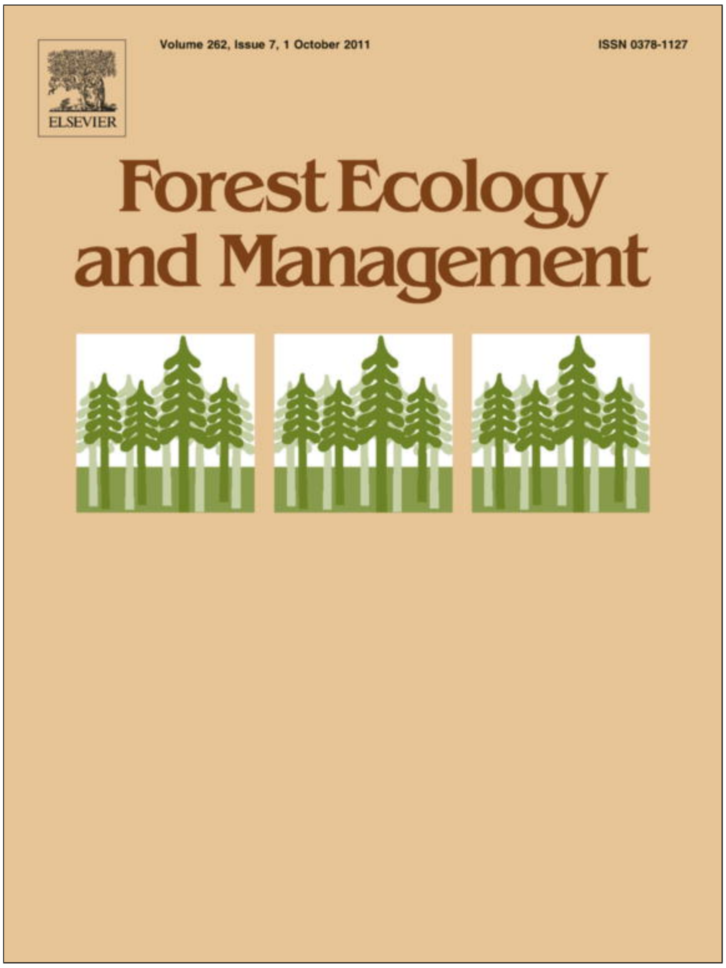
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# Post-fire analysis of pre-fire mapping of fire-risk: A recent case study from Mt. Carmel (Israel)

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ABSTRACT

The recent devastating wildfire on Mt. Carmel provided a unique opportunity to evaluate a fire-risk map constructed for the region, published two years ago in this journal. This largest forest fire in the history of Israel, occurred during December 2010, covering 2180 ha, burning more than half-million trees and causing the loss of life of 45 people.

A study of fire risk in this area was conducted between 2007 and 2009 utilizing a combination of Monte Carlo simulation of spatial spread of fire ignition with fire behavior model (FARSITE). The fire risk map produced in 2009 is assessed here with reference to the area burnt during December 2010. The results showed that most of burnt areas corresponded to high risk levels in the risk map. According to a null model, the five lower risk levels taken together would have corresponded to 50% of the burnt area, while in fact they were presented in only 5.6% of the area. In contrast, the three highest risk levels, for which the null model expectation would be a representation of 30%, were represented in 87% of the area. Comparing the fire risk map against the map of the real recent fire provided support to the general approach, and strengthened the confidence of our fire risk model.



## 1. Introduction

Fire risk assessments are crucial in forest ecosystems, where high ecological value coincides with dense population (Shoshany and Goldshleger, 2002). High resolution fire risk maps enable managers to plan long-term strategic fire prevention activities (Galtie et al., 2003), yet until recently, fire risk maps were produced at resolutions too coarse to allow strategic planning at local levels (Pastor et al., 2003; Scott and Burgan, 2005). In a recent paper, Carmel et al. (2009) presented an approach in which fire risk was a function of the multitude of factors affecting fire behavior at high resolution, using Monte Carlo simulation of a fire behavior model (FARSITE, Finney, 1998). The model used a variety of inputs such as topography data, fuel information, weather conditions and human activity areas, among others parameters.

In the present study, Mt. Carmel National Park forest (located in northwestern Israel, Fig. 1) served as a pilot area. Although FARSITE does not have its own fuel model, it allows using custom fuel models (e.g. Anderson, 1982; Scott and Burgan, 2005). The basis for the fuel layer was a canopy cover layer coupled to a detailed map of the Mediterranean vegetation formations on Mt. Carmel (Fig. 1; see also Table 2 and more details in Carmel et al., 2009). A single fuel model was assigned to each major vegetation formation and heuristic adjustments were made to two of the fuel models of Scott and Burgan (2005). Fuel models #4 (chaparral) and #1 (herbaceous vegetation), were suppressed by a factor of two while fuel model #10 (conifer forests) was applied to the Eastern Mediterranean pine forests with an adjustment factor of 4 (see Carmel et al., 2009 for details and justification). Fig. 1 illustrates the distribution of fuel models in the study area.

Using the Monte Carlo simulations of fire spread, for each simulation run, a calendar date, fire length, ignition location, weather data and other parameters were selected randomly from known distributions of these parameters. Distance from road served as a proxy for the probability of ignition. The resulting 1000 maps of fire distribution (the entire area burnt in a specific fire) were overlaid to produce a map of 'hotspots' and 'coldspots' of fire frequency. The findings revealed a clear pattern of fires that seems to be affected by several factors including the location of urban areas, microclimate, topography and the distribution of ignition locations. Despite the fact that the results demonstrated the complexities of fire behavior, they showed a very clear pattern of risk levels even at fine scales (Carmel et al., 2009) where the distance between areas with different risk levels is only hundreds of meters or few kilometers. Our approach was then adopted in several other case studies (e.g. Bar Massada et al., 2009; Ager et al., 2010; Lorz et al., 2010).

The validation of spatially explicit models is not trivial, and in particular fire risk models are difficult to evaluate. Most fire risk studies do not provide any estimate of the associations between

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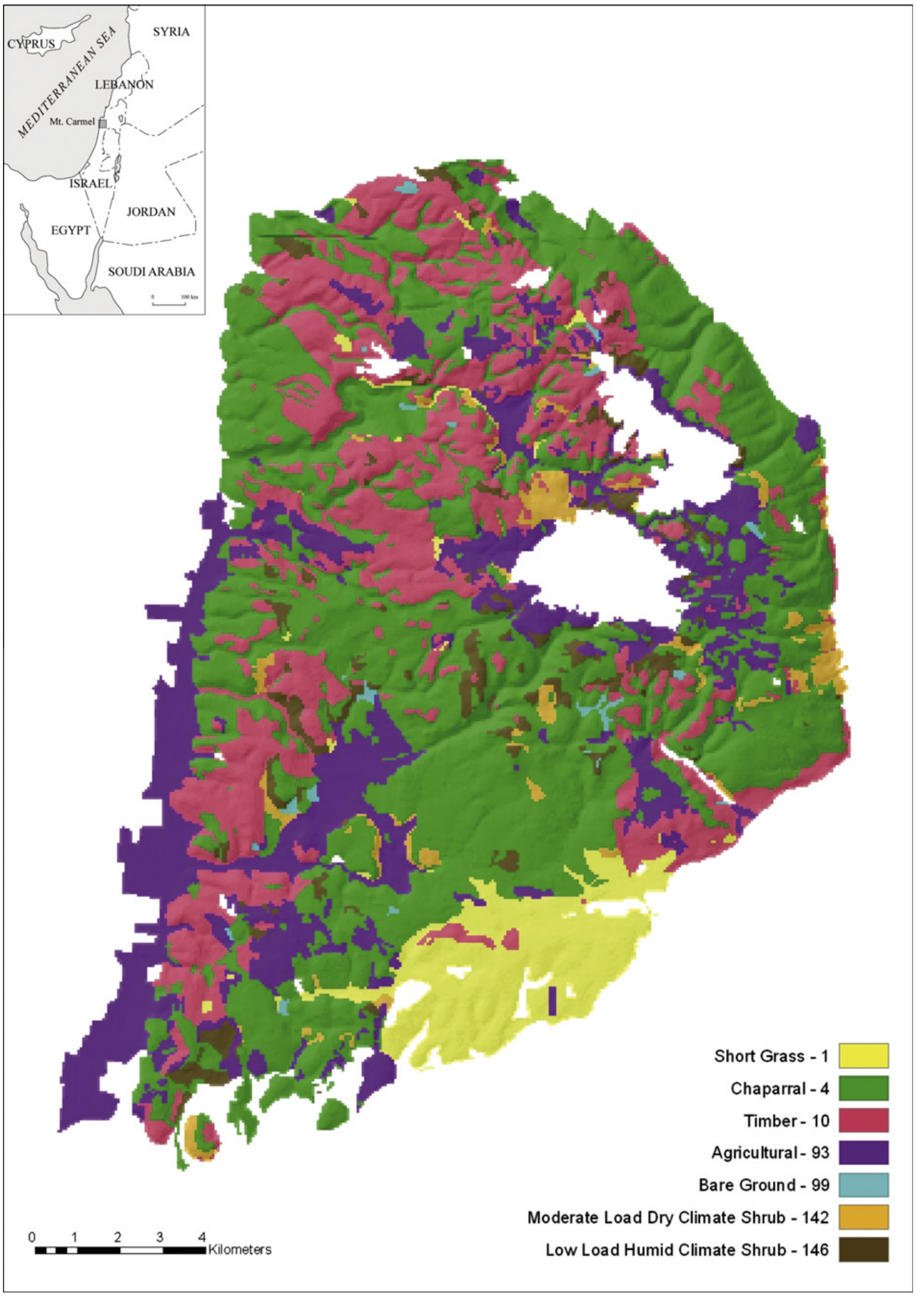


**Fig. 1.** Regional map showing the location of the Mt. Carmel study area and map of the spatial pattern of fuel model for the study region.

model and reality, and such measures are indeed very difficult to obtain. In our study, historic fires in the region served as a partial indication of model accuracy. Yet, immediate validation of a numerical model of this type has not been reported.

A unique opportunity to evaluate the reliability of the fire risk map occurred recently when a severe forest wildfire, the largest in the history of the state of Israel (since 1948), occurred in Mt. Carmel, Israel, between the 2nd and the 5th of December 2010, burnt more than half-million trees (unofficial estimate of the Israel Forest Authority). Unfortunately, the fire caused loss of life and property as well as severe damage to parts of the forest. The size of the burnt area was 2180 ha (Malkinson and Wittenberg, 2011). For comparison, according to Wittenberg et al. (2007), besides dozens of small fires, eight large wildfires were recorded on Mt. Carmel during the last three decades, each consuming areas of 80–530 ha.

During the past several decades, a sharp increase in fire events in the Mediterranean forests has been observed, especially where the anthropogenic pressure is high (FAO, 2001). This tendency exists in Mt. Carmel in which experienced increasing numbers of forest fires, as a result of increasing human activities (Wittenberg et al., 2007). Another influencing factor is the increase in drought processes as a consequence of climate change (Moriondo et al., 2006; Carvalho et al., 2010). Indeed, the weather conditions in Mt. Carmel prior to the wildfire and during its occurrence were exceptional. Summer 2010 was the warmest on record and the following fall was the warmest and driest in the last 40 years with a precipitation amount of about 10% of the perennial average rate of the season. As a result, the vegetation was unusually dry for this time of the year. December is a rainy month in Israel and there are no records of forest fires on this month. However, during the days of the recent wildfire, the air temperature was very high and the relative humidity was extremely low, below 10% (IMS, 2010). These conditions, together with strong dry eastern winds, fanned the fire and resulted in rapid spread of the fire (burnt area of 2180 ha within three days), flame elevation of 60 m and high intensity fire.

## 2. Material and methods

The aim of the current study is to compare between the fire risk map and the map of the actual recent fire, in order to validate the reliability of the model above. In principle, an actual fire can be viewed as a single realization of the fire risk model. If the model is a good predictor of fire, then we expect most of the burnt areas to correspond to high risk classes in the model map. On the other extreme, if the model is not informative at all, then the different risk levels would be represented within the burnt area proportional to their frequency in the entire model map. In the present study, the risk map was constructed using the quantile method, thus all classes occupied equal areas on the risk map. Thus, a null model (Gotelli, 2001) would prescribe a similar number of pixels in each fire risk class. Our validation involves the overlay of the actual fire polygon on top of the fire risk map and assessing the correspondence between the two layers.

In order to test the null model and to evaluate the correspondence between the modeled risk map and the map of the actual fire, we selected at random a sample of 100 cells. These cells

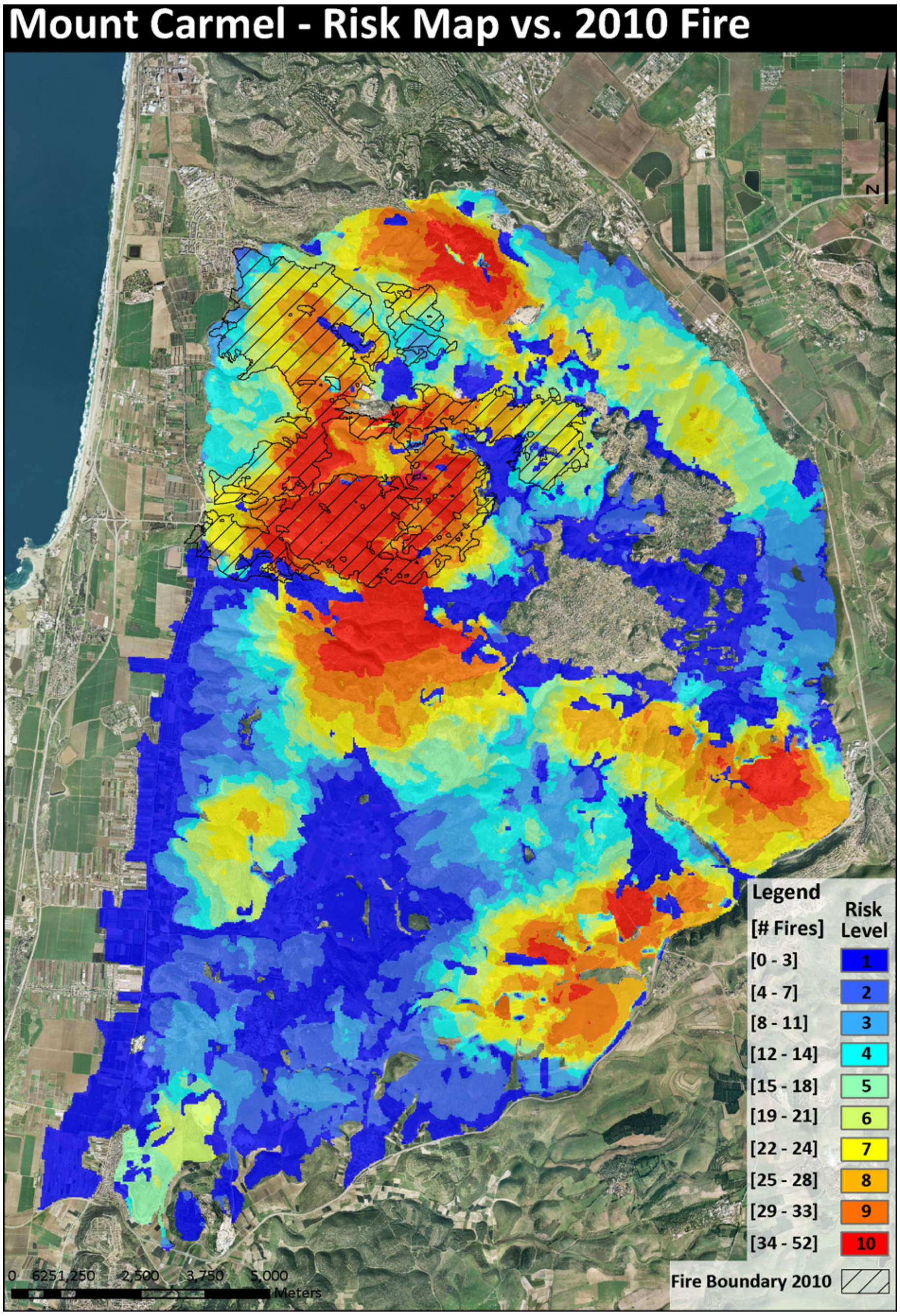


**Fig. 2.** Spatial pattern of fire risk in Mt. Carmel derived from 1000 simulations of fire spread (in colors; Jahshan, 2010) and the fire boundary of the 2010 fire (black lines, after Malkinson and Wittenberg, 2011). The numbers next to the risk level represent the corresponding numbers of simulated fires (out of a total of 1000 fires) occurring in each location. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

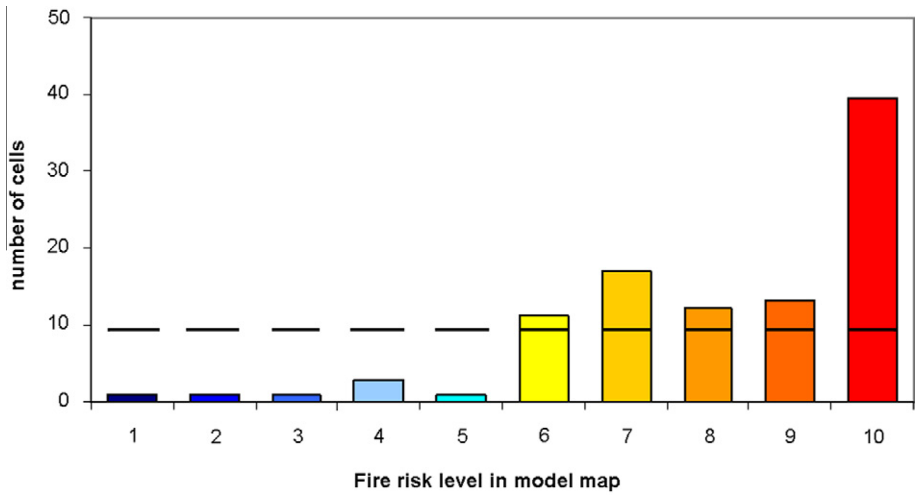


**Fig. 3.** Frequency distribution of the model risk levels for 100 randomly selected cells from the burnt area of the 2010 fire in Mt. Carmel. The broken black line denotes the expected number for each level according to a null model.

represent 0.003 of the entire burnt area, thus minimizing autocorrelation in the sample. A Chi-square test assessed the probability of the actual distribution of risk levels within the sample of burnt cells.

A digital polygon illustrating the extent of 2010 wildfire was mapped (Fig. 1) by Malkinson and Wittenberg (2011) based on infrared satellite data (ASTER-NASA) from 9th of December 2010, and kindly provided by them to this research. It was overlaid on the risk map produced by Jahshan (2010). This risk map is somewhat different than the original risk map published in Carmel et al. (2009) since during 2009 we improved the ignition component of the model. The process of selecting ignition locations for the 1000 simulations was based on a scheme of ignition probabilities – which was dependent on distance from nearest road. Areas near main roads received highest ignition probabilities, followed by secondary roads, trails, and finally areas away from any roads. After the 2009 article was published, we found a better way to select ignition locations within the entire study area, where both x and y coordinates were selected simultaneously. The map presented here is based on the corrected version.

In order to reveal possible bias in model parameter estimates during the Monte Carlo process, we used the bootstrap method (Efron and Tibshirani, 1986) to resample the pool of Monte Carlo simulations 1000 times with repetitions, and re-estimated all model parameters. The bias between the Monte Carlo estimate and the bootstrap resampling estimate was calculated for each of the location and climatic parameters. The results revealed very little bias. The maximum bias was 0.0004 and the average bias was <0.0001.

## 3. Results and discussion

The number of simulated fires that burnt in a specific location was considered as a surrogate of fire risk at that location. The region was divided into ten risk levels using an 'equal area' algorithm. We ran 1000 fire simulations, 'fire' frequency varied between 0 and 52 fires in a given location. For example, half of the area (risk levels 1–5) had fewer than 18 'fires' in any given location, while the two highest risk levels (covering 20% of the area) suffered 33 fires or more (Fig. 2).

According to the post-fire investigation, the ignition of the 2010 fire had been made at the outskirts of Isfiya (a town of 20,000 inhabitants), within an area of moderate fire risk. By the time that the Fire Brigade had arrival to the site (more than 1 h later) the fire was extended quickly westwards by the strong eastern and south-eastern winds. According to the weather station at Haifa University (Mt. Carmel), the wind speed in the region ranged from 20 to 40 km/h. It had taken more than 3 days for hundreds of fire fighters on the ground and 10 airplanes spreading retardant and water to stop the fire spread and to overcome the main fire core areas. The extent of the burnt area represents the duration of the time taken to overcome the fire together with the dominant wind directions and the distribution of potential fire fuel: primarily dry woody material and pine trees which are parameters of the FARSITE model. Overlaying the fire polygon on the fire risk map indicate that most of the burnt areas corresponded to high risk levels in the risk map (Fig. 1). The distribution of risk levels in the sample of the burnt area differed significantly from the expected under a null model (Chi-square = 129, $p < 0.001$). According to a null model based on the even distribution assumption, the five lower risk levels taken together, would have corresponded to 50% of the burnt area, while in fact they were presented in only 5.6% of the burnt area (Fig. 3). In contrast, the three highest risk levels, for which the null model expectation would be a representation of 30%, were represented in 87% of the area.

An important question that was asked in this context is – what were the elements which contributed to the apparent success of the model in predicting actual fires. Typical fire risk models are based on a single major factor – either weather or vegetation (e.g. Riaño et al., 2002; Chuvieco et al., 2004; Weise et al., 2010). Differently, a unique element in our model is the multiple inputs: fire risk is the product of the various factors which are known to affect fire behavior: ignition, topography, vegetation and fuel, and weather conditions. Ignition in particular was modeled as a function of human impact. An analysis of the weight of specific factors in determining the risk map showed that no single factor alone can explain the general pattern of the risk map. All those parameters were nearly equally important in affecting risk pattern. It seems that the combination of all the four factors yielded this specific pattern.

## 4. Conclusions

Fire risk models describe and predict a distribution of events. A fire event is a single realization of the predicted distribution. Fire is a complex phenomenon, and it is therefore reasonable to model fire risk using a complex structure that accounts for the many factors that affect fire ignition and propagation. Numerical and computational models are often the only scientific means for understanding and predicting complex, non-linear environmental phenomena. For predictive purposes, producing the model is not enough, and it is crucial to gain estimate of degree of reliability in model results (Power, 1993). Validation is an attempt to increase the degree of confidence that the events inferred by a model will in fact occur under the assumed conditions (Power, 1993). However, opportunities to compare between the model and real event are exceptionally rare. The unfortunate event of the Mt. Carmel fire provided support of this approach and therefore strengthens the reliability of our fire risk model. In the current study the results showed that most of burnt areas corresponded to high risk levels in the risk map. No single factor alone explained the general pattern of the risk map, or the successes of the model. The combination of the ignition, topography, vegetation and fuel, and weather conditions, yielded the specific pattern of the risk map and its success as a good predictor for a real fire.

As a final statement, the fire risk map for the Carmel area must be taken into account in carrying out mitigation measures such as prescribed fires, thinning, constructing fire break zones, etc. The performance of the model for Mt. Carmel indicates that similar risk maps should be constructed for other Mediterranean forest areas.

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