SENSITIVITY ANALYSIS OF A FIRE SPREAD MODEL IN A CHAPARRAL LANDSCAPE

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ABSTRACT

Due to a unique combination of environmental conditions, the chaparral shrublands of southern California are prone to large, intense wildland fires. There is ongoing work in the fire research community to establish whether fuel accumulation or weather conditions are the determining factor in the prevalence of large chaparral fires. This study introduces a framework for contributing a modeling perspective to understanding these alternative hypotheses. As models formalize our understanding of the physical process of fire spread, the sensitivity of the models to the meteorological and fuel inputs should be indicators of their relative importance. A global sensitivity analysis (GSA) was conducted on HFire, a spatially explicit raster model developed for modeling fire spread in chaparral fuels, based on the Rothermel spread equations. The GSA provided a quantitative measure of the importance of each of the model inputs on the predicted fire size. The results indicate that, under extreme weather conditions, wind speed was over three times more influential on predicted fire sizes than any other single model input. This finding supports the idea that fires burning under Santa Ana conditions are primarily driven by high wind speeds. Future research will involve extending the GSA methodology to quantify the relative importance of these inputs in terms of the long-term fire regime in chaparral ecosystems.

INTRODUCTION

Southern California is considered among the most fire-hazardous landscapes in North America due to a unique combination of environmental conditions that are favorable to the development of large fires. These conditions include volatile fuels, dense fuel growth, steep terrain, and recurrent droughts. The influence of the Santa Ana foehn winds further increases the risk of large fires. In a Santa Ana event, the normal onshore marine airflow is replaced by offshore, downslope winds. The combination of high wind speeds, dry continental air, clear skies, and increased temperatures can rapidly dry fuels. The prevailing conditions during a Santa Ana event, including low relative humidity, high wind speed, and warming, can result in "explosive" burning conditions (Schroeder *et al.* 1964).

The chaparral shrublands of southern California are dominated by periodic, large, high-intensity fires (Keeley and Fotheringham 1994, Moritz 1997). The fire research community has not reached a consensus as to the impact that fire suppression policies have had on the modern chaparral fire regime (the size, intensity, and frequency of chaparral fires). Studies have compared the historic fire regimes of southern California and Baja California (Minnich 1983, Minnich and Bahre 1995, Minnich and Chou 1997, Minnich 2001) and have concluded that fire suppression efforts in southern California result in larger and more contiguous stands of older fuels, and that this fuel accumulation leads to larger and more intense fire events. These studies hypothesize that the chaparral landscape, in the absence of fire suppression policies, would be a mosaic of stands of younger and older vegetation. Patches of younger vegetation would then serve as natural breaks, preventing smaller fires from developing into larger fires, even during Santa Ana events. Younger stands can also can also result in reduced rates of spread when reburned (Philpot 1977). Tests of the age-dependent hypothesis have analyzed similar historical data but have concluded that there is not a direct relationship between large fires and fuel accumulation, and that large fires are a natural feature of the chaparral fire regime (Keeley *et al.* 1999, Keeley and Fotheringham 2001a, Keeley and Fotheringham 2001b, Moritz 2003, Moritz *et al.* 2004). In all of these studies, one point of agreement has been that Santa Ana winds can be the driving force behind large fire events.

Fire behavior models are a conceptual representation of the physical process controlling fire spread. In fire-prone ecosystems, fire behavior models are used for a number of applications that involve assessing the various risks associated with wildland fire, including training support personnel, planning prescribed burns, predicting the behavior of active fires, and comparing the effects of various suppression strategies (Andrews 1989). Fire modeling is also important for understanding how this natural ecological process operates on the landscape (e.g., Hargrove *et al.* 2000). Fire behavior models can provide significant insight for research on ecological processes where conducting field studies can be destructive, and where there is a limited amount of data available from historical events.

The purpose of this study was to introduce a framework for incorporating information from fire behavior model predictions into fire ecology and fire regime research. As models formalize our understanding of the physical process of fire spread, the sensitivity of the models to the meteorological and fuel inputs should be indicators of their relative importance. Sensitivity analysis (SA) is the study of how the variation in the output of the model can be attributed (qualitatively or quantitatively) to the variation in the model inputs (Saltelli 2000). SA is recommended for quantifying the influence each input, sub-model, and parameter has on the output of the

model, and for assessing uncertainty in the output that is associated with uncertainty in the inputs (Cruz *et al.* 2003).

This study was also a conceptual validation of HFire, a spatially explicit model developed for predicting fire spread in chaparral fuels. The objective was to use SA techniques to quantitatively establish the way in which the output of HFire is dependent on the inputs of fuel and weather conditions. This analysis was framed in terms of predicting the size of fires during potential Santa Ana events, and the research hypothesis being tested was that wind speed accounts for more variability in simulated fire size than fuel-related variables such as fine dead fuel moisture and fuel model. The modeling framework introduced in this study could be extended by repeating the analysis under a wider range of conditions representative of the climatology of southern California, which would allow for a more complete characterization of the role that weather and fuels play in terms of the modern chaparral fire regime.

There are few examples of sensitivity analysis studies in fire research literature, nearly all of which involve what is referred to as a "local approach" (e.g., Bevins and Martin 1978, Trevitt 1991, Bessie and Johnson 1995, Hargrove *et al.* 2000, Miller and Yool 2002, Cruz *et al.* 2003). Local approaches estimate the effect of the variation of a single input or parameter by keeping all the others fixed at their nominal values. Local methods are well established and are familiar to most modelers (Campolongo *et al.* 2000). Local SA serves as an ad-hoc stability analysis, providing a measure of how stable the model is around the best estimates for the inputs (Turanyi and Rabitz 2000). The local approach is not recommended for investigating the sensitivity of non-linear models in which the uncertainty in the output associated with the uncertainty in each input may be of different orders of magnitude (Cukier *et al.* 1973).

An alternative approach to evaluating model sensitivity is global sensitivity analysis (GSA), where the input factors, which can be model inputs, sub-models, and model parameters, are defined by their probability density functions, and all the factors in the analysis vary simultaneously (Saltelli 2000). Representing factors as probability density functions allows for the exploration of the full range of potential values for each input. Samples from these distributions are used as inputs for model simulations, producing a distribution of model output. By decomposing the variance of the model output, the contribution of each input can be assessed. The sensitivity estimate for each factor, known as an "importance" measure, can be written, in terms of conditional variance, as:

$$S_i = V[E(Y|X_i)]/V(Y)$$

where Y is the output variable, X_i is an input factor, $V(Y)$ is the unconditional variance, $E(Y|X_i = x^*_i)$ is the expectation of Y conditional on X_i having a given value x^*_i. Importance measures can be compared across factors, and the more influential factors will have higher scores.

A review of GSA procedures can be found in Saltelli *et al.* (2004). Salvador *et al.* (2001) present an application of GSA techniques in fire modeling research. GSA has been applied to a number of diverse fields, including environmental policy, population dynamics, chemical reaction, and economic modeling, and a review of these applications is given in Saltelli *et al.* (2000). The implementation of global methods in other environmental modeling applications suggests that they can provide useful insight for fire modeling and fire ecology research.

HFire is a spatially explicit fire spread model that was developed for modeling fires in chaparral environments (Morais 2001). HFire is a raster model that uses the cell

contact-based approach to fire spread (Kourtz and O'Regan 1971). This approach is very computationally efficient, allowing non-uniform time steps based on the amount of time required for fire to spread from cell to cell. Similar to FARSITE (Finney 1998), the semi-empirical Rothermel fire spread equation (Rothermel 1972, with modifications by Albini 1976) is used in HFire to determine the direction and the magnitude of the maximum rate of fire spread. The Anderson (1983) empirical relationship, relating wind speed to the length-to-width ratio of fire spread, is used to calculate fire spread rates in two dimensions. In HFire, a fire spreading through a lattice of cells has eight degrees of freedom. In any three-by-three neighborhood of cells, a fire located at the center of the neighborhood has the potential of spreading to all eight adjacent neighbors. HFire keeps track of the fractional spread distance from cell center to cell center, allowing the modeled fire to simultaneously spread to all of its neighboring cells during a time step.

HFire has been demonstrated to be, on average, 92 times faster than FARSITE for modeling the same fire (Morais 2001). The faster run times allow for its use for research applications in which large numbers of simulations are required. The model can be used to simulate single fire events or multiple events occurring over a period of hundreds of years. Morais (2001) found that HFire was as accurate as FARSITE for modeling two historical chaparral fires under both extreme and moderate wind conditions. To date, the sensitivity of Rothermel-based fire spread models over full ranges of input variables has not been examined. A GSA of the HFire model is critical for understanding how input variables used for simulating wildfires contribute to the modeled fire size, and over longer time periods, fire frequency.

METHODS

Sensitivity analysis was implemented by 1) identifying a study area suited to testing the experimental hypotheses; 2) collecting the spatial information needed to run the model; 3) collecting the temporal input data; 4) defining a distribution for each input factor based on statistical analysis of the data; 5) sampling from the distributions of the input factors, and executing the model using these samples; 6) performing the sensitivity analysis in order to quantify the relative importance each input factor has on the output of the model; and 7) evaluating the hypotheses based on the results of the sensitivity analysis.

Study Domain

The domain for this study was the Santa Monica Mountains National Recreation Area (SMM), located in Los Angeles and Ventura Counties in southern California (Figure 1). SMM was the original study site for the development of the HFire model. The recreation area is located within southern

Figure 1. Study domain.

California's Mediterranean-type ecosystem. The native vegetation is a mosaic of chaparral, coastal sage scrub, oak woodland, riparian woodland, and grasslands (Radtke *et al.* 1982). Over 40 % of the fires in this region are large fires exceeding 400 ha in size, and most of these large fires occur during Santa Ana events in the fall (Radtke *et al.* 1982). A nine by nine kilometer subset was selected in an area in the western region of the park that is undeveloped and is predominately chaparral. This study required an area large enough that simulated fires would not reach the edge of the landscape. Using a larger subset was not viable due to the layout of the terrain and vegetation and the proximity to urban areas. The terrain and fuels input data were then used to artificially expand the subset by creating and inverting mirror images of the study area (Figure 2). This method alters the orientation of the fuels and the topography, but retains the connectivity between the slope of the terrain and the fuel characteristics.

Input Data

HFire requires a number of temporally and spatially dynamic inputs. The required temporal inputs to HFire are wind speed, wind direction, fine dead fuel moisture, live herbaceous fuel moisture, and live woody fuel moisture. The spatial inputs to HFire are slope, aspect, elevation, and fuel characteristics, as well as the coordinates of the ignition location.

Live herbaceous fuel moisture and live woody fuel moisture data were not available for this study domain and period. Consequently, the decision was made to fix

Figure 2. Artificial landscape.
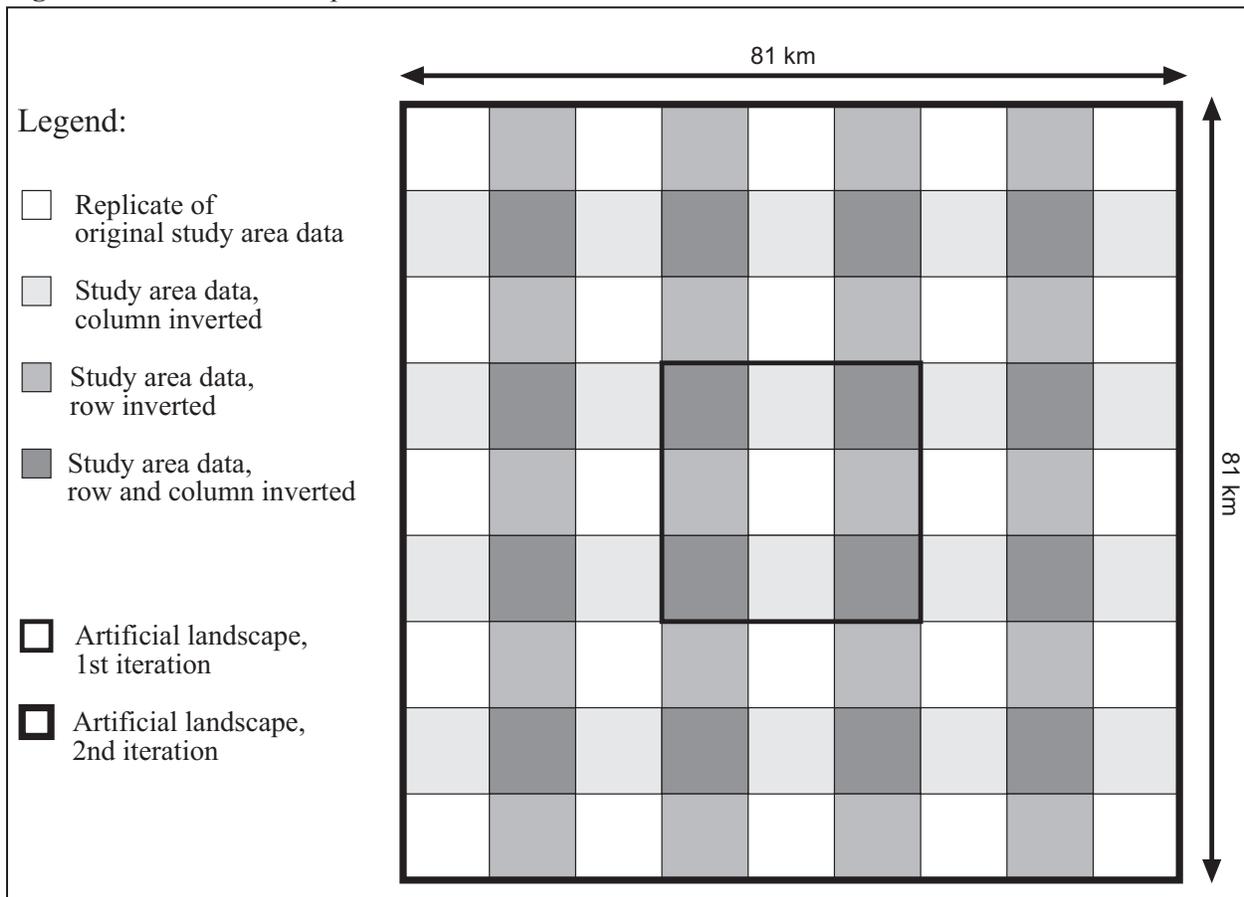
live herbaceous fuel moisture at 50%, and live woody fuel moisture at 70 %. These values were used in the HFire development to represent the lowest live fuel moisture values in the dry season for chaparral fuels (Morais 2001). As fixed values, live herbaceous and live woody fuel moistures could not be included in the GSA, as variance based approaches involve assessing the importance of each input by decomposing the variance of the output data on the variance of the input data.

Hourly data for wind speed, wind direction, and fine dead fuel moisture were obtained from the Western Regional Climate Center (WRCC 2004) for the Cheeseboro Remote Automated Weather Station (RAWS) gauge for the study years 1996-2002. The RAWS records were culled to the "peak fire season" months of September to November. The records were also culled to include only days with Santa Ana burst conditions, defined by the National Weather Service as six or more consecutive hours with prevailing winds from the northeast quadrant (Burroughs 1991). The wind direction for this study was defined as the average daily wind direction in that quadrant. Days with any missing hourly observations for any variable were removed from the dataset. Terrain variables (slope, aspect, and elevation) were based on a 10 m United States Geological Survey digital elevation model (DEM) of the Santa Monica Mountains. The DEM was resampled to spatial resolutions of 30 m and 100 m. The fuels maps were based on a map of potential natural vegetation (PNV), which represented the ultimate vegetation community, and therefore fuel type, that would occur in the long absence of fire (J. Franklin, San Diego State University, unpublished report). The PNV map was modified according to SMM maps of riparian areas and local planning agency maps of recent development. Vegetation communities capable of carrying wildfire during typical weather conditions

were then assigned to one of the 13 standard Northern Forest Fire Laboratory (NFFL) fuel models (Albini 1976) or to a custom model (Weise 1997) based on shrubland vegetation characteristics. The custom models for chaparral shrubs have a substantially lower fuel loading (the amount of available biomass, measured as the dry weight per unit area) than the standard NFFL fuel model used for chaparral (Model four — 2 m high chaparral). The HFire model does not require a fuel loading input separate from the fuel model and, in this research, the contrast between the standard and the custom fuel models serves as a surrogate variable for exploring the effects of different levels of fuel accumulation. Ignitions were seeded using a random, uniform distribution across the landscape. Ignitions that landed within cells containing no fuels were not permitted to propagate.

Distributions for input data and their associated parameters (mean and standard deviation) were assigned on the basis of statistical analysis of the empirical data (Table 1), and represent the inherent natural variation in the input data. The data were tested for normality using the Shapiro Wilks goodness-of-fit test (Royston 1982). Wind speed and fine dead fuel moisture were not normally distributed, and transformations were applied to approximate a normal distribution for sampling purposes. The mean and the standard deviation of the transformed data were used as the estimate of the mean and the standard deviation of the normal distribution. Choices in the fuel models and spatial resolutions were represented for sampling purposes by discrete uniform distributions.

In order to select the appropriate sampling method for the data, it was necessary to determine if the factors were independent (orthogonal), as many sampling methods are based on this assumption. Wind speed, fine dead fuel moisture, and the average wind direction in the northeast quadrant were all

Table 1. Description of input distributions.

Input (units)	μ, σ of the data	Shapiro-Wilks W for selected transform	Assigned distribution
Wind speed (km/hr)	12.83, 6.25	W = 0.9833, p-value = 0.0016 (inverse transform)	Normal
Fine dead fuel moisture (%)	8.59, 4.64	W = 0.9809, p-value = 0.0006 (natural log transform)	Normal
Wind direction (degrees)	56.60, 13.04	W = 0.9798, p-value = 0.0003 (square root transform)	Normal
Spatial resolution	---	---	Uniform
Fuel model	---	---	Uniform
X coordinate of ignition	---	---	Uniform
Y coordinate of ignition	---	---	Uniform

Italicized inputs are trigger factors, designed to allow for modeling choices to be represented as distributions for sampling purposes.

Table 2. Non-parametric correlations, Spearman's Rho.

	Wind speed	Fuel dead moisture	Wind direction
Wind speed	---	-0.355*	-0.365*
Fine dead fuel moisture	-0.355*	---	0.275*
Wind direction	-0.365*	0.275*	---

* Correlation is significant at the 0.01 level (two-tailed).

significantly correlated (Table 2). This correlation is a likely feature of Santa Ana events, with the associated prevailing conditions of low humidity, high wind speed, and warming. For the purposes of this study, the assumption of stochastic independence was inappropriate; therefore, this research required the use of a sampling method appropriate for correlated inputs.

Sample Generation and Model Evaluation

The recommended sampling method for correlated inputs is replicated Latin Hypercube Sampling (r-LHS) (Saltelli *et al.* 2004). SIMLAB, a software program for performing uncertainty and sensitivity analysis (Saltelli *et*

al. 2004), was used to generate 2000 input samples using the r-LHS technique. The Iman and Conover technique was used to control for correlation in the input data by matching the rank-correlation structure of the samples to the empirical data (Iman and Conover 1982). This allows the sampled values to co-vary in a manner that is consistent with the co-variation in the empirical data.

The samples were used as inputs for 2000 HFire model runs, simulating a single event lasting 24 hr in duration, and the total area burned was extracted from the output files for each simulation. Fires that reached the boundary of the synthetic landscape were re-run on a larger synthetic landscape. SIMLAB was then used to calculate the importance measures from the distribution of the model

outputs. The formulas for estimating the importance measures using r-LHS are presented in McKay (1996) and Helton and Davis (2001). In order to assess the stability of the sensitivity estimates, the analysis was repeated using a larger sample size (N = 4000).

RESULTS

In the first set of model simulations (N = 2000), 105 ignitions were not successful because the ignition cell was classified as unburnable. In the second set of model simulations (N = 4000), 216 ignitions were not successful. The descriptive statistics for the output of the model simulations are presented in Table 3, and the histograms of the outputs are presented in Figures 3a and 3b. The

majority of the observations are at the lower end of the range, with few events in the extreme end of the range, as would be expected for an extreme event. In a visual examination of the shapes of the modeled fire perimeters, it was found that simulations with higher wind-speeds resulted in burn perimeters that were generally plume shaped, while the perimeter shapes for simulations in which the wind speed was relatively low are more circular. These findings are consistent with previous classifications of fire shapes (Albini 1976).

The importance measures for wind speed, fine dead fuel moisture, and the choice of fuel models were statistically significant for both sets of simulations (Table 4). Wind speed was identified as the most influential factor, accounting for more than 40 % of the variation in the model output, followed by fine dead fuel

Table 3. Descriptive statistics, output of model simulations.

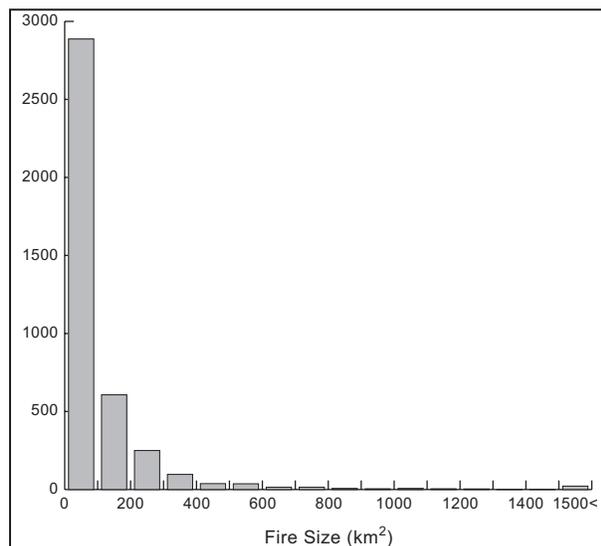| | Viable ignitions | Statistics for the total burned area (km^2), all simulations (viable ignitions) | | | |
		Minimum	Maximum	Mean	Standard deviation
Simulation set 1 (N = 2000)	1895	0.0000 (0.0009)	3094.62 (3094.62)	95.59 (100.89)	190.91 (194.77)
Simulation set 2 (N = 4000)	3784	0.0000 (0.0009)	4658.59 (4658.59)	102.47 (108.32)	238.90 (244.33)

Figure 3a. Histogram of model output, simulation set 1 (N = 2000).
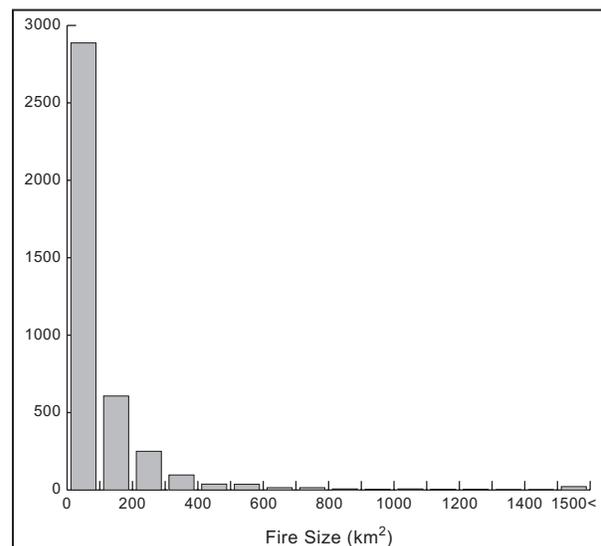

Figure 3b. Histogram of model output, simulation set 2 (N = 4000).

Table 4. Importance measures.

	Wind speed	Fine dead fuel moisture	Wind direction	Spatial resolution	Fuel model	X	Y
Simulation set 1 (N = 2000)	0.4312	0.1448	0.0214	-0.0003	0.0985	0.0210	0.0037
Simulation set 2 (N = 4000)	0.4686	0.1346	0.0408	0.0002	0.0625	0.0090	0.0142

moisture (less than 15 %), and fuel model (less than 10 %). Wind direction, spatial resolution, and the ignition locations had scores close to zero, indicating that these factors were not influential and did not have a significant main effect on the output of the model. The ranking of these factors did not change with the larger sample size.

DISCUSSION

The estimated importance measure for wind speed was more than three times that of the closest input factor of fine dead fuel moisture. This finding supports the argument that fires burning under Santa Ana conditions are wind driven events, to the extent that the Rothermel equations in the HFire model structure represent the physical process of fire spread. In contrast, fine dead fuel moisture was responsible for less than 15 % of the variation in simulated fire size. The HFire model is still being improved upon, and the identification of wind speed and fine dead fuel moisture as influential factors contributes to the conceptual validation of the model, as these inputs describe known and expected influential determinants of fire size. This research established that the model behaves in a way that conforms to the expectations for the physical system, increasing the confidence that can be placed in the model predictions.

This study was framed in terms of modeling fires in potential Santa Ana conditions, and the ranking of the input factors could change if a wider range of meteorological conditions were used. Outside of peak fire season, the fine dead fuel moisture input may have a larger influence, as conditions are more likely to be unfavorable for burning. The inputs of live herbaceous and woody fuel moistures were not included in this analysis due to the lack of available data. Depending on the seasonal trends, these inputs could be significant drivers of the model output. To test this assumption, this analysis should be repeated in a study area where live fuel moistures are regularly monitored. Other options include developing surrogate measures to estimate these inputs from available data or repeating the analysis with synthetic values for live fuel moistures.

The results of this study reflect the influence of the conditions sampled from the RAWS time series, allowing for a characterization of the sensitivity of the model to each of the climatological inputs separately. Future research will examine methods for sampling the input data in a way that preserves the temporal autocorrelation in the data. One such approach would be to randomly pick a 24 hr series from the data for each replicate. While this method would not provide a separate sensitivity measure for each of the climatological inputs, it would provide a measure of the sensitivity to the diurnal pattern in prevailing conditions. Identifying longer-term patterns may also be useful for simulations that are longer than 24 hr in duration.

The importance measure estimated for fuel model, while even smaller than that of wind speed or fine dead fuel moisture, was

significant. All of the simulations that resulted in fires that were too large for the original synthetic landscape were simulations using the NFFL fuel maps. The custom models for chaparral shrubs were developed because the NFFL fuel model for chaparral did not represent the more moderate fuel loading found in the chaparral shrublands of the SMM region. The importance of the fuel model input and the questions pertaining to the role of fuel accumulation in the chaparral fire regime suggest that this input should be of concern when modeling fires in chaparral fuels. Custom fuel models, while costly to develop, provide site-specific information on important determinants of fire spread. Even under the potential Santa Ana conditions represented in this study, when rates of spread are likely to be maximized, differences in fuel loading resulted in significantly different spread predictions. Using NFFL fuel models may result in over-predicting fire size in most chaparral landscapes.

The importance measures for spatial resolution in both sets of simulations were close to zero, indicating that changing between 30 m and 100 m resolution has no noticeable influence on the variability in predicted fire size. Spatial resolution was the least influential factor for both sets of simulations. The landscape is dominated by chaparral, and the range of possible conditions of chaparral vegetation is condensed into a small number of fuel models. It is perhaps not surprising that the model was insensitive to the way in which this relatively homogeneous landscape was divided. Miller and Yool (2002) suggest the appropriate resolution for fire modeling purposes is the resolution that represents the finest scale of heterogeneity in the landscape. It would appear that when modeling Santa Ana fires in this landscape, the 100 m resolution would be acceptable. Further investigation is needed to identify the threshold resolution that allows for the optimization of predictive efficiency and accuracy.

The importance measure for wind direction was not a strong driver of model behavior. This could be a result of the synthetic landscape, as the terrain has a directional trending in the canyons that the process of inverting the landscape fails to maintain. The relationship of wind direction to the orientation of the topography could therefore be more influential than these results would indicate. Wind direction was also held constant for the simulations and was restricted to the northeast quadrant. These restrictions were considered necessary for representing potential Santa Ana events, when the winds blow persistently from that direction. Representing the full range of wind directions and speeds outside of Santa Ana events could provide insights into the ways in which topography and wind direction and speed may interact in this region.

The importance measures for the coordinates of the potential ignitions locations were very small. The simulations were 24 hr in duration, and the location of a successful ignition was likely influential during the first few hours and less influential over time. There were relatively few unburnable ignition locations in this landscape, which led to few simulations in which no area was burned.

The inherent limitations of fire spread modeling are apparent in this research. This research did not test the assumptions of HFire, the Rothermel (1972) equations, or the Andersen (1983) ellipse model. For example, the HFire model predicts surface fire spread, and does not model the spread of fire by fire brands or by the ignition of fire gasses. The results of this analysis are specific to the prediction of fire size using the HFire model, to the chaparral landscape of the Santa Monica Mountains, to the time period of the study, and to potential Santa Ana conditions.

Global Sensitivity Analysis (GSA) is an objective and quantitative method for model evaluation that offers considerable insight for research into physical processes. Given that fire modeling is being used in research and

decision-support applications, more attention needs to be paid to incorporating GSA techniques in other fire modeling studies. HFire has the ability to stochastically simulate fire regimes, drawing from a wider range of historical climatological conditions and tracking the age of vegetation following fires. An extension of this analysis will therefore involve conducting a GSA of the model, while simulating the complexities of a long-term fire regime at the landscape scale.

Exploring the relative importance of exogenous and stochastic factors (e.g., meteorological variables) as compared to more endogenous and deterministic factors (e.g., plant characteristics) is central to understanding the fire ecology of many terrestrial ecosystems. For example, there is support for the idea that plant flammability may have played an evolutionary role in some species (Mutch 1970). Given the paucity and the infeasibility of conducting extensive field experiments, simulation modeling is one of the few ways we can investigate patterns of plant traits (e.g., Pausas and Lloret 2007) or the degree to which plants may alter their own probabilities of burning at local (e.g., Bond and Midgley 1995) and landscape scales (e.g., Moritz *et al.* 2005). Assessing the sensitivities of fire-related models may thus lead to insights in both scientific and management contexts.

ACKNOWLEDGEMENTS

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