fire and a managed forest, a goal might be to arrange barriers to fire spread among forest stands such that one

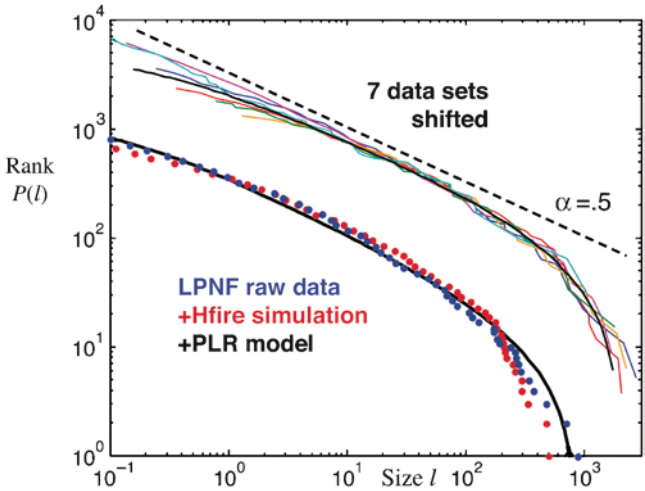


Fig. 3.2 Fire size statistics for a variety of fire datasets The lower curves include HRV fire size data for chaparral-dominated portions of Los Padres National Forest (*LPNF*) as well as for a simulation model (HFire) and the analytical model proposed by HOT (PLR). The vertical axis is the rank of the event size, while the horizontal axis is in km². The upper set of curves shows these datasets, plus 4 additional fire size catalogs from different regions of the world, rescaled to show their power law fit of slope −1/2 (i.e., exponent α = .5) over several orders of magnitude (Reprinted from Moritz et al. 2005)

minimizes the range of fire sizes observed in the system. Using linear (i.e., 1-dimensional) barriers, the analytical HOT solution to this problem leads to a size distribution of fires (~2-dimensional) that follows a power law. It has been shown that several real and modeled fire size datasets approximate a power law with slope −1/2, or 1 divided by the dimension of the events being minimized (Carlson and Doyle 2002; Moritz et al. 2005). Figure 3.2 shows a variety of fire datasets that have this characteristic shape and overall slope of −1/2 in their HRV of fire sizes.

3.8 Example Ecosystems

Although some have argued that power-law behavior should not necessarily be interpreted as evidence for ecological organization or inherent ecosystem structure (e.g., Reed and McKelvey 2002; Solow 2005), the consistent shape of many fire size datasets indicates an apparent "functional form" and is quite compelling. Furthermore, the power law slope of some of these distributions is that predicted by HOT, which would suggest a tendency in these systems toward minimizing the size range of disturbances. It is not clear, however, how HOT as a mechanism might accomplish this. How would tradeoffs in the influence of bottom-up (e.g., topography and vegetation) vs. top-down (e.g., fire weather and climate patterns) controls

consistently generate a specific distribution of fire patterns under different combinations of environmental conditions? For HOT to apply in fire-prone ecosystems, one would expect consistencies between ensembles of fences and corridors for fire across ecosystems, as well as feedbacks that could at least partially create these generic structures.

In the remaining sections of this chapter, we further examine the origin, controls, and methods for identifying power law distributions in fire size data. A first example focuses on a crown-fire-adapted chaparral ecosystem, where fire severity essentially functions as a constant across all fire event sizes. In this example, we demonstrate application of HOT as a theoretical framework, which leads into several questions about fitting statistical distributions to fire size data and how to interpret the results. This is followed by a second example analyzing a variety of landscapes, including surface fire, crown fire, and mixed surface and crown-fire-adapted ecosystems, where fire-severity patterns vary considerably. The importance of rigorous statistical distribution fitting methods is also emphasized, as well as more mechanistic relations to topographic and physiographic controls on fire size distributions.

3.9 Fire Size Distributions in Chaparral Ecosystems

Our goal here is to demonstrate application of HOT to fire datasets to see how well they do or do not adhere to the distribution of fire sizes predicted by this framework. In particular, we aim to contrast regions that have varying degrees of similarity in fire regime controls, to determine if adjacent regions with different top-down influences still hold to HOT predictions.

Many fire size datasets show evidence of power law behavior over some mesoscale range (e.g., Fig. 3.2), with a "cutoff" at the upper event sizes (Burroughs and Tebbens 2001). A steepening of the slope in the largest fire-size range may correspond to some upper limit to the growth of fires in the study domain. Such an upper truncation could be caused by large fires stopping when they eventually reach landscape boundaries, such as adjacent oceans or deserts, ridgetops, or catchment boundaries. The upper limit could also be dictated by the duration of fire weather episodes (e.g., hot, dry, and strong wind events that typically last less than a week), which would constrain the final size of the largest events. A steepening of slope in the heavy tails of these distributions is therefore not a contradiction to HOT predictions; on the contrary, it is indicative of the scale of spatial controls operating in the creation of the largest patches.

One issue worth mentioning here is the choice of study domain size: How do we identify the most appropriate scale at which this type of analysis is to be performed? One could compile fire size data from a very large study area, which would contain many different ecosystems with quite different fire regimes. In that case, we might not expect evidence of a clear cutoff in the large fire size range, since many different upper limit boundaries are being mixed together in the dataset. Mixtures of fire

regimes with different large event cutoffs could also lead to steeper power-law slopes over what would otherwise constitute the meso-scale range of the distribution (Doyle and Carlson 2000). Identifying the spatial limits of a region with a roughly homogeneous fire regime is thus an important and under-explored area of study.

In the smaller fire size range (the left tail of the fire size distribution), a shallower slope and the opposite tendency is often observed—i.e., relatively large increases in size between the probability of one fire and the next largest—up to a meso-scale range exhibiting power law behavior (e.g., see Fig. 3.2). One explanation for this flattening of slope could be that many of the events below the lower cutoff size are unrecorded, undetected, or undetectable, and their inclusion would steepen this portion of the distribution. Another explanation is that the interaction of factors driving and/or constraining the spread of smaller fires is basically different than that occurring across the meso-scale range displaying power law behavior, leading to a differing slope.

The analytical solution to the HOT model that minimizes average fire sizes (l) has the following cumulative form (referred to as the PLR or probability-loss-resource model, Moritz et al. (2005) and references therein), after including both the small (C) and large (L) event cutoffs:

$$P(l) \sim (C+L)^{-\alpha} - (C+L)^{-\alpha} \tag{3.2}$$

Similar to Eq. 3.1 above, a constant is applied to the right-hand side of Eq. 3.2 to normalize units of probability P. The constant, the truncation parameters for the cutoffs, and the exponent can be chosen through an objective fitting algorithm (e.g., maximum likelihood), or values may be selected based on other criteria (e.g., smallest and largest events in record, hypothesized slope). Regardless of the slope or the mechanism in question, this lower- and upper-truncated power law function provides a simple tool for examining fire size data and the range over which power law behavior applies. In this example, we are not objectively fitting algorithms to determine parameter values; instead, we specify the cutoffs from the data themselves.

3.9.1 Exposed vs. Sheltered from Extreme Fire Weather

So far we have considered the meso-scale domain of fire regime controls to be that across which fire sizes display a power-law distribution, presumably structured by various feedbacks and forcing factors. If there are specific ensembles of fences and corridors characteristic of particular fire regimes – our hypothesized signature of landscape resilience – it is not yet obvious how broad-scale differences in top-down controls might alter fire size distributions from the "functional form" with power law slope of −1/2 described above.

One of the datasets examined in Moritz et al. (2005) and shown in Fig. 3.2 is for the combined chaparral-dominated shrublands of Los Padres National Forest (LPNF) in central coastal California. In analyzing the degree to which time since

the last fire constrains subsequent burning probabilities, it has been shown that most shrublands of the region do not show a strong relationship between the age of fuels and the hazard of burning (Moritz 2003; Moritz et al. 2004). This is largely because these regions are routinely exposed to seasonal drought and Santa Ana wind episodes, which can drive fires through all age classes of vegetation. There is one region of LPNF, however, that is sheltered from Santa Ana winds and actually shows a moderate degree of age dependence in burning probabilities. Although the region near the town of Santa Barbara is subject to highly localized fire weather events known as "sundowner winds," the alignment of local mountain ranges appears to shelter the region from the more synoptic-scale Santa Ana winds that case massive fires in other parts of California (Moritz 2003; Moritz et al. 2004).

Disaggregating the fire data for LPNF into the Santa Barbara region and the adjacent Ventura region, we see in Fig. 3.3 that both distributions display quite similar shapes and hold closely to HOT predictions. These two regions vary markedly, however, in the amount of area burned in very large fires. The ten largest events, for example, comprise a total of ~95,000 and 213,000 ha burned in the Santa Barbara and Ventura regions, respectively (encircled in Fig. 3.3 and plotted in Fig. 3.4). Notably, the largest ten events account for the vast majority (~95%) of the difference in area burned by all fires shown for these regions.

Despite striking differences in conditions under which most of the area burns, the adjacent regions shown in Fig. 3.3 both appear to be good fits to a power law

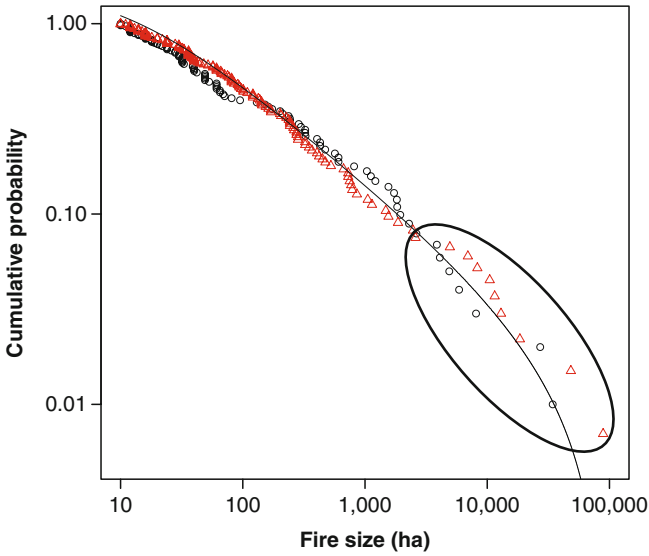


Fig. 3.3 Fire size distributions for subregions of Los Padres National Forest. Data includes fires > 10 ha and since 1950 for Santa Barbara (*black circles*) and Ventura (*red triangles*) regions, with largest 10 events encircled in lower *right*. *The black line* shows the HOT prediction of slope −1/2 (Eq. 3.2, $C = 10$ and $L = 100{,}000$)

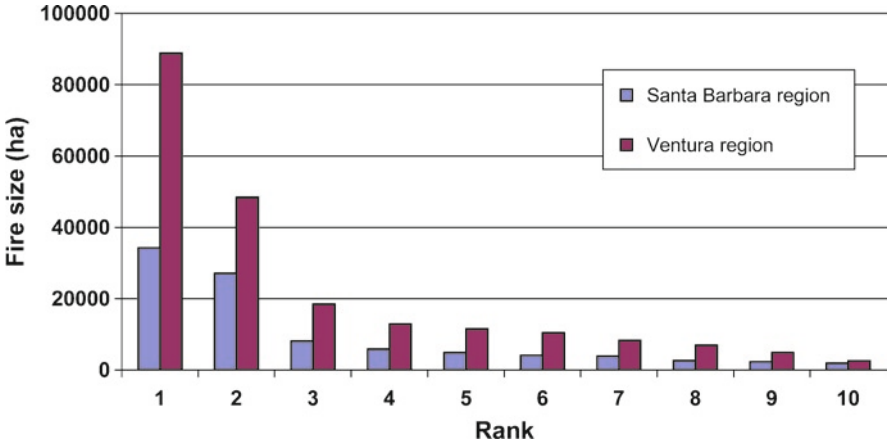


Fig. 3.4 Size comparison of 10 largest events for regions within the Los Padres National Forest

with a slope of −1/2. The fire size data for the Santa Barbara region are not as heavy-tailed as that of the Ventura region, but in a log-log plot, this difference is not as large a deviation as the total area burned would indicate. The majority of fire events occurring in the meso-scale range of the fire regime still exhibit a remarkably similar form in terms of fire-size distributions. This suggests somewhat similar types and scales of landscape heterogeneity between the regions examined. In other words, comparable ensembles of fences and corridors for fire spread may be encountered for most events in the fire regime of both regions.

3.9.2 Landscape Resilience in Chaparral

For the chaparral-dominated shrublands examined here, the interplay of endogenous and exogenous controls apparently maintains a specific structure in the fire size distributions, despite major differences in top-down fire weather types and frequencies. How does this relate to ecological resilience on a fire-prone landscape?

As noted earlier, an ecologically severe fire in chaparral would tend to involve short fire intervals in a given location. This is because several dominant chaparral plants have specialized life histories that for their persistence on the landscape require a seedbank to accumulate locally before the next fire. Thus, frequent fires can lead to the replacement of some of the native dominants by invasive annual species (Zedler et al. 1983). In and of themselves, large and intense fires are not ecologically severe events, as long as they are well separated in time. Maintaining this separation is at least partly dependent on ignition patterns, since more ignitions will increase the likelihood that a fire actually occurs under extreme fire weather conditions and be capable of burning through young and regenerating stands of

vegetation. As this trend continues, larger and larger portions of the landscape become type-converted into highly flammable species that can support fire every year–a positive feedback that is known as the "grass/fire cycle" (D'Antonio and Vitousek 1992). Landscape resilience can thus be fundamentally altered, leading eventually to a new alternative state, if system sensitivities are challenged repeatedly and ecological thresholds are eventually crossed.

HOT provides a promising conceptual and analytical framework for understanding the ensemble of fences and corridors that structure fire patterns on landscapes subject to this natural disturbance. Admittedly, however, we have not rigorously demonstrated that the best-fitting slope for the truncated power law in Fig. 3.3 is actually −1/2. It is also possible that a different statistical distribution altogether may be a better fit to the fire size data we examined. Although chaparral ecosystems appear to have an inherent resiliency against infrequent large events in the tails of fire size distributions, the tradeoffs between constraints and drivers hypothesized in HOT have yet to be identified. Steps toward linking fire regimes to various endogenous and exogenous factors driving them would therefore include a more statistically rigorous approach to fitting fire-size data to statistical distributions, and direct evaluation of relations between endogenous and exogenous factors and the distributions themselves. We undertake these steps below.

3.10 Fire Size Distributions in Ecoregions of California

Much of the discussion of landscape and ecosystem resilience to date has been descriptive and theoretical in nature. Recently, however, several researchers have begun to take quantitative methods from laboratory simulation experiments and apply them to natural systems, as in the application of the HOT model to California chaparral just described. This is important on several levels, since it allows observation of natural systems that may be under purely endogenous (syn. fine scale, bottom-up), purely exogenous (syn. broad scale, top-down), or mixed controls (syn. meso-scale). Evidence for power-law relations among wildfire events has largely relied on the log-linear relationship of the frequency-size distributions of fires. Power laws have been suggested with satisfactory fits of ordinary least squares linear regression to log-log transformed, cumulative (CDF) or non-cumulative frequency-size distributions (Malamud et al. 1998). Distributions tend to be described using the one-parameter Pareto I distribution introduced earlier or some variation on it (e.g., the truncated form in Eq. 3.2). However, the intricacies of demonstrating a good power-law fit in the first place have received relatively little attention.

The underlying goals of this analysis were to objectively evaluate evidence for (1) power law behavior in the event size distributions of wildfires in California, and (2) potential top-down (exogenous) and bottom-up (endogenous) controls over the structure of these distributions. In ecological systems, we suspect that interactions among constraining and contextual influences (*sensu* Wu and Loucks 1995) may offer a fuller explanation for what drives system structure. We therefore attempt

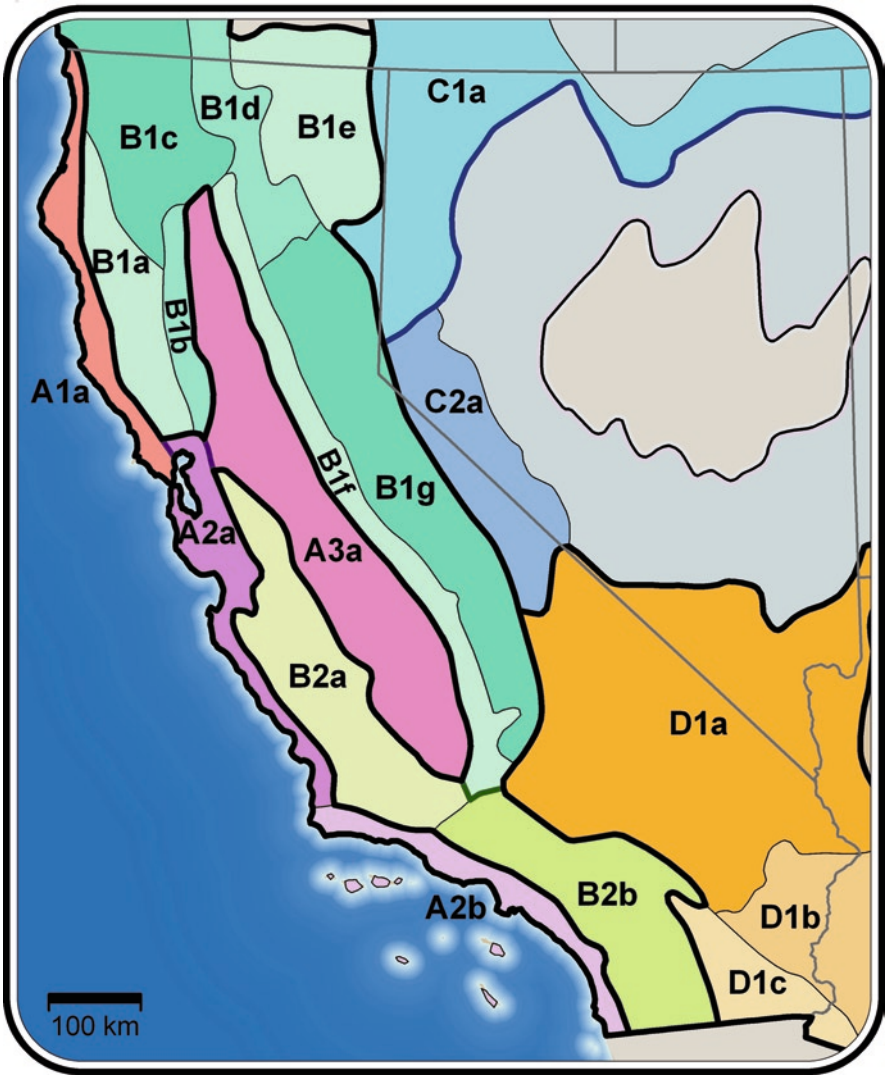
here to test for different forcing factors in a variety of fire-prone ecosystems, at the observation scale of ecoregions, for the State of California. Our objective was to provide quantitative evidence of both endogenous and exogenous forms of spatial control in natural systems, while also distinguishing their control domains.

We used an atlas of recorded fire event sizes in California for the period 1900–2007. Because fire records were spotty for the first half of the 20th century, we pared the atlas down to the period 1950–2007 to avoid the greatest potential bias in recording event-size distributions. We also note the likely incompleteness of the dataset for wildfires less than 40 ha occurring in forest or 120 ha in grass or shrubland habitats. These are threshold sizes when a fire start is considered a large wildfire incident, from a suppression standpoint. We assumed that most so-called large wildfire incidents were recorded, but that record-keeping of the smaller events was likely uneven due to their lesser operational importance.

An on-line geodatabase for the Bailey nested "ecoregions" was acquired (Bailey 1995, *http://www.fs.fed.us/rm/ecoregions/products/map-ecoregions-united-states/*), including spatial layers for the division, province, and section levels. We used the multi-level regionalization to determine whether the biogeoclimatic setting of the fires explained differences in event-size distributions, and at which scales of observation distributions showed the highest goodness-of-fit. Where ecoregions at one scale minimized variance in event-size distribution when compared with other scales of observation, this would be quantitative evidence of the approximate scale of top-down spatial control on event size distributions. To accomplish this, we stratified the California fire event atlas for the period 1950–2007 by the Bailey division, province, and section strata (Fig. 3.5). We then submitted the stratified fire-size distributions to the set of distribution fitting and goodness-of-fit techniques.

3.10.1 Distribution Fitting

Our first objective was to fit the HOT model to fire event sizes within Bailey's nested divisions, provinces, or sections across California (Fig. 3.5). We began by fitting the model using the constant slope of −0.5 (hereafter, the HOT_{2D} model), and then by using maximum likelihood estimation (MLE, Nash 1990) to find the best slope of the PLR model for the data (hereafter, the HOT_{MLE} model). As described earlier, the dimensionality of the HOT_{2D} model arises from the notion that fire event size increases as a function of a 2-dimensional spreading fire front with 1-dimensional perimeters of active fire spread or extinguishment. In essence, fire spread is constrained by polygons of fuel/non-fuel conditions, topography, and fire suppression (e.g., fences and corridors), the strength of which is moderated by climate and fire weather events. For each instance above (HOT_{2D} and HOT_{MLE}), fire size distributions were sequentially left-censored to find the range of patch sizes that best fit the distribution of the PLR models. We assessed PLR model goodness-of-fit (GOF) to the data using a bootstrapped version of the one-sample Kolmogrov-Smirnov (K-S) test through 2,500 iterations (Clauset et al. 2009). Acceptable model GOF


C1a
B1d
B1e
B1c
B1a
B1b
A1a
C2a
B1f
B1g
A2a
A3a
B2a
D1a
B2b
A2b
D1b
D1c
100 km

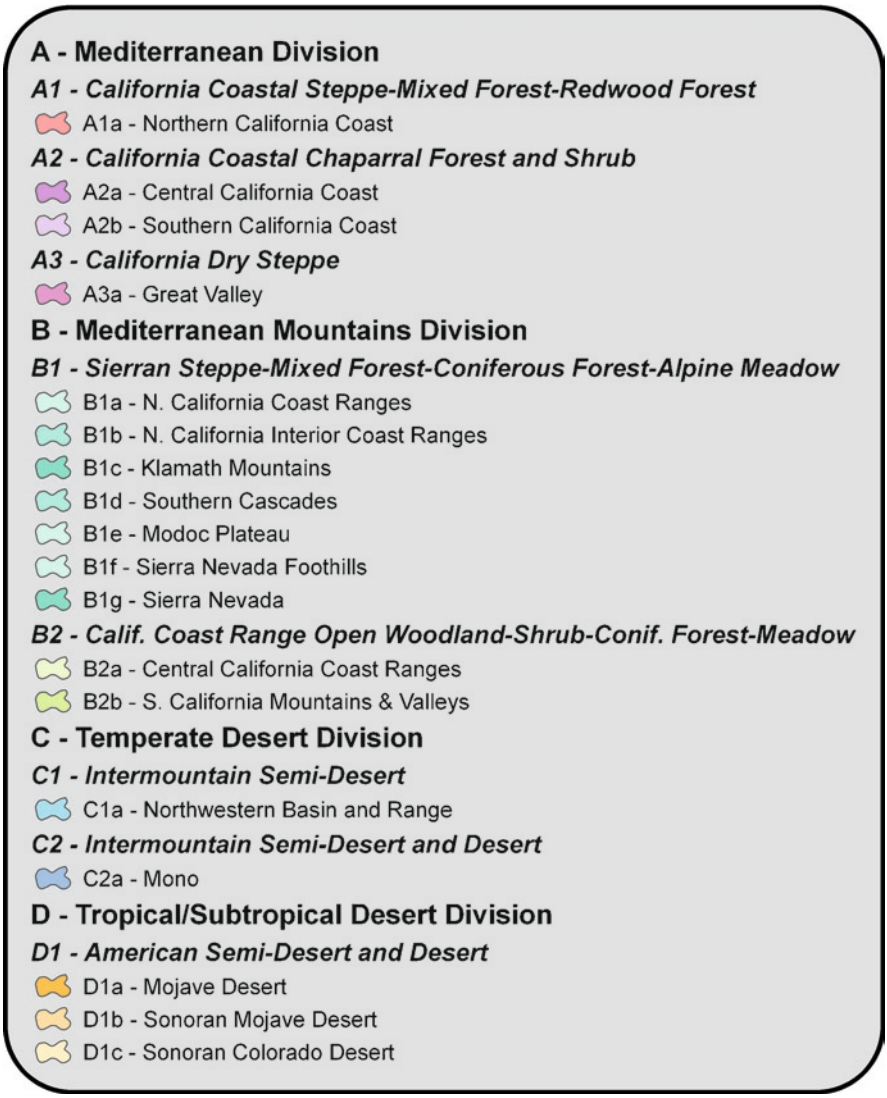


Fig. 3.5 Bailey's (1995) ecoregions within California. The analysis used all three levels of the classification: divisions (*single letters in caption*), regions (*letter + number*), and sections (*letter + number + lower-case letter*)

was indicated by $p > 0.10$, which indicates no significant difference between the data and the respective PLR model.

We also examined a variety of additional statistical distributions. Distribution fitting techniques in power law studies generally come in two flavors: (1) fitting ordinary least squares regressions to the log-log transform of either the empirical cumulative or non-cumulative frequency-size distributions (CDF), and (2) fitting the 1-parameter Pareto I distribution (P-I) using MLE, and assessing the fit of this model to the data using one of a variety of goodness-of-fit (GOF) tests (e.g., Chi-square, Kolmogrov-Smirnov tests). Several recent articles have convincingly argued for the latter method, because it is most appropriate for estimating the parameters of a Pareto model and its goodness-of-fit to data (White et al. 2008; Clauset et al. 2009).

We evaluated potential power-law behavior in three ways: (1) by fitting a variety of 2-, 3-, and 4-parameter complex Pareto models with known power law behavior, (2) directly fitting Pareto I (P1) and truncated Pareto I (TP1) models to fire-size distributions following the methods of Clauset et al. (2009), and (3) fitting broken-stick regression models to the inverse of the empirical CDF (Boer et al. 2008). Each of these methods has advantages and disadvantages (Table 3.1), and we used them to objectively evaluate the presence and scale(s) of power-law behavior in fire size distributions.

In the first assessment, we objectively fit a closely related family of Pareto and Generalized Beta II models to the inverse of log-log transformed empirical CDFs of fire event sizes using MLE. The distributions within the Generalized Beta II (GBII = Feller-Pareto, Arnold 1983) and Pareto families are 2–4 parameter models, including the Lomax (2P; = Pareto II), Inverse Lomax (2P), Fisk (2P; = Pareto III), Paralogistic (2P), Inverse Paralogistic (2P), Singh-Maddala (3P; = Pareto IV), and Dagum (3P) distributions. These models all have in common implied presence of power-law behavior in the middle and/or right tail of the distribution (Clark et al. 1999). MLE was performed using vector generalized linear models within the VGAM package in R version 2.9.1 (Yee 2006, 2008). To select the best model, we favored model parsimony and the minimum K-S test statistic. In the second assessment, we employed the methods of Clauset et al. (2009) to identify the lower boundary of the fire event sizes (*x.min*), above which power-law behavior most likely occurred. The third assessment involved fitting 1- or 2-break broken-stick regression models to the inverse CDFs to identify whether more than one scaling region was possible, as outlined by Boer et al. (2008). Scaling regions could indicate unique process domains and degrees of influence on fire event size. We assessed model GOF for the first two methods as described above under PLR distribution fitting.

3.10.2 Evaluating Top-down and Bottom-up Controls

For each of the three Bailey ecoregion levels, we evaluated the effect of top-down forcing by quantitatively comparing the fire event-size distributions among ecoregions. We used pairwise (two sample) K-S tests to determine the best stratification level for the data.

Table 3.1 Advantages and disadvantages of methods for determining the adequacy of power law model goodness-of-fit to fire event size distributions

Method	Advantages	Disadvantages
Fitting complex Pareto and GB II models with suspected power law tails to the entire distribution of patch-sizes (see Clark et al. 1999)	Can model the distribution of patch-sizes over entire range of observation using maximum-likelihood estimation (MLE)	Visually approximates the range of patch-sizes where power law behavior occurs Lack of model fit does not eliminate the possibility of power law behavior in the distributions
	Can implement modified goodness-of-fit (GOF) tests to determine adequacy of model fits to the observed distributions	Goodness-of-fit is dependent on the type or class of test used in analysis (e.g., KS, Chi-square, Anderson-Darling)
	Can compare model fit and parameter estimates within and among empirical distributions	
Fitting a 1-parameter Pareto I (power law) model to the right-tail of the distribution (see Clauset et al. 2009)	Fits power law model using MLE	Location and GOF is dependent on the type of GOF test employed
	Adequacy of fit can be assessed using modified GOF tests	May miss the presence of a power law scaling region where model departures occur at the extreme end of the right-tail; these departures may be intuitively explained as upper physical or ecological limits on power law behavior
	Objectively determines scaling region in the right tail based on the Kolmogrov-Smironov (K-S) test statistic; most power law behavior in systems is known to exist in the right-tail (Clauset et al. 2009)	Cannot identify multiple scaling regions in the data
Fitting a 1- or 2- parameter broken-stick model to identify scaling regions (see Boer et al. 2008)	Method is based on MLE and not on ordinary least-squares regression	GOF tests can be misleading as a good fit of the model to the data is not imperative in identifying scaling regions
	Can control the parameter number (breakpoints) in the model	GOF tests will generally favor highly parameterized models
	Can objectively determine lower and upper bounds on power law behavior, and identify multiple scaling regions, where present	Breaks may/may not be ecologically meaningful

To evaluate influence of bottom-up forcing, we evaluated patch size distributions of simple *aspect* (N or S) topographies derived from a 90-m digital elevation model (DEM). We also evaluated slope, curvature, and combined topographies but settled on aspect because it showed the best GOF when a left truncated Pareto-I model was fit to the aspect patch size data. Distribution fitting using MLE and GOF assessment for the topographic features followed the same methods used for the fire event-size distributions. We directly evaluated the influence of topography on fire event sizes by again using a pairwise K-S test on all event sizes and aspect patch sizes greater than the estimated *x.min* for the best fitting Pareto I model. To find the region of concordance between the aspect patch and fire event size distributions, we sequentially removed the patches from the right tail until a $p > 0.10$ was reached.

3.10.3 Characteristics of California Fires

Fire event sizes across California from 1950 to 2007 followed a distinctive pattern over most of the state, where small- to medium-sized fires were most common, and large fires >10,000 ha in size were relatively rare events. Fires ranged in size from 1 to 100,000 ha in size.

The greatest numbers of fires recorded were located in the Southern California Mountain Valley and Coast sections with 0.11 and 0.08 fires km^{-2}, respectively. Vegetation communities in this area are dominated by fire-adapted species, and physiognomies range from grasslands/shrublands and open hardwood woodlands in the foothills to ponderosa pine forests in lower-montane settings. Human population is also highest in these sections, with high concentration of anthropogenic ignitions. Fires of southern California are also influenced by Santa Ana (foehn) winds that have been linked with extreme fire behavior (Moritz 1997).

For most ecoregions, the 2- or 3-parameter GBII and Pareto models adequately fit the CDFs, based on a bootstrapped version of the K-S GOF test. These distributions all have in common the likely presence of an embedded power law region, suggesting that power law behavior is likely found above a certain minimum fire size. In the left tail of the fire event size distributions, where most of the fire events occurred (but represented the least part of wildfire affected area), there was evidence of a distinct change in slope at around $10^{1.5–2}$ ha, for most ecoregions, as can be seen in the empirical inverse CDF plots in Fig. 3.6. Factors accounting for this behavior may be: (1) fire reporting, recording, or mapping errors, (2) variable fire suppression efficacy, and (3) endogenous forcing. It is not possible to determine from the distributions alone which of these factors had the greatest influence on event sizes. However, highly dissimilar ecoregions, which vary in the amount of fire reporting errors and suppression efficacy, each followed this trend, indicating that endogenous factors may account for the lack of fit of the Pareto I model to the left-tails of the distributions.

3.10.4 Selecting an Optimal Ecoregion Scale

When attempting to detect direct evidence for controls on response variables, it is reasonable to first evaluate various regroupings of the data to observe those that are ecologically most intuitive and best minimize variance within the data. We used Bailey's ecoregion hierarchy to select an appropriate scale of observation for displaying potential top-down controls on fire event size distributions. Results of fitting various distributions to fire event sizes in Bailey's nested divisions, provinces, and sections showed that top-down ecoregional controls were best observed at the section level. At the division level 67% of the pairwise K-S test comparisons showed significant differences among ecoregions, while at the province and section

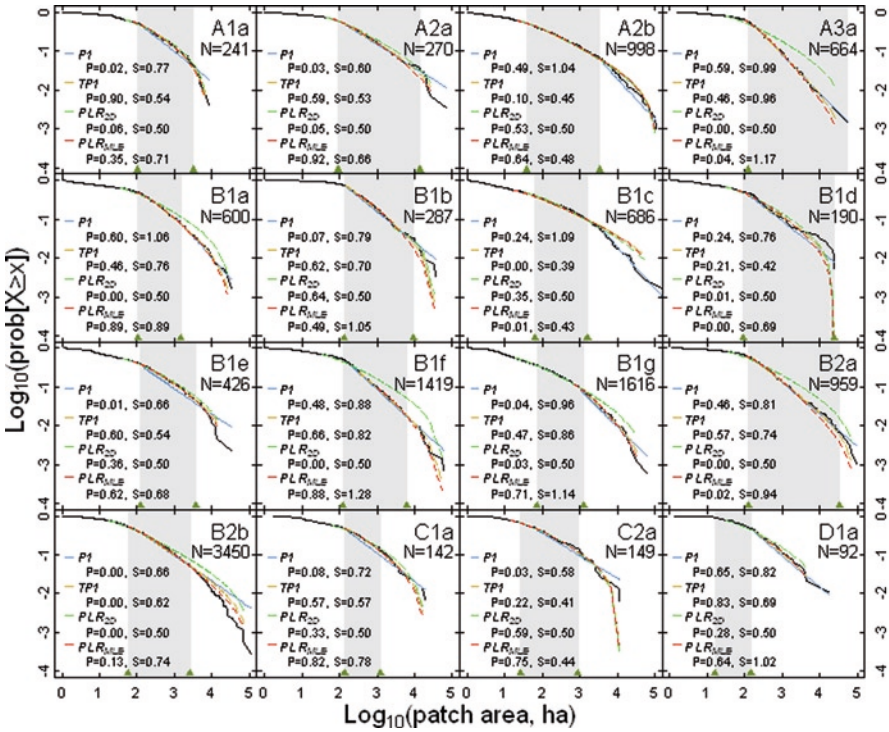


Fig. 3.6 The log-log plots of the empirical inverse cumulative distribution functions (CDFs) for event-size distributions of wildfires (> 1 ha) within Bailey's sections in California from 1950–2007. *Black* lines represent the empirical inverse CDF for fire patch-sizes. *Blue* lines represent the best-fit 1-parameter Pareto I (*P1*) distribution to the right-tail of the data, *orange dashed lines* represent the best truncated P1 fits, and the *green* and *red dashed lines* represent the best HOT_{2D} and HOT_{MLE} fits to the data, respectively. *Green triangles* represent the break-points for broken-stick regression models estimated by maximum-likelihood. Shaded areas represent a meso-scale domain where we theorize that endogenous and exogenous factors jointly influence the distribution of patch sizes

levels 79% and 88% of the comparisons were different, respectively. Thus, we report modeling results summarized to sections only.

3.10.5 Distribution Fits for California Fires

Results from our distribution fitting exercise support those from the earlier analysis we performed on a small chaparral-dominated region, and they provide evidence of HOT behavior for wildfires across much of California. Fourteen of 16 (88%) Bailey's sections showed support for HOT behavior; i.e., significant fits to the HOT_{2D} or HOT_{MLE} models, for fires larger than ~100 ha (Table 3.2).

Exceptions were the Great Valley and Central California Coast Range sections (Fig. 3.6), which we take up later.

The HOT_{2D} model fit seven of the 16 ecoregions (44%), based on the bootstrapped version of the K-S test. Sections located in desert (Mojave), semi-desert (NW Basin and Range, Mono), or chaparral (Southern California Coast) generally provided the best examples of the HOT_{2D} model (Table 3.2, Fig. 3.6). The Southern California Coast section represented the clearest example of a HOT_{2D} model, consistent with our earlier chaparral case study above, and this section includes the whole of that study area. The group of sections best explained by the HOT_{2D} model is dominated by fire-prone grassland or shrubland vegetation communities, all of which naturally have a high-severity or stand-replacement fire regime. Where fire

Table 3.2 Fit of the Pareto 1 (P1), truncated Pareto 1 (TP1), and HOT probability-loss-resource (PLR) models to the event size distributions of California wildfires > 100 ha for the period 1950–2007

Bailey's (1994) ecosection	N	P-1	TP1	PLR_{2D}	PLR_{MLE}
Northern California Coast	241	0.02	**0.90**	0.06	**0.35**
Central California Coast Ranges	270	0.03	**0.59**	0.05	**0.92**
Southern California Coast	998	**0.49**	**0.10**	**0.53**	**0.64**
Great Valley	664	**0.59**	**0.46**	0.00	0.04
Northern California Coast Ranges	600	**0.60**	**0.46**	0.00	**0.89**
Northern California Interior Coast Ranges	287	0.07	**0.62**	**0.64**	**0.49**
Klamath Mountains	686	**0.24**	0.00	**0.35**	0.01
Southern Cascades	190	**0.24**	**0.21**	0.01	0.00
Modoc Plateau	426	0.01	**0.60**	**0.36**	**0.62**
Sierra Nevada Foothills	1,419	**0.48**	**0.66**	0.00	**0.88**
Sierra Nevada	1,616	0.04	**0.47**	0.03	**0.71**
Central California Coast Ranges	959	**0.46**	**0.57**	0.00	0.02
Southern California Mountains and Valleys	3,450	0.00	0.00	0.00	**0.13**
Northwestern Basin and Range	142	0.08	**0.57**	**0.33**	**0.82**
Mono	149	0.03	**0.22**	**0.59**	**0.75**
Mojave Desert	92	**0.65**	**0.83**	**0.28**	**0.64**

Values in **bold** type face are significant ($p > 0.10$)

severity functions more or less as a constant, the HOT_{2D} model appears to most elegantly explain the origin of fire-size distributions. Thus, the map of grassland and shrubland landscapes functions as a mosaic of fuel/non-fuel patches resulting from prior disturbance and recovery, and event-sizes are driven by the magnitude and period of the climatic or weather influence during events. Similarly, fire event size distributions are highly relevant to understanding vegetation and disturbance patch dynamics, because fire-event and fire-severity patch-size distributions are more or less equivalent. Where fire severity is more variable, we theorize that fire event sizes are much less important. Rather, fire severity patch size distributions are likely the key.

The Klamath Section, which also fit the HOT_{2D} model, was a notable exception. The Klamath comprises roughly equal parts of rangeland and forest physiognomies (Bailey 1995). We hypothesize that the fire regime and forest type complexity of the Klamath should be further subdivided to better understand top-down and bottom-up controls on fire event-size distributions. The same is likely true for the Modoc Plateau Section (Table 3.2, Fig. 3.6).

Allowing for variable slopes, the HOT_{MLE} model fit 88% of fire event-size distributions at the section level, despite large ecological and geographical variation. Slope values for most sections were steeper than that of the HOT_{2D} model with the exception of the Klamath, Mono and Southern California Coast sections (Fig. 3.6). Where slopes are steeper than −0.5, the dimensionality of wildfires may be lower than that predicted by the HOT_{2D} model (Carlson and Doyle 1999). In California, this occurs in sections where relatively higher spatial complexity of topography, forest and rangeland types, structural conditions, climatic influences, and fire regimes is apparent. Falk et al. (2007) hypothesize that these relations might be expected. For example, they suggest that climatic anomalies that magnify weather extremes or lengthen fire seasons may lead to more variability in the distribution of fire sizes and larger maximums, which would tend to flatten the slope of the fire size distribution. In contrast, highly dissected topographies would tend to retard fire growth under non-extreme fire weather conditions, thereby reducing the largest fire sizes, which would tend to steepen the slope of the fire size distribution. (Carlson and Doyle 1999).

Doyle and Carlson (2000) posit that "landscapes which naturally break forests into regions of fractal dimension lower than 2 [slope is < −0.50] *would* have steeper [sloped] power laws by definition." With few exceptions, our results confirm that observation. A simple one-dimensional model, such as a network or flow route of linear features, would show a slope of around 1. In montane forests, winds during fires tend to be directional and wind flow is routed and concentrated by topography. Perhaps HOT model slopes tending towards 1 reflect a primary influence of fire flow routing in event size distribution. An important area of near-term research is unraveling the ecological meaning of differing slope values and their causal connections.

Several additional models (i.e., P1 and TP1) fit to all but one of the Bailey's sections; the Southern Mountain Valley Section. Similar to the HOT model GOF, these models fit best to fires larger than ~100 ha (Table 3.2). The P1 model fit best

to the Great Valley (A3a), Mojave (D1a), Southern Cascades (B1d), Sierra Foothills (B1f), and Central Coast Ranges (B2a). For most other sections, the largest event sizes in these sections were smaller than those predicted by a pure power-law fit. This effect may be caused by physical constraint on the size distribution of aspect patches (and perhaps curvature and slope patches) imposed by geomorphic processes of an ecoregion. The best fitting section to the P1 model was the Great Valley. In the Great Valley, topography is flat to rolling, climatic influence is relatively more constant, and the land is highly parceled, owing to spatially continuous development and agriculture. As a consequence, we observe mostly anthropogenic and endogenous controls on wildfire spread. The Klamath and Southern California Coast sections shared a significant fit of the P1 to only the largest fire sizes, indicating that the largest fires in these sections might be under different controls than smaller fires.

3.11 The Meso-Scale Process Domain and a Role for Topography

We theorized that fire event sizes are controlled by different processes operating at different spatial scales (Fig. 3.9). For example, at fine scales ($<10^2$ ha), endogenous factors such as the spatial patterns of micro-topography and environment, stand dynamics and successional processes, and endemic insect and pathogen disturbances may affect fire size, regardless of human influence. At broad scales ($>10^4$ ha), exogenous factors may contribute to large and very large fire sizes, regardless of human influence (Fig. 3.9). Broad-scale controls might include climatic events such as multi-year droughts, multi-decadal climatic oscillations such as the PDO and ENSO (Heyerdahl et al. 2002; Hessl et al. 2004; Schoennagel et al. 2005), and gradient or foehn winds (Moritz 1997). At meso-scales ($\sim 10^2 - 10^4$ ha), however, fire-event sizes are influenced by a mixture of both endogenous and exogenous controlling factors (Turner 1989), and human influence can be most effective in influencing the distribution of medium to large fire sizes (Fig. 3.9).

We used broken-stick regression analysis to identify a possible meso-scale domain where exogenous and endogenous influences were both at work. Evidence from this analysis confirmed a meso-scale process domain likely exists between about 10^2 and 10^4 ha. These results, combined with the distribution modeling, indicate the presence of different scaling regions and process domains (fine, meso, and broad). Different forcings on fire-size distributions act independently (within their domain) and interact (on the edges of their domain) to control the distribution of wildfire event sizes.

Power-law behavior in a variety of earth systems has been studied and described extensively (Hergarten 2002, and references therein). Results from our analysis of topographies in California sections showed strong power law behavior in the distribution of north and south (N/S) aspect polygons. The left-censoring technique, which finds the minimum patch-size where the power law model best fits the data,

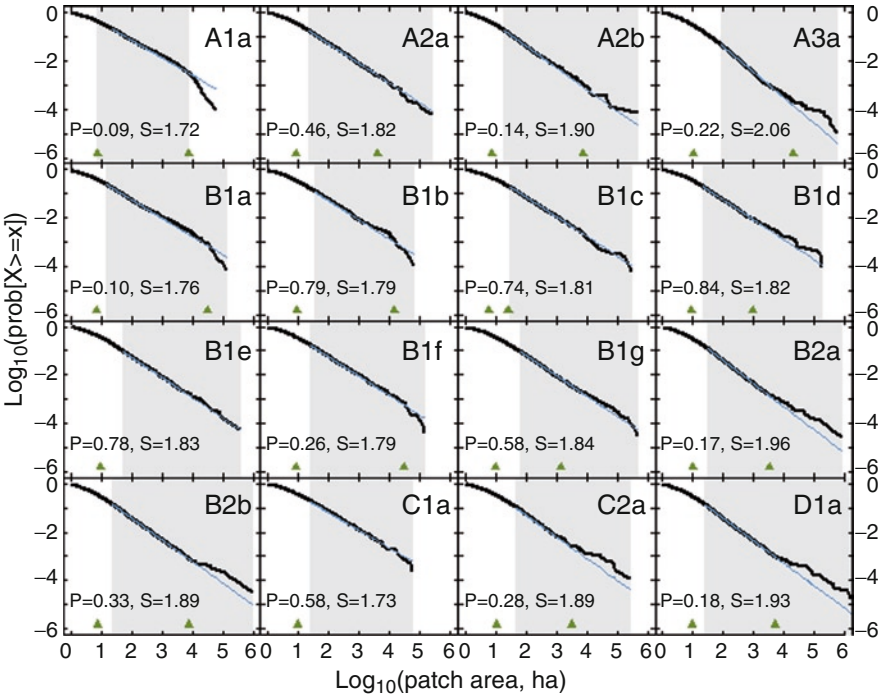


Fig. 3.7 The log-log plots of the empirical inverse cumulative distribution functions for size distributions of aspect (N/S) patches (> 1 ha) within Bailey's sections in California. *Black* lines represent the aspect patch-size data; *blue lines* represent the best-fitting 1-parameter Pareto I (*P1*) distribution to the *right*-tail of the data from the estimated lower cut-off (*vertical dotted line*). *Green triangles* represent the break-points for broken-stick regression models (*BSRS*) estimated by maximum-likelihood. Shaded areas represent the meso-scale domain as predicted by BSRs. *P-values* ≥ 0.10 indicate acceptable fits of the data to the P1 distribution; *S-value*s indicate the slope of the best fitting P1 model

consistently identified power-law behavior for the distribution of patches $>10^2$ ha (Fig. 3.7). The scaling parameters for the Pareto I distributions of aspect patch sizes were generally slightly steeper than for the fire-size distributions, averaging ~ 1.85–1.9, depending on the Bailey's level.

Because the topographic and fire event-size patches were analyzed on equal logarithmic scales, they were directly comparable, and these results indicated that simple aspect N/S likely provides bottom-up controls on fire-size distributions (Fig. 3.8). In Fig. 3.8, for the meso-scale domains of the aspect and fire event size distributions shown, there was no significant difference between the two models, suggesting that meso-scale topographies may be entraining event size distributions in the same size range. We also evaluated slope and curvature topographies and combinations, and these showed significant control relations, but aspect produced the strongest apparent bottom-up spatial control.

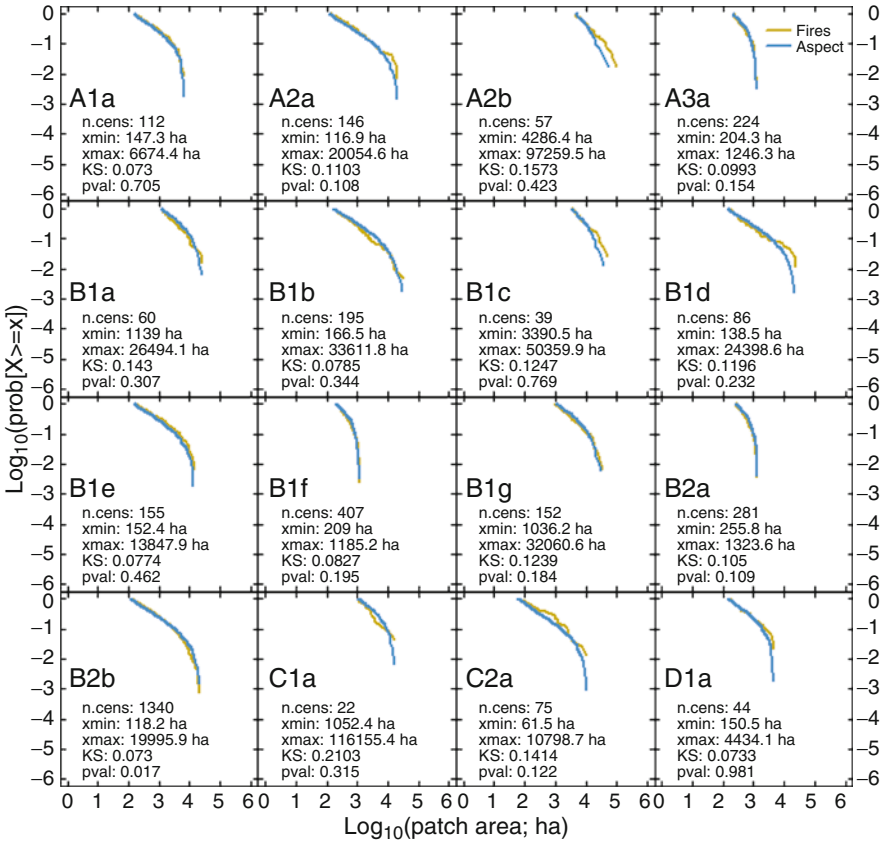


Fig. 3.8 The log-log plots of the statistical concordance between the empirical inverse cumulative distribution functions (*CDFs*) of aspect patch (N/S, >1 ha) and fire event size distributions within Bailey's sections in California. Over the regions shown, there is no significant difference between the two models (two-samples K-S test). The value of *n.cens* is the number of observations censored from the original value of N (see Fig. 3.6) for a given section

Results from our analysis suggest that both top-down geoclimatic and bottom-up topographic factors interact to control the distribution of fire event sizes in California and constrain the scales at which power law behavior is observed (Fig. 3.9). Topographic features such as aspect and slope (results not shown) have been shown to produce a myriad of effects on ecological patterns and processes at fine to meso-scales. Our results suggest that aspect may play an important role in controlling fire size distributions. This landscape effect of topography was observed over a large and diverse California landscape as seen by the similarities in fire-size distributions of sections. While these distributions shared features in common, there were also differences in fire size distributions among ecoregions (Fig. 3.6), in the best-fitting models, and in model parameters. Furthermore, individual section models provided consistently better P1 and TP1 fits than did the pooled sections model.

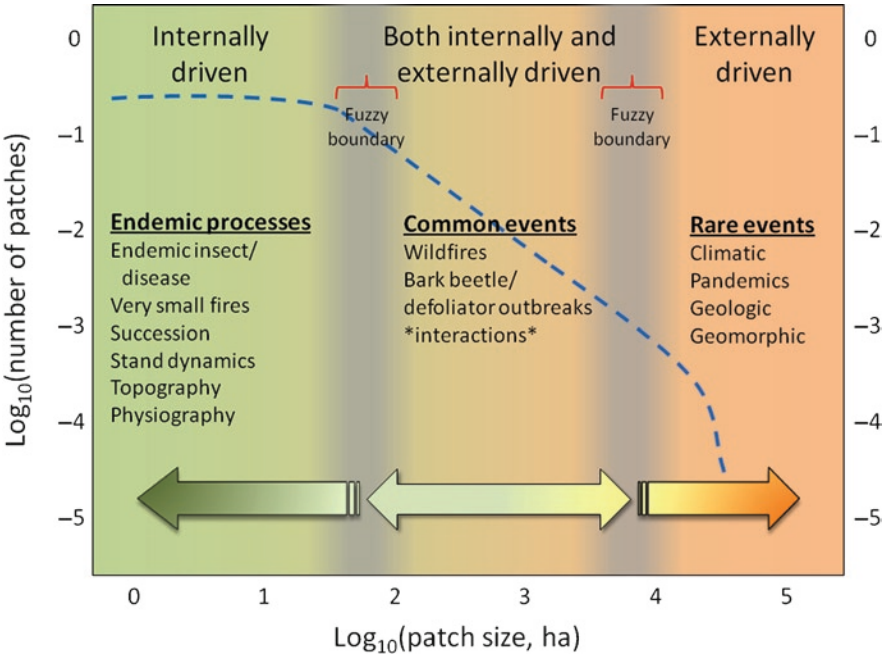


Fig. 3.9 Conceptual diagram of the spatial controls on fire event sizes. In the *left* tail, endogenous factors primarily influence event sizes. Analogously, in the *right* tail, exogenous factors primarily influence event sizes. In a meso-scale region, both endogenous and exogenous factors influence fire event sizes. The meso-scale domain has fuzzy boundaries that change as a consequence of the strength of endogenous and exogenous factors over time

These results suggest that top-down biophysical controls also have distinguishable effects on fire sizes.

3.12 From Whence Come the Distributions?

All of the previously described frameworks contribute to our understanding of landscape resilience, but none fully explains causal mechanisms behind apparently self-organized structure in California wildfires. In this work, we have used alternative ways of looking at California wildfire systems, in the same manner that one might look at some aspect of the world through different colored eye glasses. From what we have discovered thus far, we propose that landscape resilience in these ecosystems stems from the ongoing re-structuring of vegetation conditions by wildfires, controlled spatially and temporally from above by broad gradients of regional and subregional geology, geomorphology, and climate influence. From below, the underlying template of topography appears to cause relatively strong entrainment. Fires themselves are also advanced or retarded by the timing, severity, and spatial

extent of prior disturbances, and their subsequent recovery regime. The net result is an ever-shifting template of fences and corridors, a structured heterogeneity of biotic and abiotic conditions that gives rise to the future mosaic of disturbed and recovering patches. This structured heterogeneity is the resistance surface that advances or retards the penetration of processes, especially disturbance processes, at all points in space or time.

Our observations are consistent with that proposed by Peterson (2002), who suggested that systems have an "ecological memory," whereby past disturbance and recovery create a patchwork mosaic of resistances to penetration by processes. Peterson found that ecological memory was a significant driver of the structure and organization in modeled systems. We provide evidence here for a structure to that ecological memory in natural ecosystems. Specifically, we find that controls on disturbance spread have identifiable scale-dependent domains, with endogenous factors likely dominating at finer scales (fires $<10^2$ ha) and exogenous controls dominating at broad scales (fires $>10^4$ ha).

Organization in natural systems is not static, but instead varies within a broad envelope of potential conditions, a function of the timing, severity, extent, and type of previous disturbances, the topographic setting, and climatic context. During relatively constant climatic conditions, this envelope develops the appearance of stationarity, while not being truly stationary. Under various climatic forcings, the envelope shifts as a function of the strength and duration of the climatic shifting. Nevertheless, within the meso-scale range of fire sizes ($\sim 10^2$–10^4 ha), tradeoffs between various factors controlling fire spread – the shifting surface of fences and corridors that fire must repeatedly negotiate – lead to a relatively predictable power-law distribution of fire sizes. Topography, in particular, appears to play a previously under-appreciated role in generating the heterogeneity important to resilience in many fire-prone ecosystems. Therefore, even as the envelope of potential conditions shifts in a given region, topography remains (more or less) static, partially mediating climatic shifts and providing a template for ecological memory.

Power law relations are scale-invariant, meaning that the shape of patch-size distributions of the system in question is constant regardless of the scale of observation. This is an important relationship in SOC theory, because the mechanisms behind the organization of these hypothetical systems are solely dependent on the internal fuel configuration of the system and the frequency of ignitions. This unrealistic degree of internal regulation simply cannot apply in real fire-prone ecosystems. Similarly, few fire regimes could be entirely driven by exogenous forcings (e.g., wind events). In contrast to such one-sided views, HOT theory predicts that both bottom-up and top-down influences create fire regimes and ecosystems that are resilient to the degree of environmental variation experienced there. This is directly analogous to the HRV associated with a given ecosystem, which is commonly seen as important to resilience. HOT also predicts scale invariance and power law slopes of roughly $-1/2$, a theoretical result of minimizing the spread of two-dimensional events. Our observations show that scale invariance in natural systems does indeed occur over the meso-scale region of fire event sizes across California landscapes.

Perhaps we should not be at all surprised to find power-law distributions in fire sizes, as long as there is an approximate balance between fire growth and fire extinguishment (Reed and McKelvey 2002). It is conceivable that this will someday be intrinsically linked to ecosystem metabolism, with fire acting as fast respiration as biomass accumulates. Regardless, it is remarkable that so many regions in California have fire regimes that approximate a power-law distribution of fire sizes. Many of these regions appear to display a somewhat steeper slope than the −1/2 predicted by HOT, which may result from entrainment by the steeper size distribution of topographic characteristics. Fire in these regions could also be interpreted as following more of a network flow (i.e., closer to one-dimensional), since most are mixed-severity systems in which topography more strongly affects the paths of fires and intensities at which they burn.

We posit that in many fire-prone systems in California, the very large and rare fires play an important role in resetting the mosaic to different degrees, thereby affecting future fire spread, succession, and recovery processes. In most Bailey's sections the largest 10–15% of fires affected two-thirds to three-quarters of the section area. The largest and rarest fires must therefore be an integral part of the entrainment of future fires. [In forests, we suspect that it is the heterogeneous mosaic of fire severity patches within the area contributed by the largest fire events and the large fire event areas themselves that contribute to the entrainment of future fires.] Because of the inherent heterogeneity embedded across meso-scale landscapes, large fires are not necessarily associated with the "unraveling" of ecosystems. When their frequency exceeds that of HRV, however, such increases can exceed the resilience capacity of the system. Conditions for these rare events are mediated both externally by climatic factors and internally by the level of contagion inherent to the system at the time of disturbance. Anthropogenic forces also play a role: As humans increase the availability of ignitions during the most critical climatic conditions, the frequency of large events can approach levels that are destabilizing and far outside HRV.

3.13 Concluding Thoughts

The foregoing observations have implications for restoring a more naturally resilient fire ecology to fire-prone landscapes. If the meso-scale domain of event sizes provides an organizational structure for future fire sizes, then intentional human influences, whether positive or negative, will likely have the greatest impact in that domain. Large and rare events will occur regardless of human intervention, because they are under broad-scale spatial controls. Similarly, small events will occur regardless of human intervention, because they are governed by endemic fine-scale properties of ecosystems. However, in the middle domain, where endogenous and exogenous factors interact, humans may be able to rescale disturbance event size distributions by manipulating the patterns, conditions, and sizes of the patches that make up the fences and corridors that influence disturbance. For example, during

typical wildfires in many forests (non-extreme event conditions), the flaming front is highly responsive to spatial mosaics of canopy and surface fuels (Finney et al. 2007). Conditions conducive to maintaining surface fires in forests typically yield surface fired patches and low- or mixed-severity effects. Those conducive to crown fire yield canopy fires and a preponderance of stand replacement. Likewise, root diseases, dwarf mistletoes, bark beetles, and defoliators are highly host specialized. Mosaics of differing actual vegetation cover type, stand age, density, size, and clumpiness represent varying degrees of resistance to spread of these processes. In the meso-scale range of patch sizes (~ 50 – 5,000 ha), restoration tactics appropriate to the natural fire ecology of the ecosystem will likely have the greatest effect on system meta-stability (Wu and Loucks 1995) and resilience.

It is yet unclear in fire-prone ecosystems exactly how factors other than topography might be involved in the production of specific power law fire size distributions across the meso-scale, although ecologically relevant mechanisms have been suggested (e.g., Moritz et al. 2005). It is likely that variation in fire severity patterns is really at the heart of landscape resilience, with fire event size distributions acting as a surrogate measure in most systems. We suggest that ecosystem-wide heterogeneity in fire effects, as well as landscape resilience that is associated with them, emerge primarily from patterns and processes operating at the meso-scale (Fig. 3.9). Linking distributions of fire severity patches to the HRV in fire sizes, frequencies, seasons, and intensities is an area ripe for a significant amount of new research.

How realistic are fire growth and fire extinguishment (Reed and McKelvey 2002) in generating power law distributions in fire sizes? It is intuitive that there should be some inherent limits on the growth and eventual sizes of typical fire events (Moritz et al. 2005), but how does this occur? In terms of ecosystem energetics, there must be a kind of see-saw balancing act between combustion of biomass and the primary productivity of a landscape. For a simple landscape in which fire is the only "consumer" of vegetation (e.g., Bond and van Wilgen 1996; Bond et al. 2005), one might expect rates of burning to roughly equal rates of biomass accumulation, when examined over broad scales of space and time. We already know that such relationships exist at the global scale, where fire activity shows strong links to net primary productivity patterns (Krawchuk et al. 2009). We do not yet understand all of the precise mechanisms behind the generation of fences and corridors that influence fire's dance across space and time. Pursuit of these questions and others should improve our ability to understand and further quantify the elusive nature of resilience, its variations, and its evolutionary mechanisms.

References

Agee, J.K. 1993. *Fire ecology of Pacific Northwest forests*. Washington: Island Press.
Arnold, B.C. 1983. *Pareto distributions*. Fairland: International Co-operative Publishing House.
Bailey, R.G. 1995. Descriptions of the ecoregions of the United States. 2nd ed. Misc. Publ. No. 1391, Map scale 1:7,500,000, U.S. Forest Service.

Bak, P. 1996. *How nature works: The science of self-organized criticality*. New York: Copernicus.

Boer, M.M., R.J. Sadler, R.A. Bradstock, A.M. Gill, and P.F. Grierson. 2008. Spatial scale invariance of southern Australian forest fires mirrors the scaling behaviour of fire-driving weather events. *Landscape Ecology* 23: 899–913.

Bond, W.J., and B.W. van Wilgen. 1996. *Fire and plants*. London: Chapman & Hall.

Bond, W.J., F.I. Woodward, and G.F. Midgley. 2005. The global distribution of ecosystems in a world without fire. *The New Phytologist* 165: 525–538.

Brown, R.T., J.K. Agee, and J.F. Franklin. 2004. Forest restoration and fire: Principles in the context of place. *Conservation Biology* 18: 903–912.

Burroughs, S.M., and S.F. Tebbens. 2001. Upper-truncated power laws in natural systems. *Pure and Applied Geophysics* 158: 741–757.

Carlson, J.M., and J. Doyle. 1999. Highly optimized tolerance: A mechanism for power laws in designed systems. *Physical Review E* 60: 1412–1427.

Carlson, J.M., and J. Doyle. 2000. Highly optimized tolerance: Robustness and design in complex systems. *Physical Review Letters* 84: 2529–2532.

Carlson, J.M., and J. Doyle. 2002. Complexity and robustness. *Proceedings of the National Academy of Science* 99(Suppl 1): 2538–2545.

Clark, R.M., S.J.D. Cox, and G.M. Laslett. 1999. *Geophysical Journal International* 136: 357–372.

Clauset, A., C. Shalizi, and M.E.J. Newman 2009. Power-Law Distributions in Empirical Data. *SIAM Review* 51(4): 661–703.

D'Antonio, C.M., and P.M. Vitousek. 1992. Biological invasions by exotic grasses, the grass/fire cycle, and global change. *Annual Review of Ecology and Systematics* 23: 63–87.

Davis, F.W., and M.A. Moritz. 2001. Mechanisms of disturbance. In *Encyclopedia of biodiversity*, ed. S. Levin, 153–160. New York: Academic.

Díaz-Delgado, R., F. Lloret, X. Pons, and J. Terradas. 2002. Satellite evidence of decreasing resilience in Mediterranean plant communities after recurrent wildfires. *Ecology* 83: 2293–2303.

Doyle, J., and J.M. Carlson. 2000. Power laws, highly optimized tolerance, and generalized source coding. *Physical Review Letters* 84: 5656–5659.

Falk, D.A., C. Miller, D. McKenzie, and A.E. Black. 2007. Cross-scale analysis of fire regimes. *Ecosystems* 10: 809–823.

Finney, M.A., R.C. Seli, C.W. McHugh, A.A. Ager, B. Bahro, and J.K. Agee. 2007. Simulation of long-term landscape-level fuel treatment effects on large wildfires. *International Journal of Wildland Fire* 16: 712–727.

Gill, A.M. 1975. Fire and the Australian flora: A review. *Australian Forestry* 38: 4–25.

Grimm, V., and C. Wissel. 1997. Babel, or the ecological stability discussions–an inventory and analysis of terminology and a guide for avoiding confusion. *Oecologia* 109: 323–334.

Gunderson, L.H., and C.S. Holling. 2002. *Panarchy: Understanding transformations in human and natural systems*. Washington: Island Press.

Hann, W.J., J.L. Jones, M.G. Karl, P.F. Hessburg, R.E. Keane, D.G. Long, J.P. Menakis, C.H. McNicoll, S.G. Leonard, R.A. Gravenmier, and B.G. Smith. 1997. An assessment of landscape dynamics of the Basin. In *An assessment of ecosystem components in the interior Columbia Basin and portions of the Klamath and Great Basins*. General Technical Report PNW-GTR-405, tech. eds. T.M. Quigley and S.J. Arbelbide. Portland: U.S. Forest Service.

He, H.S., and D.J. Mladenoff. 1999. Spatially explicit and stochastic simulation of forest-landscape fire disturbance and succession. *Ecology* 80: 81–90.

Hergarten, S. 2002. *Self-organized criticality in earth systems*. Germany: Springer.

Herrera, C.M. 1992. Historical effects and sorting processes as explanation for contemporary ecological patterns: Character syndromes in mediterranean woody plants. *The American Naturalist* 140: 421–446.

Hessburg, P.F., B.G. Smith, and R.B. Salter. 1999a. Detecting change in forest spatial patterns from reference conditions. *Ecological Applications* 9: 1232–1252.

Hessburg, P.F., B.G. Smith, and R.B. Salter. 1999b. *Using natural variation estimates to detect ecologically important change in forest spatial patterns: A case study of the eastern Washington Cascades.* Research Paper PNW-RP-514. Portland: U.S. Forest Service.

Hessburg, P.F., J.K. Agee, and J.F. Franklin. 2005. Dry mixed conifer forests and wildland fires of the inland Northwest: Contrasting the landscape ecology of the pre-settlement and modern eras. *Forest Ecology and Management* 211: 117–139.

Hessl, A.E., D. McKenzie, and R. Schellhaas. 2004. Drought and Pacific decadal oscillation linked to fire occurrence in the inland Pacific Northwest. *Ecological Applications* 14: 425–442.

Heyerdahl, E.K., L.B. Brubaker, and J.K. Agee. 2002. Annual and decadal climate forcing of historical fire regimes in the interior Pacific Northwest, USA. *Holocene* 12: 597–604.

Holling, C.S. 1973. Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics* 4: 1–23.

Holling, C.S., and L.H. Gunderson. 2002. Resilience and adaptive cycles. In *Panarchy: understanding transformations in human and natural systems*, eds. C.S. Holling and L.H. Gunderson, 25–62. Washington: Island Books.

Johnson, E.A., and S.L. Gutsell. 1994. Fire frequency models, methods and interpretations. *Advances in Ecological Research* 25: 239–287.

Kauffman, S.A. 1993. *The origins of order: Self-organization and selection in evolution*. Oxford: Oxford University Press.

Krawchuk, M.A., M.A. Moritz, M.A. Parisien, J. Van Dorn, and K. Hayhoe. 2009. Global pyrogeography: The current and future distribution of wildfire. *PLoS ONE* 4(4), e5102. doi:10.1371/journal.pone.0005102.

Landres, P., P. Morgan, and F. Swanson. 1999. Overview of the use of natural variability in managing ecological systems. *Ecological Applications* 9: 1279–1288.

Levin, S.A. 1992. The problem of pattern and scale in ecology. *Ecology* 73: 1943–1967.

MacGillivray, C.W., and J.P. Grime. 1995. Testing predictions of the resistance and resilience of vegetation subjected to extreme events. *Functional Ecology* 9: 640–649.

Malamud, B.D., G. Morein, and D.L. Turcotte. 1998. Forest fires: An example of self-organized critical behavior. *Science* 281: 1840–1842.

Malamud, B.D., and D.L. Turcotte. 2006. The applicability of power law frequency statistics to floods. *Journal of Hydrology* 322: 168–180.

Malamud, B.D., J.D.A. Millington, and G.L.W. Perry. 2004. Characterizing wildfire regimes in the United States. *Proceedings of the National Academy of Sciences* 102: 4694–4699.

Martin, R.E., and D.B. Sapsis. 1992. Fires as agents of biodiversity: Pyrodiversity promotes biodiversity. In *Proceedings of the symposium on biodiversity of northwestern California*. Santa Rosa, ed. H.M. Herner, 28–31. Berkeley: University of California Center for Wildland Resources Report 29.

Millar, C.I., N.L. Stephenson, and S.L. Stephens. 2007. Climate change and forests of the future: Managing in the face of uncertainty. *Ecological Applications* 17: 2145–2151.

Moritz, M.A. 1997. Analyzing extreme disturbance events: Fire in Los Padres National Forest. *Ecological Applications* 7: 1252–1262.

Moritz, M.A. 1999. Controls on disturbance regime dynamics: Fire in Los Padres National Forest. Ph.D. dissertation, University of California, Santa Barbara.

Moritz, M.A. 2003. Spatio-temporal analysis of controls of shrubland fire regimes: Age dependency and fire hazard. *Ecology* 84: 351–361.

Moritz, M.A., and S.L. Stephens. 2008. Fire and sustainability: Considerations for California's altered future climate. *Climatic Change* 87(Suppl 1): S265–S271.

Moritz, M.A., J.E. Keeley, E.A. Johnson, and A.A. Schaffner. 2004. Testing a basic assumption of shrubland fire management: How important is fuel age? *Frontiers in Ecology and the Environment* 2: 67–72.

Moritz, M.A., M.E. Morais, L.A. Summerell, J.M. Carlson, and J. Doyle. 2005. Wildfires, complexity, and highly optimized tolerance. *Proceedings of the National Academy of Sciences of the United States of America* 102: 17912–17917.

Moritz, M.A., T.J. Moody, L.J. Miles, M.M. Smith, and P. de Valpine. 2009. The fire frequency analysis branch of the pyrostatistics tree: Sampling decisions and censoring in fire interval data. *Environmental and Ecological Statistics* 16: 271–289.

Nash, J.C. 1990. *Compact numerical methods for computers: Linear algebra and function minimisation*. New York: IPO Publishing.

Newman, M.E.J. 2005. Power laws, Pareto distributions and Zipf's law. *Contemporary Physics* 46: 323–351.

Nonaka, E., and T.A. Spies. 2005. Historical range of variability in landscape structure: A simulation study in Oregon, USA. *Ecological Applications* 15: 1727–1746.

Odion, D.C., E.J. Frost, J.R. Strittholt, H. Jiang, D.A. DellaSala, and M.A. Moritz. 2004. Patterns of fire severity and forest conditions in the western Klamath Mountains, northwestern California, U.S.A. *Conservation Biology* 18: 927–936.

Odion, D.C., M.A. Moritz, and D.A. DellaSala. 2009. Alternative community states maintained by fire in the Klamath Mountains, USA. *Journal of Ecology* 98: 96–105.

Parisien, M.A., and M.A. Moritz. 2009. Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecological Monographs* 79: 127–154.

Pausas, J.G., R.A. Bradstock, and D.A. Keith. 2004. Plant functional traits in relation to fire in crown-fire ecosystems. *Ecology* 85: 1085–1100.

Pickett, S.T.A., and P.S. White. 1985. *The ecology of natural disturbance and patch dynamics*. New York: Academic.

Perera, A.H., and L.J. Buse. 2004. Emulating natural disturbance in forest management: An overview. In *Emulating natural forest landscape disturbances: Concepts and applications*, eds. A.H. Perera, L.J. Buse, and M.G. Weber, 3–7. New York: Columbia University Press.

Peterson, G.D. 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. *Ecosystems* 5: 329–338.

Peterson, G.D., C.R. Allen, and C.S. Holling. 1998. Ecological resilience, biodiversity, and scale. *Ecosystems* 1: 6–18.

Polakow, D.A., and T.T. Dunne. 1999. Modelling fire-return interval T: Stochasticity and censoring in the two-parameter Weibull model. *Ecological Modelling* 121: 79–102.

Polakow, D.A., and T.T. Dunne. 2001. Numerical recipes for disaster: Changing hazard and the stand-origin-map. *Forest Ecology and Management* 147: 183–196.

Reed, W.J., and K.S. McKelvey. 2002. Power-law behavior and parametric models for the size-distribution of forest fires. *Ecological Modelling* 150: 239–254.

Ricotta, C., G. Avena, and M. Marchetti. 1999. The flaming sandpile: Self-organized criticality and wildfires. *Ecological Modelling* 119: 73–77.

Robert, C., J.M. Carlson, and J. Doyle. 2001. Highly optimized tolerance in epidemic models incorporating local optimization and growth. *Physical Review E* 63: 056122.

Romme, W. 1980. Fire history terminology: report of the ad hoc committee. In *Proceedings of the fire history workshop*. General Technical Report RM-GTR-81, eds. M.A. Stokes and J.H. Dieterich, 135–137. Fort Collins: U.S. Forest Service.

Romme, W.H., E.H. Everham, L.E. Frelich, M.A. Moritz, and R.E. Sparks. 1998. Are large infrequent disturbances qualitatively different from small frequent disturbances? *Ecosystems* 1: 524–534.

Schmidt, K.M., J.P. Menakis, C. Hardy, D.L. Bunnell, and W.J. Hann. 2002. *Development of coarse-scale spatial data for wildland fire and fuel management.* General Technical Report RMRS-GTR-87. Fort Collins: U.S. Forest Service.

Schoennagel, T., T.T. Veblen, W.H. Romme, J.S. Sibold, and E.R. Cook. 2005. ENSO and PDO variability affect drought-induced fire occurrence in Rocky Mountain subalpine forests. *Ecological Applications* 15: 2000–2014.

Schoennagel, T., E.A. Smithwick, and M.G. Turner. 2008. Landscape heterogeneity following large fires: Insights from Yellowstone National Park, USA. *International Journal of Wildland Fire* 17: 742–753.

Solow, A.R. 2005. Power laws without complexity. *Ecology Letters* 8: 361–363.

Song, W.G., F. Weicheng, B.H. Wang, and J.J. Zhou. 2001. Self-organized criticality of forest fire in China. *Ecological Modelling* 145: 61–68.

Strauss, D., L. Bednar, and R. Mees. 1989. Do one percent of forest fires cause ninety-nine percent of the damage? *Forest Science* 35: 319–328.

Swetnam, T.W., and J.L. Betancourt. 1998. Meso-scale disturbance and ecological response to decadal climatic variability in the American Southwest. *Journal of Climate* 11: 3128–3147.

Swetnam, T.W., C.D. Allen, and J.L. Betancourt. 1999. Applied historical ecology: Using the past to manage the future. *Ecological Applications* 9: 1189–1206.

Turcotte, D.L. 1999. Self-organized criticality. *Reports on Progress in Physics* 62: 1377–1429.

Turcotte, D.L., and B.D. Malamud. 2004. Landslides, forest fires, and earthquakes: Examples of self-organized critical behaviour. *Acta Physica* 340: 580–589.

Turner, M.G. 1989. Landscape ecology: The effects of pattern on process. *Annual Review of Ecology and Systematics* 20: 171–197.

Turner, M.G., and W.H. Romme. 1994. Landscape dynamics in crown fire ecosystems. *Landscape Ecology* 9: 59–77.

White, E., B. Enquist, and J.L. Green. 2008. On estimating the exponent of power-law frequency distributions. *Ecology* 89: 905–912.

White, P.S., and A. Jentsch. 2001. The Search for Generality in Studies of Disturbance and Ecosystem Dynamics. *Progress in Botany* 62: 399–450.

Wu, J., and O.L. Loucks. 1995. From balance of nature to hierarchical patch dynamics: A paradigm shift in ecology. *The Quarterly Review of Biology* 70: 439–466.

Yee, T.W. 2006. Constrained additive ordination. *Ecology* 87: 203–213.

Yee, T.W. 2008. The VGAM package. *R News* 8: 28–39.

Zedler, P.H., C.R. Gautier, and G.S. McMaster. 1983. Vegetation change in response to extreme events: The effect of a short interval between fires in California chaparral and coastal scrub. *Ecology* 64: 809–818.

Zhou, T., and J.M. Carlson. 2000. Dynamics and changing environments in highly optimized tolerance. *Physical Review E* 62: 3197–3204.

Zhou, T., J.M. Carlson, and J. Doyle. 2002. Mutation, specialization, and hypersensitivity in highly optimized tolerance. *Proceedings of the National Academy of Sciences of the United States of America* 99: 2049–2054.