Spatial Modeling of Fire in Shrublands using HFire:
II. Fire Regime Sensitivities

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Abstract: Despite inherent difficulties, long-term simulation modeling is one of the few approaches available for understanding fire regime sensitivities to different environmental factors. This paper is the second in a series that documents a new raster-based model of fire growth, HFire, which incorporates the physical principles of fire spread (Rothermel, 1972) and is also capable of extended (e.g., multi-century) simulations of repeated wildfires and vegetation recovery. Here we give a basic description of long-term HFire implementation for a shrubland-dominated landscape in southern California, a study area surrounded by urban development and prone to large, intense wildfires. We examined fire regime sensitivities to different input parameters, namely ignition frequency, fire suppression effectiveness (as measured by a stopping rule based on fire rate of spread), and extreme fire weather event frequency. Modeled outputs consisted of 500-yr series of spatially explicit fire patterns, and we analyzed changes in fire size distributions, landscape patterns, and several other descriptive measures to characterize a fire regime (e.g., fire cycle and rates of ignition success). Our findings, which are generally consistent with other analyses of fire regime dynamics, include a relative insensitivity to ignition rates and a strong influence of extreme fire weather events. Although there are several key areas for improvement, HFire is capable of efficiently simulating realistic fire regimes over very long time scales, allowing for physically based investigations of fire regime dynamics in the future.

1. Introduction

Fire has long been seen as an integral process in the health of many terrestrial ecosystems, and maintaining natural fire regimes is now a common goal in ecosystem management. Despite this awareness, we often face uncertainties in characterizing natural fire regimes (e.g., Baker and Ehle, 2001; Morgan et al., 2001) or in predicting fire patterns (e.g., Hargrove et al., 2000; Keane et al., 2002; Jones et al., 2004). Although we may be able to adapt and reach a more sustainable coexistence with wildfire in the future, how fire regimes may change under altered future climates is largely unknown (Moritz and Stephens, in press). Experiments are therefore needed to better understand fire behavior and variables that control it, but the threat to human lives and structures may hinder such activities, even under the relatively controlled conditions of a prescribed fire. In addition to risks to humans, fires with “unnatural” characteristics (i.e., in terms of fire size, intensity, frequency, or seasonality) can have negative ecological consequences (e.g., D’Antonio and Vitousek, 1992; Allen et al., 2002; Odion and Tyler, 2002). We therefore recognize fire as a crucial force in many ecosystems, yet we lack a deep understanding of how fire behaves and functions, both in the short- and long-term.

Ongoing disagreement over effects of fire suppression highlights how much we have yet to learn about natural fire dynamics in different ecosystems. In western U.S. forests that prehistorically experienced frequent, low-intensity surface fires, recent fire suppression has generally allowed the accumulation of surface biomass, or “ladder fuels,” that can carry fire vertically into tree canopies. It is not always clear, however, which forest fire regimes have been altered by modern fire suppression (e.g., Odion et al., 2004; Schoennagel et al., 2004). Similar disagreements exist over whether large fires are the direct result of fire suppression in Mediterranean-type shrublands, particularly in southern and central California (e.g., Keeley and

Fotheringham, 2001; Minnich, 2001; Moritz et al., 2004). Large fire probabilities are also central to investigations of mechanisms structuring complex systems dynamics. For example, a mechanism known as "highly optimized tolerance" (HOT) has recently been proposed as a basis for organization in fire-prone ecosystems (Moritz et al., 2005). HOT incorporates concepts from engineering, statistical physics, and biological evolution to explain how complex systems are structured to be robust to typical environmental variations, but fragile and prone to large fluctuations in extreme circumstances (Carlson and Doyle, 2002).

Fire modeling is one of the few viable approaches for increasing our knowledge of fire regime dynamics on different landscapes and under a variety of conditions. There are several available fire modeling frameworks and methods, and these are covered in recent reviews (Perry, 1998; Gardner et al., 1999; Finney, 1999; Keane et al., 2003; Cary et al., 2006). Long-term simulation of fire and vegetation response is becoming increasingly possible and has been used to examine variation in existing landscape patterns (e.g., Keane et al., 2002; Venevsky et al., 2002), fire effects on possible vegetation dynamics (e.g., Franklin et al., 2001), and scenarios of management activities (e.g., Haydon et al., 2000; Miller and Urban, 2000) and climate change (e.g., Davis and Michaelsen, 1995; Miller, 1999). Another application of long-term modeling has been to assess basic sensitivities and controls on fire regime dynamics (Hargrove et al., 2000; Cary et al., 2006), similar to the work described here.

Using a new model called HFire, we are able to generate and analyze extended simulations of fire regimes. HFire is a "physical" or "mechanistic" model that simulates fire growth from physical principles and the Rothermel (1972) equations of fire spread. A detailed description of fire spread modeling can be found in a companion paper that introduces HFire in single-event mode (Dennison et al., submitted), and a basic description is also given below.

While modeling fire from a physical basis is inherently attractive and has become popular for simulating individual fire events (e.g., Finney, 1998), such models are often considered too complex, computer intensive and/or the data requirements too vast for use in long-term fire regime simulations (Gardner et al., 1999; Hargrove et al., 2000; Keane et al., 2004). Physically based fire regime modeling is therefore relatively rare, despite the potential for revealing much about the relative importance of different controls on fire regime dynamics (although see: Davis and Michaelsen, 1995; Keane et al., 1996). In this paper we describe an application of HFire in long-term simulation mode for a fire-prone shrubland landscape in southern California, incorporating stochastic aspects of environmental factors. In addition to model parameterization and validation for 500-yr runs, we report on fire regime sensitivity to several important input parameters.

2. Methods

2.1 Modeling fire spread

HFire is a spatially explicit, raster-based model of fire growth that is embedded in a long-term simulation environment (Morais, 2001; Dennison et al., submitted). Detailed documentation of HFire code and input parameters can be found at the model's website (http://firecenter.berkeley.edu/hfire/). Inputs necessary for modeling an individual event in HFire are nearly identical to those for the widely used fire spread simulator FARSITE (Finney, 1998), including ignition locations, weather conditions, and digital maps of topography and fuel types. One-dimensional predictions from the Rothermel (1972) equations are fit to two dimensions, using the solution to the "fire containment problem" (Albini and Chase, 1980) and the empirical double ellipse formulation of Anderson (1983). A new technique implemented in HFire is based upon finite fractional distances between cell centers and addresses the problem of distorted fire shapes, inherent to raster models of fire spread (French et al., 1990). Solving this distortion problem in a raster environment allows HFire to model fire growth very efficiently, a crucial advantage in long-term simulation studies like those presented here. To incorporate the fact that fires must eventually stop spreading, either through natural extinction or human suppression activities, HFire also has an extinction rate of spread threshold; fire propagation in a given cell is stopped if the rate of spread is slower than the specified threshold. In addition to accommodating the natural extinction process, by raising this threshold one can loosely model advances in fire suppression technology.

HFire allows for the control of three temporally dynamic variables that are critical for fire regime modeling: ignitions, weather, and vegetation regrowth. User-specified input variables control the average number of ignitions per year and the spatial distribution of ignitions. Ignition probabilities can be spatially homogeneous or based on landscape features such as the distance to the nearest road. The actual number of ignitions and locations of these ignitions per year are then stochastically generated during simulation runs. HFire allows for both "standard" and "extreme" weather inputs. Standard and extreme weather files can be populated with historical weather observation data from single or multiple weather stations. Weather-related variables on non-extreme days are stochastically drawn from the standard weather file representing typical diurnal conditions, and these variables vary for each hour of simulated time. The user can also specify an average number of extreme fire events per year, with the timing and number of extreme events per year being stochastically determined by HFire. After a simulated fire, regenerating vegetation progresses through a series of fuel classes over time (i.e., simulating succession) until it burns again. Vegetation and related successional "paths" of fuel development are represented through standard fuel models (Albini, 1976) used for fire behavior and fire growth modeling. More detail on parameter estimation for ignitions, weather, and vegetation regrowth is provided in upcoming sections.

Model accuracy, sensitivity to fuels, and sensitivity to data resolution have been evaluated in HFire by comparing observed and predicted fire spread during historical events (Morais, 2001; Dennsion et al., submitted). HFire has also been utilized previously in a comparison of empirical fire data, modeled fire regimes, and HOT as the structuring mechanism for complexity (Moritz et al., 2005). Additional sensitivity analyses using HFire are forthcoming (Clark et al., submitted). Limitations of HFire include the fact that it currently lacks modules for crown fire behavior and for “spotting” (i.e., ignitions blown ahead of the flaming front). In addition, as with other “physical” models of fire spread based on Rothermel (1972), HFire does not capture the feedbacks between a fire and the local changes in weather that can occur. Nonetheless, Dennison et al. (submitted) has found that HFire is able to approximate the size of a single fire in shrub and grass fuel types. As we will show here, fire sizes and patterns can also be predicted remarkably well in long-term simulations, another validation that HFire may be capturing the essential elements of what drives and constrains fire behavior on the landscape. HFire is capable of modeling relatively long time periods (e.g., hundreds or thousands of years), simulating individual fire events and tracking regeneration of vegetation on the landscape until it burns again. Similar to a real landscape, HFire also allows for the possibility of multiple fires burning at the same time within the simulation domain. Despite its complexity and flexibility, HFire is very efficient and runs very quickly (e.g., 500 yr scenarios in ~12 hr). Outputs include digital maps of fire perimeters at any specified time step, which allow for analysis in a GIS.

2.2 Study area, fuel characteristics, and vegetation dynamics

The simulation domain for this project was a ~96,000 ha region encompassing the Santa Monica Mountains National Recreation Area (SMM), abutting the Pacific Ocean and the densely populated Los Angeles metropolitan area in southern California (Fig. 1). Our study area has a Mediterranean-type climate characterized by hot, dry summers and cooler, wet winters. Topography is rugged, with mountain peaks over 500 m in height just a few kilometers inland from sea level (Fig. 1A). SMM is dominated by sclerophyllous, fire-dependent chaparral and coastal scrub shrublands, although there are also riparian corridors, patches of invasive annual grasses, and vegetation typical of the local wildland-urban interface (WUI) (e.g., mixed native and non-native landscaping). The combination of steep terrain, expanses of highly combustible fuels, routine episodes of extreme fire weather (i.e., “Santa Ana winds”), and close proximity to both human development and ignition sources makes SMM a relevant area for fire-related research.

Spatial fuels data for the entire SMM area were derived from a 100 m resolution regional potential natural vegetation (PNV) map (Franklin 1997), which represented the ultimate vegetation community, and therefore fuel type, that would occur in the long absence of fire. The PNV map was modified according to SMM maps of riparian areas and local planning agency maps of recent development. Vegetation communities (Fig. 1B) capable of carrying wildfire during typical weather conditions were then assigned to one of the 13 standard fuel models (Albini, 1976) or to a custom model (Weise, 1997) based on shrubland vegetation characteristics. Vegetation types and their associated fuel models are shown in Table 1, and details of the fuel models are summarized in online appendix Table A1. Simulations were run at 100 m X 100 m cell resolution for fuels and other spatially explicit inputs. Finer spatial resolutions were not investigated, as HFire output has been found to be relatively insensitive to cell size (Morais, 2001; Clark et al., submitted).

The progression of fuels after a fire depended on the local PNV type. Some types regenerate on an annual basis (e.g., grass-dominated areas) and others remain relatively constant (e.g., WUI type). Most vegetation, however, is allowed to develop toward its “climax” PNV type and was successively assigned fuel models that reflect accumulating biomass and larger stem diameters (Table A1). Vegetation dynamics in the simulations reported here are thus limited to fixed paths of development, although a site could burn whenever conditions allow. Incorporation of possible vegetation type conversion (e.g., stochastically driven changes in PNV type based on fire frequency at a site) and more complex variations in fuel model pathways is currently an area of additional research. All simulations were first initialized with vegetation stand age patterns that corresponded to the actual mapped fire history of SMM as of 1999 (Fig. 2), and then HFire was run for 600 yr for each scenario. Scenarios were arbitrarily assigned the year 2000 as a starting point. To address possible sensitivities to initial conditions, the first 100 yr of each run was discarded, and the remaining 500 yr of simulations was retained for analysis.

Average live fuel moistures were set at moderate levels of 85% and 105% (dry weight) for woody and herbaceous material, respectively. In preliminary runs these levels were found to produce reasonable fire spread patterns. We did not implement the typical trend of high fuel moisture in spring and a steady decrease as the fire season progressed, and this is admittedly an unrealistic simplification. Instead, we chose to omit this source of variation to allow for better detection of sensitivities to other selected parameters. Fuel moisture levels were therefore held constant through the fire season during simulations, although they were allowed to vary stochastically between years (standard deviation of 5%).

2.3 Estimation of input parameters

In addition to vegetation inputs described above, our HFire simulations required a baseline parameterization of various environmental factors to generate a fire regime that is realistic, given historical fire patterns in shrublands and average fire return intervals appropriate to life history tolerances of local plant species. We then used the output from the baseline parameterization as a yardstick for examining other simulated fire regimes, generated by varying the following input parameters: 1) ignitions, 2) suppression effectiveness, and 3) fire weather conditions.

An ignition can be any source for combustion, regardless of whether or not it propagates beyond its initial location. Most ignitions are not likely to propagate and become "fires" in reality, as they are extinguished by human activity quickly or they go out before successfully igniting fuels that will promote further spread. Although HFire allows one to specify ignition locations or tendencies (e.g., increased probabilities along roads), we employed spatially homogeneous ignition probabilities and varied only the average frequency per year. Because the mapped fire history for SMM contains only the largest events, it was not possible to estimate average ignition frequencies from this dataset. Los Padres National Forest (LPNF), however, is a nearby shrubland-dominated region with a relatively complete ignition and fire perimeter record (Moritz 1999), providing rough estimates of ignition frequencies per unit area. On average, shrublands of LPNF experienced a total of ~0.37 ignitions per km^2 over the period 1911-1995. Therefore, for a region the size of SMM (~960 km^2), a baseline estimate of ~4 ignitions per year was chosen.

Fires can go out naturally when they encounter conditions that slow them to the point of extinction (e.g., moist or sparse vegetation), or they may be actively suppressed. In theory, with increasing suppression effectiveness, a fire would need to be moving faster and faster to exceed the extinction rate of spread (ERS) threshold specified in HFire. Identifying a baseline value for the ERS threshold is difficult, however, because there is little published information about this topic. In addition, a baseline ERS should be one that generates realistic fire patterns under a variety of weather conditions, vegetation types, and suppression effectiveness scenarios. After preliminary runs of HFire, we chose a baseline ERS threshold of 0.033 m/s, which equates to an hourly spread of 6 chains (i.e., a traditional land survey measure equaling approximately 20 m). This is a reasonable estimate, based on discussions with various fire behavior personnel, other fire simulation work in shrublands (e.g., Davis and Burrows 1993), and comparison of preliminary model output with mapped fire history for SMM (e.g., fire sizes, shapes, frequencies).

Fire weather conditions can have a very strong influence on fire regimes, and this is especially true for most chaparral-dominated shrublands (Davis and Michaelsen, 1995, Moritz, 1997, Keeley and Fotheringham, 2001; Moritz, 2003, Moritz et al., 2004). In fact, the "Santa Ana" winds which affect our study area each year have been considered the most extreme fire weather in the world (Schroeder et al. 1964). We therefore separated fire weather for our simulations into either "typical" or "extreme" days, based on hourly weather station data for 2 fire seasons (1998 and 1999) from 2 local stations (Figure 1). Santa Ana wind events were relatively easy to identify from local historical weather records, because winds do not follow the normal coastal pattern of offshore flow in the evening through the morning hours, then switching to onshore flow during the day. Instead, during extreme fire weather (EFW) conditions, Santa Ana winds tend to be strong and consistently offshore (i.e., out of the N or NE for our study area) and are also relatively hot and dry. After accounting for missing observations and isolating

Santa Ana days into a separate dataset, we had ~500 days of hourly observations for "typical" weather; the "extreme" fire weather dataset is ~5% this size, consisting of 28 days of hourly observations. Estimates of Santa Ana frequency and duration can vary substantially, depending on the location in question and how an event is detected or defined. Based on local historical data and published analyses by Schroeder et al. (1964) and Raphael (2003), we chose a baseline estimate in the HFire simulations of 4 EFW events annually (during the fire season) with a duration of 4 days each.

2.4 Comparing simulation scenarios

To examine fire regime sensitivities to input parameters, we ran 500-yr HFire simulations and varied ignition frequencies, suppression effectiveness through the ERS, and extreme fire weather event frequencies. The specific scenarios we tested are listed in Table 2, along with the baseline parameter settings chosen for SMM. In general, parameter settings that produced fire intervals in the 20-100 yr range were examined, because intervals much longer or shorter than this could eventually alter the persistence of dominant plant species in the study area. In some simulation runs, however, Santa Ana events were restricted to allow detection of sensitivities to other parameters, even though quite long fire intervals resulted. The average interval across the landscape was calculated as the fire cycle (FC), or the number of years it would take to burn an area equivalent to the study area, given annual average burning amounts. For parameters that were held constant in a given scenario (Table 2), baseline settings were typically used; deviations from this guideline were also examined in some cases and are described in the Results below.

From simulated annual fire maps for each scenario, we quantified fire size probability distributions, which often exhibit power law statistics (e.g., Malamud et al., 2005; Moritz et al., 2005). In this paper we do not focus on detailed statistical fits to the power law exponent, but rather use the full distributions, focusing on changes in the slope and tails, to compare different scenarios. To characterize spatial patterns observed in different fire regime scenarios, we also calculated landscape pattern metrics using the software program FRAGSTATS (McGarigal and Marks, 1995). Landscape shape index (LSI), which essentially measures the perimeter-to-area ratio for the landscape as a whole, was used to quantify patchiness at decadal intervals. For example, repeated large fires will tend to produce a landscape with large, aggregated stands that are in the same age classes. In this case, the total length of perimeter between stand age classes will be short, relative to a more fragmented landscape with many stands that are small and disaggregated. LSI standardizes the length of stand age class perimeter by area (Milne, 1991; Bogaert et al., 2000). The metric is calculated as the total length of perimeter within the landscape (including the study area boundary), divided by the smallest possible length of perimeter that preserves the stand age class area. The minimum possible index (LSI = 1) will result from complete aggregation of each stand age class into a square patch. Increasing LSI indicates more patchy, fragmented stands (e.g., LSI = 2 indicates that the total perimeter between stand age classes is twice the minimum perimeter between stand age classes). LSI has been used to quantify the patchiness of forest stand age maps derived from remote sensing data (Sachs et al., 1998) and simulated landscapes produced by a fire disturbance model (Pausas, 2003). Within the SMM, Swenson and Franklin (2000) used LSI to examine changes in landscape fragmentation occurring under modeled urbanization scenarios.

3. Results

3.1 Baseline simulation runs

The baseline parameterization of HFire simulated a fire regime that is representative of general fire patterns in SMM, even to the point of showing gaps in areas burned that were similar to long unburned areas in the historical mapped record (Fig. 2). Average fire intervals in the baseline simulations were also within a range that may be tolerable for shrubland species in SMM (FC = ~33 yr; Table 3). Due to the relatively short period of record for the SMM mapped fire history and the emphasis on recording larger events, we did not compare simulated versus historical landscape patterns using LSI for the baseline scenario. The almost total lack of smaller events affects LSI enough to make such comparisons meaningless.

The distribution of fire sizes observed in the baseline simulation was similar to that of actual fire regimes, being characterized by many very small events and relatively few extremely large events (Strauss et al., 1989; Moritz, 1997; Moritz et al., 2005). This skewness in fire sizes is indicated by the relatively large difference between median and mean fire sizes shown in Table 3. Again, due to the sparse mapped fire history for SMM, the empirical fire perimeter dataset was not useful for comparison against simulated results. As a yardstick for comparison, we instead used fire size records from nearby LPNF shrublands, which represents a much more complete fire history that includes even very small events (Moritz, 1999). Plots of simulated and actual fire size distributions (Fig. 3) demonstrate that the baseline parameter settings generated distributions that are nearly identical in form to that of the chaparral-dominated portions LPNF, indicating that simulated fire regimes approximate those observed in real shrubland ecosystems to a remarkable degree. Other measures characterizing the simulated baseline fire regime, such as the percentage of ignitions propagating to become fires (34%) and the coefficient of variation

(CV) in fire size (4.1), are also given in Table 3 and then also included for scenario comparisons in the following sections.

3.2 Varying ignitions

We examined two groups of parameter settings to investigate the importance of average ignition rates, and simulated 500-yr fire regimes appeared to be relatively insensitive to this parameter. To isolate the effect of varying ignition rates on a fire regime (i.e., 2, 4, and 8 per yr; Table 2) in the absence of other confounding factors, we first omitted extreme fire weather events from these scenarios. Due to the lack of Santa Ana wind episodes, simulated fire regimes do not exhibit many large fires (left side of Fig. 4A; upper portion of Fig. 4B), and average fire cycles are much longer than those typically observed in shrublands (Table 4). Although unrealistic in terms of fire intervals, these results highlight a striking similarity in fire size distributions within this set of ignition frequency runs. Mean and median fire sizes also remain relatively stable with increasing ignition rates (upper rows of Table 4).

After allowing a typical number of extreme fire weather events per year, larger fires and much more realistic fire cycles were observed (bottom rows of Table 4). Regardless, the consistent slope and form of fire size distributions within this set of ignition frequency runs indicated that event size probabilities were still relatively insensitive to varying ignition rates (right side of Fig 4A). There were occasional very large fires in these simulation runs (bottom portion of Fig. 4B), as fires in this set of runs occasionally coincided with Santa Ana wind episodes. A slightly higher percentage of ignitions actually propagate to become fires than in the absence of extreme fire weather, and fires tend to be bigger and more variable in size (bottom rows of 4B). A notable response for all runs in this scenario (i.e., 0 and 4 SA) is that of shorter fire cycles with more frequent ignitions, being roughly proportional to the change in ignition rate. Regardless of whether extreme fire weather events occur, however, shorter fire cycles are simply the result of more fires burning across the spectrum of possible fire sizes for a given scenario. Fire size distributions were therefore insensitive to changes in ignition rates (Fig. 4A), and we did not observe notable changes in fire sizes with more frequent ignitions.

The different spatial patterns generated by fire regimes were quantified through the LSI for each set of varying ignition frequency runs (Fig. 4C). The landscape pattern metric captures the clear difference in the degree of landscape patchiness between the simulation runs that included extreme fire weather events and those that did not (Fig. 4B). Without extreme fire weather events, simulations contained many more small fires and were much less variable in terms of landscape pattern (upper portion of Fig. 4B). The steady trend of increasing LSI (upper portion of Fig. 4C) indicates that the cumulative effect of more ignitions can be an increasingly fragmented landscape, in the absence of extreme fire weather. This trend is more pronounced with more frequent ignitions (i.e., higher LSI), but it is largely because HFire records the many 1-ha ignition cells as “burned” (i.e., ignited but never progressing past the initial location to become a fire). In contrast, the simulations that included Santa Ana episodes all had similar trajectories over time, showing a lack of a trend, periodic “resetting” of the landscape pattern by large fires (i.e., reducing patchiness and thus LSI), and comparable amounts of decadal variation in LSI (bottom portion of Fig. 4C).

3.3 Varying suppression

Similar to the ignition rate scenarios just described, we examined two groups of parameter settings for the extinction rate of spread threshold, which is a surrogate for the effectiveness of fire suppression technology. To examine the effect of varying ERS on a fire regime in the absence of extreme fire weather, we chose propagation thresholds that produced a realistic range of fire cycle values, although possibly quite slow in reality (i.e., 0.022, 0.024, and 0.026 m/s; Table 2). As a result, even without including Santa Ana wind episodes, some very large fires were observed under the most lenient ERS setting (top curve of Fig. 5A and top age surface in Fig. 5B); in fact, fires in this particular simulation run displayed the largest median size and highest fraction progressing beyond the initial ignition point of any run reported in this study (top row of Table 5). Raising the ERS (i.e., requiring faster spread to propagate into neighboring cells) generally resulted in fewer and smaller fires on simulated landscapes (upper portion of Fig. 5B), and fire size distributions reflected this change through discrete shifts downward (Fig. 5A). The overall ease with which fires tended to ignite and spread in these scenarios also led to less variation in fire sizes (upper portion of Table 5) than in most other simulation runs.

To maintain a somewhat realistic range of simulated fire cycles after including extreme fire weather events, higher ERS thresholds were examined in the second group of runs (i.e., 0.022, 0.024, and 0.026 m/s; Table 2). Nonetheless, varying ERS in these simulations had roughly the same effect as when Santa Ana wind episodes were excluded. With faster propagation thresholds, fires were generally smaller (bottom portion of Fig. 5B), fire cycles were shorter, and ignitions successfully became fires less often (bottom rows of Table 5). With the possibility of extreme fire weather events, however, the largest few fires observed in this group of runs all converged at approximately the same size (biggest events in Fig. 5A). Also unlike the other group of runs in this scenario, raising the ERS produced increasingly variable fire sizes (bottom rows of Table 5).

Spatial patterns and LSI under the scenario of varying ERS (Fig. 5C) exhibited several similarities to the varying ignitions scenario (Fig. 4C). In particular, the effect of changing the propagation threshold on LSI was minimal and secondary to that of allowing extreme fire weather events (i.e., upper versus lower set of curves in Fig. 5C). In simulations that excluded Santa Ana wind episodes, the landscape became increasingly fragmented with higher ERS thresholds (i.e., more small fires and 1-ha burned cells that never spread past the ignition point, thus an increasing trend in LSI). Landscape patchiness in simulated fire regimes did not appear to be sensitive to variation in the propagation threshold when extreme fire weather episodes are possible.

3.4 Varying extreme fire weather

In this scenario we examined the importance of altering the average number of Santa Ana wind episodes each year (i.e., from 0-6 per yr; Table 2), holding the ERS threshold and average ignition rate at levels that would keep fire cycles near reasonable ranges. Simulated 500-yr fire regimes displayed somewhat predictable responses as more Santa Ana episodes were allowed to happen. In general, increasingly frequent extreme fire weather events caused fire cycles to shorten, fires to be larger, and the number of ignitions progressing to actually become fires to increase (Table 6). This trend of increasing fire size is clearly evident in the simulated fire size distributions (upward shifts in Fig. 6A).

Stand age patchiness was quite dependent on the average number of yearly Santa Ana wind events. As in other scenarios, the landscape became highly fragmented if extreme fire weather events were excluded (top of Fig. 6B), and this is reflected in a long-term increasing trend in LSI (top curve in Fig. 6C). There was an interesting transition in the fire regime as a single Santa Ana event per year is allowed, which caused intermittent and sharp drops in LSI (Fig. 6C) and highly variable fire sizes (second row of Table 6); this threshold transition was also evident in a marked upward shift in the tail of the fire size distributions, while the smaller fire probabilities showed little change (Fig. 6B). As the number of extreme fire weather events increased, the fire regime then exhibited more large fires that effectively "reset" the landscape mosaic and erased the heterogeneity created by previous smaller fires. LSI therefore lacked a long-term trend for scenarios with more frequent extreme fire weather events (lower curves in Fig. 6C).

4. Discussion

4.1 General trends and possible limitations

Despite limited validation of HFire for individual fire event modeling (Dennison et al., submitted), an alternative and complementary diagnostic for evaluating a fire model has been provided here by successfully simulating a realistic long-term fire regime (e.g., fire frequency vs. size statistics). From the scenarios we examined, it is also clear that fire regimes simulated by HFire display a range of sensitivities to variation in parameters thought to be important in driving landscape fire dynamics. Outputs that we analyzed include simple fire regime metrics (e.g., FC and ignition success), fire size distributions, and time series of changes in landscape pattern (e.g., LSI). Holding other parameters constant, we found simulated 500-yr fire regimes to be relatively insensitive to variation in ignition rates and somewhat more sensitive to suppression effectiveness as represented by the extinction rate of spread threshold. Modeled fire regimes were most sensitive to whether or not extreme fire weather events occurred during simulations, and threshold dynamics appeared at the transition of 0 to 1 extreme weather episodes per year in simulation runs. Our findings are in agreement with other modeling work, such as a general insensitivity to ignitions (e.g., Haydon et al., 2000) and the relative importance of weather-related factors (e.g., Bessie and Johnson, 1995; Cary et al., 2006).

Although HFire's performance and outputs are promising, we should note a few key assumptions and possible limitations of our research. For example, the current implementation of HFire does not incorporate spot fires generated by embers thrown ahead of a fire's flaming front. This limitation might lead one to expect that the fire size distributions of some scenarios, particularly those including extreme fire weather events and high winds, may under-estimate the largest events and therefore over-estimate metrics like FC. Even so, it is likely that most of the basic trends and sensitivities observed here would not change substantially with the addition of spotting embers. Spotting can certainly increase the overall spread rate of a fire across a landscape, and this has been observed in fire simulation modeling studies (Hargrove et al., 2000). Many potential spot fires are eventually overtaken by the main fire, however, meaning that the majority of short-range spotting may not have a major cumulative effect (Rothermel, 1983). This is an important area for future model development, and it will improve both short- and long-term fire simulation with HFire.

The emphasis of work presented here was to examine fire regime sensitivities to factors not directly related to fuels, although there are many open research questions concerning vegetation. Even so, fuel-related variables have been found to be relatively unimportant in other simulation model comparisons (Cary et al., 2006), and the age and spatial patterns of fuels appear to be less of a constraint during the large fires responsible for most of the area burned in chaparral-dominated shrublands of southern California (Moritz et al., 2004). Nonetheless, several questions remain about the importance of different fuel model paths of flammability during post-fire succession (i.e., fixed in Table 1), and we aim to eventually incorporate "dynamic" fuel models that may change within or between fire seasons (Scott and Burgan, 2005). Given the importance of fuels characteristics in studies aimed at fire management (e.g., Finney, 2001), further research is needed about conditions under which spatial fuel patterns may be strong constraints on fire probabilities.

It is also important to note that HFire was developed to model stand-replacing fires in shrubland fuels; therefore, HFire does not currently model the local, vertical transition of surface fire to crown fire in a forest canopy. As such, the general fire regime sensitivities we observed may or may not hold in ecosystems where this local transition has a large effect on landscape-scale spatial fire patterns and long-term fire regime dynamics. Although not employed in the simulations described here, HFire is capable of incorporating spatially explicit wind fields as weather inputs, similar to the fire spread model FARSITE (Finney, 1998). However, like most models used in simulating fire regime dynamics, feedbacks between a burning fire and the weather generated by that event are not incorporated.

4.2 Future fire regimes

Climate change is likely to have major effects on ecosystem structure and function, and changing fire regimes will play an important role on many terrestrial landscapes. Past fire simulation work has shown some sensitivity to changes in averages of climatic parameters like temperature and precipitation (e.g., Davis and Michaelsen, 1995; Miller, 1999). Unfortunately, we know very little about the direction and timing of future changes in temperature and precipitation at specific locations; in addition, global climate models (GCMs) do not produce short-term episodes of extreme fire weather. The results presented here demonstrate a relatively high degree of fire regime sensitivity to fire weather, particularly when such episodes are novel occurrences (i.e., transitioning from 0 to 1 EFW event annually). Our findings therefore support the notion that future changes in fire weather may be a strong driver of many fire regimes (e.g., Turner and Romme, 1994; Beer and Williams, 1995; Stocks et al., 1998; Moritz et al., 2004), highlighting the importance of addressing such episodic phenomena in climate change research.

Future patterns of urbanization could potentially have major effects on ecological processes and habitat quality. In California alone, over 5 million homes are located in wildland-urban interface (WUI) areas (Radeloff et al., 2005), and this problem will get drastically worse in coming decades. Urbanization in our study area, for example, is projected to cause increasing fragmentation and losses of natural habitat over time (Swenson and Franklin, 2000). Future landscapes like these will also experience increasing rates of human-caused ignitions. Due to the general insensitivity to ignitions observed here and elsewhere, it is possible that increasing ignition rates will not result in fundamental changes to an existing fire regime. This lack of change is clearly dependent on the fire regime not being ignition limited in the first place. Our observed insensitivity to ignitions (within a limited range) is also likely to depend on the persistence of current vegetation types on the landscape. It is doubtful, however, that native plant species which dominate many shrublands of California will be able to tolerate increasingly frequent ignitions and the shorter fire cycles that accompany them. For many fire-dependent chaparral species, there is a threshold in fire return intervals below which plants are not able to successfully regenerate (e.g., Zedler et al., 1983).

Once a threshold is crossed and native vegetation is type converted into non-native invasive grasses, further alterations to vegetation patterns and fire regimes are likely through positive feedback cycles (D'Antonio and Vitousek, 1992). In fact, early parameterization of

HFire demonstrated this type of fire-vegetation feedback, when annual grasses were investigated as the fuel model for the first few years of post-fire regeneration in shrublands. In these scenarios, multi-year increases in fire activity were observed as large portions of the landscape were temporarily trapped in the young and highly flammable grass stage of development (Fig. 7). When grass fuels were allowed to “invade” in early succession, there were discrete and short (<10 yr) pulses of burning, during which more than half the study area burned (Fig. 7, dark dashed circles: 97% in yr 105-112, 76% in yr 130-136, 60% in yr 186-194). By comparison, the largest pulse of area burned in the more realistic fuel path specification is considerably less (Fig. 7, lighter gray dashed circle: 43% in yr 157-161). This ecological sensitivity to invasive annual fuels and overly short fire intervals is a fundamental difference between simulating fire-vegetation interactions in chaparral shrublands and those in forests naturally dominated by surface fire regimes (e.g., simulations of Covington et al., 2001).

4.3 Ecosystem development and resilience

It remains to be seen how well our simulated findings translate to real fire-prone environments. Except for the fixed fuel development paths of existing vegetation types, long-term feedbacks between fire and vegetation pattern development (e.g., species establishment and survival) are not modeled in the current implementation of HFire. In contrast to the sensitivities and shifts observed here, empirical fire size distributions have shown a remarkably consistent form across many locations, suggesting a general set of self-organizing feedbacks between vegetation patterns and the fire regime that emerges (Moritz et al., 2005). This consistency in the form of event size distributions may reflect an inherent resilience to typical perturbations, developed as a result of HOT, a structure common in systems able to persist in fluctuating environments (Carlson and Doyle, 2002).

The first studies of HFire in long-term simulation mode were very promising (Moritz et al., 2005), forming one component of a three-way link between a detailed simulation model, historical fire records, and an abstract model based on the HOT mechanism for complexity. A key concept from HOT theory is that tuning for robustness involves tradeoffs subject to constraints, and that the very mechanisms and interdependencies which increase robustness to common events also introduce new sensitivities or fragilities to rare or unanticipated perturbations. In ecological applications “organization" is more appropriate than “optimization." This organized structure reflects the distinction between HOT and random, disorganized configurations, as well as highlighting the importance of structured interdependencies which evolve via feedback among and between biotic and abiotic variables. Fundamentally, HOT describes nongeneric, structured systems which succeed (due to some selection that weeds out less effective configurations) in the face of tradeoffs, and thus reflecting regularities in their environment and their history (Carlson and Doyle, 2002). Our earlier work (Moritz et al., 2005) provides both a first step towards understanding the surprisingly strong agreement between simulation modeling and complexity theory, as well as a baseline for future scenarios involving land management decisions and climate change. Such studies will require more detailed and scenario-specific descriptions of input details, as well as mechanisms for evolution of vegetation patterns, than the scenarios documented here.

Even if HOT has played a role in ecosystem development, it is not clear that fire regimes will exhibit a general resilience in the face of drastic environmental changes (e.g., large shifts in land cover or climate). The landscape vegetation patterns that support and depend on a given fire regime probably arise through complex positive feedbacks and positive interactions (Moritz et al., 2005). Such ecological sorting and development of ecosystem structure presumably occur over time, possibly on longer temporal scales than will be faced in future climate change scenarios. The rate and magnitude of change can be particularly important if a natural disturbance regime is prone to large fluctuations and possible threshold transitions (Turner et al., 1993; Romme et al., 1998).

5. Conclusions

Because simulation modeling is one of few approaches available for investigating fire regime dynamics, new tools like HFire are useful for exploring sensitivities and possible future scenarios. HFire's implementation of the Rothermel (1972) equations allows for multi-century modeling of fire regimes, with simultaneous fires burning on a landscape and regrowth of vegetation between fires, despite the fact that detailed and physically based fire growth algorithms are often considered too complex and computationally intensive for long-term simulations. In our simulations, we did not investigate possible fuels-related variations in parameter settings. Although there are likely to be complex interactions between fire regime controls, our simulations demonstrated the highest sensitivity to extreme fire weather events, while ignition frequency had the least influence on fire regimes. Simulations exhibited a moderate sensitivity to changing the effectiveness of fire suppression, but results were dependent on the frequency of extreme fire weather events.

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Tables

Table 1. Vegetation, regrowth characteristics, and associated fuel models. These classes represent the mapped PNV types within the study area and their simplified paths of fuel regrowth after a fire. For classes that are assumed to accumulate biomass with age, fuel models change with time since fire, and the relevant time periods for each stage are given in parentheses. Both standard (Northern Forest Fire Laboratory, NFFL) and custom fuel model parameter estimates are provided in Online Appendix table A1.

PNV vegetation type	Area (ha)	Immediately following fire	Early stage	Later stage
Agricultural	1461	Not burnable	Not burnable	Not burnable
Coastal dune scrub	844	Not burnable	Not burnable	Not burnable
Coastal strand	295	Not burnable	Not burnable	Not burnable
Riparian (NPS)	3431	Not burnable	Not burnable	Not burnable
Rock outcrops	201	Not burnable	Not burnable	Not burnable
Salt marsh	156	Not burnable	Not burnable	Not burnable
Unknown	19	Not burnable	Not burnable	Not burnable
Water	485	Not burnable	Not burnable	Not burnable
Non-native annual grass	3421	NFFL 1	NFFL 1	NFFL 1
Coastal cactus scrub	402	NFFL 1	NFFL 1	NFFL 1
Valley oak	474	NFFL 1	NFFL 1	NFFL 1
Walnut	127	NFFL 1	NFFL 1	NFFL 1
Coast live oak	1742	NFFL 3	NFFL 3	NFFL 3
Non-native conifer/hardwood	26	NFFL 9	NFFL 9	NFFL 9
Riparian (sycamore/oak)	678	NFFL 9	NFFL 9	NFFL 9
Chamise chaparral	1450	NFFL 5 (1-2 yr)	Custom 17 (3-15 yr)	Custom 15 (>16 yr)
Red shank chaparral	322	NFFL 5 (1-2 yr)	Custom 17 (3-15 yr)	Custom 15 (>16 yr)
Coastal scrub/chaparral mix	418	NFFL 5 (1-3 yr)	Custom 21 (4-12 yr)	Custom 21 (>13 yr)
Northern mixed chaparral	36737	NFFL 5 (1-2 yr)	Custom 18 (3-12 yr)	Custom 16 (>13 yr)
Coastal sage scrub	18922	NFFL 5 (1-3 yr)	Custom 21 (4-15 yr)	Custom 18 (>16 yr)
Development (WUI)	24241	Custom 20	Custom 20	Custom 20

Table 2. Baseline parameter settings for current fire regime in SMM and possible future scenarios. Sensitivities were assessed by varying individual parameters, while holding others constant.

Scenario	**Ignitions (#/yr)**	**Santa Anas (#/yr)**	**Suppression effectiveness (m/s)**
Baseline	8	4	0.033
Vary ignitions	2, 4, 8	0	0.033
	2, 4, 8	4	0.033
Vary ERS	8	0	0.022, 0.024, 0.026
	8	4	0.028, 0.033, 0.038
Vary EFW	8	0, 1, 2, 4, 6	0.033

Table 3. Fire regime metrics for baseline parameter settings. The first column indicates the scenario (Igs: average annual number of ignitions; EFW: average annual number of Santa Ana events; ERS: minimum rate of spread in m/s for fire propagation to neighboring cells). Columns 2-7 indicate the following: number of actual ignitions simulated over the period analyzed; percentage of ignitions becoming fires; fire cycle, median fire size, mean fire size, and coefficient of variation (CV) in fire size.

Scenario: Baseline	**Total Ignitions (#/500 yr)**	**Become fires (%)**	**Fire cycle (yr)**	**Median fire size (ha)**	**Mean fire size (ha)**	**CV fire size (ha)**
Igs:8, EFW:4, ERS:0.033	4035	34	33	19	989	4.1

Table 4. Fire regime metrics under scenarios that vary average annual ignition frequency. (See Table 3 for column descriptions.)

Scenario: Vary ignitions	**Total Ignitions (#/500 yr)**	**Become fires (%)**	**Fire cycle (yr)**	**Median fire size (ha)**	**Mean fire size (ha)**	**CV fire size (ha)**
Igs:2, EFW:0, ERS:0.033	1013	31	1219	13	118	2.5
Igs:4, EFW:0, ERS:0.033	1924	33	544	14	131	3.1
Igs:8, EFW:0, ERS:0.033	3953	32	254	14	140	3.0
Igs:2, EFW:4, ERS:0.033	965	35	163	23	825	4.6
Igs:4, EFW:4, ERS:0.033	1974	34	68	23	985	4.5
Igs:8, EFW:4, ERS:0.033	4035	34	33	19	989	4.1

Table 5. Fire regime metrics under scenarios that vary the extinction rate of spread threshold. (See Table 3 for column descriptions.)

Scenario: **Vary ERS**	**Total Ignitions (#/500 yr)**	**Become fires (%)**	**Fire cycle (yr)**	**Median fire size (ha)**	**Mean fire size (ha)**	**CV fire size (ha)**
Igs:8, EFW:0, ERS:0.022	3967	44	28	59	929	2.5
Igs:8, EFW:0, ERS:0.024	4016	40	54	39	517	2.6
Igs:8, EFW:0, ERS:0.026	4033	38	96	23	304	2.5
Igs:8, EFW:4, ERS:0.028	3932	40	17	39	1643	3.4
Igs:8, EFW:4, ERS:0.033	4035	34	33	19	989	4.1
Igs:8, EFW:4, ERS:0.038	3914	31	53	17	711	4.6

Table 6. Fire regime metrics under scenarios that vary average annual Santa Ana frequency. (See Table 3 for column descriptions.)

Scenario: **Vary EFW**	**Total Ignitions (#/500 yr)**	**Become fires (%)**	**Fire cycle (yr)**	**Median fire size (ha)**	**Mean fire size (ha)**	**CV fire size (ha)**
Igs:8, EFW:0, ERS:0.033	3953	32	254	14	140	3.0
Igs:8, EFW:1, ERS:0.033	3927	31	143	16	258	6.0
Igs:8, EFW:2, ERS:0.033	3968	34	46	22	720	4.9
Igs:8, EFW:4, ERS:0.033	4035	34	33	19	989	4.1
Igs:8, EFW:6, ERS:0.033	3988	37	18	29	1678	3.3

Figures

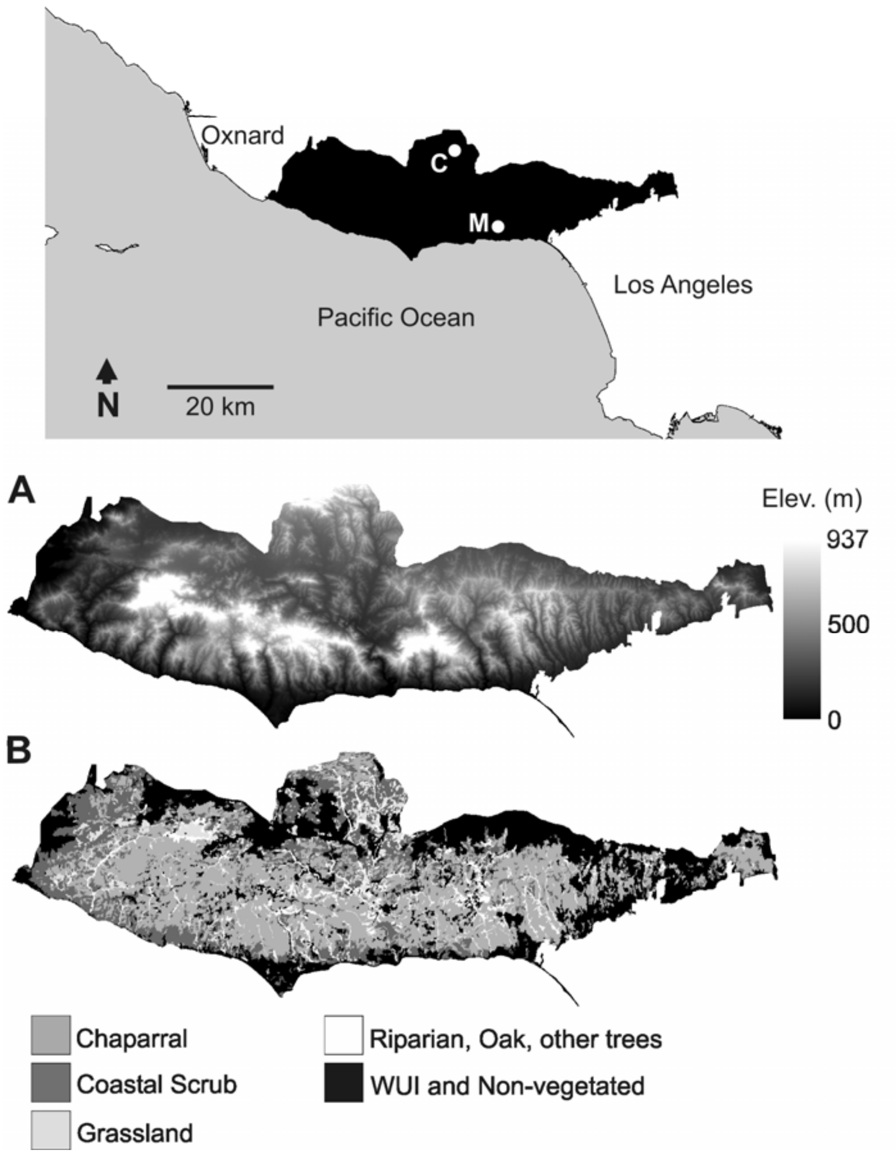

Figure 1. Topography and vegetation of study area. The inset at top shows the location of the SMM study area along the coast of southern California. Points C and M indicate the locations of weather stations Cheesebro and Malibu, respectively, from which hourly weather data were obtained. Panel A demonstrates the patterns of topography in the study area. Panel B indicates aggregated vegetation class patterns in SMM (see Table 1 for detailed breakdown).

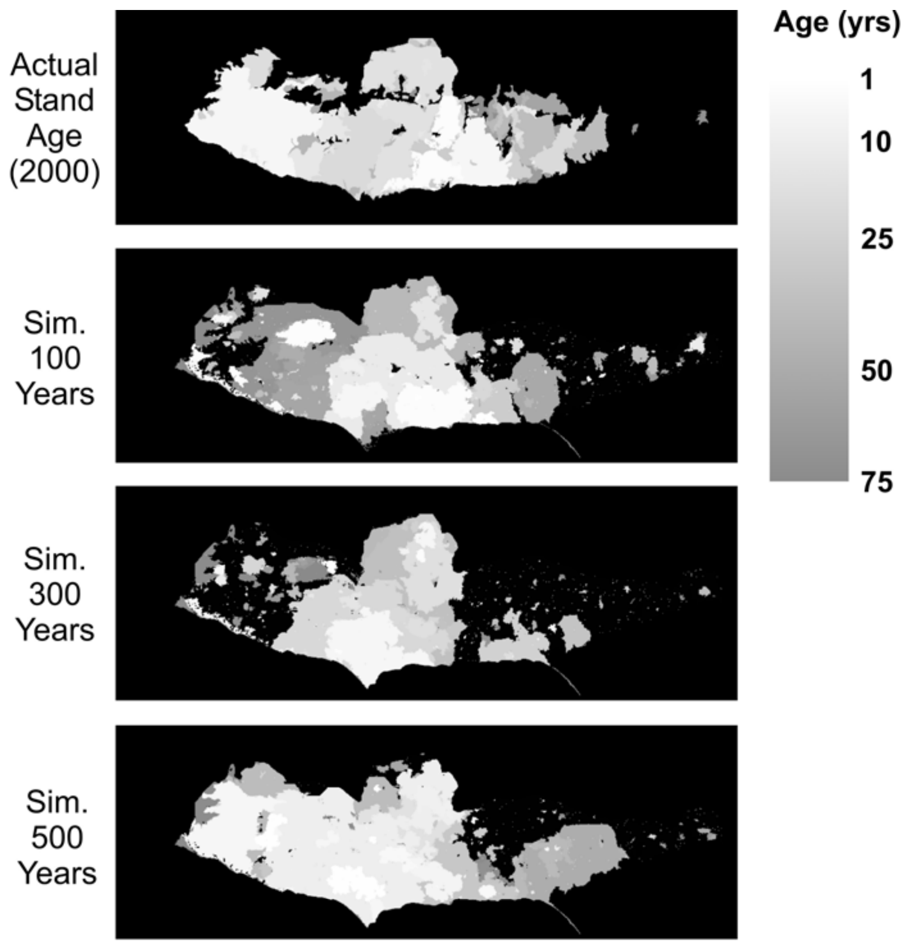

Figure 2. Actual stand age mosaic in SMM versus simulated patterns in baseline scenario. The top panel shows the stand age patterns of the mapped fire history in SMM (1925-1999). The lower three panels demonstrate snapshots of modeled landscape age mosaics after 100, 300, and 500 yr of simulation time with baseline parameter settings, which generated realistic patterns as shown here and in summary fire regime statistics (Table 3).

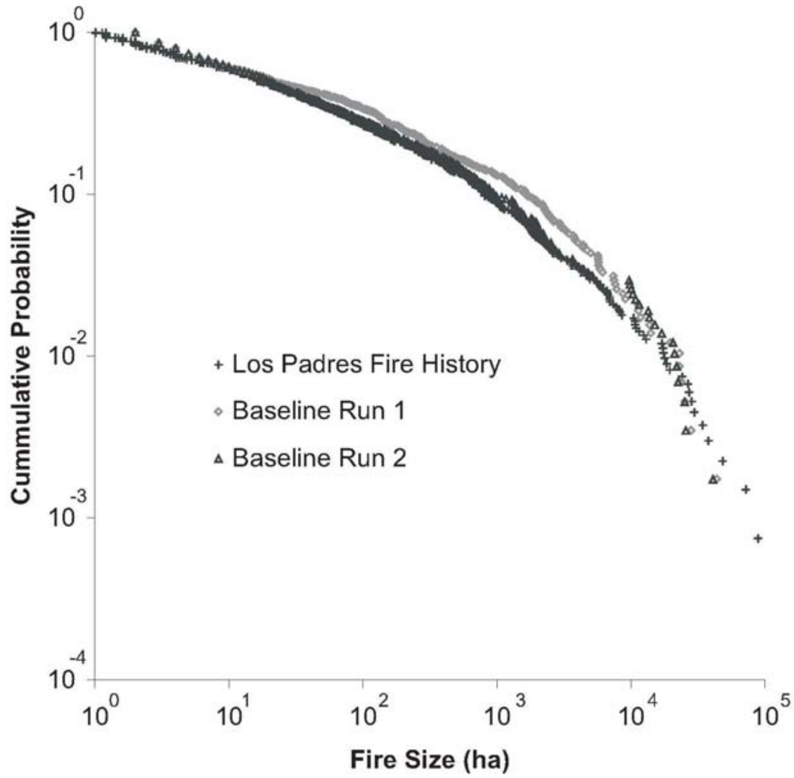

Figure 3. Historical versus simulated fire size distributions. For actual fire history data, only the chaparral-dominated portions of nearby LPNF were used (see text for explanation). For comparison, two simulation runs were made using the baseline parameter settings (runs were 200 yr in length, which generated roughly the same number of events > 1 ha as in LPNF).

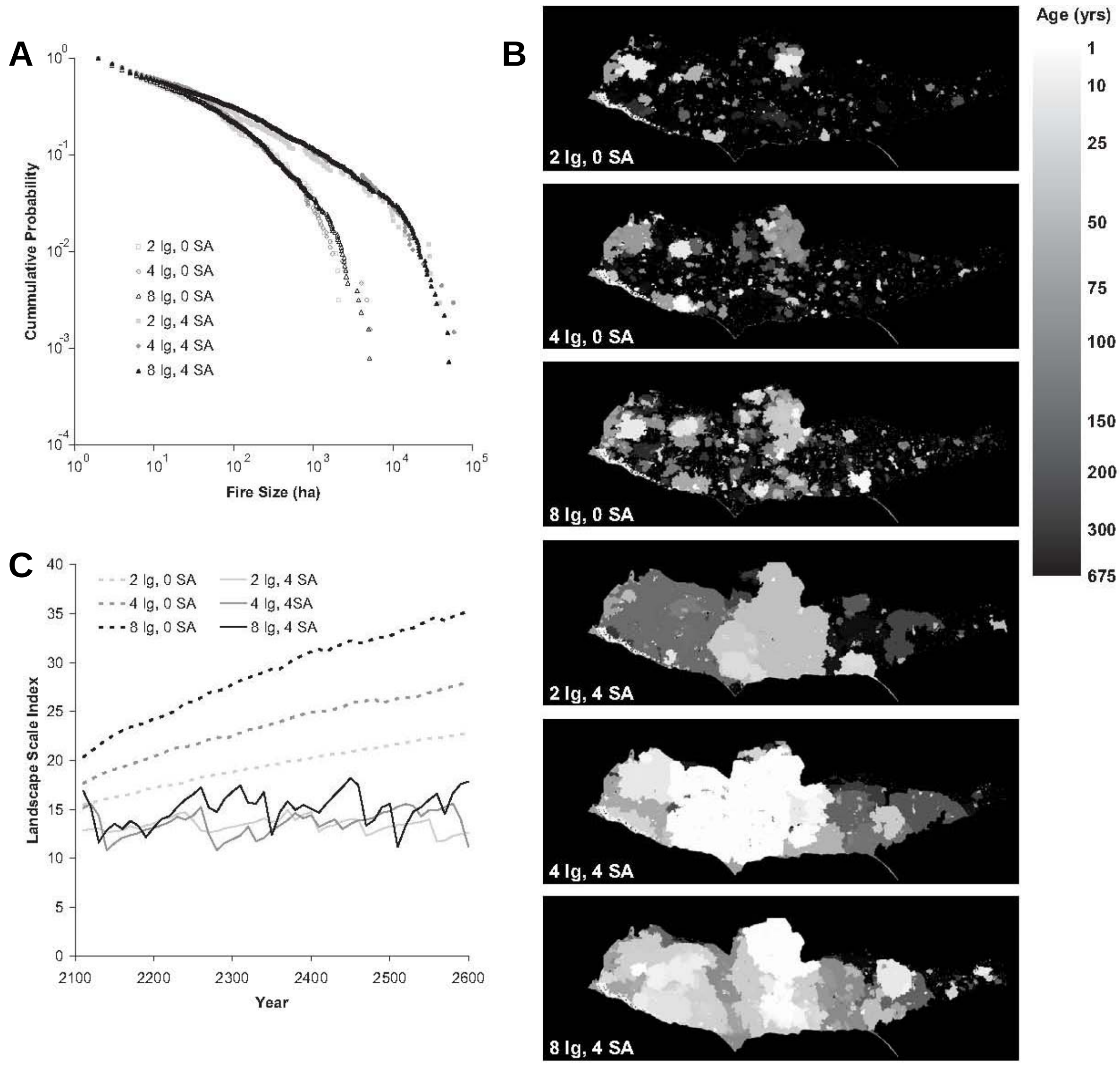

Figure 4. Simulation output demonstrating sensitivity to varying frequency of ignitions. Panel A shows fire size distributions, Panel B shows final landscape age mosaics, and Panel C shows LSI trends.

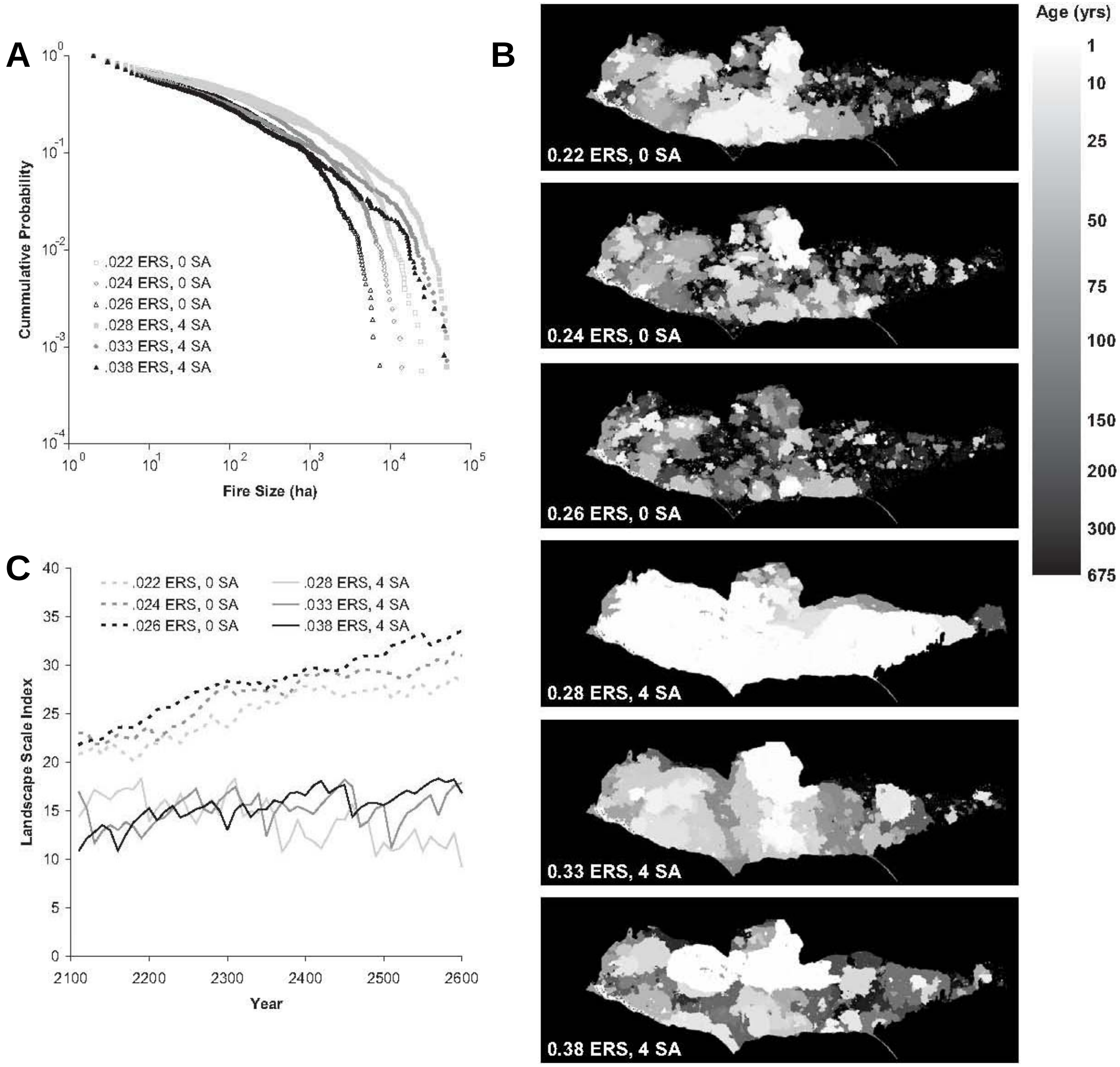

Figure 5. Simulation output demonstrating sensitivity to varying extinction rate of spread threshold. Panel A shows fire size distributions, Panel B shows final landscape age mosaics, and Panel C shows LSI trends.

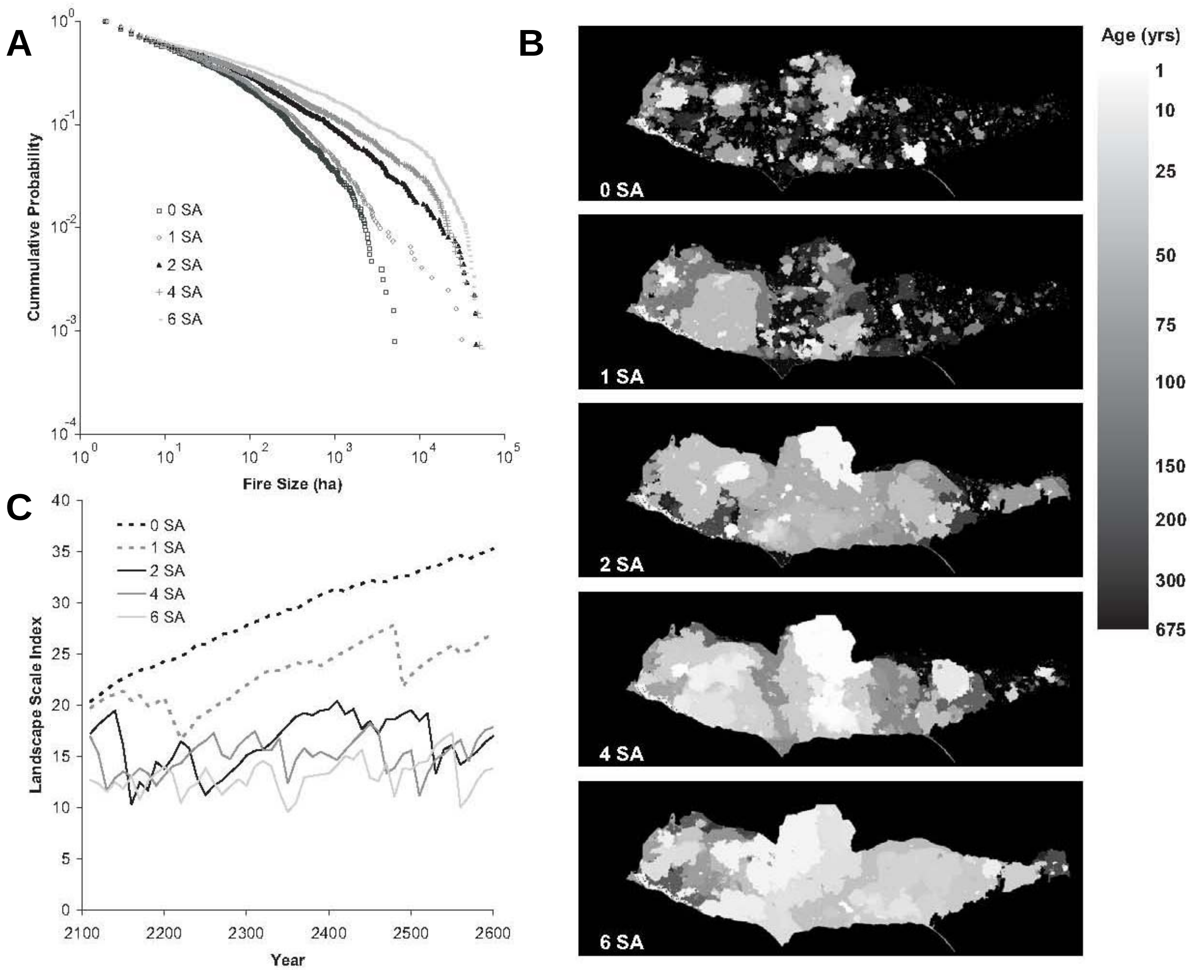

Figure 6. Simulation output demonstrating sensitivity to varying extreme fire weather event frequency. Panel A shows fire size distributions, Panel B shows final landscape age mosaics, and Panel C shows LSI trends.

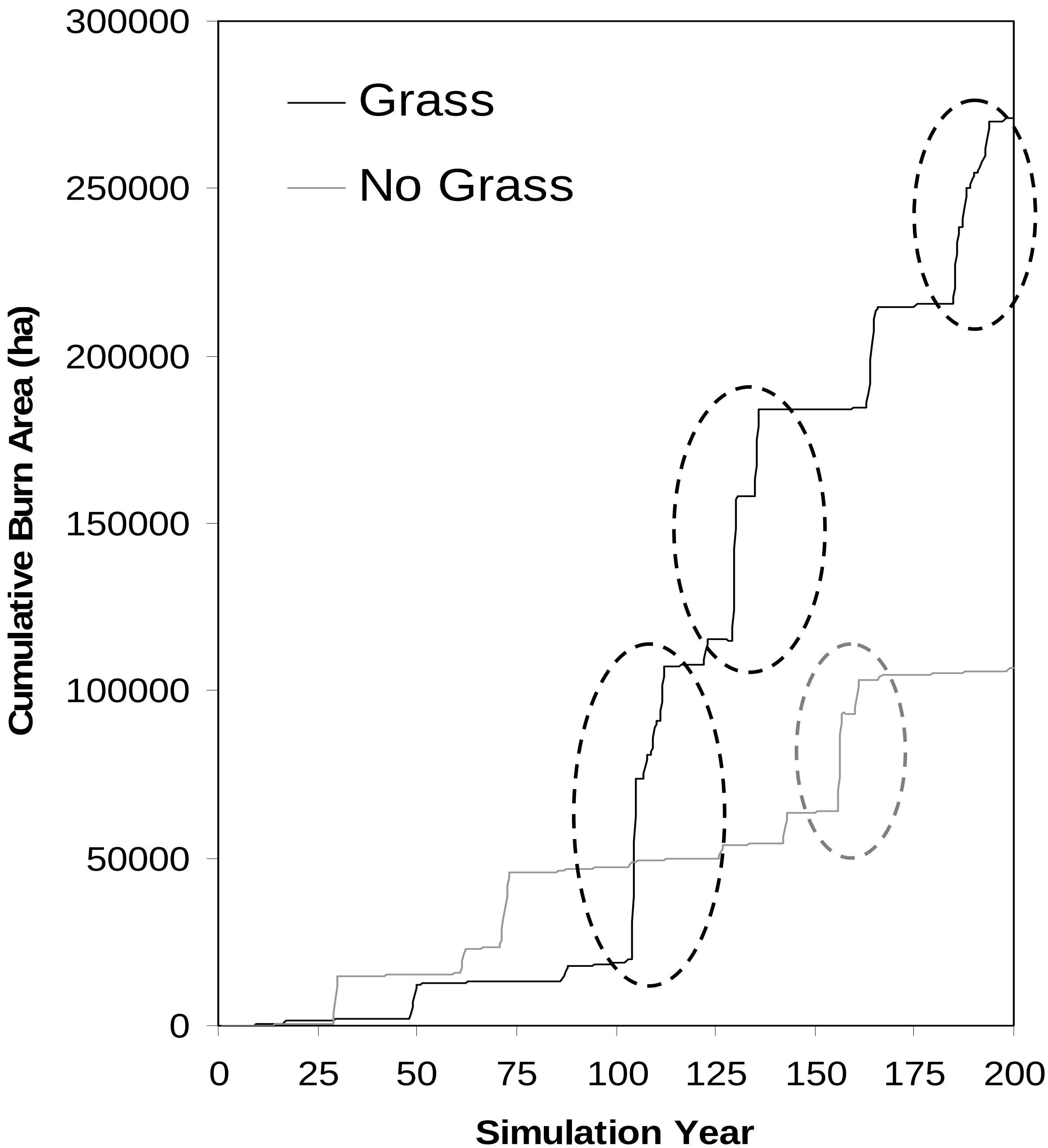

Figure 7. Area burned comparison showing dynamics typical of invasive grass-fire cycle. Both runs used "baseline" parameter settings (top row of Table 2) for 200-yr trial runs, although fuel development paths during post-fire succession in shrubland types differed. The darker line indicates area burned when shrublands had annual grass (model NFFL 1) specified in the first few years; the lighter gray line indicates area burned with more realistic young fuels in this stage (Table 1). The dashed lines identify "pulses" of burning during which very large portions of the landscape burn in a short time (see text for further explanation).

Online supporting materials: Appendix Table and Model Descriptions

Table A1. Standard Northern Forest Fire Laboratory (NFFL, Albini, 1976) fuel model and custom (Weise, 1997; Morais, 2001) fuel model characteristics.

Fuel Model	Description	Dry Biomass of Dead Fuels (<0.635 cm) Mg/ha	Dry Biomass of Dead Fuels (0.635-2.54 cm) Mg/ha	Dry Biomass of Dead Fuels (2.54-7.62 cm) Mg/ha	Dry Biomass of Live Herb. Fuels Mg/ha	Dry Biomass of Live Woody Fuels Mg/ha	Surface Area-to-Volume Ratio of <0.635 cm Dead Fuels (1/cm)	Surface Area-to-Volume Ratio of Live Herb. Fuels (1/cm)	Fuel Bed Depth (cm)	Dead Fuel Moisture of Extinction (%)	Dead Fuel Heat Content (J/kg)	Live Fuel Heat Content (J/kg)
NFFL 1	short grass	1.66	0	0	0	0	105.98	0	30.48	12	18608	18608
NFFL 3	tall grass	6.75	0	0	0	0	45.42	0	76.20	25	18608	18608
NFFL 5	brush	2.24	1.12	0	0	4.48	60.56	0	60.96	20	18608	18608
NFFL 9	hardwood litter	6.55	0.92	0.34	0	0	75.7	0	6.10	25	18608	18608
Custom 15	old chamise	4.48	6.73	2.24	1.12	4.48	19.37	66.61	91.44	13	23260	23260
Custom 16	ceanothus	5.04	10.76	4.04	6.73	6.28	15.14	45.42	182.88	15	18608	18608
Custom 17	young chamise	2.91	2.24	2.24	4.48	4.48	19.37	66.61	121.92	20	18608	18608
Custom 18	sagebrush and buckwheat	12.33	1.79	0.22	1.68	5.6	19.37	45.42	91.44	25	21399	21399
Custom 20	WUI	1.66	4.19	3.36	0	0.83	105.98	45.42	53.34	40	18608	18608
Custom 21	SMM CSS	5.5	0.7	0	1.6	3	19.37	45.42	91.44	25	21399	21399

Model Name: **"Short Grass"**
Fuel Model Number: **1**
Source: **Albini, 1976**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) and cover was identified from Franklin, 1997 as consisting of:
• dominated by exotic annual grasses
• Valley Oak (*Quercus lobata*) savanna
• open Walnut (*Juglans californica*) woodlands
• coastal cactus scrub consisting of Prickly Pear (*Opuntia oricola*) and exotic annual grasses

Model Name: **"Tall Grass"**
Fuel Model Number: **3**
Source: **Albini, 1976**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) was identified from Franklin, 1997 as consisting of:
• Coast Live Oak (*Quercus agrifolia*) woodland

Model Name: **"Brush"**
Fuel Model Number: **5**
Source: **Albini, 1976**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) and cover was identified from Franklin, 1997 as consisting of:
• dominated by northern mixed chaparral AND less than or equal to 2 years maturity
• > 80% cover of Chamise (*Adenostoma fasciculatum*) AND less than or equal to 2 years maturity
• dominated by Redshank (*Adenostoma sparsifolium*) chaparral AND less than or equal to 2 years maturity
• dominated by coastal sage scrub AND less than or equal to 3 years maturity
• dominated by a mixed coastal sage scrub and northern mixed chaparral community AND less than or equal to 2 years maturity

Model Name: **"Hardwood Litter"**
Fuel Model Number: **9**
Source: **Albini, 1976**
Description:
This model corresponds to riparian areas identified from a 1997 National Park Service field-based inventory as well as the following subclasses in Franklin, 1997:
• riparian corridors
• non-native conifers and hardwoods

Model Name: **"Old Chamise"**
Fuel Model Number: **15**
Source: **Weise, 1997**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) was identified from Franklin, 1997 as consisting of:
• > 80% cover of Chamise (*Adenostoma fasciculatum*) AND greater than 15 years maturity
• dominated by Redshank (*Adenostoma sparsifolium*) chaparral AND greater than 15 years maturity

Model Name: **"Ceanothus"**
Fuel Model Number: **16**
Source: **Weise, 1997**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) was identified from Franklin, 1997 as consisting of:
• dominated by northern mixed chaparral AND greater than 12 years maturity
• dominated by a mixed coastal sage scrub and northern mixed chaparral community AND greater than 12 years maturity

Model Name: **"Young Chamise"**
Fuel Model Number: **17**
Source: **Weise, 1997**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) was identified from Franklin, 1997 as consisting of:
• > 80% cover of Chamise (*Adenostoma fasciculatum*) AND greater than or equal to 3 years maturity AND less than or equal to 15 years maturity
• dominated by Redshank (*Adenostoma sparsifolium*) chaparral AND greater than or equal to 3 years maturity AND less than or equal to 15 years maturity

Model Name: **"Sagebrush and Buckwheat"**
Fuel Model Number: **18**
Source: **Weise, 1997**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) was identified from Franklin, 1997 as consisting of:
• dominated by coastal sage scrub AND greater than 15 years maturity
• dominated by northern mixed chaparral AND greater than or equal to 3 years maturity AND less than or equal to 12 years maturity

Model Name: **"Wildland Urban Interface"**
Fuel Model Number: **20**
Source: **Morais, 2001**
Description:
This model orresponds to stands where the cover was identified from Franklin, 1997 as consisting of:
• rural residential or urban land use
This fuel model is meant to mimic the exotic landscape vegetation commonly surrounding homes in the Santa Monica Mountains. The grass component of the wildland urban interface fuels is represented by values of D1H and DSAV taken from NFFL 1. The exotic landscaped vegetation component of the wildland urban interface fuels is represented by values of D10H, D100H, LH, LW, LHSAV, and LWSAV taken from NFFL 7. The fuel bed depth is the numerical average of NFFL 1 and NFFL 7.

Model Name: **"Santa Monica Mountains Coastal Sage Scrub"**
Fuel Model Number: **21**
Source: **Morais, 2001**
Description:
This model corresponds to stands where the Potential Natural Vegetation (PNV) was identified from Franklin, 1997 as consisting of:

- dominated by coastal sage scrub AND greater than 3 years maturity AND less than or equal to 15 years maturity
- dominated by a mixed coastal sage scrub and northern mixed chaparral community AND less than or equal to 12 years maturity

Fuel biomass data collected from destructive sampling of coastal sage scrub sites in the Santa Monica Mountains displayed much lower loading values as compared to model 18 developed by the US Forest Service. The values used for fuel biomass in this fuel model represent values closer to what was recorded from the destructive samples taken in the Santa Monica Mountains.