

1 **Spatial Modeling of Fire in Shrublands using HFire:**

2 **II. Fire Regime Sensitivities**

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

1 **1. Introduction**

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

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

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

8 Fire modeling is one of the few viable approaches for increasing our knowledge of fire
9 regime dynamics on different landscapes and under a variety of conditions. There are several
10 available fire modeling frameworks and methods, and these are covered in recent reviews (Perry,
11 1998; Gardner et al., 1999; Finney, 1999; Keane et al., 2003; Cary et al., 2006). Long-term
12 simulation of fire and vegetation response is becoming increasingly possible and has been used
13 to examine variation in existing landscape patterns (e.g., Keane et al., 2002; Venevsky et al.,
14 2002), fire effects on possible vegetation dynamics (e.g., Franklin et al., 2001), and scenarios of
15 management activities (e.g., Haydon et al., 2000; Miller and Urban, 2000) and climate change
16 (e.g., Davis and Michaelsen, 1995; Miller, 1999). Another application of long-term modeling has
17 been to assess basic sensitivities and controls on fire regime dynamics (Hargrove et al., 2000;
18 Cary et al., 2006), similar to the work described here.

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

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

12

13 **2. Methods**

14 *2.1 Modeling fire spread*

15 HFire is a spatially explicit, raster-based model of fire growth that is embedded in a long-term
16 simulation environment (Morais, 2001; Dennison et al., submitted). Detailed documentation of
17 HFire code and input parameters can be found at the model's website
18 (<http://firecenter.berkeley.edu/hfire/>). Inputs necessary for modeling an individual event in HFire
19 are nearly identical to those for the widely used fire spread simulator FARSITE (Finney, 1998),
20 including ignition locations, weather conditions, and digital maps of topography and fuel types.
21 One-dimensional predictions from the Rothermel (1972) equations are fit to two dimensions,
22 using the solution to the "fire containment problem" (Albini and Chase, 1980) and the empirical
23 double ellipse formulation of Anderson (1983). A new technique implemented in HFire is based

1 upon finite fractional distances between cell centers and addresses the problem of distorted fire
2 shapes, inherent to raster models of fire spread (French et al., 1990). Solving this distortion
3 problem in a raster environment allows HFire to model fire growth very efficiently, a crucial
4 advantage in long-term simulation studies like those presented here. To incorporate the fact that
5 fires must eventually stop spreading, either through natural extinction or human suppression
6 activities, HFire also has an extinction rate of spread threshold; fire propagation in a given cell is
7 stopped if the rate of spread is slower than the specified threshold. In addition to accommodating
8 the natural extinction process, by raising this threshold one can loosely model advances in fire
9 suppression technology.

10 HFire allows for the control of three temporally dynamic variables that are critical for fire
11 regime modeling: ignitions, weather, and vegetation regrowth. User-specified input variables
12 control the average number of ignitions per year and the spatial distribution of ignitions. Ignition
13 probabilities can be spatially homogeneous or based on landscape features such as the distance to
14 the nearest road. The actual number of ignitions and locations of these ignitions per year are
15 then stochastically generated during simulation runs. HFire allows for both “standard” and
16 “extreme” weather inputs. Standard and extreme weather files can be populated with historical
17 weather observation data from single or multiple weather stations. Weather-related variables on
18 non-extreme days are stochastically drawn from the standard weather file representing typical
19 diurnal conditions, and these variables vary for each hour of simulated time. The user can also
20 specify an average number of extreme fire events per year, with the timing and number of
21 extreme events per year being stochastically determined by HFire. After a simulated fire,
22 regenerating vegetation progresses through a series of fuel classes over time (i.e., simulating
23 succession) until it burns again. Vegetation and related successional “paths” of fuel development

1 are represented through standard fuel models (Albini, 1976) used for fire behavior and fire
2 growth modeling. More detail on parameter estimation for ignitions, weather, and vegetation
3 regrowth is provided in upcoming sections.

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

23

1 2.2 *Study area, fuel characteristics, and vegetation dynamics*

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

14 Spatial fuels data for the entire SMM area were derived from a 100 m resolution regional
15 potential natural vegetation (PNV) map (Franklin 1997), which represented the ultimate
16 vegetation community, and therefore fuel type, that would occur in the long absence of fire. The
17 PNV map was modified according to SMM maps of riparian areas and local planning agency
18 maps of recent development. Vegetation communities (Fig. 1B) capable of carrying wildfire
19 during typical weather conditions were then assigned to one of the 13 standard fuel models
20 (Albini, 1976) or to a custom model (Weise, 1997) based on shrubland vegetation characteristics.
21 Vegetation types and their associated fuel models are shown in Table 1, and details of the fuel
22 models are summarized in online appendix Table A1. Simulations were run at 100 m X 100 m
23 cell resolution for fuels and other spatially explicit inputs. Finer spatial resolutions were not

1 investigated, as HFire output has been found to be relatively insensitive to cell size (Morais,
2 2001; Clark et al., submitted).

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

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

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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 km² over the period 1911-1995. Therefore, for a region the size of SMM (~960 km²), 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

1 increasing suppression effectiveness, a fire would need to be moving faster and faster to exceed
2 the extinction rate of spread (ERS) threshold specified in HFire. Identifying a baseline value for
3 the ERS threshold is difficult, however, because there is little published information about this
4 topic. In addition, a baseline ERS should be one that generates realistic fire patterns under a
5 variety of weather conditions, vegetation types, and suppression effectiveness scenarios. After
6 preliminary runs of HFire, we chose a baseline ERS threshold of 0.033 m/s, which equates to an
7 hourly spread of 6 chains (i.e., a traditional land survey measure equaling approximately 20 m).
8 This is a reasonable estimate, based on discussions with various fire behavior personnel, other
9 fire simulation work in shrublands (e.g., Davis and Burrows 1993), and comparison of
10 preliminary model output with mapped fire history for SMM (e.g., fire sizes, shapes,
11 frequencies).

12 Fire weather conditions can have a very strong influence on fire regimes, and this is
13 especially true for most chaparral-dominated shrublands (Davis and Michaelsen, 1995, Moritz,
14 1997, Keeley and Fotheringham, 2001; Moritz, 2003, Moritz et al., 2004). In fact, the “Santa
15 Ana” winds which affect our study area each year have been considered the most extreme fire
16 weather in the world (Schroeder et al. 1964). We therefore separated fire weather for our
17 simulations into either “typical” or “extreme” days, based on hourly weather station data for 2
18 fire seasons (1998 and 1999) from 2 local stations (Figure 1). Santa Ana wind events were
19 relatively easy to identify from local historical weather records, because winds do not follow the
20 normal coastal pattern of offshore flow in the evening through the morning hours, then switching
21 to onshore flow during the day. Instead, during extreme fire weather (EFW) conditions, Santa
22 Ana winds tend to be strong and consistently offshore (i.e., out of the N or NE for our study area)
23 and are also relatively hot and dry. After accounting for missing observations and isolating

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

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9 *2.4 Comparing simulation scenarios*

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

22 From simulated annual fire maps for each scenario, we quantified fire size probability
23 distributions, which often exhibit power law statistics (e.g., Malamud et al., 2005; Moritz et al.,

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

21

1 **3. Results**

2 *3.1 Baseline simulation runs*

3 The baseline parameterization of HFire simulated a fire regime that is representative of general
4 fire patterns in SMM, even to the point of showing gaps in areas burned that were similar to long
5 unburned areas in the historical mapped record (Fig. 2). Average fire intervals in the baseline
6 simulations were also within a range that may be tolerable for shrubland species in SMM (FC =
7 ~33 yr; Table 3). Due to the relatively short period of record for the SMM mapped fire history
8 and the emphasis on recording larger events, we did not compare simulated versus historical
9 landscape patterns using LSI for the baseline scenario. The almost total lack of smaller events
10 affects LSI enough to make such comparisons meaningless.

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

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

3

4 *3.2 Varying ignitions*

5 We examined two groups of parameter settings to investigate the importance of average ignition
6 rates, and simulated 500-yr fire regimes appeared to be relatively insensitive to this parameter.

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

15 After allowing a typical number of extreme fire weather events per year, larger fires and
16 much more realistic fire cycles were observed (bottom rows of Table 4). Regardless, the
17 consistent slope and form of fire size distributions within this set of ignition frequency runs
18 indicated that event size probabilities were still relatively insensitive to varying ignition rates
19 (right side of Fig 4A). There were occasional very large fires in these simulation runs (bottom
20 portion of Fig. 4B), as fires in this set of runs occasionally coincided with Santa Ana wind
21 episodes. A slightly higher percentage of ignitions actually propagate to become fires than in the
22 absence of extreme fire weather, and fires tend to be bigger and more variable in size (bottom
23 rows of 4B). A notable response for all runs in this scenario (i.e., 0 and 4 SA) is that of shorter

1 fire cycles with more frequent ignitions, being roughly proportional to the change in ignition
2 rate. Regardless of whether extreme fire weather events occur, however, shorter fire cycles are
3 simply the result of more fires burning across the spectrum of possible fire sizes for a given
4 scenario. Fire size distributions were therefore insensitive to changes in ignition rates (Fig. 4A),
5 and we did not observe notable changes in fire sizes with more frequent ignitions.

6 The different spatial patterns generated by fire regimes were quantified through the LSI
7 for each set of varying ignition frequency runs (Fig. 4C). The landscape pattern metric captures
8 the clear difference in the degree of landscape patchiness between the simulation runs that
9 included extreme fire weather events and those that did not (Fig. 4B). Without extreme fire
10 weather events, simulations contained many more small fires and were much less variable in
11 terms of landscape pattern (upper portion of Fig. 4B). The steady trend of increasing LSI (upper
12 portion of Fig. 4C) indicates that the cumulative effect of more ignitions can be an increasingly
13 fragmented landscape, in the absence of extreme fire weather. This trend is more pronounced
14 with more frequent ignitions (i.e., higher LSI), but it is largely because HFire records the many
15 1-ha ignition cells as “burned” (i.e., ignited but never progressing past the initial location to
16 become a fire). In contrast, the simulations that included Santa Ana episodes all had similar
17 trajectories over time, showing a lack of a trend, periodic “resetting” of the landscape pattern by
18 large fires (i.e., reducing patchiness and thus LSI), and comparable amounts of decadal variation
19 in LSI (bottom portion of Fig. 4C).

20

21 *3.3 Varying suppression*

22 Similar to the ignition rate scenarios just described, we examined two groups of parameter
23 settings for the extinction rate of spread threshold, which is a surrogate for the effectiveness of

1 fire suppression technology. To examine the effect of varying ERS on a fire regime in the
2 absence of extreme fire weather, we chose propagation thresholds that produced a realistic range
3 of fire cycle values, although possibly quite slow in reality (i.e., 0.022, 0.024, and 0.026 m/s;
4 Table 2). As a result, even without including Santa Ana wind episodes, some very large fires
5 were observed under the most lenient ERS setting (top curve of Fig. 5A and top age surface in
6 Fig. 5B); in fact, fires in this particular simulation run displayed the largest median size and
7 highest fraction progressing beyond the initial ignition point of any run reported in this study
8 (top row of Table 5). Raising the ERS (i.e., requiring faster spread to propagate into neighboring
9 cells) generally resulted in fewer and smaller fires on simulated landscapes (upper portion of Fig.
10 5B), and fire size distributions reflected this change through discrete shifts downward (Fig. 5A).
11 The overall ease with which fires tended to ignite and spread in these scenarios also led to less
12 variation in fire sizes (upper portion of Table 5) than in most other simulation runs.

13 To maintain a somewhat realistic range of simulated fire cycles after including extreme
14 fire weather events, higher ERS thresholds were examined in the second group of runs (i.e.,
15 0.022, 0.024, and 0.026 m/s; Table 2). Nonetheless, varying ERS in these simulations had
16 roughly the same effect as when Santa Ana wind episodes were excluded. With faster
17 propagation thresholds, fires were generally smaller (bottom portion of Fig. 5B), fire cycles were
18 shorter, and ignitions successfully became fires less often (bottom rows of Table 5). With the
19 possibility of extreme fire weather events, however, the largest few fires observed in this group
20 of runs all converged at approximately the same size (biggest events in Fig. 5A). Also unlike the
21 other group of runs in this scenario, raising the ERS produced increasingly variable fire sizes
22 (bottom rows of Table 5).

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

10

11 *3.4 Varying extreme fire weather*

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

20 Stand age patchiness was quite dependent on the average number of yearly Santa Ana
21 wind events. As in other scenarios, the landscape became highly fragmented if extreme fire
22 weather events were excluded (top of Fig. 6B), and this is reflected in a long-term increasing
23 trend in LSI (top curve in Fig. 6C). There was an interesting transition in the fire regime as a

1 single Santa Ana event per year is allowed, which caused intermittent and sharp drops in LSI
2 (Fig. 6C) and highly variable fire sizes (second row of Table 6); this threshold transition was also
3 evident in a marked upward shift in the tail of the fire size distributions, while the smaller fire
4 probabilities showed little change (Fig. 6B). As the number of extreme fire weather events
5 increased, the fire regime then exhibited more large fires that effectively “reset” the landscape
6 mosaic and erased the heterogeneity created by previous smaller fires. LSI therefore lacked a
7 long-term trend for scenarios with more frequent extreme fire weather events (lower curves in
8 Fig. 6C).

9

10 **4. Discussion**

11 *4.1 General trends and possible limitations*

12 Despite limited validation of HFire for individual fire event modeling (Dennison et al.,
13 submitted), an alternative and complementary diagnostic for evaluating a fire model has been
14 provided here by successfully simulating a realistic long-term fire regime (e.g., fire frequency vs.
15 size statistics). From the scenarios we examined, it is also clear that fire regimes simulated by
16 HFire display a range of sensitivities to variation in parameters thought to be important in
17 driving landscape fire dynamics. Outputs that we analyzed include simple fire regime metrics
18 (e.g., FC and ignition success), fire size distributions, and time series of changes in landscape
19 pattern (e.g., LSI). Holding other parameters constant, we found simulated 500-yr fire regimes to
20 be relatively insensitive to variation in ignition rates and somewhat more sensitive to suppression
21 effectiveness as represented by the extinction rate of spread threshold. Modeled fire regimes
22 were most sensitive to whether or not extreme fire weather events occurred during simulations,
23 and threshold dynamics appeared at the transition of 0 to 1 extreme weather episodes per year in

1 simulation runs. Our findings are in agreement with other modeling work, such as a general
2 insensitivity to ignitions (e.g., Haydon et al., 2000) and the relative importance of weather-
3 related factors (e.g., Bessie and Johnson, 1995; Cary et al., 2006).

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

17 The emphasis of work presented here was to examine fire regime sensitivities to factors
18 not directly related to fuels, although there are many open research questions concerning
19 vegetation. Even so, fuel-related variables have been found to be relatively unimportant in other
20 simulation model comparisons (Cary et al., 2006), and the age and spatial patterns of fuels
21 appear to be less of a constraint during the large fires responsible for most of the area burned in
22 chaparral-dominated shrublands of southern California (Moritz et al., 2004). Nonetheless, several
23 questions remain about the importance of different fuel model paths of flammability during post-

1 fire succession (i.e., fixed in Table 1), and we aim to eventually incorporate “dynamic” fuel
2 models that may change within or between fire seasons (Scott and Burgan, 2005). Given the
3 importance of fuels characteristics in studies aimed at fire management (e.g., Finney, 2001),
4 further research is needed about conditions under which spatial fuel patterns may be strong
5 constraints on fire probabilities.

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

15

16 *4.2 Future fire regimes*

17 Climate change is likely to have major effects on ecosystem structure and function, and changing
18 fire regimes will play an important role on many terrestrial landscapes. Past fire simulation work
19 has shown some sensitivity to changes in averages of climatic parameters like temperature and
20 precipitation (e.g., Davis and Michaelsen, 1995; Miller, 1999). Unfortunately, we know very
21 little about the direction and timing of future changes in temperature and precipitation at specific
22 locations; in addition, global climate models (GCMs) do not produce short-term episodes of
23 extreme fire weather. The results presented here demonstrate a relatively high degree of fire

1 regime sensitivity to fire weather, particularly when such episodes are novel occurrences (i.e.,
2 transitioning from 0 to 1 EFW event annually). Our findings therefore support the notion that
3 future changes in fire weather may be a strong driver of many fire regimes (e.g., Turner and
4 Romme, 1994; Beer and Williams, 1995; Stocks et al., 1998; Moritz et al., 2004), highlighting
5 the importance of addressing such episodic phenomena in climate change research.

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

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

1 HFire demonstrated this type of fire-vegetation feedback, when annual grasses were investigated
2 as the fuel model for the first few years of post-fire regeneration in shrublands. In these
3 scenarios, multi-year increases in fire activity were observed as large portions of the landscape
4 were temporarily trapped in the young and highly flammable grass stage of development (Fig. 7).
5 When grass fuels were allowed to “invade” in early succession, there were discrete and short
6 (<10 yr) pulses of burning, during which more than half the study area burned (Fig. 7, dark
7 dashed circles: 97% in yr 105-112, 76% in yr 130-136, 60% in yr 186-194). By comparison, the
8 largest pulse of area burned in the more realistic fuel path specification is considerably less (Fig.
9 7, lighter gray dashed circle: 43% in yr 157-161). This ecological sensitivity to invasive annual
10 fuels and overly short fire intervals is a fundamental difference between simulating fire-
11 vegetation interactions in chaparral shrublands and those in forests naturally dominated by
12 surface fire regimes (e.g., simulations of Covington et al., 2001).

13

14 *4.3 Ecosystem development and resilience*

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

1 result of HOT, a structure common in systems able to persist in fluctuating environments
2 (Carlson and Doyle, 2002).

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

21 Even if HOT has played a role in ecosystem development, it is not clear that fire regimes
22 will exhibit a general resilience in the face of drastic environmental changes (e.g., large shifts in
23 land cover or climate). The landscape vegetation patterns that support and depend on a given fire

1 regime probably arise through complex positive feedbacks and positive interactions (Moritz et
2 al., 2005). Such ecological sorting and development of ecosystem structure presumably occur
3 over time, possibly on longer temporal scales than will be faced in future climate change
4 scenarios. The rate and magnitude of change can be particularly important if a natural
5 disturbance regime is prone to large fluctuations and possible threshold transitions (Turner et al.,
6 1993; Romme et al., 1998).

7

8 **5. Conclusions**

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

21

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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:	Total Ignitions (#/500 yr)	Become fires (%)	Fire cycle (yr)	Median fire size (ha)	Mean fire size (ha)	CV fire size (ha)
Baseline						
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:	Total Ignitions (#/500 yr)	Become fires (%)	Fire cycle (yr)	Median fire size (ha)	Mean fire size (ha)	CV fire size (ha)
Vary ignitions						
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:	Total Ignitions (#/500 yr)	Become fires (%)	Fire cycle (yr)	Median fire size (ha)	Mean fire size (ha)	CV fire size (ha)
Vary ERS						
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:	Total Ignitions (#/500 yr)	Become fires (%)	Fire cycle (yr)	Median fire size (ha)	Mean fire size (ha)	CV fire size (ha)
Vary EFW						
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

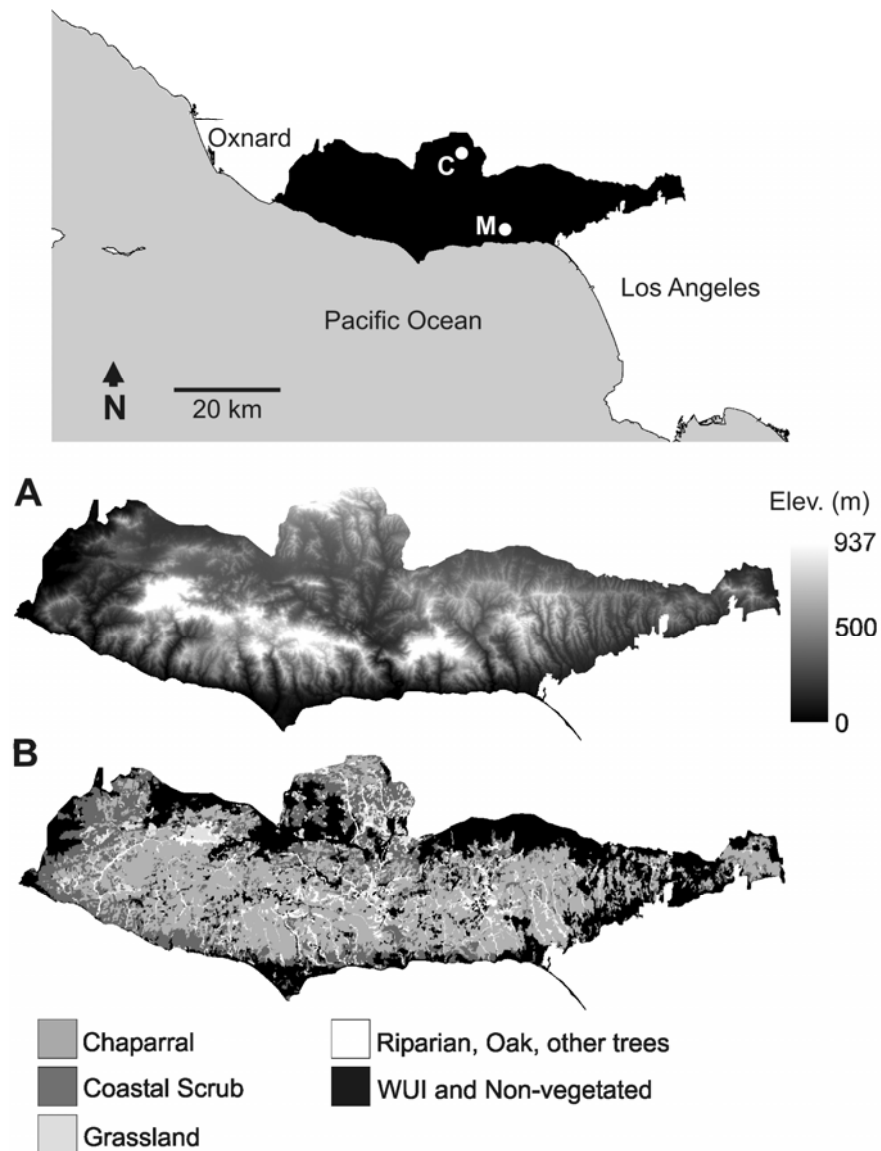


Figure 1. Topography and vegetation of study area. The inset at top shows the location of the SMM study area along the coast of southern California. Points C and M indicate the locations of weather stations Cheesebro and Malibu, respectively, from which hourly weather data were obtained. Panel A demonstrates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

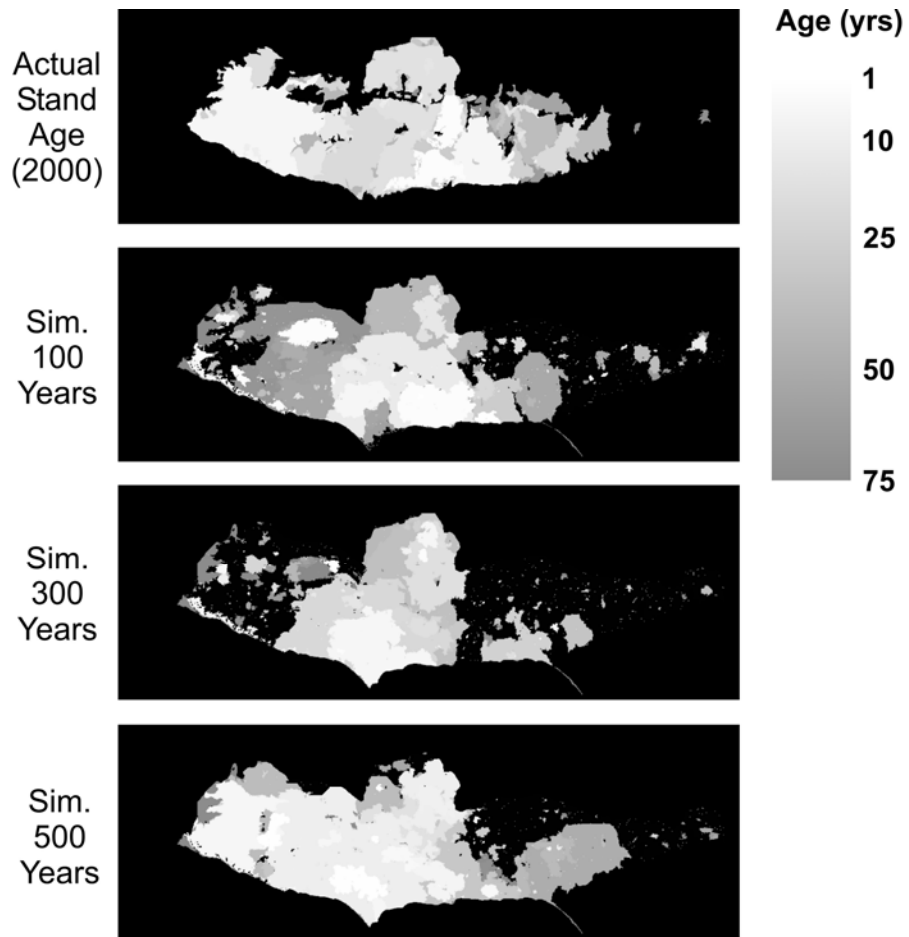


Figure 2. Actual stand age mosaic in SMM versus simulated patterns in baseline scenario. The top panel shows the stand age patterns of the mapped fire history in SMM (1925-1999). The lower three panels demonstrate snapshots of modeled landscape age mosaics after 100, 300, and 500 yr of simulation time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

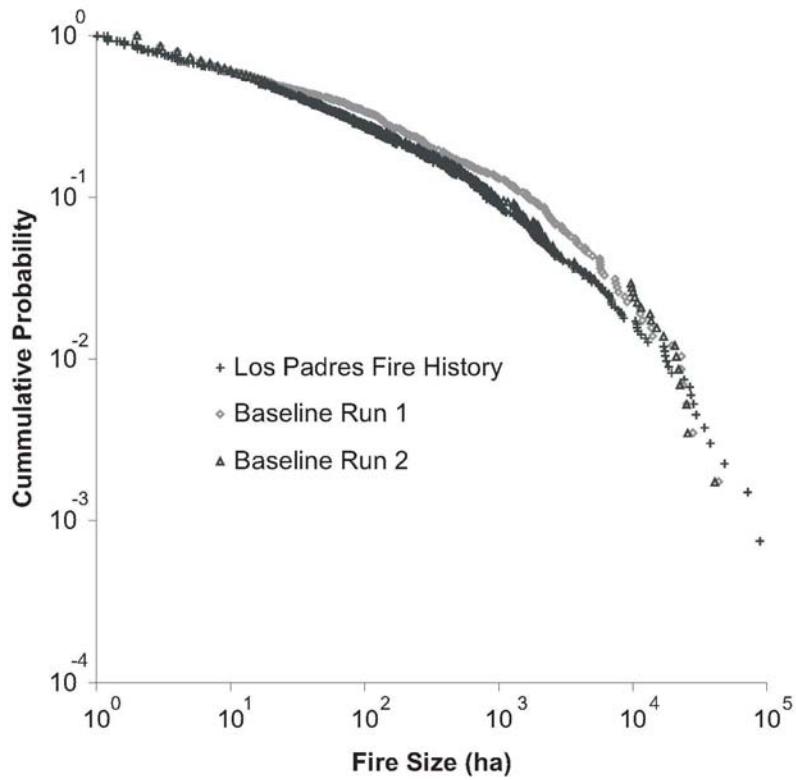


Figure 3. Historical versus simulated fire size distributions. For actual fire history data, only the chaparral-dominated portions of nearby LPNF were used (see text for explanation). For comparison, two simulation runs were made using the baseline parameter settings (runs were 200 yr in length, which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

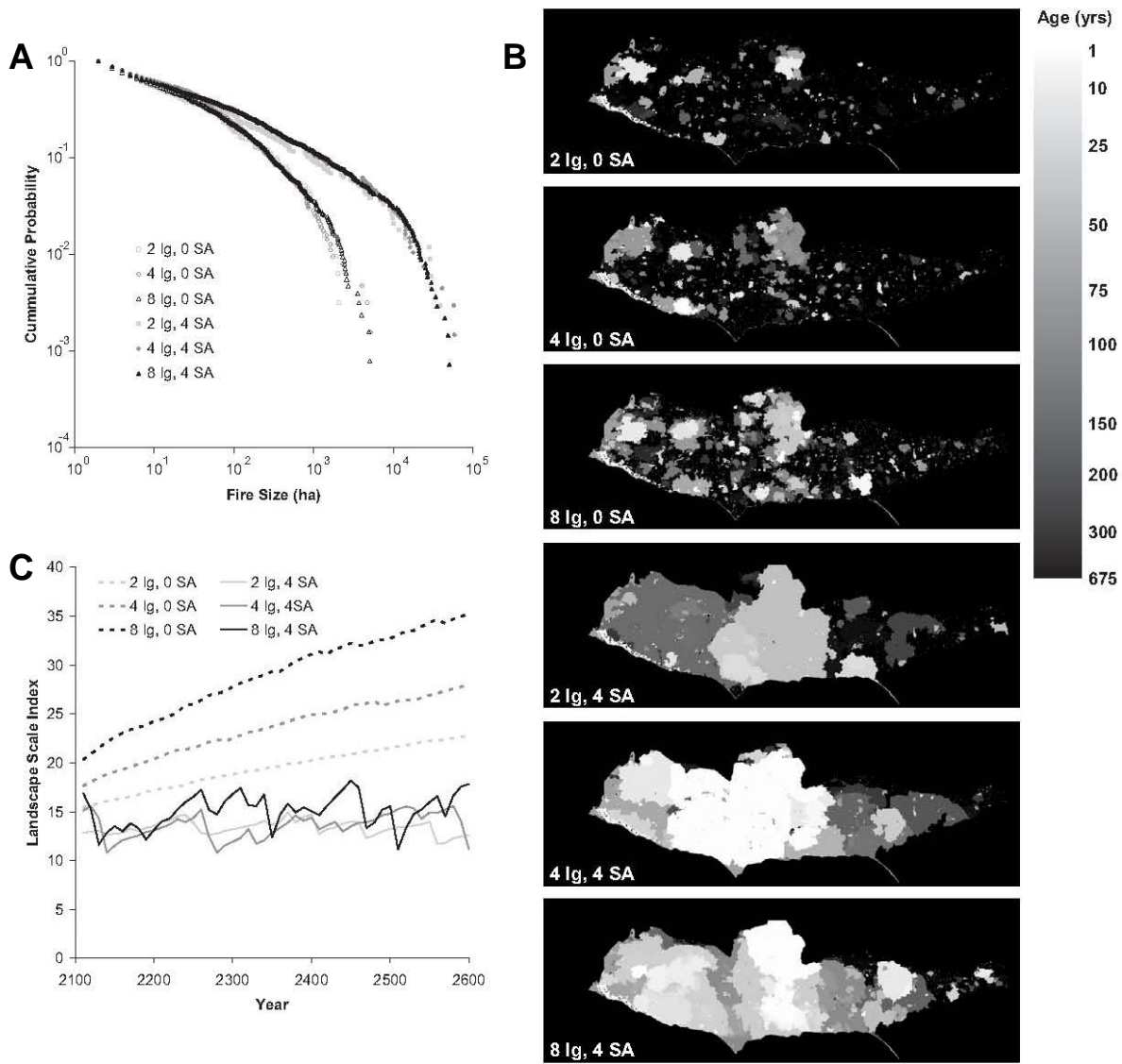


Figure 4. Simulation output demonstrating sensitivity to varying frequency of ignitions. Panel A shows fire size distributions, Panel B shows final landscape age mosaics, and Panel C shows LSI trends.

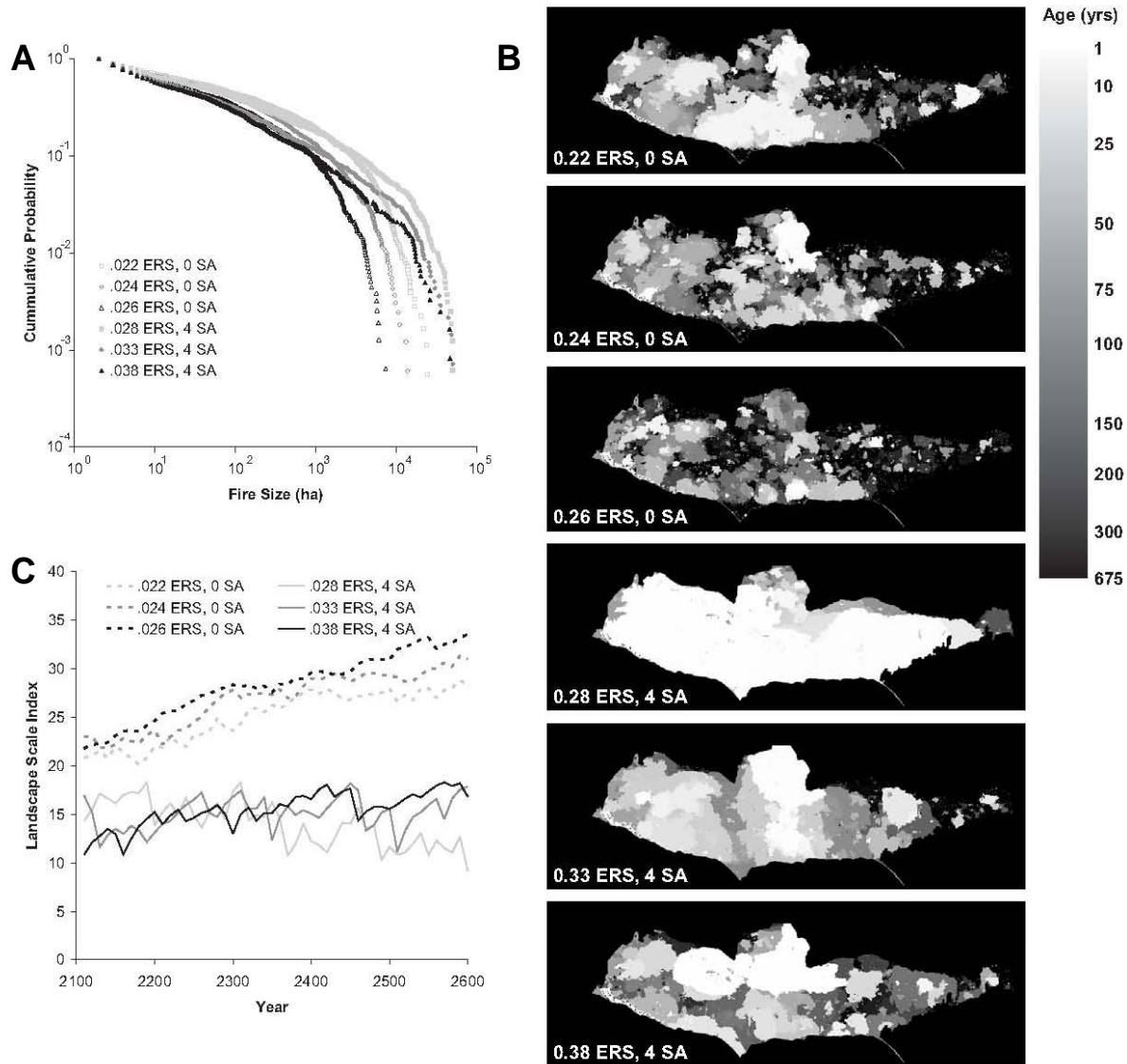


Figure 5. Simulation output demonstrating sensitivity to varying extinction rate of spread threshold. Panel A shows fire size distributions, Panel B shows final landscape age mosaics, and Panel C shows LSI trends.

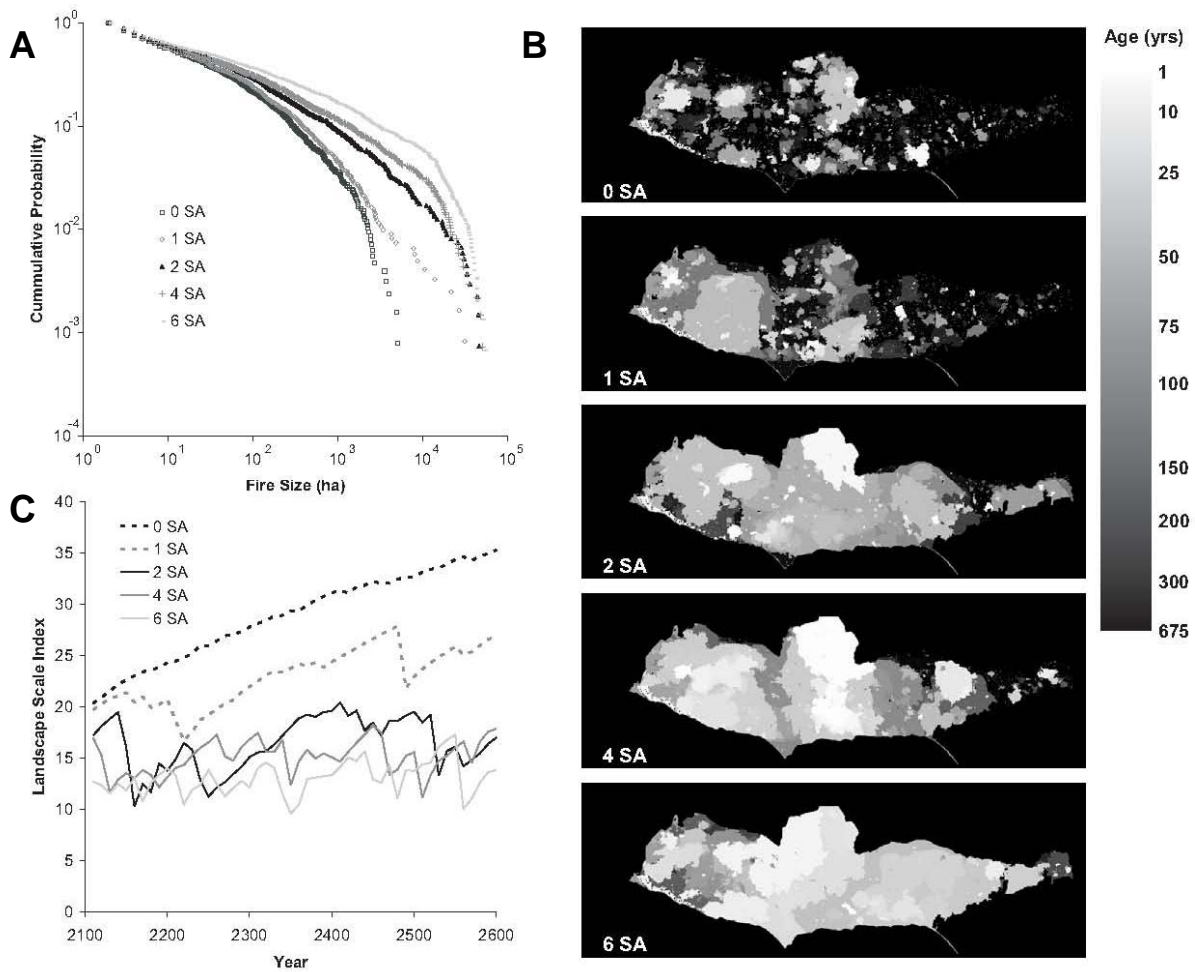


Figure 6. Simulation output demonstrating sensitivity to varying extreme fire weather event frequency. Panel A shows fire size distributions, Panel B shows final landscape age mosaics, and Panel C shows LSI trends.

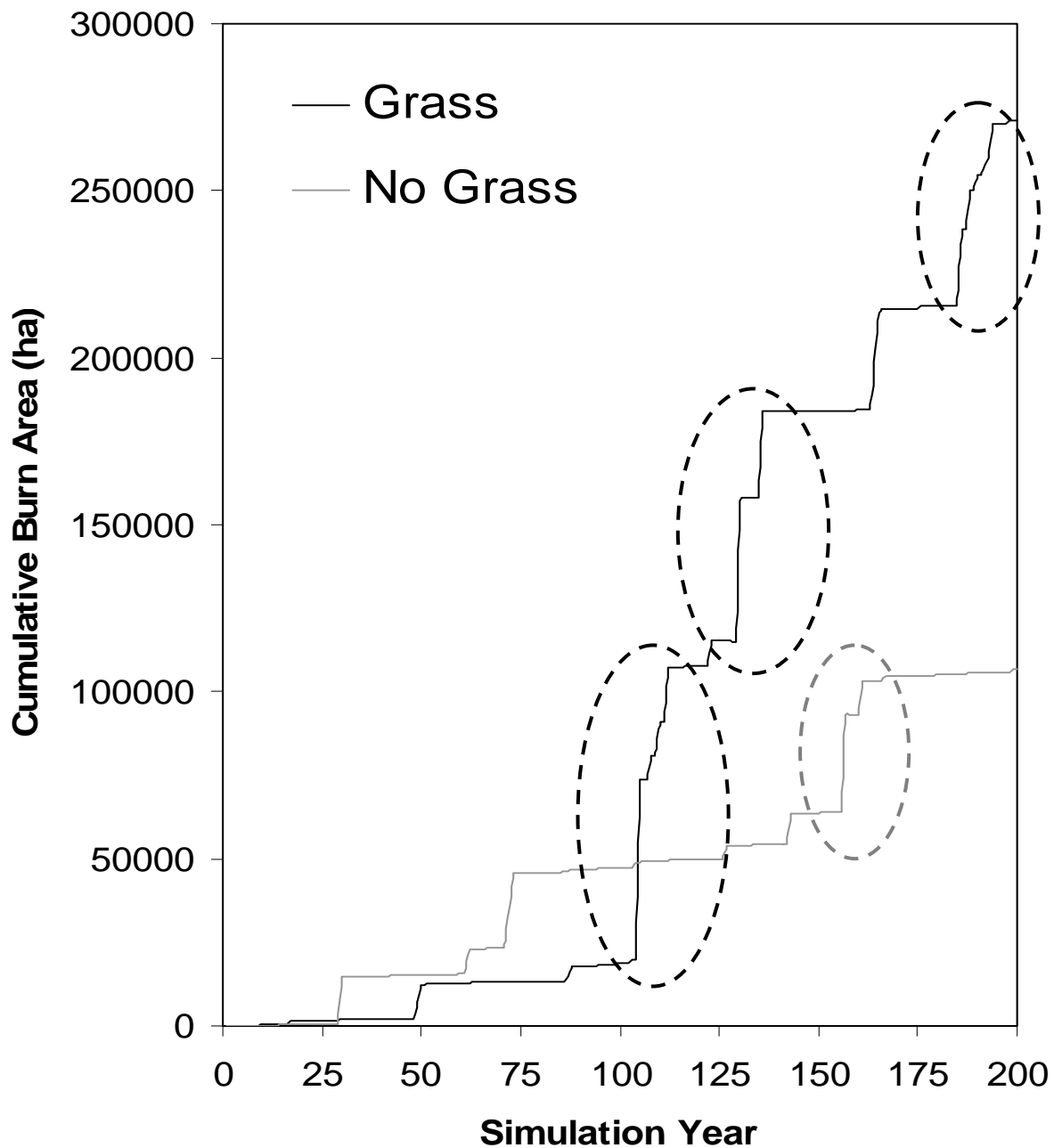


Figure 7. Area burned comparison showing dynamics typical of invasive grass-fire cycle. Both runs used “baseline” parameter settings (top row of Table 2) for 200-yr trial runs, although fuel development paths during post-fire succession in shrubland types differed. The darker line indicates area burned 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 Dead Fuels (<0.635 cm) (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 corresponds 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, LHS AV, and LWS AV 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.