# Wildfire Risk Assessment in a Typical Mediterranean Wildland–Urban Interface of Greece

Ioannis Mitsopoulos · Giorgos Mallinis · Margarita Arianoutsou

Received: 15 April 2014/Accepted: 11 December 2014 © Springer Science+Business Media New York 2014

**Abstract** The purpose of this study was to assess spatial wildfire risk in a typical Mediterranean wildland-urban interface (WUI) in Greece and the potential effect of three different burning condition scenarios on the following four major wildfire risk components: burn probability, conditional flame length, fire size, and source-sink ratio. We applied the Minimum Travel Time fire simulation algorithm using the FlamMap and ArcFuels tools to characterize the potential response of the wildfire risk to a range of different burning scenarios. We created site-specific fuel models of the study area by measuring the field fuel parameters in representative natural fuel complexes, and we determined the spatial extent of the different fuel types and residential structures in the study area using photointerpretation procedures of large scale natural color orthophotographs. The results included simulated spatially explicit fire risk components along with wildfire risk exposure analysis and the expected net value change. Statistical significance differences in simulation outputs between the scenarios were obtained using Tukey's significance test. The results of this study provide valuable information for decision support systems for short-term

I. Mitsopoulos (🖂)

The Global Fire Monitoring Center (GFMC) Fire Ecology Research Group, c/o Freiburg University, Georges-Köhler-Allee 75, 79110 Freiburg, Germany e-mail: ioanmits@gmail.com

#### G. Mallinis

M. Arianoutsou

Department of Ecology and Systematics, Faculty of Biology, University of Athens, 15784 Athens, Greece predictions of wildfire risk potential and inform wildland fire management of typical WUI areas in Greece.

Keywords Wildfire risk  $\cdot$  Landscape fire modeling  $\cdot$  Fine scale fuel mapping  $\cdot$  wildland–urban interface  $\cdot$  Mediterranean basin

# Introduction

During the last several decades, there has been rapid growth in housing in and near forest areas in many countries worldwide. The processes of rural depopulation, land abandonment, and reduction of traditional forest use have resulted in forest ecosystems that are more combustible and vulnerable, thus increasing the associated fire hazard and risk. Wildfires in wildland–urban interfaces (WUIs) are a serious threat to communities in many countries worldwide as they can be extremely destructive, killing people and destroying homes and other structures, as was the case in California in 2003 and 2007, in Greece in 2007, and in Victoria State, Australia in 2009 (Mell et al. 2010; Haynes et al. 2010).

The wildland–urban interface fire problem in Greece first became apparent 30 years ago when large wind-driven fires destroyed many residential structures in the northern suburbs of Athens on August 4, 1981, and the peri-urban forest that surrounded Kavala in Northern Greece in 1985. In 1995, a large fire on Penteli Mountain on the outskirts of the Athens urban area destroyed approximately 100 structures and caused panic among the population. A fire in the same area in 1998 and a fire that burned the most of the forest surrounding Thessaloniki in July 1997 were equally destructive. Numerous fires devastated large areas of lowland pine forests at the Chalkidiki peninsula in 1981, 1985,

Department of Forestry & Management of the Environment and Natural Resources, Democritus University of Thrace, 68200 Orestiada, Greece

and 1990, resulting in detrimental and costly effects on local tourism. The fire season of 2007 in Greece was the worst in recent history as it set new records in regard to damages and loss of life. A total of 78 people, mostly civilians, lost their lives. More than 270,000 hectares of vegetation burned and more than 110 villages were affected directly by the fire fronts. The number of seriously damaged or completely destroyed homes exceeded 3,000 (Xanthopoulos 2009).

Fire risk is the product of the likelihood of a fire occurring, the associated fire behavior, and the fire's effects (Finney 2005; Scott 2006; Calkin et al. 2010). Fire risk mitigation is achieved when any of the three parameters (likelihood, behavior, and/or effects) are reduced. Fire risk has been used in a variety of ways (Bachmann and Allgower 2001; Finney 2005; Chuvieco et al. 2010). For example, Hardy et al. (2001) use risk to refer to the probability of fire occurrence (i.e., the chance of a fire occurring via ignition or spread in a specific location). Other authors define risk not simply as whether a fire occurs but also as the likely behavior given that a fire does occur. In such cases, risk describes the probability of fire at a given flame length (Ager et al. 2010). Additionally, some authors characterize risk as the product of wildfire probability and expected wildfire damages (Bachmann and Allgower 2001). Chuvieco et al. (2012) described a conceptual model, the methods to generate the different input variables, and the approaches to merge those variables into synthetic risk indices taking into consideration components such as the human factor, lightening probability, and fuel moisture content. Similarly, Blanchi et al. (2002) defined fire risk as the combination of fire hazard, risk potential, and vulnerability and Carmel et al. (2009) used landscape fire behavior coupled with Monte Carlo simulations to characterize fire frequency and risk in complex Mediterranean landscapes.

Recent advances in landscape wildfire behavior modeling (Andrews et al. 2007; Finney et al. 2009, 2011) have led to a number of new tools and approaches for applying risk frameworks to fire management problems. By introducing landscape wildfire behavior modeling, land managers are able to estimate the three primary fire risk components (likelihood, intensity, and effects) to a number of high-value resources located within forest stands and lands. Exposure analysis explores the predicted scale and spatiotemporal relationships of several risk factors (Fairbrother and Turnley 2005). Risk factors such as wildfire likelihood and intensity are difficult to predict for severe wildfires at the large landscape scales that are meaningful and suitable to fire and land managers (Ager et al. 2012). This definition of fire risk differs from that in studies where fire risk is viewed mainly as the chance that a fire might start (Hardy 2005). Recently, the substantial development and improvement of tools for risk analysis have resulted in software improvements, systems integration, greater data availability, and improved GIS and simulation techniques (Finney 2006). Computer models can now perform spatially explicit fire simulations over heterogeneous fuels and map fire behavior characteristics across large landscapes. Current approaches estimate fire risk using the Minimum Travel Time (MTT) fire spread algorithm of Finney (2002), as implemented in Randig-a command line version of the FlamMap spatial fire behavior system (Finney 2006). The MTT algorithm simulates fire growth following the Huygens' principle (Richards 1990; Finney 2002), where fire growth and behavior is modeled as a vector or wave front; this technique reduces the distortion and response of fire shape to temporally varying environmental conditions with respect to cellular models (Finney 2002; Ager et al. 2010). Thompson et al. (2011) used this approach to analyze high risk areas by geographic region for the continental United States. Salis et al. (2013) utilized various fire risk simulations in order to achieve a complete wildfire exposure study for various highly resources assets in Sardinia, Italy. A comprehensive review of the three components of fire risk (likelihood, intensity, and effects) and recent advances in addressing fire risk through landscape fire behavior modeling can be found in Miller and Ager (2013). Wildfire risk is affected both by changing patterns of the landscape values at risk (i.e., residential structures) and the factors generating the risk (fire ignition and spread). The large and increasing number of lives and structures that are potentially exposed to wildfire hazard highlights the need to quantify wildfire risk in the WUI so that this risk can be minimized by applying fire and fuel management techniques (Massada et al. 2009).

Wildfire simulation methods have been recently incorporated as a key element for assessing fire risk in wildfire management in the United States (Calkin et al. 2011). Furthermore, they are used to support tactical and strategic decisions related to the mitigation of wildfire risk (Andrews et al. 2007). Recent advances in landscape fire modeling, fine scale geospatial analysis, remotely sensed fuel classification schemes, and weather and climate forecasting coupled with web technologies have made information sharing and decision support more available. Outputs from wildfire simulation models have been combined with geospatial identification of human and ecological values to build risk-based decision support systems (Calkin et al. 2010). The result has been rapid advance in the application of fire risk analysis across a full range of wildfire management activities and post-fire impacts from the individual fuel treatments (Wu et al. 2013), to forest carbon pools estimation (Ager et al. 2010), to forest restoration (Ager et al. 2007), and to post-fire soil erosion and loss potential (Thompson et al. 2013).

Fire risk studies in Mediterranean basin are mainly focused on socioeconomic (Catry et al. 2009; González-Olabarria and Pukkala 2011; Moreira et al. 2011), human (Romero-Calcerrada et al. 2008; Martínez et al. 2009), and climate (Vasilakos et al. 2007; Karali et al. 2013) factors affecting fire occurrence and they do not assess fire risk components based on fire spread and intensity as it is required for estimating high valuable resources and assets exposure to fire.

The objectives of this study are (a) to assess and map fire risk components in a typical WUI landscape in Greece and (b) to investigate how different weather and burn conditions affect the predicted fire risk of the landscape and the wildfire exposure of the structures in the WUI.

# Methods

#### Outline of the Methodology

The approach for assessing the wildfire risk in a typical wildland–urban interface in a Mediterranean area of Greece is depicted in Fig. 1. The MTT fire simulation algorithm using the FlamMap software was performed to characterize the potential response of wildfire risk components to a range of different weather and fuel burning scenarios. Furthermore, wildfire risk exposure and expected net value change (ENVC) were estimated using the

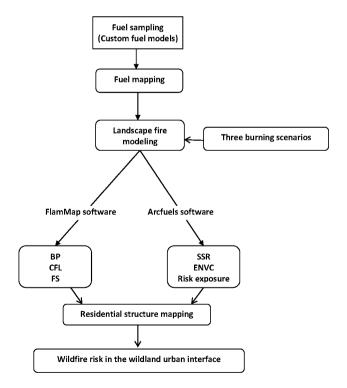


Fig. 1 Flowchart of the overall methodological approach

ArcFuels software. Site-specific (local) fuel models of the study area were created by measuring fuel parameters in the field in representative natural fuel complexes, while the spatial extent of the different fuel types and residential structures was determined using photointerpretation procedures of large scale natural color orthophotographs.

## Study Area

Mt. Penteli is situated 30 km northeast of Athens, and the study area covers 16,025 hectares (Fig. 2). The terrain in general is abrupt as it reaches an altitude of 1,200 m in the center of the site. In the east-southeast parts of the area, the mild slopes and the low elevation traditionally favored agricultural activities. Geologically, the area belongs to the Attiko-Cyclades geotectonic zone. The parent rock materials are mainly limestone and schists and a small part is covered by sedimentary formations. The slope gradient is 15-30 %. The climate is characterized as Mediterranean type (Csa) according to the Koeppen classification. The annual amount of rainfall is 413 mm, and the dry period has an average duration of 5-6 months, lasting from April to September. Extended woodlands found in the area over the 1950s and 1960s were replaced with areas of low vegetation and tree-covered patches as a result of the recurrent large fires. The ecosystem is dominated mainly by Aleppo pine (Pinus halepensis Mill.), with a shrub understory of the maquis species and transitional woodland-shrub (which occupies approximately 16 % of the landscape) followed by sclerophyllous vegetation areas. The study area has clear characteristics of wildland-urban intermix and suffered dramatic changes in land use during the last decades. The mountain is nowadays surrounded by

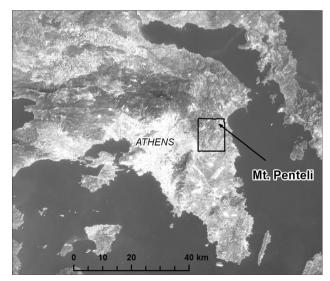


Fig. 2 Study area

rapidly expanding settlements. During the second part of the 20th century, several fire events and human pressure led to changes in the vegetation cover and the land cover of the mountain. Several large fires affected the area during the last 20 years (1995, 1997, 1998, 2005, 2007, and 2009), which have destroyed hundreds of residential structures and settlements (Xanthopoulos 2009).

# Forest Fuel Sampling

All the areas in the study site were stratified on vegetation maps according to the dominant vegetation type. All the stratified areas were surveyed on site and 40 representative locations with typical ("average") fuel conditions for each area were selected. Surface fuel load was estimated with the Brown et al. (1982) method for inventorying surface fuel biomass. Eleven fuel parameters were measured in each location as follows (Brown et al. 1982):

- (1) The 1, 10, 100, 1,000-h, and total fuel loads were measured with the transect-line method (four 30 m-long transects)
- (2) Foliage load, litter load and depth, and shrub (up to 2.0 m in height) and herbaceous (live and dead) vegetation loads were measured in six 10 m<sup>2</sup> sampling plots with the clip and weight method.
- (3) The height of the shrub and herbaceous vegetation layers was also measured in the sampling plot.

The 1, 10, 100, and 1,000-h fuels correspond to plant parts (branches) with diameters of 0.0-0.5, 0.6-2.5, 2.6-7.5, and >7.5 cm, respectively (Brown et al. 1982). The clip-and-weigh method was used to determine all fuel loads by size category. The percentage of the total area covered by each fuel type (shrub herbaceous, litter, etc.) was determined with the line intercept method in the fuel transects (30 m-long) that were used for fuel measurements (Bonham 1989). All fuel loads (fuel weight per unit surface area) were expressed on a dry weight basis.

#### Fuel and Residential Structures Mapping

Image segmentation applied to natural color orthophotographs delineated homogeneous land cover polygons. With the bottom-up segmentation algorithm, embedded within the commercial software Trimble eCognition (ver. 8.7), individual image pixels were perceived as the initial regions, which were then sequentially merged pairwise into larger ones with the intent of minimizing the heterogeneity of the resulting objects. The sequence of the merging objects, as well the size and shape of the resulting objects, were empirically determined by the user (Mallinis et al. 2008). The poor spectral resolution of the orthophotographs put limitations on the use of automated classification techniques. Therefore, fuel types were identified based on manual visual interpretation procedures of various features on the mosaicked orthoimages based on shade, shape, size, texture, and association of features.

In order to delineate residential structures, the Urban Atlas of European Environmental Agency (EEA), at a scale of 1:10,000 and derived upon Earth Observation (EO) data with 2.5 m spatial resolution data, was used (European Union 2011). The European Urban Atlas is part of the local component of the GMES/Copernicus land monitoring services. It provides reliable, inter-comparable, high-resolution land use maps for 305 Large Urban Zones (more than 100,000 inhabitants) and their surroundings for the reference year 2006. Minor edits were needed for the update of the Urban Atlas information based on the natural color orthophotographs acquired in 2007.

# Fire Simulation

In order to assess fire risk, we used a landscape fire behavior modeling approach. Simulated wildfire spread and behavior were performed with the MTT algorithm (Finney 2002) as implemented in FlamMap software (Finney 2006). The MTT algorithm replicates fire growth according to the Huygen's principle, where the growth and behavior of the fire edge is a vector or wave front (Richards 1990; Finney 2002). MTT performance, as it is embedded in FlamMap software, has been successfully evaluated and calibrated in the study area by comparing its simulation results against recent real fire events (Mitsopoulos et al. 2013). Simulations were conducted using as input data the DTM of the area, the spatial extent of the fuel models, and the fuel parameter values of each model in the study area. The latter data were used to build 30 m  $\times$  30 m raster input files for fire simulations. Canopy cover information of the forest area was extracted from satellite imagery. Heat content and surface area-to-volume ratio values for the fuel models developed were obtained by Dimitrakopoulos and Panov (2001). Canopy fuel themes (canopy bulk density and canopy base height) for the Aleppo pine (Pinus halepensis Mill.) fuel model were estimated by following the methodology proposed by Mitsopoulos and Dimitrakopoulos (2014) using the species-specific regression equations based on common stand measurements obtained from the forest management plan of the study area. Since fire history ignition data for the study area is lacking, we used MTT to simulate fire behavior by applying 10,000 random ignitions across the study area (Fig. 3). The duration of all fires was set to 480 min since, according to the historical fire records, all fires in the region are suppressed within that average period (Dimitrakopoulos 2001). Crowing and spotting modules in FlamMap software were activated, and simulated fire behavior was performed using three different weather and

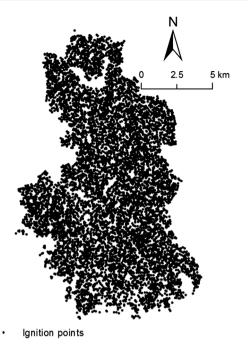


Fig. 3 Ignition point map of the 10,000 random ignitions used in fire simulations

fuel moisture conditions. Wind speed and fuel moisture content per fuel category were adjusted representing extreme, moderate, and low summer burning scenarios (Table 1). Dominant wind speed, wind direction, and fuel moisture values in each burning condition were obtained from the historical fire occurrence data observed in the study area using the PYROSTAT software (Dimitrakopoulos 2001). Wind fields for FlamMap simulations in ASCII grid format were obtained by running a mass consistent model (WindNinja) from which wind speed and direction were estimated at 6.1 m above vegetation height (Forthofer 2007). The data of wind speed and direction were provided as inputs to the WindNinja model, taking into account the three different burning conditions.

The outputs obtained for every simulation were burn probability (BP), conditional flame length (CFL), and fire

**Table 1** Weather and fuel moisture parameters used in the firesimulations representing three different burning conditions andscenarios

Parameters	Extreme	Moderate	Low
1-h fuel (0-0.64 cm) (%)	5	7	9
10-h fuel (0.65-2.5 cm) (%)	7	9	11
100-h fuel (2.51-7.5 cm) (%)	9	11	13
Live woody fuel (%)	80	90	100
Live herbaceous fuel (%)	100	110	120
Wind speed (km h <sup>-1</sup> )	28	24	20
Wind direction	NE	NE	NE

size (FS). The conditional BP output defines the probability of each pixel burning for 20 0.5 m intervals of flame length (from 0 to 10 m). So, BP is the chance that a pixel will burn at a given flame length interval considering one ignition in the whole study area under the assumed fuel moisture and weather conditions (Ager et al. 2010). BP is defined as

$$BP_{xy} = \left(\frac{F_{xy}}{n_{xy}}\right),\tag{1}$$

where  $F_{xy}$  is the number of times the pixel xy burns and  $n_{xy}$  is the number of simulated fires (10,000).

Moreover, CFL is a weighted probability of flame length given a fire occurrence and is defined as

$$CFL = \sum_{i=l}^{20} \left(\frac{BP_i}{BP}\right)(F_i)$$
<sup>(2)</sup>

where  $F_i$  is the flame length (m) midpoint, and  $BP_i$  is the BP on the *i*th category. Conditional flame length is the average flame length given among the simulated fires that burned a given pixel and is a measure of wildfire hazard (Scott et al. 2013).

FlamMap also generates text files containing the fire size (FS, ha) and ignition x-y coordinates for each simulated fire. These outputs were used to analyze spatial variation in fire size. FS refers to the average FS (ha) for all fires that originated from a given pixel.

To measure wildfire transmission among the different residential structure categories, the source–sink ratio (SSR) approach proposed by Ager et al. (2012) was used. SSR is calculated as the ratio of fire size generated by an ignition to BP

$$SSR = \log(FS/BP) \tag{3}$$

The SSR ratio measures a pixel's wildfire contribution to the surrounding landscape (FS) relative to the frequency with which it is burned by fires that originated elsewhere (BP) or were ignited on the pixel. The SSR ratio depicts pixels that have a high BP but do not generate large fires from an ignition (wildfire sinks) and those that generate large fires when an ignition occurs and have low BP (wildfire sources).

# Fire Risk Estimation

Spatial analysis and fire risk assessment were performed using the ArcFuels ver.10 for ArcGIS software. ArcFuels10 is a streamlined fuel management planning and wildfire risk assessment system that creates a trans-scale (stand to large landscape) interface to apply various forest growth and fire behavior models within an ArcGIS platform (Vaillant et al. 2013). Fire risk assessment was performed using a conceptual model for assessing wildfire risk combining exposure and effects analysis (Calkin et al. 2010). Equation 4 presents the mathematical formulation for calculating risk (Finney 2005), where E(NVCi) is the ENVC to resource j, and RFi and is a "response function" for resource j as a function of fire intensity i and a vector of geospatial variables Xi that influence fire effects to resource j.

$$E(NVCj) = \Sigma BPiRFj(i, Xj)$$
(4)

Net value change was estimated using the customized response function embedded in ArcFuels software. The response function obtained various negative values (loss) based on the flame length categories resulted by the Flammap simulations. Fire effects represent the negative impact of fire on landscape values, such as damage to structures (e.g., houses). For the purposes of this study, a response function was used that reflects the loss of structures from slight to strong as the fire intensity (flame length categories) increases adapted from Andrews et al. (2011) (Table 2). The residential structures map was overlaid on the BP maps, and for each structure group the fire risk was derived from the BP map using a proximity analysis approach within a 100 m buffer. Furthermore, exposure analysis was performed by creating scatter plots that depict the spatial coincidence of the expected wildfire CFL and FS versus BP with the location of the residential structures found in the area.

# Results

The five fuel models that resulted from the field sampling represent all the major vegetation types of the study area (Fig. 4). The dense shrublands (maquis) fuel model incorporates maquis with heights up to 2.0 m, a high proportion of foliage load, and a substantial part of the fuel load distributed to the large size class, while the sparse shrublands fuel model is characterized by low height and ground cover shrubs. The understory of Aleppo pine forests is mainly composed of shrubs that present reduced fuel load values and height compared to the dense shrublands fuel model and increased values compared to sparse shrublands fuel model. The grasslands and the agricultural fields (mainly litter from olive trees) demonstrated limited spatial heterogeneity and are represented by fuel model 4 for grasslands (total fuel load of  $4.31 \text{ t ha}^{-1}$ ) and fuel model 5 for agricultural areas (total fuel load of  $2.28 \text{ t ha}^{-1}$ ). The variation of total fuel load was low in all fuel models, as suggested by the magnitude of the standard deviation (S.D.). The total loads of all fuel models were found to be statistically different at 0.05 (one-way ANOVA and Duncan's multiple range test). The fuel values represented by the models fall well within the range reported for vegetation types in Greece and for Mediterranean vegetation types in other parts of the world (Dimitrakopoulos 2002). Two distinct fuel types (dense and sparse) for open shrublands ecosystems have been created since they reflect differences in the total amount and distribution of the fuel load in size classes and, consequently, different fire behavior outcomes are expected. Shrubs which dominate understory of Aleppo pine stands are clearly involved in the initiation of crown fires by increasing fire intensity and serving as the ladder that establishes continuity between the understory and overstory fuel layers. Fuel sampling in Aleppo pine understory resulted in reduced fuel load and height compared to the two open shrublands types, therefore, constitute a separate fuel model.

The majority of the study area is occupied by sparse shrublands having an area of 6,189 ha (39 % of the area). Aleppo pines, having an area of 5,149 ha (32 %), are mainly distributed in the west-northwest parts of the mountain. Dense shrublands (2,540 ha) are found mainly in the central part of the area and are surrounded by open, sparse shrublands areas. Finally, agricultural areas (2,056 ha) were identified in the northern part, while only 107 hectares were identified as grasslands (approximately 1 %). The residential areas of the Urban Atlas, updated

CFL ranges (m)	Fireline Intensity (kW m <sup>-1</sup> )	Expected fire behavior	Potential structure damage	Response functions used
<1.22	<350	Low-moderate intensity surface fire	Only low resistance structures are exposed.	-10
1.23-2.44	351-1,700	High-intensity surface fire	Interface structures are highly exposed	-40
2.45-3.40	1,701–3,500	Very high-intensity surface fire and numerous firebrands.	Very high exposure for all structures, many simultaneous ignitions, with high probabilities of severe damage.	-60
>3.41	>3,500	Crowning, spotting, and major fire runs.	Only very low susceptibility and ignitability structures stand the fire	-80

 Table 2
 Response functions used in the present study for fire risk to structures based on the expected fire intensity and behavior obtained from Andrews et al. (2011)

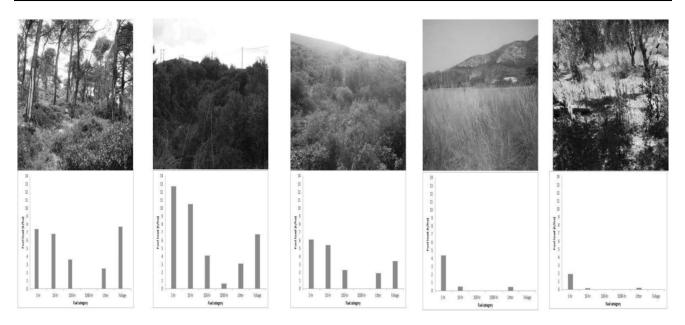
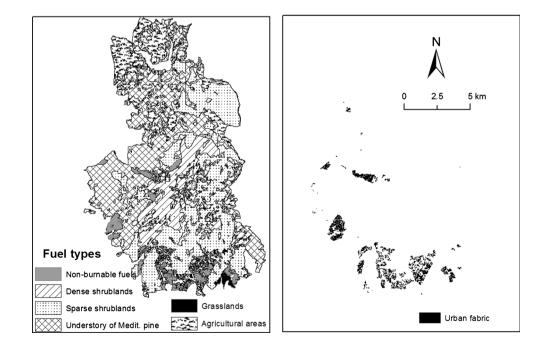


Fig. 4 Fuel types resulting from field sampling in the study area

from the visual photointerpretation of the natural color orthophotographs, have a significant presence, with almost 1,437 ha. As can be observed in Fig. 5, residents are found along the perimeter of the mountain, presumably due to the mild terrain and the accessibility of these areas.

Fire simulation outputs for BP (BP, Fig. 6) showed complex patterns that were generally related to the dominant fuel type in all scenarios. Areas with high BP were found in several locations around the study area, although the largest concentration was in the understory of Aleppo pine forests and the dense shrublands in the southwestern part of the study area, where heavy fuel load created conditions favorable for large fire growth. BP was lower in and around areas that had been recently burned numerous times by wildfires, especially in the vicinity of the grasslands and sparse shrublands region.

The source–sink ratio (SSR, ratio of fire size to BP) measured the relative contribution of fire to the landscape from a given pixel relative the BP (SSR, Fig. 6). The simulation outputs suggested that several regions of the study area



**Fig. 5** Forest fuel types and residential structures' spatial extent in the study area

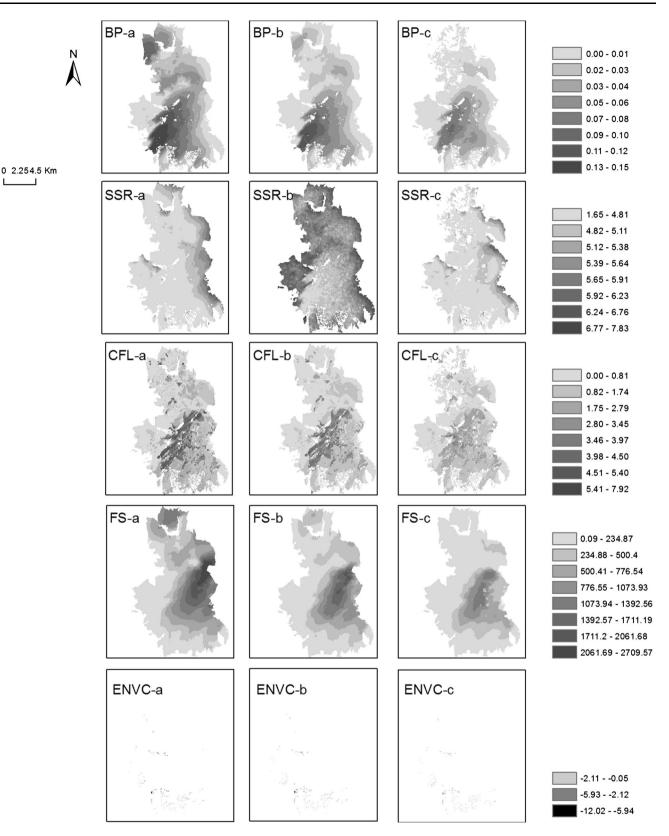


Fig. 6 Maps of burn probability, SSR, conditional flame length, fire size, and expected net value change under the three different burning scenarios (a extreme, b moderate, c low)

were sinks (small SSR) versus sources (large SSR). Sink areas for fire were evident around non-burnable features that prevented fire growth across the landscape. These areas received fire from the surrounding landscape, but ignitions did not generate large fires. Areas with heavy fuel load located in the south of non-burnable features were source areas. These latter areas generally occurred on the south side of non-burnable features. A large northeast part of relatively high SSR was observed for the central part of the study area, where ignitions generated large fires in areas of high BP.

Conditional flame length is the average flame length observed on a given pixel ( $30 \times 30$  m). Spatial patterns in conditional flame length (CFL, Fig. 6) presented similar to BP spatial patterns and showed that the dense shrublands fuel type exhibited higher CFL. Agricultural areas and grassland fuel types showed lower values (<2.5 m) due to the low values of fuel load found in these fuel types. Sharp transitions in CFL were directly related to changes in fuel type extent, especially where dense shrublands transitioned into areas with sparse shrublands and/or grasslands.

The FS (ha) map showed the area burned from each ignition point. The fire size data were smoothed with a nearest neighbor procedure to fill intervening areas that did not receive an ignition. The spatial patterns in fire size (FS, Fig. 6) reflected fuel along the east direction, and the highest values were associated with large areas of contiguous fuel. Sharp transitions in FS were observed where non-burnable features (e.g., barren, rocks, structures) prevented fire propagation. Many of the largest fires were generated by ignitions on the eastern portion of the study area, which is comprised of large areas of Aleppo pine stands with a shrub understory and high predicted fire spread rates. The smaller fires resulted from ignitions adjacent to non-burnable lands.

Table 3 presents the four wildfire risk component values (BP, CFL, FS, SSR) resulted from the FlamMap simulations and the ArcFuels ArcGIS add-in software. Maximum BP reached up to 0.06 for the low burning scenario, 0.11

**Table 3** Fire simulation results from Arcfuels for the study area ineach burning scenario

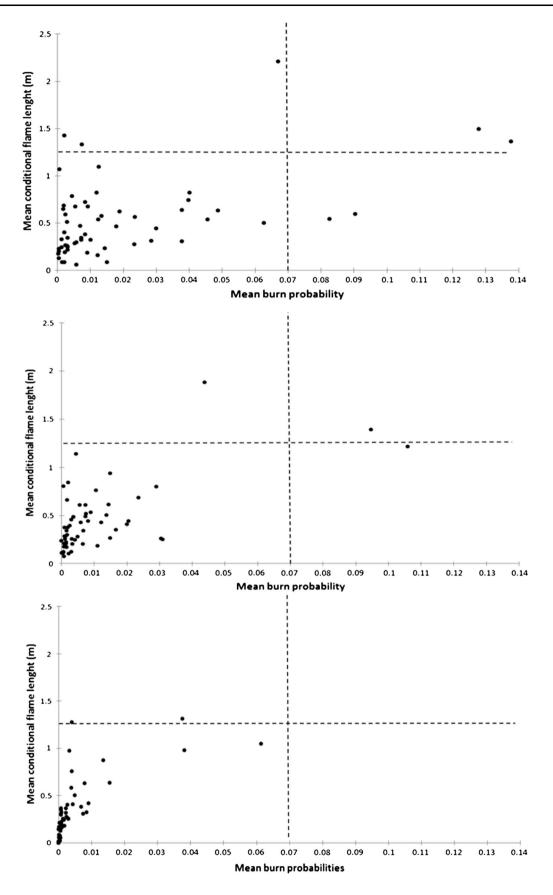
Burning conditions	Mean	Mean FS	Mean	Mean	Mean
	BP	(ha)	CFL (m)	SSR	ENVC
Extreme	0.020 <sup>A</sup>	637.2 <sup>A</sup>	0.53 <sup>A</sup>	5.94 <sup>A</sup>	$-3.17^{A}$
Moderate	0.011 <sup>B</sup>	297 <sup>B</sup>	0.44 <sup>A</sup>	4.76 <sup>B</sup>	$-2.63^{B}$
Low	0.004 <sup>B</sup>	104.4 <sup>B</sup>	0.31 <sup>B</sup>	4.14 <sup>C</sup>	$-1.41^{B}$

Values with the same letter are not significantly different at P = 0.05 according to Tukey's multiple comparison test

BP is burn probability; FS is the fire size, CFL the conditional flame length, SSR the source-sink ratio and ENVC the expected net value change

for the moderate burning scenario, and 0.15 for the extreme burning scenario. Maximum CFL reached up to 3.4, 5.3, and 5.9 m for each burning scenario, respectively. Maximum FS reached up to 980 ha for the low burning scenario, 1,690 ha for the moderate burning scenario, and 2,672.3 ha for the extreme burning scenario, while the maximum SSR reached up to 6.7, 7.8, and 6.7 for each burning scenario, respectively. Statistical differences among the three scenarios were performed by Analysis of Variance (ANOVA) and Tukey's multiple comparison test (95 % confidence level). The analysis showed statistical differences among the wildfire risk component values. The low burning scenario had the lower wildfire risk component mean values compared to the other scenarios. However, only the SSR values were significantly different between all the scenarios. BP and FS presented significant difference only in the extreme burning scenario compared to the other two examined burning scenarios, and CFL showed significant difference only between the extreme and the low burning scenarios. The spatial extent of ENVC in each scenario is also shown in Fig. 6. As it was expected, the mean ENVC presented different values between the burning scenarios. Residential structures are in strong loss of their extent under the extreme burning scenario (ENVC: -3.17), while slighter loss was calculated for the low burning scenario (ENVC: -1.41).

Wildfire exposure analysis-which assesses relative risk in terms of likelihood (BP), potential intensity (mean CFL), and expected FS for the individual WUI sites is shown in Figs. 7 and 8. Each point in the scatter plots represents the average value for the WUI polygons. The scatter plots were divided into four equal quadrants. The bottom-right quadrant shows areas with high burn probabilities and low potential intensity and/or FS, while the upper-right quadrant presents areas with high burn probabilities and high potential intensity and/or FS. The bottom-left quadrant depicts locations with low burn probabilities and low potential intensity and/or FS, while the upper-left quadrant features locations with low burn probabilities and high potential intensity and/or FS. In all burning scenarios, most of the residential structures are allocated in the lower-left quadrant, thus revealing that they are not posing strong loss potential from wildfires. However, a few structures appear in the other quadrants in the different burning conditions without following a particular pattern. Scatter plots of average BP vs. CFL values for the residential structures showed a wide range of fire behavior within the study area. Overall, the residential structures located within the study area exhibited a wide range of BP values but in general showed a relatively low CFL (up to 2.5 m) in all burning scenarios due to the fact that most of them are located in areas covered by grasslands and sparse scrublands and thus feature relatively



◄ Fig. 7 Scatter plots showing burn probability versus conditional flame length for the residential structures under the extreme (*upper*), moderate (*middle*), and low (*bottom*) burning scenarios

low to moderate fuel load values. Even though some structures can present fire suppression difficulties for the firefighting forces under the extreme scenario, the expected intensity values, as resulted from the simulation study, might not totally overcome the suppression capabilities. Under the low burning scenario, all of the residential structures found in the area are fall into the bottom-left quadrant presenting low burn probabilities and low potential intensity and/or FS. The plot of average patch FS versus BP showed that, in general, FS and BP were positively correlated, a finding that was expected since larger fires lead to higher BP.

# Discussion

The purpose of this study was to assess the spatial patterns of major wildfire risk components in a Mediterranean fireprone region in relation to highly valued social and economic features such as the residential structures found in the area. This study represents one of the first attempts at landscape wildfire behavior simulation in the Mediterranean with an aim to estimate wildfire exposure and ENVC. Similar approaches have been conducted mainly in Sardinia Island, Italy; Salis et al. (2013) assessed fire risk exposure of human and ecological values to wildfire by employing coarse scale geospatial fuel data which has been corresponded to Corine land cover map. Arca et al. (2012) estimated changes in BP under different future climate change scenarios, while Salis et al. (2014) analyzed the spatiotemporal changes of wildfire exposure in relation to ignition patterns to weather and to fire suppression activities. The advantages of the present study approach are several. First, by performing the simulations with a large number of random ignitions, it became possible to determine the important scale-related factors that drive wildfire likelihood. The main strength of a multi-simulation approach is the potential to account simultaneously for the effects of the weather, wind, and ignitions that affect fire spread. In the case of weather and wind, these factors can either be based on actual data, can represent extreme cases, or may be assessed using future weather predictions from models (Keane et al. 2008; Massada et al. 2009). Secondly, the methods generated fine-scale measurements of fuel types, which allowed the mapping of the fuel models' spatial extent in the area. Based on this knowledge of the spatial extent of the fuels, national authorities and fire managers can design fire prevention, detection, suppression, and fire effects assessment strategies, such as the use and distribution of available firefighting resources, fuel treatment practices and fire tower and water tank construction as well as be able to trace gas emissions and monitor post fire vegetation recovery (Mallinis et al. 2008).

Visual photointerpretation is one of the most commonly used techniques for the reliable and accurate mapping of vegetation and fuel types, while automated segmentation can significantly reduce the time and human resources needed (Arroyo et al. 2008). Even though it is more timeconsuming than newer approaches, visual assignment of image segments to fuel types is a good compromise between costs and precision, particularly when working at fine scales, and is widely employed by governmental agencies (Arroyo et al. 2008). As reported by other authors (van Wilgen et al. 1985), fire behavior prediction simulations have been extensively validated in areas different from those where the models were originally developed, and they stated that specific custom models need to be developed to account for both the fuel characteristics and the high heterogeneity of Mediterranean vegetation. Arca et al. (2007) also suggest that localized, site-specific fuel models give more reliable and accurate fire predictions using the FlamMap simulator. The dense shrubland fuel type demonstrated the most severe fire potential in all burning scenarios due to the heavier fuel load. The grassland and agriculture fuel types produced low-intensity fires due to the reduced fuel load that was composed of dry, fine fuels. The simulation results showed a strong effect of the fuel models on BP, FS, and CFL; in particular, the combined effect of the dense shrublands and the low elevation pine forest areas and complex topography on CFL was relevant, especially in the southwestern part of the study area, while herbaceous fuels such as shrublands were in general characterized by lower CFL but higher BP. Among the three different burning conditions studied, the extreme scenario had the highest BP, FS, and CFL values.

The large growth that fires can achieve in these areas is mainly attributed to the high rates of spread in the surrounding areas, which are covered by grass and/or sparse shrublands, and to the absence of non-burnable fuels. These areas were historically characterized by a relatively low number of fire ignitions due to fire suppression activities. The high exposure to severe and large fires seen in the simulations highlighted the need for fuel treatments and fire management activities in specific locations. Regarding the residential structure features, different spatial patterns were been observed in the study area, with few patches where high values of BP and average FS were strongly correlated. In these areas, potential issues such as fire threat as a direct risk to people and structures due to FS and intensity and to related effects (i.e., smoke) are expected. The incidence of high intensity fires close to residential

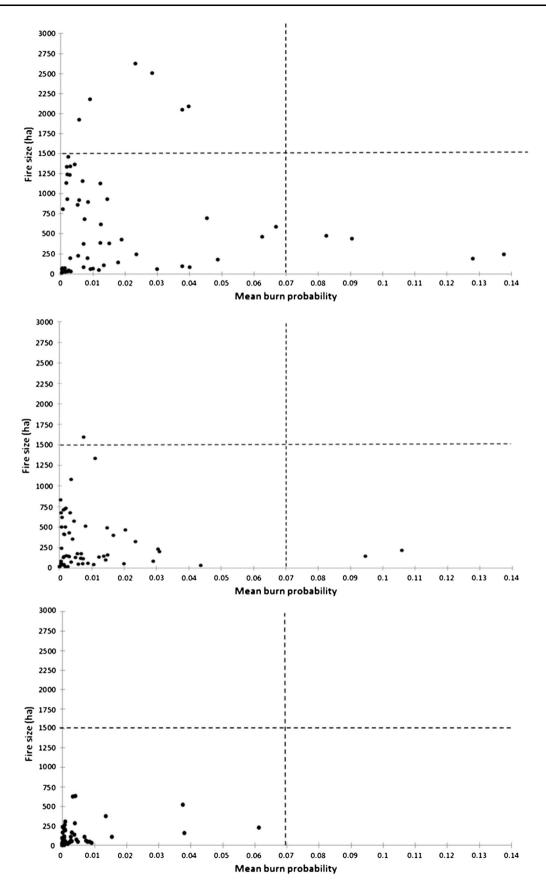


Fig. 8 Scatter plots showing burn probability versus fire size for the residential structures under the extreme (*upper*), moderate (*middle*), and low (*bottom*) burning scenarios

structures could be an issue for people's safety in the region. The results of the study assist in the identification and monitoring of specific areas and can be useful in applying fuel treatments and evacuation strategies in order to avoid the entrapment of people in the areas with the highest wildfire exposure. This is very important considering the fact that in past years the study area faced severe wildfire events resulting in injuries, casualties, and the total destruction of residential structures.

The incorporation of residential structures in the current study comparing wildfire risk on public lands adjacent to wildlands is crucial since community wildfire protection planning ignores the exposure that is potentially transmitted over long distances from large fires originating elsewhere. The simulation outputs suggested wide variation in wildfire exposure to the residential structures. The scatter plots of exposure can be used to prioritize risk management activities in the area.

The estimation of potential transmission of fire risk according to the source–sink relationship showed that areas with high SSR generated large fires relative to the frequency that they burned and can be considered precursor areas for large fires. On the contrary, sinks are areas that burned from fires originating elsewhere relative to the amount of fire they contribute to the larger landscape (Ager et al. 2012). Fire mitigation strategies located in source areas have a higher potential to transmit fire that could lead to severe impact to high resource values found in the area. Wildland regions located in sink areas are more fire prone and potential impacts from fires that originate elsewhere. SSR values showed large variation around fuel breaks (i.e., bare soils, structures, etc.) and no correlation between BP, CFL, and FS.

The ENVC under the three different burning conditions resulted in improved and complementary information for assessing potential fire consequences. The spatial intersection of highly valued resources and assets such as the residential structures of the study area with pixel-based BP estimates enables the quantification of WUI exposure to wildfire. Spatially explicit BP is increasingly applied to assess wildfire risk to highly valued resources and assets (HVRAs) and to justify the development of mitigation strategies (Carmel et al. 2009; Massada et al. 2009; Calkin et al. 2011; Thompson et al. 2011, 2012; Parisien et al. 2012).

According to Calkin et al. (2014), the reduction of risk of residential structure loss as a result from wildfires burning in the area is composed of four basic components: (a) the reduction of wildfire occurrence, (b) the reduction of wildfire size and intensity, (c) the reduction of human development in fire-prone areas, and (d) the increase of homes' resistance to ignition. The results of the current study can be incorporated in a synergic manner with fire occurrence studies and home ignition resistance standards in order to achieve integrated fire management in the WUI areas of Greece. Additionally, the development of WUI maps comprising housing conjunction and vegetation characteristics would substantially help in assessment of WUI dynamics and associated fire risk mitigation efforts (Lampin-Maillet et al. 2010). In the Mediterranean areas, as elsewhere, the WUI will likely continue to expand into fire-prone wildland areas (Theobald and Romme 2007). Information on the interface where the built environment meets wildland areas is crucial for communities, firefighting personnel, and decision-makers, all of whom can use the maps created with this approach to target areas for wildfire hazard reduction such as clearing vegetation and creating defensible space (Cleve et al. 2008). Advances in remote sensing and spatial analysis have facilitated WUI mapping and analysis by expanding the data and methods available to analysts.

Overall, the fire risk maps generated in this study allowed for quantitative assessment of wildfire exposure at a scale that is not possible by other approaches, like for instance analyzing ignition data without taking into account fire spread and intensity at landscape level, a common approach for most of the fire risk studies found in Mediterranean basin (Moreira et al. 2011). This work can provide useful guidelines to policy makers and land managers to identify residential areas at risk and to select the most appropriate prevention and mitigation activities to protect human communities from wildfire losses. Furthermore, this study can help improving fine-scale awareness and understanding of wildfire likelihood and intensity spatial patterns, thus allowing to inform different actions aimed to reduce landscape susceptibility and to contrast wildfire spread and ignitions, which in the study area are human caused and not natural. Another attractive point of the study is the use of high-resolution datasets for the implementation of the approach which allow fine scale fire simulation and risk evaluation. Yet, while this is a local scale approach due to the extent of the area and the resolution of the data, it is highly transferable across Euro-Mediterranean WUI areas, considering that the Urban Atlas dataset is readily available across Europe.

# Conclusions

This study assessed four important wildfire risk component (BP, CFL, FS, and SSR) values and investigated the potential effects under three different burning scenarios for a typical WUI area in the eastern Mediterranean. Localized

fuel models have been developed based on extensive fieldwork. Site-specific fuel models should be adopted to provide more reliable spatial fire risk predictions, especially in the case of the fragmented and heterogeneous Mediterranean landscape. FlamMap simulations resulted in high fire risk in the dense shrubland and Aleppo pine fuel types under the extreme burning scenario. Furthermore, wildfire exposure and ENVC of the residential structures in the area has been determined, thus providing an overall fire risk assessment to human values in the area.

The proposed methodology presents an integration of fuel sampling, fuel mapping, and landscape fire behavior simulation for fire management planning across the landscape. The final fire risk maps are the end product, and they can be fully exploited operationally by local fire management authorities without further processing. Outputs created from this study can be used as valuable components of judicial short- and long-term wildland fire prevention and management in Greece. Further studies of fire risk methods in the field are necessary in order to validate and calibrate the outcomes of the FlamMap fire simulators, especially in Mediterranean vegetation conditions. Additionally, the potential future change of fuel spatial extent and fuel load values could be further examined to allow researchers and land managers to address potential future changes to fire severity and regimes, shifts in fire risk distributions, potential carbon emission released from wildfires, post-fire soil erosion, and the ecological restoration of degraded ecosystems/landscapes after wildfires.

Work is currently in progress to map Mediterranean fuels with very high-resolution imagery and to couple wildfire risk simulations with accurate statistical models able to account for interactive effects of topographic, climate, socioeconomic and human factors on fire risk. The methodologies used in this work can inform a spectrum of wildfire management activities, from real-time support during the fire season to fuel management and landscape planning, with the general goal of reducing fire exposure and losses of residential structures from future wildfires.

Acknowledgments This work was partially supported by the European Community's Seventh Framework Programme (2010–2013) FUME: Forest fire under climate, social and economic changes in Europe, the Mediterranean and other fire-affected areas of the World. (Grant agreement no 243888). We would like to thank the two anonymous reviewers and the Editor whose insightful comments helped to substantially improve this manuscript.

#### References

Ager A, McMahan A, Barrett J, McHugh C (2007) A simulation study of forest restoration and fuels treatments on a wildland-urban interface. Landscape Urban Plan 80:292–300

- Ager A, Finney M, McMahan A, Cathcart J (2010) Measuring the effect of fuel treatments on forest carbon using landscape risk analysis. Nat Hazard Earth Syst 10:2515–2526
- Ager A, Vaillant N, Finney M, Preisler H (2012) Analyzing wildfire exposure and source-sink relationships on a fire-prone forest landscape. For Ecol Manage 267:271–283
- Andrews P, Finney M, Fischetti M (2007) Predict Wildfires Sci Am 1:47–55
- Andrews P, Heinsch F, Schelvan L (2011) How to generate and interpret fire characteristics charts for surface and crown fire behavior. USDA, Forest Service, Rocky Mountain Research Station, General Technical Report, RMRS-GTR-253. Fort Collins, CO
- Arca B, Duce P, Laconi M, Pellizzaro G, Salis M, Spano D (2007) Evaluation of FARSITE simulator in Mediterranean maquis. Int J Wildland Fire 16:563–572
- Arca B, Pellizzaro G, Duce P, Salis M, Bacciu V, Spano D, Ager A, Finney M, Scoccimarro E (2012) Potential changes in fire probability and severity under climate change scenarios in Mediterranean areas. In: Spano D, Bacciu V, Salis M, Sirca C (eds) Modelling fire behaviour and risk. NuovaStampacolor, Sassari, pp 92–98
- Arroyo L, Pascual C, Manzanera J (2008) Fire models and methods to map fuel types: the role of remote sensing. For Ecol Manage 256:1239–1252
- Bachmann A, Allgower B (2001) A consistent wildland fire risk terminology is needed. Fire Manage Today 61:28–33
- Blanchi R, Jappiot M Alexandrian D (2002) Forest fire risk assessment and cartography. A methodological approach. In: Viegas, D (ed). Proceedings of the IV International Conference on Forest Fire Research. Luso, Portugal
- Bonham C (1989) Measurements for terrestrial vegetation. Wiley, New York
- Brown J, Oberheu R, Johnston C (1982) Handbook for inventorying surface fuels and biomass in the Interior West. USDA Forest Service, Intermountain Forest and Range Experiment Station General Technical Report INT-129. Ogden
- Calkin DE, Ager AA, Gilbertson-Day J (2010) Wildfire risk and hazard: Procedures for the first approximation. USDA, Forest Service, Rocky Mountain Research Station, General Technical Report, RMRS-GTR-235. Fort Collins, CO
- Calkin D, Ager A, Thompson M (2011) A comparative risk assessment framework for wildland fire management: the 2010 cohesive strategy science report. USDA, Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-262. Fort Collins, CO
- Calkin D, Cohen J, Finney M, Thompson M (2014) How risk management can prevent future wildfire disasters in the wildland–urban interface. PNAS 111(2):746–751
- Carmel Y, Paz S, Jahashan F, Shoshany M (2009) Assessing fire risk using Monte Carlo simulations of fire spread. For Ecol Manage 257:370–377
- Catry F, Rego F, Bação L, Moreira F (2009) Modelling and mapping wildfire ignition risk in Portugal. Int J Wildland Fire 18:921–931
- Chuvieco E, Aguado I, Yebra M, Nieto H, Salas J, Martín M, Zamora R (2010) Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecol Model 221:46–58
- Chuvieco E, Aguado I, Jurdao S, Pettinari M, Yebra M, Salas J, Hantson S, de la Riva J, Ibarra P, Rodrigues M, Echeverria M, Azqueta D, Roman M, Bastarrika A, Martinez S, Recondo C, Zapico E, Martinez-Vega F (2012) Integrating geospatial information into fire risk assessment. Int J Wildland Fire 2:69–86
- Cleve C, Kelly M, Kearns F, Moritz M (2008) Classification of the wildland-urban interface: a comparison of pixel- and object-

based classifications using high-resolution aerial photography. Comput Environ Urban Syst 32:317–326

- Dimitrakopoulos A (2001) PYROSTAT—a computer program for forest fire data inventory and analysis in Mediterranean countries. Environ Modell Softw 16:351–359
- Dimitrakopoulos A (2002) Mediterranean fuel models and potential fire behaviour in Greece. Int J Wildland Fire 11:127–130
- Dimitrakopoulos A, Panov P (2001) Pyric properties of some dominant Mediterranean vegetation species. Int J Wildland Fire 10:23–27
- European Union (2011) Mapping Guide for a European Urban Atlas, p 31
- Fairbrother A, Turnley J (2005) Predicting risks of uncharacteristic wildfires: application of the risk assessment process. For Ecol Manage 211:28–35
- Finney M (2002) Fire growth using minimum travel time methods. Can J For Res 32:1420–1424
- Finney M (2005) The challenge of quantitative risk analysis for wildland fire. For Ecol Manage 211:97–108
- Finney M (2006) An overview of FlamMap modeling capabilities. In: Andrews P, Butler B (eds.) Fuels Management—How to measure success: Conference Proceedings. USDA, Forest Service, Rocky Mountain Research Station, General Technical Report, RMRS-P-41, pp 213–219
- Finney M, Grenfell I, McHugh C (2009) Modeling containment of large wildfires using generalized linear mixed-model analysis. For Sci 55:249–255
- Finney M, Grenfell I, McHugh C, Seli R, Tretheway D, Stratton R, Brittain S (2011) A method for ensemble wildland fire simulation. Environ Model Assess 16:153–167
- Forthofer J (2007) Modeling wind in complex terrain for use in fire spread prediction Fort Collins, CO: Colorado State University, Ph.D.Thesis
- González-Olabarria J, Pukkala T (2011) Integrating fire risk considerations in landscape-level forest planning. For Ecol Manage 261:278–287
- Hardy C (2005) Wildland fire hazard and risk: problems, definitions, and context. For Ecol Manage 211:73–82
- Hardy C, Schmidt M, Menakis P, Sampson N (2001) Spatial data for national fire planning and fuel management. Int J Wildland Fire 10:353–372
- Haynes K, Handmer J, McAneney J, Tibbits A, Coates L (2010) Australian bushfire fatalities 1900–2008: Exploring trends in relation to the 'Prepare, stay and defend or leave early' policy. Environ Sci Policy 13:185–194
- Karali A, Hatzaki M, Giannakopoulos C, Roussos A, Xanthopoulos G, Tenentes V (2013) Sensitivity and evaluation of current fire risk and future projections due to climate change: the case study of Greece. Nat Hazards Earth Syst Sci 1:4777–4800
- Keane R, Holsinger L, Parsons R, Gray K (2008) Climate change effects on historical range and variability of two large landscapes in western Montana, USA. For Ecol Manage 254:375–389
- Lampin-Maillet C, Jappiot M, Long M, Bouillon C, Morge D, Ferrier J (2010) Mapping wildland–urban interfaces at large scales integrating housing density and vegetation aggregation for fire prevention in the South of France. J Environ Manage 91:732–741
- Mallinis G, Mitsopoulos I, Dimitrakopoulos A, Gitas I, Karteris M (2008) Integration of local scale fuel type mapping and fire behavior prediction using high spatial resolution imagery. IEEE J Sel Topics Appl Earth Observ 4:230–238
- Martínez J, Vega-Garcia C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention planning in Spain. J Environ Manage 90:1241–1252

- Massada A, Redeloff V, Stewart S, Hawbaker T (2009) Wildfire risk in the wildland–urban interface: a simulation study in northwestern Wisconsin. For Ecol Manage 258:1990–1999
- Mell WR, Manzello SL, Maranghides A, Butry D, Rehm RG (2010) The wildland–urban interface fire problem—current approaches and research needs. Int J Wildland Fire 19:238–251
- Miller C, Ager A (2013) A review of recent advances in risk analysis for wildfire management. Int J Wildland Fire 22:1–14
- Mitsopoulos I, Dimitrakopoulos A (2014) Estimation of canopy fuel characteristics of Aleppo pine (*Pinus halepensis* Mill.) forests in Greece based on common stand parameters. Eur J For Res 133:73–79
- Mitsopoulos I, Mallins G, Arianoutsou M (2013) Assessing fire behavior simulation accuracy with customized fuel models in Mediterranean ecosystems using real-world historical fire data. In: Proceedings of the 16th Hellenic Forestry Conference. 6–9 October 2013. Thessaloniki, Greece, pp. 164–174
- Moreira F, Viedma O, Arianoutsou M, Curt T, Koutsias N, Rigolot E, Barbati A, Corona P, Vaz P, Xanthopoulos G, Mouillot F, Bilgili E (2011) Landscape—wildfire interactions in southern Europe: implications for landscape management. J Environ Manage 92:2389–2402
- Parisien M, Snetsinger S, Greenberg J, Nelson C, Schoennagel T, Dobrowski S, Moritz M (2012) Spatial variability in wildfire probability across the western United States. Int J Wildland Fire 21:313–327
- Richards G (1990) An elliptical growth model of forest fire fronts and its numerical solution. Int J Numer Meth Eng 30:1163–1179
- Romero-Calcerrada R, Novillo C, Millington J, Gomez-Jimenez I (2008) GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (Central Spain). Landsc Ecol 23:341–354
- Salis M, Ager A, Arca B, Finney M, Bacciu V, Duce P, Spano D (2013) Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. Int J Wildland Fire 22:549–565
- Salis M, Ager A, Finney M, Arca B, Spano D (2014) Analyzing spatiotemporal changes in wildfire regime and exposure across a Mediterranean fire-prone area. Nat Hazards 71:1389–1418
- Scott JH (2006) An analytical framework for quantifying wildland fire risk and treatment benefit. In: Andrews PL, Butler BW (eds) Fuels management—how to measure success: conference proceedings. USDA, Forest Service, Rocky Mountain Research Station, RMRS-P-41. Fort Collins, CO, pp. 169–184
- Scott J, Thompson M, Calkin D (2013) A wildfire risk assessment framework for land and resource management. USDA Forest Service, Rocky Mountain Research Station, General Technical Report, RMRS-GTR-315
- Theobald D, Romme W (2007) Expansion of the US wildland–urban interface. Landsc Urban Plan 83:340–354
- Thompson M, Calkin D, Finney M, Ager A, Gilbertson-Day J (2011) Integrated national-scale assessment of wildfire risk to human and ecological values. Stochast Environ Res Risk Assess 25:761–780
- Thompson M, Calkin D, Finney M, Gebert K, Hand M (2012) A riskbased approach to wildland fire budgetary planning. For Sci 59:63–77
- Thompson M, Scott J, Langowski P, Julie Gilbertson-Day, Haas J, Bowne E (2013) Assessing watershed-wildfire risks on national forest system lands in the rocky mountain region of the United States. Water 5:945–971
- Vaillant N, Ager A, Anderson J (2013) ArcFuels10 system overview. USDA, Forest Service, Pacific Northwest Research Station, General Technical Report. PNW-GTR-875. Portland, OR

- van Wilgen B, le Maitre D, Kruger F (1985) Fire modeling in South African fynbos (macchia) vegetation and predictions from Rothermels fire model. J Appl Ecol 22:207–216
- Vasilakos C, Kalabokidis K, Hatzopoulos J, Kallos G, Matsinos J (2007) Integrating new methods and tools in fire danger rating. Int J Wildland Fire 16:306–316
- Wu Z, He H, Liu Z, Liang Y (2013) Comparing fuel reduction treatments for reducing wildfire size and intensity in a boreal forest landscape of northeastern China. Sci Total Environ 1:454–455
- Xanthopoulos G (2009) Wildland fires: Mediterranean. Crisis Response Journal 5:50–51