Effects of ignition location models on the burn patterns of simulated wildfires

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ABSTRACT

Fire simulation studies that use models such as FARSITE often assume that ignition locations are distributed randomly, because spatially explicit information about actual ignition locations are difficult to obtain. However, many studies show that the spatial distribution of ignition locations, whether human-caused or natural, is non-random. Thus, predictions from fire simulations based on random ignitions may be unrealistic. However, the extent to which the assumption of ignition location affects the predictions of fire simulation models has never been systematically explored. Our goal was to assess the difference in fire simulations that are based on random versus non-random ignition location patterns. We conducted four sets of 6000 FARSITE simulations for the Santa Monica Mountains in California to quantify the influence of random and non-random ignition locations and normal and extreme weather conditions on fire size distributions and spatial patterns of burn probability. Under extreme weather conditions, fires were significantly larger for non-random ignitions compared to random ignitions (mean area of 344.5 ha and 230.1 ha, respectively), but burn probability maps were highly correlated ($r = 0.83$). Under normal weather, random ignitions produced significantly larger fires than non-random ignitions (17.5 ha and 13.3 ha, respectively), and the spatial correlations between burn probability maps were not high ($r = 0.54$), though the difference in the average burn probability was small. The results of the study suggest that the location of ignitions used in fire simulation models may substantially influence the spatial predictions of fire spread patterns. However, the spatial bias introduced by using a random ignition location model may be minimized if the fire simulations are conducted under extreme weather conditions when fire spread is greatest.

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1. Background

The spatio-temporal patterns of wildfire occurrence, spread, and behavior depend on the interactions among climate, fuels, topography, ignition, and suppression (Falk et al., 2007; Moritz et al., 2005; Pyne et al., 1996). Ignition timing and location may be especially important as they interact with weather patterns (temperature, moisture, and wind), fuels (types, loads, and spatial configurations), and topography (elevation, slope, and aspect) to determine fire behavior and spread and ultimately the extent and intensity of the resulting fires (Bessie and Johnson, 1995; Cary et al., 2009; LaCroix et al., 2006). While there are two general sources of ignitions, natural and human, both are associated with complex drivers that influence where and when they occur (Sturtevant and Cleland, 2007; Krawchuk et al., 2006). Although the factors that influence their spatial distribution may differ, both natural and human ignition patterns are non-random, and they vary in both timing and location. Many studies show that the location of ignitions strongly influences subsequent spatio-temporal patterns of wildfire and resulting impacts (Cardille et al., 2001; Kasischke et al., 2002; Prestemon et al., 2002; Syphard et al., 2007). Despite the importance of ignition location on fire extent and effect, most fire simulation studies have been conducted using the assumption that ignitions are distributed randomly across space and time.

One of the primary reasons that fire simulation studies have used the assumption of random ignition locations was that spatially explicit information about actual ignition locations was difficult to obtain. However, two recent developments may help to decrease this reliance on random ignition patterns; 1) the increasing quality and availability of spatial ignition data, and 2) the increasing awareness of the role of human ignition in altering fire regimes (Keeley et al., 1999; Pyne, 2001). In fact, recent studies have incorporated methods

(e.g., statistical modelling, point pattern analysis, and kernel density surfaces) of analyzing ignition location data to explain and map the spatial patterns of ignitions or fire occurrence locations. Some papers have focused exclusively on modelling lightning occurrence using biophysical variables (Diaz-Avalos et al., 2001; Wotton and Martell, 2005), while others have incorporated both anthropogenic and biophysical variables to model human and lightning ignition locations (Genton et al., 2006; Yang et al., 2007), or just human ignition locations (Martinez et al., 2009; Pew and Larsen, 2001; Syphard et al., 2008). Collectively, these studies show that the spatial distribution of both human and lightning ignitions can be estimated and mapped using readily available social and biophysical data layers. Social and biophysical data can be combined with historical fire records to generate empirical ignition location models that predict spatially explicit ignition probabilities. In general, up-to-date data about fuel characteristics, coupled with the spatial location of human development and activities may be able to predict areas of increased ignition probabilities due to anthropogenic causes. Such data are region-specific though, and highlight the need to develop unique ignition models for different regions, depending on their social and biophysical properties. Important social variables include (among others): distance to development, level of development, distance to roads or road density, and distance to trails (Syphard et al., 2008); population density, housing density, median home value, and distance to railroad (Sturtevant and Cleland, 2007). Important biophysical variables include: temperature, elevation, slope gradient, topographic aspect (south-westness), and vegetation type (Syphard et al., 2008); water holding capacity, historical fire rotation, precipitation, percentage of a given land cover class, and soil class (Sturtevant and Cleland, 2007). Among these, vegetation type (fuel) poses a specific challenge to modelers, since it changes with time according to successional processes.

For example, we compared three ignition location models that were developed for different regions (Table 1). Syphard et al. (2008) used a multiple logistic regression model to predict ignition probabilities in the Santa Monica Mountains, California. Given that almost all of the ignitions in that area are human-caused, they found that human variables that described the distance to anthropogenic features (development, roads, and trails), together with the overall amount of wildland urban interface (WUI) area, were the best predictors of fire ignition. Two biophysical variables, land cover type and minimum January temperature, were also significant.

Analyzing a much larger area, Sturtevant and Cleland (2007) used classification and regression trees (CART) to explain fire occurrence in Northern Wisconsin. Again, they found that the human variables were the most important, including housing density, road density, and distance to railroads. They also found that a purely social variable, the percentage of owner occupied homes, was an important variable. The most important biophysical variables were land cover (expressed as percentage of agricultural and grassland cover) and forest flammability.

The third study, by Yang et al. (2007), quantified the spatial and temporal patterns of fire ignitions in the Missouri Ozark Highlands. Using a Poisson multiple regression, the main human variables again reflected development (distance to towns, roads), and social aspects (type of land ownership). The biophysical variables were related to land cover type (with mixed forest being the most important, followed by deciduous forest and grassland), as well as slope and aspect (which affects flammability by altering fuel moisture conditions).

Since the 1980s, fire simulation modelling has emerged as a powerful tool for wildfire research as well as for fire management and suppression planning (e.g., the US Forest Service RAVAR (http://www.fs.fed.us/rm/wfdss_ravar/)), and studies of fire and vegetation dynamics (Keane et al., 2004). There are several deterministic spatially explicit fire simulation models, but the most commonly used and widely recognized model is FARSITE (Finney, 1998), while other models include MTT (Finney, 2002); FireStation (Lopes et al., 2002); Prometheus (Tymstra et al., 2010), EMBYR (Hargrove et al., 2000); and more recently the dynamic fire extension of LANDIS-II (Sturtevant et al., 2009). Examples of how these models are used include: the assessment of fire risk in a Mediterranean landscape (Carmel et al., 2009); predicting threat to structures in the wildland urban interface (Bar Massada et al., 2009); evaluating the habitat of an endangered owl species (Ager et al., 2007); assessing fire potential in Brazilian Savannahs (Mistry and Berardi, 2005); analyzing the effects of landscape management on fire spread (LaCroix et al., 2006); and evaluating the effect of fuel treatment strategies on fire risk (Ager et al., 2006; Miller et al., 2008; Parisien et al., 2007) and behavior (Duguy et al., 2007; Schmidt et al., 2008; Stephens, 1998; Stratton, 2004; Suffling et al., 2008; van Wagtendonk, 1996). In these applications, fire spread has been simulated from one or more ignition points. Eight of these studies used random ignition locations, four used locations based on human-decisions, one used the ignition locations of historical fires, and one (Miller et al., 2008) used an empirical ignition model.

Since ignition locations may have a significant effect on subsequent fire behavior and spread (depending on the spatial configuration of fuels in the vicinity of the ignition point), it is possible that fire simulation studies based on random ignition locations generate inaccurate results. However, the magnitude of such inaccuracies is hard to quantify because ignition location models will vary among study areas and climatic conditions. Since fire simulation models are being increasingly used, both for research and management purposes, the problem of using an incorrect ignition location model has significant implications for the validity of the results obtained from these models, and for any interpretations based on those results. Therefore, it is desirable to quantify the effects of using random versus empirical ignition location models in spatially explicit fire simulation models.

Table 1
Comparison of three existing empirical ignition location models.

|	Syphard et al. 2008	Sturtevant and Cleland 2007	Yang et al. 2007
Model type	Multiple logistic regression	Classification and regression trees	Poisson regression
Spatial extent (km^2)	600	58,000	1287
Anthropogenic predictive variables (in order of importance)	Distance to development	Housing density	Distance to town
	Distance to roads	Road density	Distance to road
	Level of WUI	%owner occupied homes	Ownership − public
	Distance to trails	Distance to railroads	Ownership − private
Biophysical predictive variables (in order of importance)	Vegetation type	%agriculture/grassland cover	Pine-Oak mixed forest
	January minimum temperature	Relative forest flammability	Deciduous forest
			Grassland
			Slope
			Aspect category (flat)
			Aspect category (xeric)
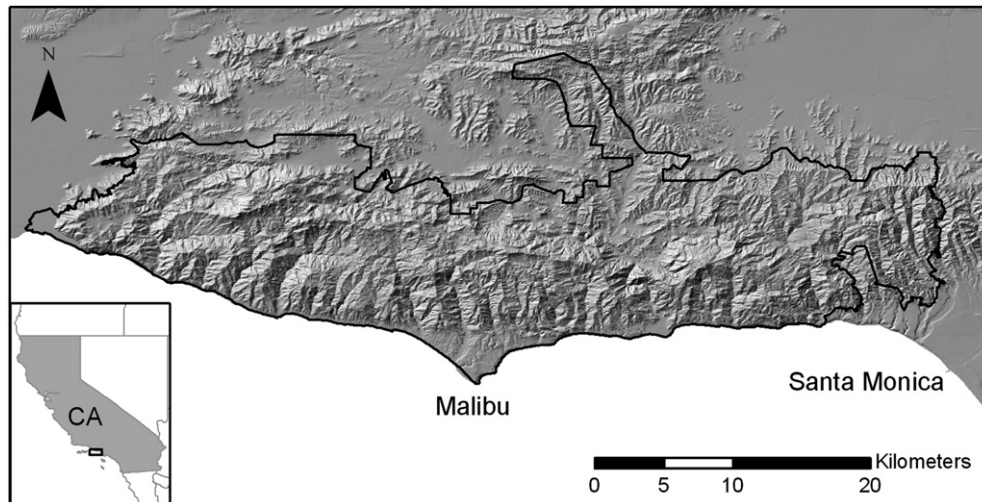
Fig. 1. The Santa Monica Mountains, California, USA.

The goal of this research was to quantify the effects of using a random versus an empirical ignition location model on the spatial pattern of fire occurrence and spread in FARSITE. We also assessed whether different weather conditions (normal and extreme) interact with ignition models to affect estimates of extent and location of modeled fires. The domain of our simulations was a mountainous Mediterranean landscape in southern California using a multiple simulation approach with FARSITE.

2. Methods

2.1. Study area

The study area included the majority of land within the Santa Monica Mountain National Recreational Area, which is an administrative unit that encompasses approximately 60,000 ha of rugged, coastal mountains adjacent to Los Angeles, CA (Fig. 1). The mountains have a Mediterranean climate, characterized by cool, wet winters and warm to hot, dry summers. The vegetation is dominated by chaparral (approximately 60%) and coastal sage scrub (approximately 25%) shrublands, which are highly flammable due to low decomposition rates, dense community structure, and low fuel moisture − particularly in the late summer and autumn after a long drought (Conrad and Regelbrugge, 1994; Radtke et al., 1982). The fire frequency is moderate in the Santa Monica Mountains (average fire return interval of 32 years), and has been increasing steadily over the last 75 years (NPS, 2005). More than 95% of the ignitions are caused by humans, and the largest fires, which account for most of the area burned, tend to occur during extreme fire weather fanned by Santa Ana winds. Because fire cannot easily be controlled during high-wind conditions, the shrublands burn in large, stand-replacing, high-intensity fires that explode across the landscape (Keeley and Fotheringham, 2003).

2.2. Ignition location models

We used two ignition locations models in this study: an empirical model by Syphard et al. (2008), and a random model. To develop the empirical model of ignition locations, we related multiple anthropogenic and biophysical variables to ignition occurrence locations (126 ignitions from 1981 to 2003) using a multiple logistic regression modelling approach (Syphard et al., 2008). It is impossible to select true absence point locations for ignitions because areas that have not experienced ignitions in the past could potentially ignite in the future. Therefore, we compared ignition point locations to a random sample of 700 control points distributed across the landscape. This design enabled us to determine whether the explanatory variables influenced the 126 ignition locations differently than what would be expected by chance.

After exploring bivariate regression models for each of our explanatory variables and checking to ensure that there were no collinearity problems (by implementing the variance inflation factor collinearity diagnostic procedure), we entered the variables into a multiple logistic regression model and selected the final model through a backwards stepwise elimination process using the Akaike Information Criterion (AIC) (Venables and Ripley, 1999). The variables retained in the multiple-regression model indicated that ignitions were most likely to occur close to development ($p < 0.001$), roads ($p = 0.002$), and trails ($p = 0.08$); in areas with warmer January temperatures ($p = 0.016$); and differentially according to vegetation type ($p = 0.002$), and amount of surrounding Wildland Urban Interface ($p = 0.011$). We evaluated the performance of the multiple-regression model through a leave-one-out cross-validation approach, which iteratively drops a single data point (i.e., an ignition), refits the model, and predicts the probability of ignition at the data point (Bautista et al., 1999). The overall area under the curve (AUC) of the cross-validated model was 0.71. The AUC reflects the probability that our model would correctly distinguish between an ignition and non-ignition point when those points are drawn at random.

We converted our multiple-regression model into a predictive map surface by applying the formula and coefficients to the entire study area using GIS map layers of the explanatory variables. For the logistic regression, if we let P_i be the probability of an ignition in cell i, and x_{ji} be the value of the jth covariate in cell i, the formula is:

$$P_i = \exp\{\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_n x_{ni}\}/(1 + \exp\{\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_n x_{ni}\})$$

where β_0 is the intercept and β_n are regression coefficients for the explanatory variables, x_n. The result was a continuous map depicting the relative probability of fire ignition across the study area

Based on the predictive map generated from the statistical modelling, we generated 6000 ignition locations as input for the fire simulation modelling (Fig. 2) using the 'generate random points' (and use raster as a probability distribution) tool
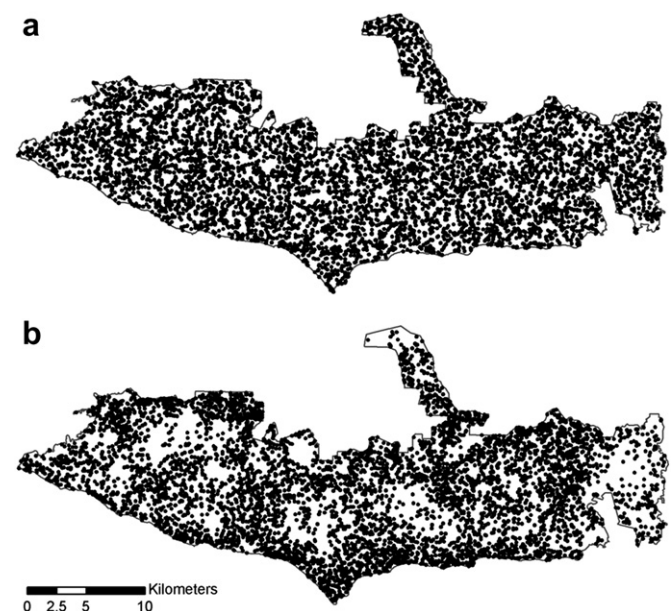

Fig. 2. Random (a) and empirical (b) ignition points used for the FARSITE simulations. The non-random ignitions are based on the model of Syphard et al. (2008).

in Hawth's Analysis Tools for ArcGIS (Beyer, 2004). When the predictive map was used as a probability distribution, ignition probability influenced the locations of ignition points since map pixels with higher ignition probabilities were more likely to be assigned an ignition point. For the random ignition location model, we used the same software tool to randomly generate 6000 ignition locations across the study area, this time without any consideration of the predictive map (Fig. 2).

2.3. Fire model

Fire simulations were conducted using the Fire Area Simulator (FARSITE, Finney, 1998). FARSITE is a spatially explicit fire simulation model that is based on Huygens's principle of wave propagation, and it determines the expansion of a polygonal fire front through time (Richards, 1990). FARSITE distinguishes between two fire behaviors and uses separate models for surface fires (Rothermel, 1972) and crown fires (Van Wagner, 1977). The operation of FARSITE requires input data capturing weather, fuels, and topographic elements. Weather data have to be supplied as streams of temporal data for the duration of the simulation time period, consisting of minimum and maximum daily temperature and relative humidity (and their corresponding time of day), daily precipitation, and hourly wind speed, hourly wind direction, and hourly cloud cover. The properties of different fuel types in a study area can either be represented as one of the 13 Anderson fuel models (Anderson, 1982), the 40 Scott and Burgan fuel models (Scott and Burgan, 2005), or as custom fuel models. Additional input data include GIS raster layers of elevation, slope, aspect, canopy cover, crown height, crown base height, and crown bulk density. The user defines the ignition points and the length of the simulation. The model generates the following outputs: fire arrival time, fireline intensity, flame length, rate of spread, heat per unit area, reaction intensity, crown fire activity, and spread direction.

We chose to use FARSITE for the analysis because it is based on the simulation mechanism most widely used in management and research (FARSITE and FSPro, used by the Forest Service, share a simulation mechanism). Previous research has shown that the accuracy of FARSITE ranges from low (underestimated rate of spread and fire perimeter, Fujioka, 2002; Butler et al., 2005) to moderate (Cohen's Kappa of 0.61–0.82, Arca et al., 2007). Inaccuracies result from limitations of the model, especially in the way it simulates spotting, which has a large effect on the spread of severe wildfires, and the difficulty of obtaining reliable inputs for the model, such as fuels (Mutlu et al., 2008), and wind data (Arca et al., 2007). Yet, although FARSITE is imperfect, it is the most reliable of the currently available fire simulation models, and is widely accepted among fire managers in the United States, as well as in other countries (e.g., Brazil (Mistry and Berardi, 2005), Spain (Duguy et al., 2007), and Israel (Carmel et al., 2009)).

2.4. Fire simulations

To account for variability in ignition locations, we applied a multiple simulation approach, similar to Carmel et al. (2009) and Bar Massada et al. (2009) in which a large number of fires were simulated. We used two scenarios of ignition locations (random and empirical) and two weather scenarios (normal and extreme). Six thousand individual FARSITE simulations were conducted for each ignition/weather scenario, with a single ignition point per simulation, to set an average ignition density of roughly one ignition per 10 ha. Overall, we conducted 24,000 simulations (6000 × 2 ignition location models × 2 weather scenarios). The large number of FARSITE simulations was carried out by automating the graphical user interface of FARSITE using HP QuickTest professional, a functional software testing program.

We conducted FARSITE simulations under two weather scenarios: normal fire season weather and extreme weather. Weather data was based on actual, hourly weather streams measured by the Malibu Hills Remote Automated Weather Station (RAWS) in the center of the study area. The extreme scenario was based on the weather during the 2007 Corral fire, which burned 1983 ha between November 24th and 27th (Fig. 3). The fire started from a campfire in the hilly area of Malibu Creek State Park, under conditions of very low relative humidity (∼ 10%) high-wind speeds (gusts up to 100 km/h), and an average daily temperature of 18.7 °C. The weather stream used for the simulations corresponded with the first 13 h of Corral fire starting at 3:00 AM.

For the normal fire weather we selected data from a week before the Corral fire, on a day that was characterized by moderate relative humidity, low wind speeds (Fig. 3) and an average daily temperature of 14.5 °C. Again, fire duration was 13 h, and the fire started at 3:00 AM, matching the actual timing of the Corral fire. Fire durations were held constant across all simulations in order to improve comparability among scenarios by eliminating the effect of fire duration on fire size. In each simulation, weather condition streams (13 hourly weather parameters) were held constant regardless of ignition location. This modelling assumption may lead to an underestimate of the extent of fires burning under extreme weather conditions, as they tend to last longer than fires burning at regular weather conditions. To solve that, we would have needed to account for the natural variability of fire durations, and this would have required us to significantly increase the number of simulations. Due to technical limitations, increasing the number of simulations was impossible.

The conditioning period for fuel moisture was one week before the ignition date (November 10th for normal and November 17th for the extreme weather scenarios),
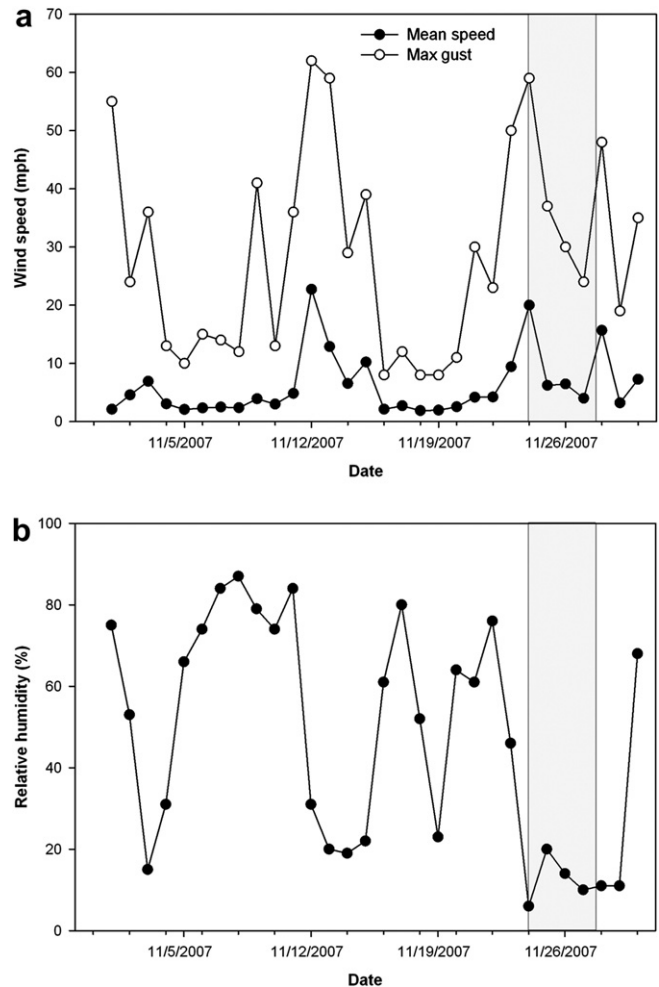

Fig. 3. Daily averages of wind speed (a) and relative humidity (b) as measured by the Malibu Hills RAWS station in November 2007. The period of Corral fire is highlighted.

based on the actual weather data. Spot fires were allowed to start with a 5% ignition probability. Live fuel moisture was set to 70%, which corresponds to the occurrence of most large wildfires in the study area (Dennison et al., 2008).

The spatial data required for running FARSITE was obtained from the LANDFIRE project (Rollins and Frame, 2006) at 30-m resolution. We used the 40-category fuel model map of Scott and Burgan (2005) in order to increase spatial detail. However, the representation of roads is incomplete in the LANDFIRE fuel maps, and this can bias the results of fire simulations by introducing breaches in roads that otherwise would have served as surface fuel breaks (Bar Massada et al., 2009). We corrected roads using the US Census Bureau TIGERLINE road data (available from the Environmental Systems Research Institute website: http://www.esri.com/data/download/census2000_tigerline/index.html). The vector road data was rasterized at 30-m resolution and combined with the fuel map, and the road pixels were reclassified as the urban fuel type (Scott and Burgan code NB1). In FARSITE, this fuel type blocks the spread of surface fire, but does not block fires that spread through spotting, which is important for this study area because many fires jump across roads under extreme weather conditions (Halsey, 2008).

At the end of each simulation, the burned area of each fire was calculated. For each scenario, we overlaid the maps of the 6000 resulting fires and summed them for each pixel. This resulted in a "number of burns" map, where the number in each pixel corresponded to the number of times this pixel experienced a fire. Dividing this map by the number of fires (6000) yielded a burn probability map, depicting the probability of each pixel to burn under a given ignition location model and weather scenario.

2.5. Statistical analysis

For each scenario, we calculated the size distribution of fires and the distribution of burn probabilities. In addition, we calculated the non-parametric spatial correlation between burn probability maps under the same weather conditions but different ignition location models. Using a Wilcoxon rank-sum test (Sokal and Rohlf, 2003),

since fire sizes were not normally distributed, we also investigated whether fire size distributions were significantly different between ignition location models.

We calculated the differences in burn probability values under extreme weather conditions by subtracting the random ignition burn probability map from the empirical ignition burn probability map. We overlaid the empirical ignition points on the difference map to assess whether the differences in burn probabilities were related to ignition pattern and density.

3. Results

Fire sizes were an order of magnitude larger under extreme conditions compared to normal conditions (Fig. 4). The average fire sizes under extreme conditions were 230.1 ha and 344.5 ha for the random and empirical ignition locations, respectively. In addition, the empirical ignitions generated more large fires than the random ignitions under extreme weather conditions. Under normal conditions, mean fire sizes were and 17.5 ha and 13.3 ha for the random and empirical ignitions, respectively. The fire size distributions were significantly different between ignition location models for each weather scenario (Wilcoxon rank-sum test, $p < 0.001$) in both cases, although the magnitude of the difference was greatest under extreme weather conditions.

The burn probability maps varied by weather scenario and by ignition location model. As expected, the extreme weather simulations exhibited higher burn probabilities than the normal weather simulations (Fig. 5). The highest average burn probability was obtained for the empirical ignitions under extreme conditions

(mean burn probability of 0.26%), followed by the random/extreme scenario (0.17%), the random/normal scenario (0.013%), and finally the empirical/normal scenario (0.01%). In other words, weather conditions and ignition locations interacted in ways that significantly changed the outcomes. Ignitions location models produced opposite effects on burn probabilities under extreme weather compared to normal weather.

Comparing outcomes associated with the two ignition location models, the correlation between burn probability maps was lower for the normal weather conditions (Spearman's $r = 0.54$), compared to the extreme weather conditions ($r = 0.83$). Under extreme weather conditions, hotspots of fire activity generally occurred in the same areas, though there was pronounced fine scale variation in burn probabilities (Fig. 6). Under normal weather conditions, spatial differences were more pronounced, probably because fires were much smaller (Fig. 7).

The burn probability difference map for the extreme weather scenario (Fig. 8) revealed that in most cases, variations in burn probabilities were caused by differences in ignition densities. Areas in which the burn probability map of random ignitions had higher values than the burn probability map of empirical ignitions (negative values in Fig. 8) were areas with low empirical ignition densities (while random ignition densities were almost constant). The opposite trend occurred in areas that had a large number of empirical ignitions (positive values in Fig. 8). However, this pattern was not solely related to ignition density, as there were also areas that had low empirical ignition densities (compared to random ignition densities), but similar burn probabilities for both ignition location models.

4. Discussion

We used a multiple simulation approach to assess the effects of ignition locations on modeled fire spread in an actual landscape. Our results show that choice of ignition locations can have a strong impact on the outcomes of spatially explicit fire simulation models. While there were distinct differences between the empirical and random models of ignition locations in our study, the exact effect of ignition location models on simulated burn patterns may vary from region to region, depending on the complex interactions among ignition locations, the spatial configuration of fuels and topography, and weather conditions (Parisien et al., 2010). Nevertheless, our results suggest that the use of random ignition location models for fire simulation studies may result in erroneous conclusions due to the difference in the spatial patterns of burn probability. The use of empirical ignition locations for fire simulations, introduced here as an alternative to random ignition locations, offers a practical tool for exploring these complex interactions, and to quantify burn probabilities with higher accuracy. The increasing quality and availability of ignition location data makes it possible to use empirically based ignition location predictions in future studies, and this research suggests the value it adds to simulation-based fire research.

We expected that a random ignition location model would generate larger fire sizes and higher burn probabilities, since any location in the landscape has the same probability of ignition, and therefore any area in the landscape has a chance to burn (compared to the empirical ignition location model, which predicts higher probabilities for ignitions to occur near human development, thus decreasing the ignition probabilities of remote areas that have continuous fuels, which in turn can support larger fires). We also expected the variability of fire size distribution to be higher for random ignition locations. In contrast, we expected that the empirical ignition location model would limit the chances of some areas to burn because these areas would have fewer ignition points. Moreover, because the empirical ignition location model gives higher ignition
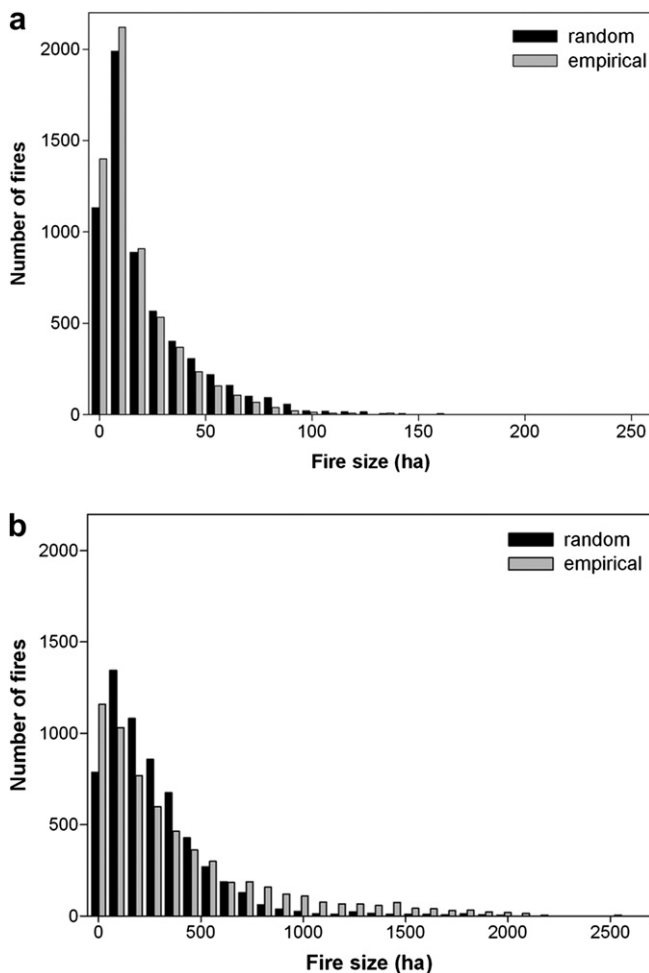

Fig. 4. Fire size distributions under normal (a) and extreme (b) weather conditions for random ignitions (black bars) and non-random ignitions (gray bars). Notice the difference in the scale of the x-axis.
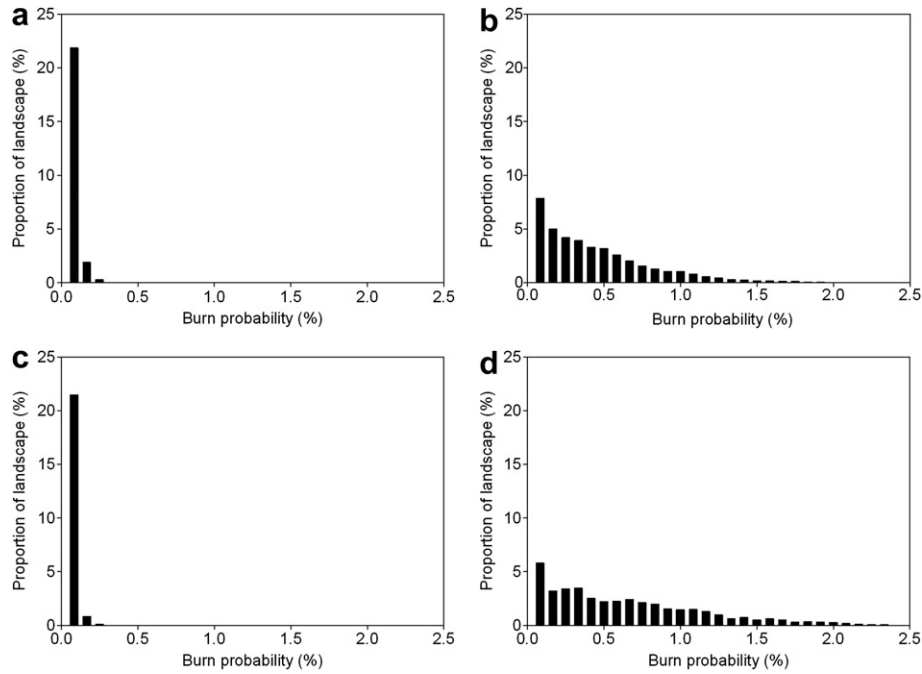
Fig. 5. Distributions of burn probability for random (a, b) and empirical (c, d) ignition location models under normal (a, c) and extreme (b, d) weather conditions.

probabilities to areas where there is more human activity, we expected these areas to experience smaller fires because they may be characterized by discontinuous fuels and greater extent of non-burnable areas. Although we did not model suppression, more heavily populated areas may also be coupled with more intense suppression efforts and enhanced accessibility for suppression forces. This led us to expect that, regardless of weather conditions, the random locations model would produce larger fires. The simulation results, however, painted a more complex picture.

Under normal weather conditions, our expectations proved to be correct, and the random ignition location model yielded significantly larger fires and higher burn probabilities, but the differences in the mean area compared to empirical ignition locations was only 4 ha, which is relatively small. Under normal weather conditions, fires were less likely to produce long-distance embers and fire brands, thus fuel discontinuity (abundant in high ignition probability areas in the non-random ignition location model) limited fire spread. In contrast, under extreme weather conditions, the opposite trend occurred and empirical ignition locations yielded larger fires and higher burn probabilities. Under these conditions, fuel discontinuity played a smaller role since significant amounts of long distance spotting occurred. Yet, the
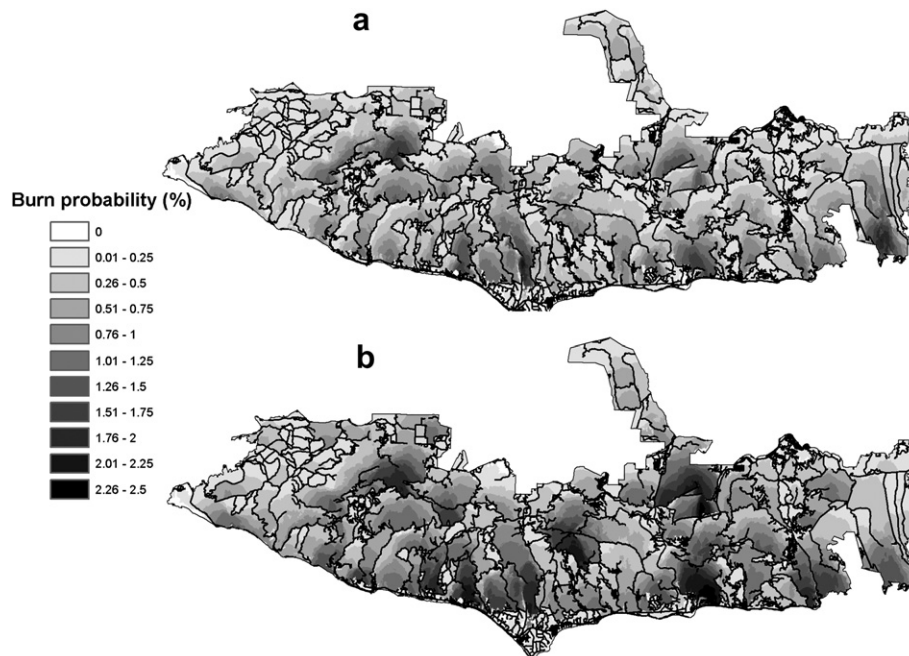

Fig. 6. Burn probability maps for random ignitions (a) and empirical ignitions (b) under extreme weather conditions.
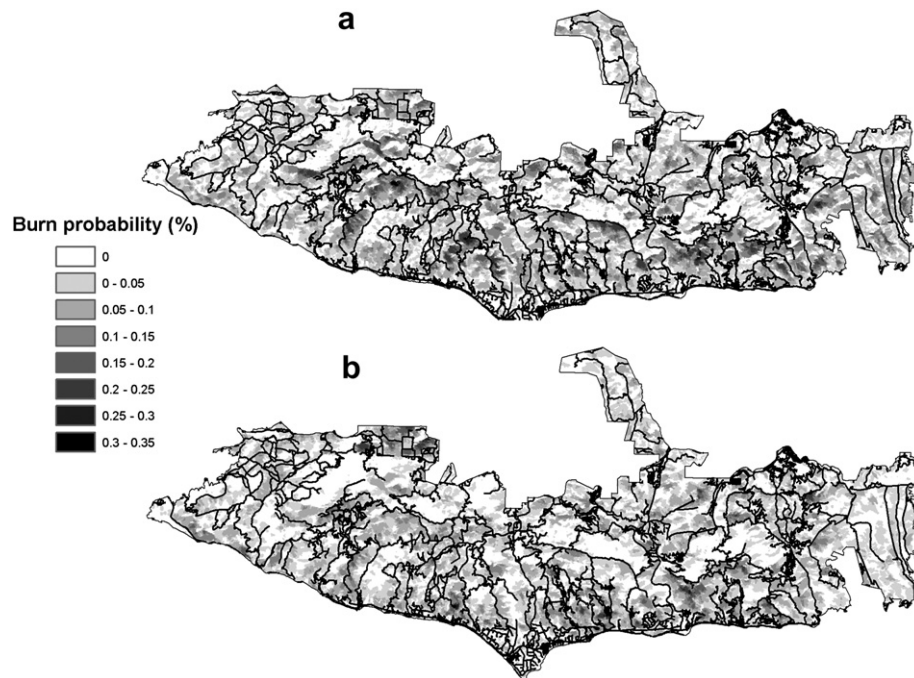
Fig. 7. Burn probability maps for random ignitions (a) and empirical ignitions (b) under normal weather conditions.

question still is: why do non-random ignition locations produce larger fires than random ignition locations? The answer may be related to the specific properties of the study area and the empirical ignition location model. The results of Syphard et al. (2008), who developed the empirical model, show a positive spatial correlation between ignition locations and potential for fire spread areas in the Santa Monica Mountains. This means that, historically most fires tended to start under extreme weather conditions in places that promoted extensive fire spread, while other parts of the landscape, better captured by the random ignition location models, promote relatively smaller extreme-weather fires but larger normal-weather fires. This may also be related to the direction of Santa Ana winds. The Santa Monica Mountains are an east-west trending range, and the canyons parallel Santa Ana wind directions. Therefore, large fires may be spatially constrained to wind corridors under severe weather, which may not be the case under other conditions. In addition, there was an inherent limitation to the usage of the modeled

ignition locations in this study, since the model did not allow us to account for spatial variations in ignition locations due to weather conditions. Ignition locations may be affected by weather conditions (since the ignition locations model was based on actual fires, that happened under specific weather conditions), but the model that we used did not account for that, and we therefore had to assume that ignition locations were the same under both normal and extreme weather conditions. Another modelling assumption was that all ignition locations (empirical or random) could support large fires. Yet, the empirical ignition location model did not account for fire size. Thus, it is possible that small fires and large fires have different spatial patterns of ignitions. In the U.S., fires that start near human settlements are detected earlier compared to backcountry fires (prompting faster suppression) and often occur in areas of discontinuous fuels which hamper their spread and make suppression more effective. Backcountry fires are detected later, and are harder to suppress due to fuel continuity and lack of accessibility. Therefore, backcountry ignitions, which
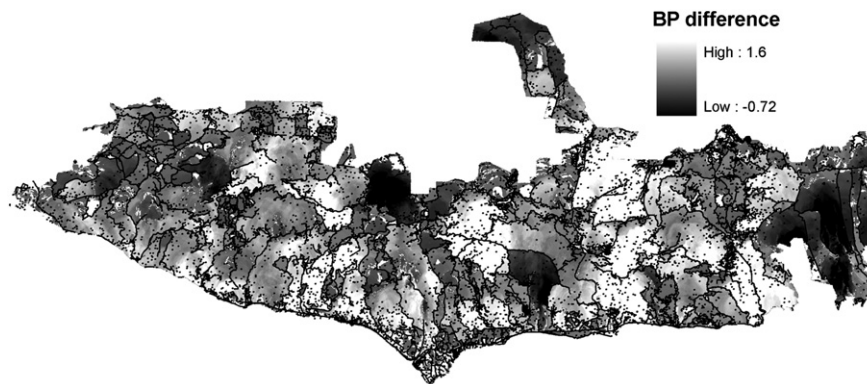

Fig. 8. Differences in burn probabilities between the empirical and random ignitions burn probability maps. Positive values (bright colors) depict areas where empirical ignitions yielded higher burn probabilities, while negative values (dark colors) depict areas where random ignitions generated higher burn probability values. The empirical ignition locations appear as black dots and roads are depicted by black lines.

have a different spatial pattern compared to wildland urban interface ignitions, often yield larger fires.

The use of two weather scenarios, normal and extreme, without accounting for the full variability of weather conditions, was a simplified representation of the full range of fire behaviors. Furthermore, normal conditions are rarely considered in fire risk assessments, since practically all large fires are an outcome of extreme weather conditions (assuming that large-scale thresholds of fire drivers are met, e.g., Slocum et al., 2010). Technical limitations prevented us from exploring a wider range of weather conditions, especially in the extreme end (since simulations of very large fires required a prohibitively long computer processing time). Therefore, we view our results as a conservative estimate of the effects of weather on the interactions between ignition locations and the spatial pattern of fires. More extreme weather conditions could promote even larger fires, and that would further emphasize our conclusion that under extreme conditions, the effect of ignition locations diminishes. We also suggest that this general conclusion holds true in other regions as well, especially in areas where human development is low, topography is relatively homogeneous, and fuels are continuous (e.g., the boreal forest).

The high spatial correlation between the extreme weather burn probability maps for the two ignition location models suggested that, at least in this study area, using a random ignition location model produced acceptable results if one is interested in the general spatial patterns of fire under extreme weather only. Under normal weather, differences are more pronounced, and a random ignition location model should not be used for spatially explicit predictions of burn probability. For any fire risk assessment that is based on multiple simulations, it is desirable to use a custom non-random ignition location model that is based on the fire history of the area, simply because the differences between random and non-random ignition location models cannot be predicted in advance. However, in regions where fire history is scarce, it may not be possible to produce a custom ignition location model, and even worse, empirical ignition location models may be biased due to limited training data. In these cases, we recommend that spatially explicit analyses of fire risk be based on extreme weather conditions, since these conditions may be able to limit the impacts of an inaccurate ignition location model. Nevertheless, this approach would have obvious drawbacks if the objective of the study were to explore fire patterns under non-extreme weather conditions.

Another possible tactic would be to assess the deviation of anthropogenic landscape features (especially roads, as they are often influential predictors of fire ignitions) from a uniform or random pattern. In landscapes with a spatially uniform road network, random ignition location models are likely to work better than in landscapes with clustered roads. For example, road networks in the upper Great Lakes states are quite often dense and uniform due to the ease of building roads; while networks in mountainous terrain leave larger areas distant from roads (Watts et al., 2007). In places where the pattern of road networks and anthropogenic development are uniform (and in the absence of a good empirical ignition location model) the usage of a random ignition location model may be justified.

Here and in other studies (Bar Massada et al., 2009; Carmel et al., 2009), FARSITE has proven to be a valuable tool for exploring the spatial components of fire behavior. We assessed the effects of ignition locations with FARSITE since it belongs to a widely used family of fire models (e.g., FsPro, BEHAVE) that are based on Rothermel's fire spread equations (Rothermel, 1972). We assume that similar results could be obtained from any other model that is based on the same equations.

The results of our analysis may be different in modelling frameworks that do not employ the same mechanisms and approximations contained in FARSITE. FARSITE characteristics that may affect the results of our analysis are the simplified spot fire module (since spotting can alter the spatial pattern of a fire, especially under extreme weather conditions) and the constant wind direction (since local wind direction has a significant effect on fire spread) (Lopes, 2003; Sharples et al., 2010). Furthermore, the usage of FARSITE requires a large amount of spatial data about fuels and topography, in addition to temporal weather data. We used the freely available LANDFIRE spatial data (Rollins and Frame, 2006), and this dataset performed overall very well in our study. However, there are several issues regarding the thematic accuracy (Krasnow et al., 2009) and the way LANDFIRE represents roads that may act as fuel breaks (Bar Massada et al., 2009). Since the main objective of our research was to compare ignition location models (and not to conduct an actual risk assessment for the Santa Monica Mountains), we used LANDFIRE data because of its availability and despite its limitations. Similarly, we used climate data from a single weather station, although the topographical variability of the study area, coupled with its size, implies that there is also a pronounced spatial variability of weather conditions that cannot be adequately described by a single weather station. It is therefore possible that our results are somewhat biased due to unrepresentative weather conditions, especially wind speed and direction that are expected to vary in a complex terrain like the study area, and are also two of the most influential determinants of fire spread. However, for a practical fire risk assessment study that is based on the multiple simulations approach, it is crucial to use the best available fuels and climate data, since FARSITE tends to produce low-accuracy results when inaccurate fuels (Mutlu et al., 2008) and constant wind vectors (Arca et al. 2007) are used in the course of the simulations.

In summary, the results of our research highlight the importance of selecting an adequate ignition location model for spatially explicit fire simulations. Given the advances in ignition modelling, it is desirable that future studies will be based on empirical models of ignition locations, mainly in areas where there is sufficient historical fire data. In areas lacking such data, studies would still need to rely on crude assumption about ignition locations, or even random ignitions. The type of empirical ignition model that we used in our study is straightforward to repeat, since we employed standard multiple-regression modelling methods. However, because fire regimes and ignition sources (i.e., human versus lightning) vary substantially from region to region, it would be important for anyone developing an ignition model to carefully consider which explanatory variables are appropriate for their region of interest. Indeed, the primary differences in the models presented in Table 1 were in the number and importance of explanatory variables. An encouraging implication of our results is that, in studies that simulate fires under extreme weather conditions (often in risk assessments), the bias introduced by using random instead of empirical ignition locations is somewhat reduced.

Acknowledgments

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