Arab J Geosci (2016) 9:688
DOI 10.1007/s12517-016-2717-y

ORIGINAL PAPER

Application of a CA-based model to predict the fire front in Hyrcanian forests of Iran

Saeedeh Eskandari [1]

Received: 10 January 2016 / Accepted: 12 October 2016

Abstract Forest fire is one of the most important source of land degradation that lead to deforestation and desertification processes. Thus, prediction of forest fire front is necessary to control it. In this study, Alexandridis model based on Cellular Automata (CA) rules was applied to predict the fire front in a part of Hyrcanian forests of Iran. The data of effective factors on fire front in the model (including vegetation type and density, wind speed and direction, and ground elevation) were provided from Mazandaran Natural Resources Administration (MNRA), Mazandaran Meteorological Administration (MMA), and Digital Elevation Model (DEM) of ASTER sensor. The model was used to simulate the front of a wildfire that burned a part of District Three of Neka-Zalemroud forests (DTNZ) on December of 2010. The required data of actual fire for simulation of fire front (including actual fire map, fire area, fire start point, etc.) were provided from MNRA. All effective factors maps for actual fire confine were organized in a Geographic Information System (GIS). The simulation environment was provided based on the ASCII files of altitude, vegetation density, and vegetation type matrices, together with a matrix containing the burned area. The fire front model was programmed and it was implemented by uploading of all digital layers (coding ASCII matrices) of effective variables and considering of the certain wind speed and direction in fire confine. Fire front simulation was run by considering of fire start point coordination and the fire front simulation was depicted. Finally, the number of burned and unburned cells in fire confine matrix was obtained. Results of model implementation including fire front direction and shape were compared with the actual fire confine to evaluate the accuracy of the used model qualitatively. Thus, the fire front polygon was overlaid on the actual fire polygon and the high similarity was observed between them. In addition, total accuracy and Kappa index were used to evaluate the accuracy of the used model quantitatively. The total accuracy and Kappa index were obtained 0.88 and 0.74, respectively. These results can show the accuracy of CA-based model to predict the fire front in Hyrcanian forests of Iran in current research.

Keywords Cellular Automata (CA) · District Three of Neka-Zalemroud (DTNZ) forests · Fire front model · Fire simulation · Geographic Information System (GIS)

Introduction

The extreme wildfires are the global phenomena that consistently result in loss of life, property and further impact the cultural, economic, and political stability of communities (McRae et al. 2015). The environmental effects of forest fires are enormous, and therefore, there is a constant demand for more effective firefighting and management (Good and McRae 1989). Modeling and simulation have been applied to fire fighting and management for many years, particularly in order to predict the fire behavior and front in forests under various scenarios of weather conditions. Generally, the goal of a model for prediction of fire fronting in the forests is determination of the time-evolving fire front in a physical landscape under various weather conditions (Karafyllidis and Thanailakis 1997). A model for fire fronting in the forests can be used as a real-time decision support system, in order to enhance effectiveness of firefighting strategies (Kessell and Beck 1991). Such a model could be part of a system for real-

✉ Saeedeh Eskandari
saeedeheskandari119@yahoo.com

[1] Forest Research Division, Research Institute of Forests and Rangelands, Agricultural Research, Education and Extension Organization (AREEO), Tehran, Iran

Published online: 28 October 2016

time fire front determination. Such a system would combine a Geographic Information System (GIS) and satellite imagery with a model for forest fire fronting (Beer 1989). Wildfire front is a complex spatial and temporal dynamic process that depends on many factors such as weather, topography, and fuel types. Wind direction and speed are the most important factors in such a model. Other effective factors on forest fire fronting are topography of landscape and existence of areas with different rates of fire front (Karafyllidis and Thanailakis 1997). Therefore, vegetation type and density also play the important roles in such a model.

A wide range of wildfire front modeling approaches has been developed over the last decade to describe the physical processes at flame scale as well as the interactions between the fire and the atmosphere (Rochoux et al. 2015). One of the approaches used in enhancing the dynamic modeling capability of raster-based GIS is Cellular Automata (CA) modeling. Cellular automata were first introduced by Von Neumann (1966) as mathematical representations of complex systems which consist of a grid or lattice of cells where each cell is in one of a number of finite states. The state of a cell depends on a set of rules and the state of the neighboring cells. Cells change state as a result of deterministic, probabilistic, or stochastic transition rules (Yassemi et al. 2008). Cellular automata are dynamical systems which are discrete in space and time, operate on a regular lattice, and are characterized by "local" interactions. Cellular automaton is a known method to simulate the forest fire front in the recent years. Two-dimensional cellular automata have often been used to model landscape phenomena such as bushfires, forest fire, and epidemic front (Bodrožic 2006).

Many researchers have used cellular automata for forest fire front modeling in the world (Karafyllidis and Thanailakis 1997; Li and Magill 2001; Berjak and Hearne 2002; Ohgai et al. 2004; Yongzhong et al. 2004; Yongzhong et al. 2005; Encinas et al. 2007a; Yassemi et al. 2008). Here, we imply to the recent studies. Alexandridis et al. (2008) presented the simulation results of a cellular automata model to predict the forest fire front using factors such as the type and density of vegetation, the wind speed and direction, and the spotting phenomenon. The model was used to simulate the wildfire that destroyed a major part of the Island's forest. Results showed that the proposed model predicts in a quite adequate manner the evolution characteristics in space and time of the real incident. Almeida and Macau (2010) proposed a stochastic CA model for wildfire front under flat terrain and no-wind conditions and analyzed its dynamics. The dynamics of fire front was modeled as a stochastic event with an effective fire front probability S which was a function of three probabilities: the proportion of vegetation cells across the lattice, the probability of a burning cell become burnt, and the probability of the fire front from a burning cell to a neighbor vegetation cell. The effective fire front probability was obtained from Monte Carlo simulations. Results showed that the capability of the model catches both the dynamical and static qualitative properties of fire propagation. Pak and Hayakawa (2011) proposed a CA-based forest fire dynamics model considering intensities of fires as multiple states and having the probability that fire front depends on the states of the neighboring cells. Furthermore, the idea of percolation threshold was introduced to characterize the strength of the fire propagation. Innocenti and Cancellieri (2013) suggested the use of activity paradigm to model the uncertain and imprecise nature of the local dynamics in fire fronting simulations. A new algorithm (random-activity) was presented to track activity concept in a CA model which combines activity and stochastic precepts. This algorithm enhances the realism of the spatial simulations. Results showed that the random-activity algorithm outshines the classical algorithm in terms of graphical restitutions' realism. Iudin et al. (2015) applied a new arithmetic method to a CA forest-fire model which was connected with the percolation methodology and in some sense combined the dynamic and the static percolation problems and under certain conditions exhibited critical fluctuations. By means of the new approach, it was observed that as far as user chooses an infinitesimal tree growing rate and infinitesimal ratio between the ignition probability and the growth probability, the measure or extent of the system size infinity is determined that provides the criticality of the system dynamics.

Regarding to importance and capability of cellular automata model to simulate the forest fire front, the aim of this study is prediction of the fire front based on cellular automata model in a part of Hyrcanian forests of Iran (DTNZ forests). The limit area of Hyrcanian forests and annual destruction of them by continuous fires shows the importance of improving current supervision and prediction systems in these forests (Eskandari and Chuvieco 2015). DTNZ forests located in the North of Iran include some rare plant and animal species and also have high potential for ecotourism. Unfortunately, some parts of these forests have been burned by fires in the recent years. The major fire burned a part of DTNZ forests on December of 2010. Therefore, in this study, a CA-based model was implemented to simulate the front of a wildfire which burned and destroyed a part of DTNZ forests in 2010.

In the first step of this research, a CA-based model for fire prediction is introduced; then the effective input variables and the methods to generate them as geographical data layers are described; in the second step, the CA-based model is implemented for actual fire and the fire front is simulated. Finally, the fire front simulation results are validated using data of actual fire which burned a part of DTNZ forests in 2010.

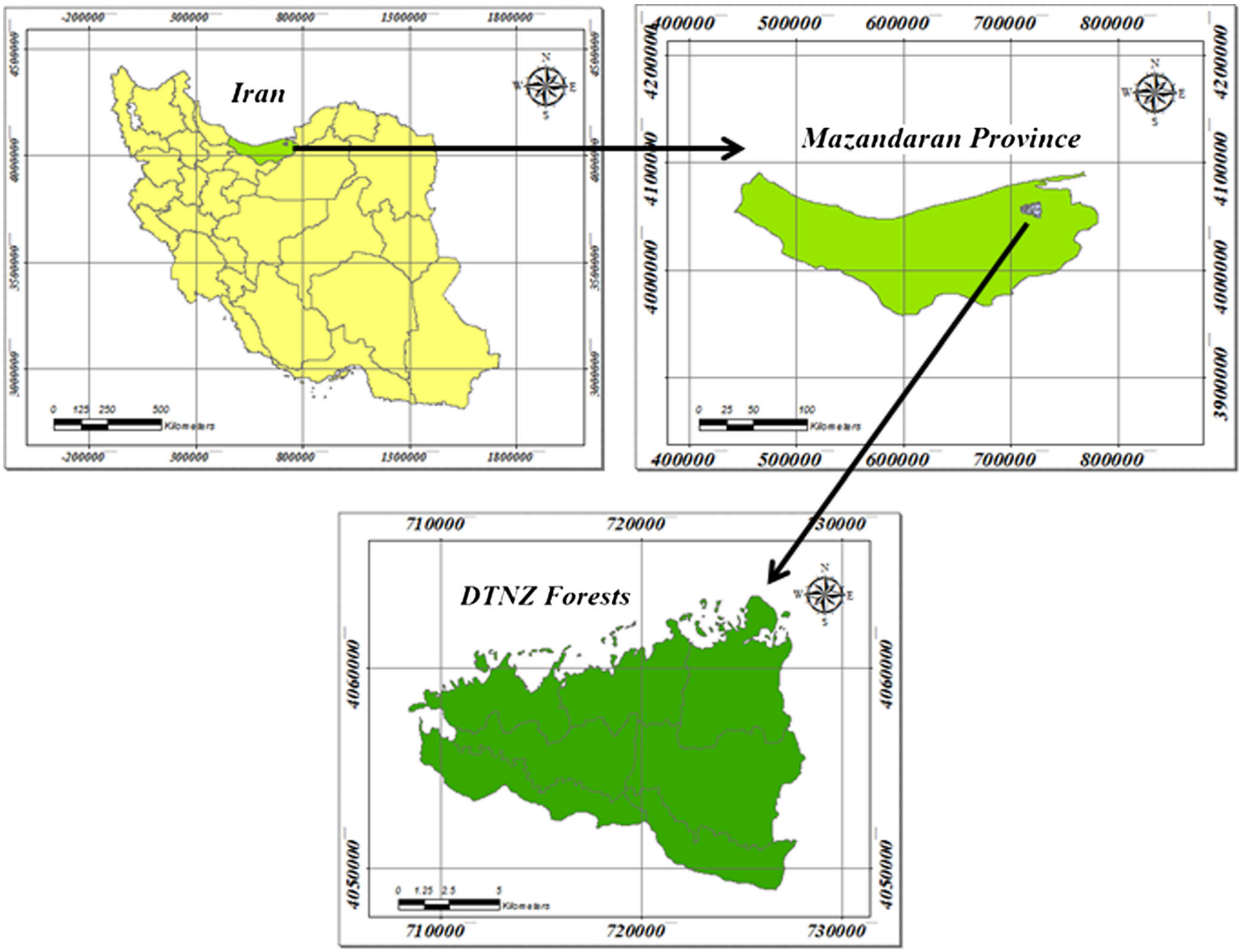


Fig. 1 Study area map

Material and methods

Study area

DTNZ forests have been located between 36° 30′ to 36° 40′ N latitude and 53° 15′ to 53° 26′ E longitude in South of Neka and Behshahr counties of the Mazandaran Province in Iran. These forests cover the area of 153.07 km^2 and are bounded by Neka-Behshahr road in the North, Chakhani and Souterabad in the East, Zarandin Khoramchamaz in the South, and Ablou in the West. Minimum and maximum altitudes from sea level are 11 and 874 m, respectively. DTNZ forests have 103.4 km forest roads, 27 km rural roads, and 21 km asphalt roads (Fig. 1).

Forests of study area have uneven-aged and mixture structure. Plant species include tree species (*Fagus orientalis*, *Carpinus betulus*, *Quercus castaneifolia*, *Alnus subcordata*, *Parrotia persica*, *Zelcova carpinifolia*, *Acer* sp., etc.), shrub species (*Buxus hyrcanus*, *Mespilus germanica*, *Crataegus pentagyna*,

Table 1 The basic data sources

Data	Source	Cell size
Topographic data (DEM)	ASTER	25-m pixel size
Vegetation type	Mazandaran Natural Resources Administration (MNRA)	25-m pixel size
Vegetation density	Mazandaran Natural Resources Administration (MNRA)	25-m pixel size
Wind direction and speed	Mazandaran Meteorological Administration (MMA)	–
Actual fire map	Mazandaran Natural Resources Administration (MNRA)	25-m pixel size
Constant coefficients of the model (P_h, a, c_1, c_2)	Alexandridis model	–

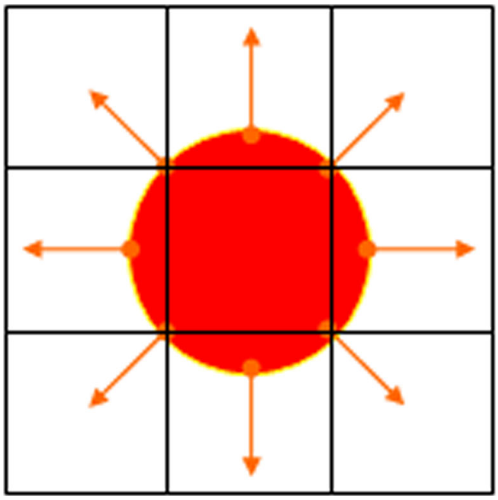


Fig. 2 Possible directions of fire propagation on a square grid

Prunus caspica, etc.), and herb species (*Asperula odorata*, *Ruscus hyrcanus*, *Siclaman* sp., *Carex* sp., *Rubus* sp., etc.) (Mazandaran Natural Resources Administration (MNRA) 2010).

Data

In this study, the basic data for fire front model based on cellular automata included DEM, vegetation type and density, wind direction and speed, and the actual fire map. The topographic data were obtained from Digital Elevation Model (DEM) derived from ASTER sensor (with 25-m pixel size). The vegetation type and density data were provided from Mazandaran Natural Resources Administration (MNRA). The wind direction and speed data were also provided from Mazandaran Meteorological Administration (MMA). The actual fire map in DTNZ forests was also provided from MNRA (Table 1). All data were organized in a GIS framework to provide the digital maps of the variables and to analyze the digital layers.

CA method for fire front prediction

Cellular automaton is one of the semi-empirical models for fire front modeling. In cellular automata model, the study area is considered as a cellular grid which fire in this grid has different front rates based on cells environmental characteristics, cells states (flammability or non-flammability), and the basic rules of fire front (Pastor et al. 2003). These rules are based on mathematical and semi-empirical models. Cellular automata use a two-dimensional grid for forest area which the grid is divided to many cells. Actually, each cell represents a small patch of the land and its shape is usually chosen as a square. Thus, there are eight possible directions for fire front (Fig. 2) (Alexandridis et al. 2008). Each cell is described by some environmental variables.

States of the cells

In cellular automata, each cell is characterized by a number of states which evolve in the discrete time. The possible states have been described in Table 2.

The state of each cell is then coded as an element of a matrix S which from now on will be called the state matrix. Figure 3 shows an example of how an area of 16 cells with random number of states is coded in a matrix form (Alexandridis et al. 2008).

Rules of fire evolution

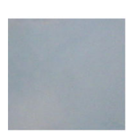
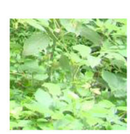
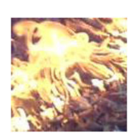
At each discrete time step t of the simulation, some rules are applied to the elements i, j of the state matrix S (and thus to all the cells). These rules have been described in Table 3.

P_{burn} (probability of burning) is a function of various parameters that affect the fire front and will be analyzed in the following paragraphs. It should be noted that, due to the square grid, we have assumed that the fire can be propagated to the neighboring cells $i \pm 1, j \pm 1$; these are the eight cells depicted in Fig. 4 (Alexandridis et al. 2008).

Fire front model

In this study, Alexandridis model based on cellular automata rules was used to model the fire front. Based on this model, the following variables can affect both the shape and rate of front of a forest fire: the vegetation type and density, the wind speed and direction, and the ground elevation effect. We removed the spotting effect from

Table 2 States of the cells

	States of the cells			
Number of state	State 1	State 2	State 3	State 4
Cell shape				
Description of state	The cell contains no forest fuel (city and rural areas)	The cell contains forest fuel that has not ignited	The cell contains forest fuel that is burning	The cell contained forest fuel that has been burned down

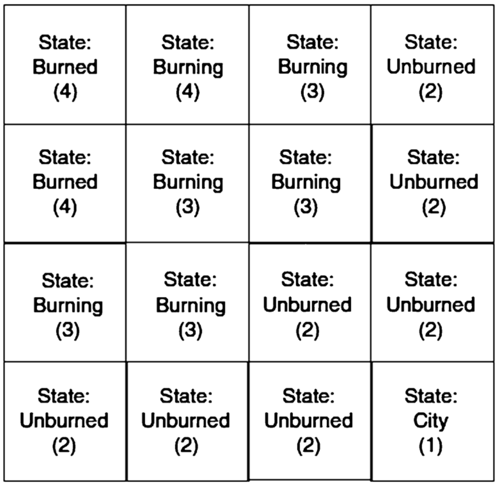


Fig. 3 Coding the state of the cells in the state matrix *S*

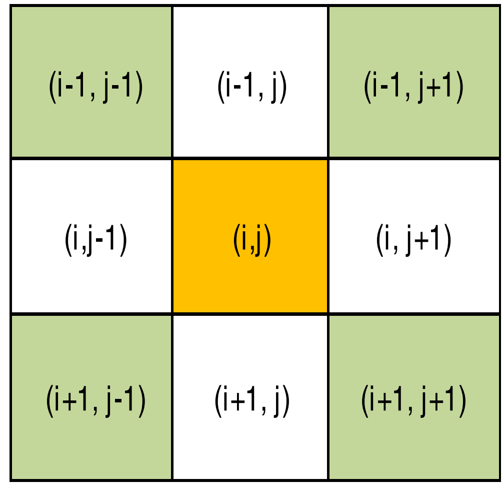


Fig. 4 Central cell and neighboring cells

model because this variable is not an effective factor in fire front in Hyrcanian forests of Iran. Hyrcanian forests of Iran are the broad leaves forests while spotting is an effective factor on fire front in the needle leaves forests. Spotting is a phenomenon where burning material is transferred by the wind or other reasons such as the fling of flaming pinecones to areas that are not adjacent to the fire front (Alexandridis et al. 2008). There is no pine in Hyrcanian forests of Iran and thus there is no report that spotting has the important role in fire front in Hyrcanian forests of Iran.

The variables that are terrain-specific, i.e., the type and density of vegetation and the ground elevation, were also coded in matrices similar to the state matrix. The p_{burn} (probability *of burning*) of each cell is calculated by Eq. 1.

$$P_{\text{burn}} = P_h\left(1 + P_{\text{veg}}\right)\left(1 + P_{\text{den}}\right)P_w P_s \tag{1}$$

Where p_h denotes the constant probability that a cell adjacent to a burning cell containing a given type of vegetation and density will catch fire at the next time step under no wind and flat terrain; p_{den}, p_{veg}, p_w, and p_s are the fire propagation probabilities that depend on the density of vegetation, the type of vegetation, the wind speed, and the slope (elevation), respectively. These probabilities are described below. Notice that these probabilities are multiplied by the constant probability p_h to obtain the corrected probability that takes into account all the aforementioned factors (Alexandridis et al. 2008). To run this model, we needed four constant empirical values regarding Eq. 1 and other equations (Eqs. 2, 3, and 4). These constant empirical values were extracted from Alexandridis model (Alexandridis et al. 2008). These values have been given in Table 4.

Table 3 The rules of the elements *i*, *j* of the state matrix *S* (cell rules)

Number of rule	Rule	Description of rule
Rule 1	If state $(i, j, t) = 1$, then state $(i, j, t + 1) = 1$.	This rule implies that the state of a cell with no forest fuel (empty cell) remains the same and thus it cannot catch fire.
Rule 2	If state $(i, j, t) = 3$, then state $(i, j, t + 1) = 4$.	This rule implies that a burning cell at the current time step will be burned down at the next time step.
Rule 3	If state $(i, j, t) = 4$, then state $(i, j, t + 1) = 4$.	This rule implies that the state of an empty cell that has been burned down in the previous step stays the same.
Rule 4	If state $(i, j, t) = 3$, then state $(i \pm 1, j \pm 1, t + 1) = 3$ with a probability p_{burn}.	This rule implies that when a cell catches fire at the current time step, the fire can be propagated to the neighboring cells at the next time step with a probability p_{burn}.

Effect of vegetation type and density

The vegetation type and density are the important effective variables in fire front rate in the forest areas. In this study, the effects of the type and density of vegetation are represented by the probabilities p_{veg} and p_{den}, respectively. More specifically, the type and the density of vegetation in the study

Table 4 Optimized values for the CA algorithm operational parameters

Parameter	Name	Value
p_h	The constant probability of fire propagation	0.58
a	The slope coefficient	0.078
c_1	The wind coefficient	0.045
c_2	The wind coefficient	0.131

Table 5 Values for the probability p_{veg} depending on the type of vegetation

Vegetation type	Classes	Fire front probability	P_{veg}
Resistant to fire	Agriculture, Bare area	Low	−0.3
Medium resistant to fire	*Quercus*, *Zelkova-Quercus*	Medium	0
Sensitive to fire	Protected area, Shurb, *Carpinus-fagus*, *Fagus-carpinus*, *Carpinus*, *Carpinus-parrotia*, *Parrotia-carpinus*	High	0.4

area are divided to some categories. The type of vegetation was clustered into three categories: resistant to fire (code −0.3), medium resistant to fire (code 0), and sensitive to fire (code 0.4) (Table 5). The density of vegetation was also scaled into three categories: sparse vegetation (code −0.4), medium vegetation density or normal (code 0), and dense vegetation (code 0.3) (Table 6). These codes were empirically considered based on influencing level of each given category in fire front rate (Alexandridis et al. 2008). These were organized into two matrices, the vegetation type matrix and the vegetation density matrix where, for each of the respective categories, a certain value (code) for the probabilities p_{veg} and p_{den} was assigned (Tables 5 and 6) (Alexandridis et al. 2008).

Effect of wind speed and direction

Modeling of fire front based on effect of the wind speed and direction is one of the current challenges in fire front modeling studies. So far, a proper model which can model the wind effect on fire front has not been presented, because wind as a fluid has a complex behavior especially in the gradient terrains. The different empirical relations have been proposed to model the wind effect in fire front modeling studies. In this study, we applied a more flexible empirical wind-effect relation which it has shown the better results in fire front modeling. In this relation, the probability that contains the effect of wind velocity and direction (p_w) is calculated by the following equations:

$$P_w = \exp(c_1 V) f_t \tag{2}$$

$$f_t = \exp(V c_2(\cos(\theta) - 1)) \tag{3}$$

Where c_1, c_2 are the constant values (Table 4); V is the wind velocity and θ is the angle between fire propagation direction

Table 6 Values for the probability p_{den} depending on the density of vegetation

Vegetation density	Classes	Fire front probability	P_{den}
Sparse	Agriculture—bare area	Low	−0.4
Normal	<100 m^3 and 100–200 m^3	Medium	0
Dense	Protected area, 200–350 m^3 and >350 m^3	High	0.3

and wind direction. Notice that, using this formula, the wind direction can receive any continuous value between 0 and 360°. While in many other models, the wind can have just some given directions.

The probability p_w is a function of the angle θ for some arbitrary values of the constant parameters c_1, c_2 and wind velocity *(V)* (Alexandridis et al. 2008).

Effect of the ground elevation

The ground elevation also is an effective variable in fire front rate. When the fire moves on the uphill slopes, distance between flame and fuel (vegetation) is decreased. It can facilitate the burning of the fuel and increases the fire front rate. This issue is inversed on the downhill slopes. In this study, the probability that models the effect of the patch-slope (p_s) is according to Eq. 4.

$$P_s = \exp(a\theta_s) \tag{4}$$

Where θ_s is the slope angle of the patch and a is a constant value (Table 4). It should be noted that due to the square grid, the slope angle is calculated in a different way depending on whether two neighboring cells are adjacent or diagonal to the burning cell (Fig. 5).

More specifically for adjacent cells, the slope angle is calculated as below:

$$\theta_s = \tan^{-1}\left(\frac{E_1 - E_2}{l}\right) \tag{5}$$

Where E_1 and E_2 are the altitude of two cells and l is the length of square side (25 m in this research).

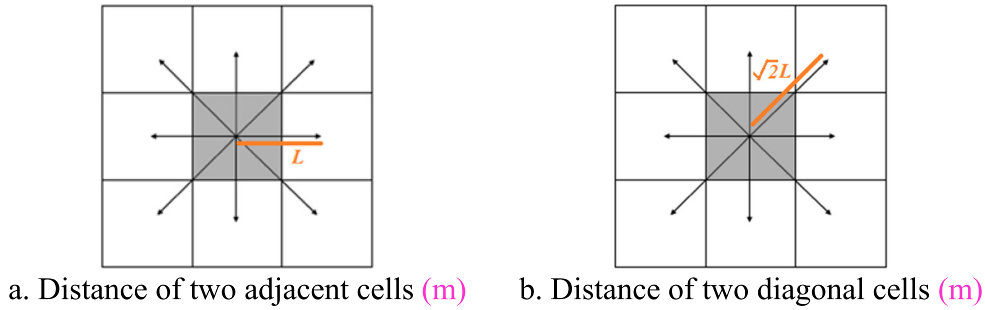
Whereas for diagonal cells, the slope angle is calculated as below (Alexandridis et al. 2008):

$$\theta_s = \tan^{-1}\left(\frac{E_1 - E_2}{\sqrt{2}l}\right) \tag{6}$$

Implementation of CA-based fire front model

The described CA-based model was applied for simulation of the front of a wildfire that burned a part of DTNZ forests on December of 2010. Unfortunately, there is not a

Fig. 5 The adjacent and diagonal cells to calculate the slope angle



complete database of fires data in Hyrcanian forests of Iran at present. In this research, we tried to use the data of a wildfire in study area which its data (fire map, fire area, fire start point, etc.) was available for testing of capability of CA-based model. About other occurred fires which the fire polygons were available, the fire areas were very small to run cellular automata model or fire data in the fire time were not available to run this model.

The wildfire in DTNZ forests on December of 2010 occurred due to unknown causes somewhere near the North of these forests and was quickly fronted to the South by Southeast winds. The fire was extinguished around 11.5 h later, after burning of a forest area about 443.69 ha. Figure 6 shows the burned area map.

The first step of implementation of fire front model for actual fire in study area was to consider a confine for fire front simulation and to collect the actual fire data at fire time. The required data of actual fire for fire front simulation in study area (actual fire map, fire area, fire start point, etc.) were provided from MNRA (Table 7)

In the second step, the vegetation type and density maps of fire confine (before fire occurrence) provided from MNRA and elevation map provided from DEM of ASTER sensor were organized in GIS. Then, the state matrices of the elevation (including the values from 35 to 706), vegetation density (including sparse, normal, and dense), and vegetation type (including resistant to fire, medium resistant to fire, and sensitive to fire) were generated based on digital geographical data. For this purpose, the coding raster-file of vegetation density and type of the fire confine were created in GIS (Figs. 7 and 8). In addition, a coding raster-file of the elevation data for fire confine was created in GIS (Fig. 9). Finally, a raster-file of the fire confine (including the burned area) was created in GIS (Fig. 6).

Based on these digital files, a raster data file was built, containing the values of all the aforementioned variables and overlaid on the grid. The side of the square grid was selected equal to 25 m. This selection was sufficient enough to give a crisp image and representation of the

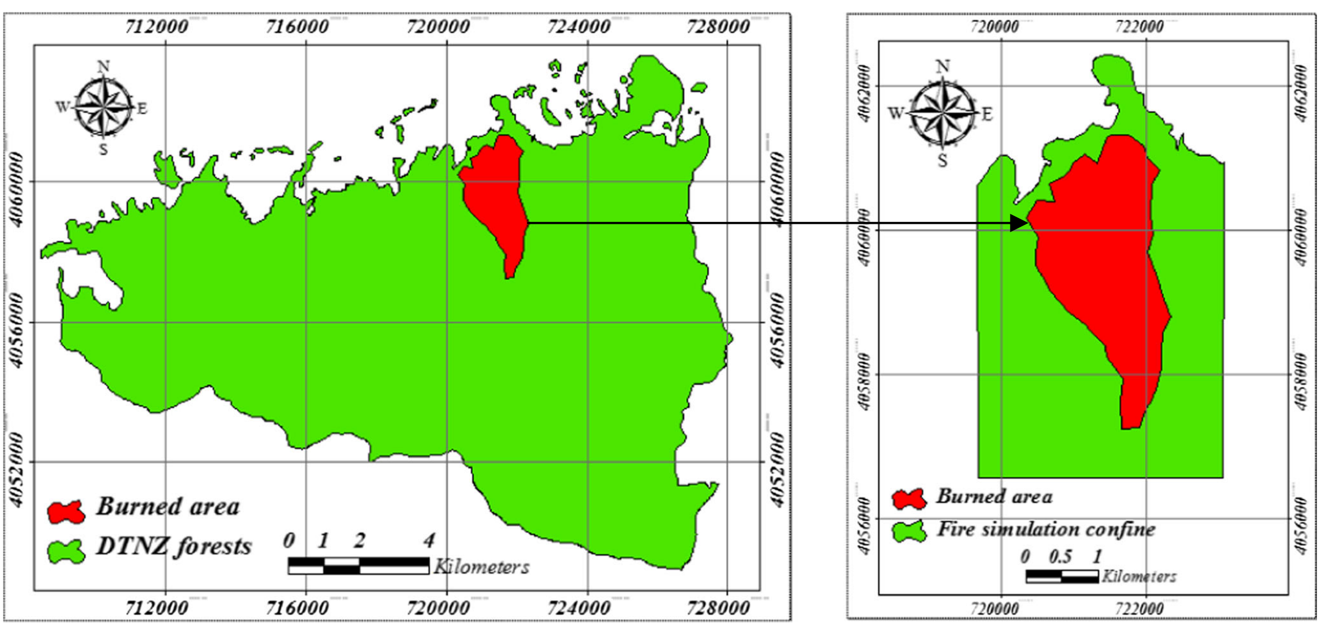


Fig. 6 The burned area (actual fire) in DTNZ forests

Table 7 The actual fire data in the study area

Fire area (ha)	Number of burned cells in fire simulation confine	Number of unburned cells in fire simulation confine	Fire start point
443.69	7100	18,706	Northwest of fire polygon

geographical data. Finally, all raster files were converted to ASCII files in GIS. Based on the ASCII files of altitude, vegetation density and vegetation type matrices, together with a matrix containing the burned area provided in MATLAB, the fire front simulation environment was created.

The wind conditions for fire day in the study area were provided from MMA (the wind data in the nearest meteorological station to the fire start point). These data were used to include the wind effect in fire front simulation. As the fire area was not very extensive (4.43 km^2), wind speed and direction were considered the same for all the cells in fire day. Thus, wind direction was considered Southeast and wind speed was considered 9 m/s in programming of fire front model in MATLAB. It is noted that the wind speed and direction usually do not change in the

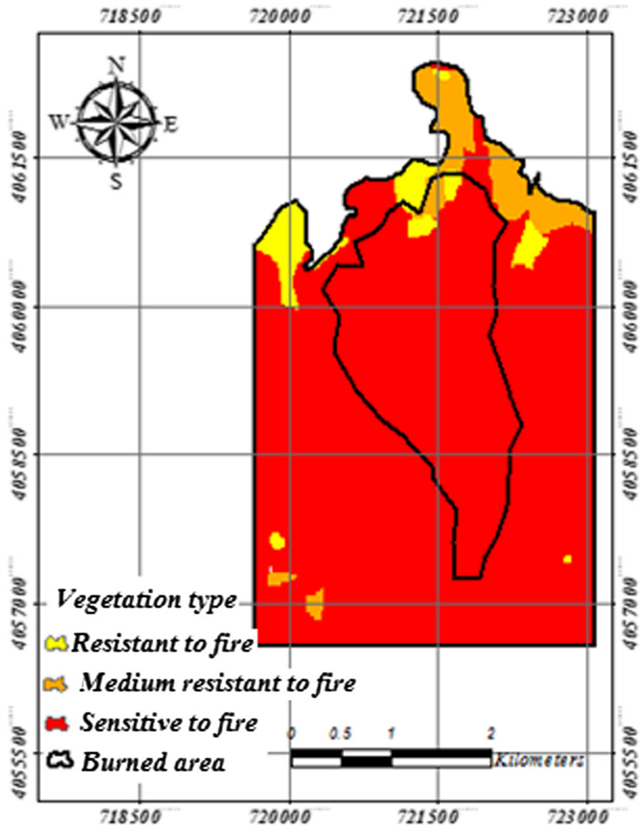


Fig. 8 Vegetation type map of fire confine

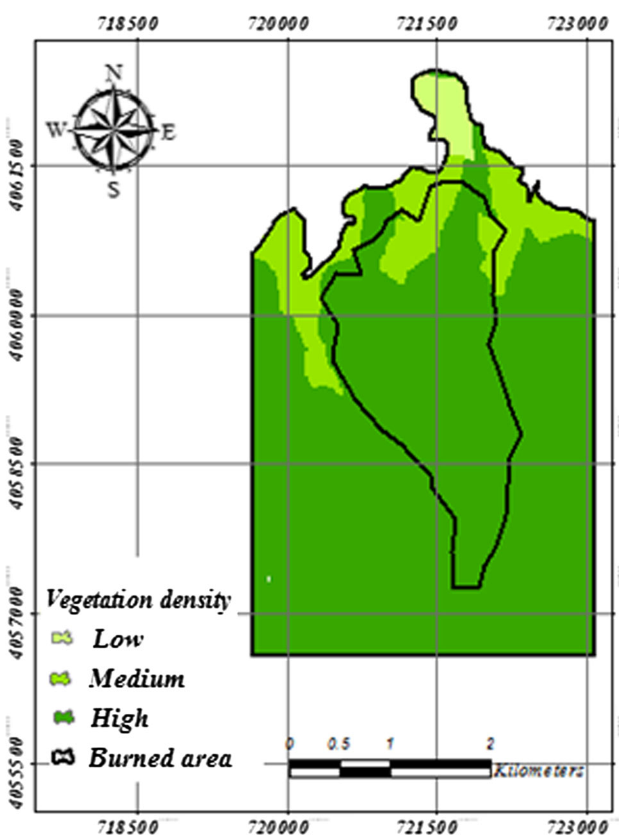


Fig. 7 Vegetation density map of fire confine

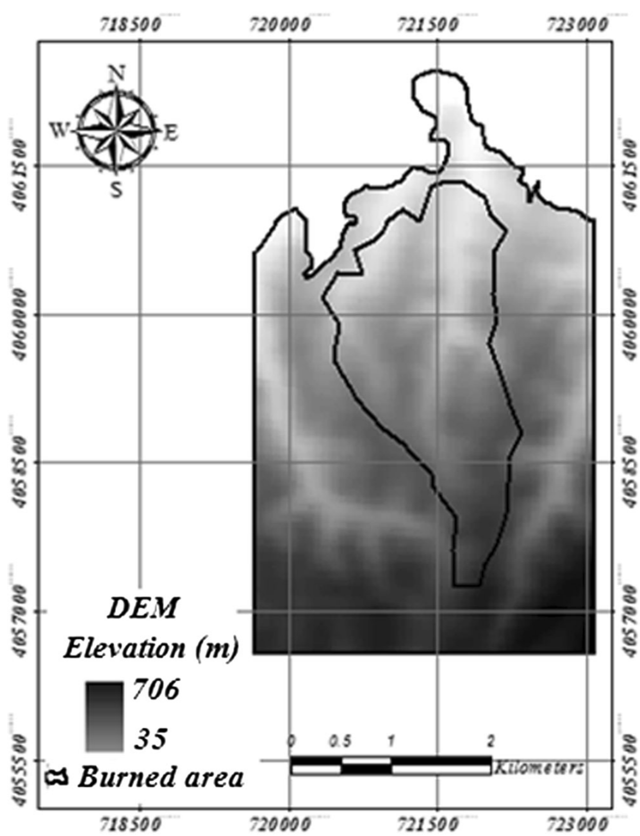


Fig. 9 Digital elevation model of fire confine

Table 8 Wind conditions at DTNZ forests in fire time

Variable	Description
Wind direction	Southeast
Wind speed	9 m/s

small areas in the nature too. The wind conditions in fire day have been given in Table 8.

The fire front model was programmed in MATLAB and it was implemented by uploading of all digital layers (coding ASCII matrices) of effective variables and considering of the certain wind speed and direction in fire confine. The fire front simulation was run by considering of fire start point coordination and the dynamic exhibition of fire front was depicted in MATLAB. The burning probability of each cell was based on P_{burn} during fire front simulation process. At each step of the fire front, the entire fire incident was simulated until the fire stopped (no burning cells). Finally, the number of burned and unburned cells in fire confine matrix was obtained in MATLAB when the fire front simulation process was ended.

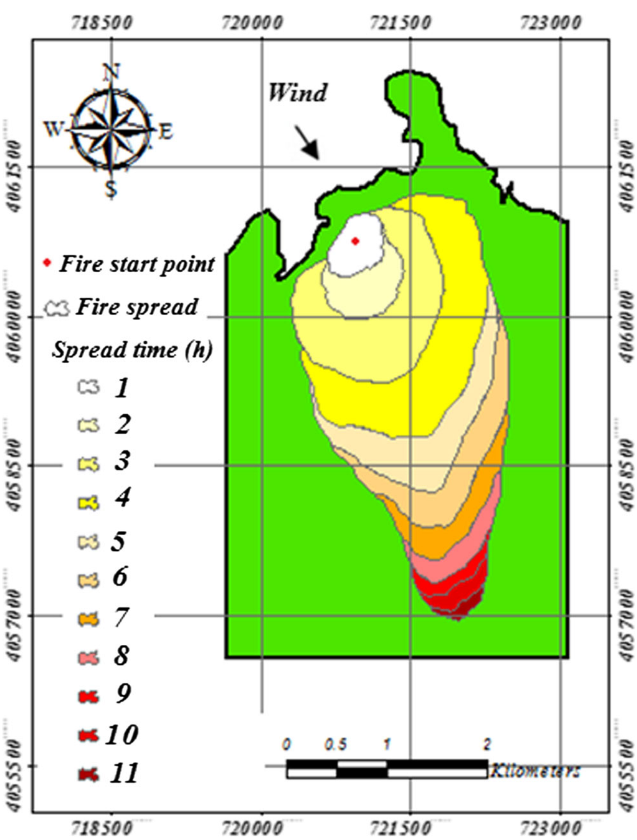


Fig. 10 The burned area predicted by the simulation (the fire start point has been shown by *red point*; while the fire front evolution has been marked by the *color contours* depicting 1-h intervals)

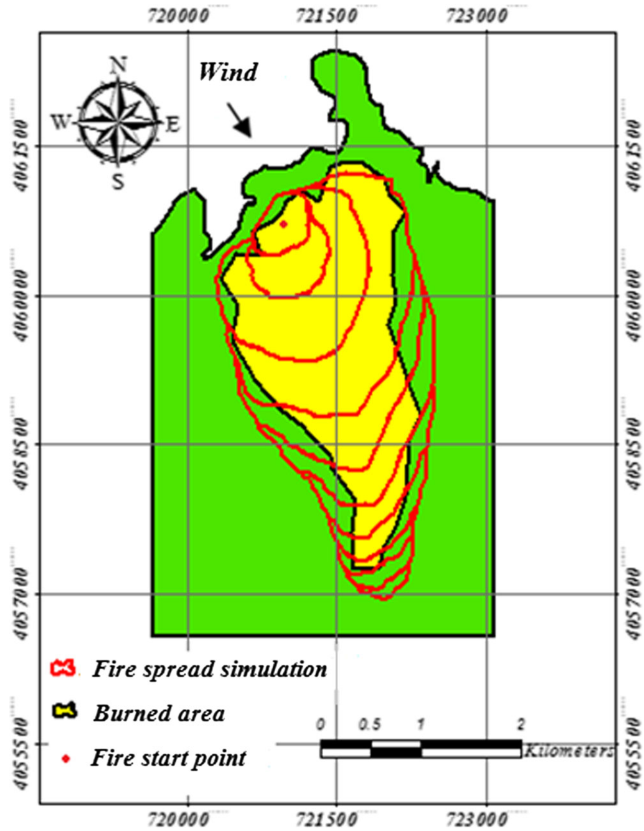


Fig. 11 Overlaying of the simulated fire and the actual fire

Validation of CA-based fire front model

Results of model implementation including fire front direction and shape were compared to the actual fire confine to evaluate the accuracy of the CA-based model qualitatively. Thus, the fire front polygon (CA-based model output) was overlaid on the actual fire polygon.

In addition, error matrix was created to compare the number of burned and unburned cells in the simulated fire and the actual fire to evaluate the accuracy of the CA-based model quantitatively. In error matrix, the real data are organized in the rows while the simulation data are organized in the columns. Finally, total accuracy and Kappa index were calculated by error matrix. Kappa index computes the frequency with which the simulated

Table 9 Error matrix obtained from comparison of actual fire data and simulated fire data

		Simulated fire		
		Burned cells	Unburned cells	Total
Actual fire	Burned cells	7021	79	7100
	Unburned cells	2870	15,836	18,706
	Total	9891	15,915	25,806

Table 10 Accuracy of the CA-based fire front simulation model

Area of predicted (simulated) burned region (ha)	Area of actual burned region (ha)	Kappa index	Total accuracy
618.23	443.69	0.74	0.88

area agrees with the observed area, with an adjustment that takes into account agreement by chance (Filippi et al. 2014). The value of Kappa index is from 0 to 1. Kappa index was calculated as follows:

$$\hat{k} = \frac{n\sum_{i=1}^{j} n_{ii} - \sum_{i=1}^{j} n_{i+} n_{+i}}{n^2 - \sum_{i=1}^{j} n_{i+} n_{+i}} \quad (7)$$

Where $\hat{k}$ is Kappa index; n is the total number of observations; n_{i+} is the number of observations in row i; n_{+i} is the number of observations in column i; n_{ii} is the number of observations in main diagonal of the matrix; and j is the number of rows in the matrix.

Results

Implementation of CA-based fire front model

The results of the fire front simulation by CA-based model in the actual fire confine have been shown in Fig. 10. The color contours show the evolution of the fire in time intervals of 1 h. In our simulations, the fire burned a total area of 618.23 ha. The actual forest fire burned a total area of 443.69 ha.

Validation of CA-based fire front model

The fire front polygon (CA-based model output) was overlaid on the actual fire polygon to evaluate the accuracy of the CA-based model qualitatively (Fig. 11).

The error matrix to evaluate the quantitative accuracy of the CA-based model has been shown in Table 9. In addition, the evaluating of the accuracy of the CA-based fire front simulation model based on total accuracy and Kappa index has been shown in Table 10.

Discussion

This research was done to simulate the fire front in a part of Hyrcanian forests of Iran using a CA-based model. Data of an actual fire in the study area was used for fire front simulation. In fact, the CA-based model was implemented for simulation of the front of a wildfire that burned a part of DTNZ forests on December of 2010. All simulation steps were done by cellular automata based on cell states and rules. The fire front simulation was run by considering of fire start point coordination. Finally, the dynamic exhibition of fire front was depicted in MATLAB. The number of burned and unburned cells in the fire confine matrix was obtained in the end of simulation.

Results of CA-based model output including fire front direction and shape were compared with the actual fire confine to evaluate the accuracy of the CA-based model qualitatively. In the simulation process, fire conditions were considered just like fire conditions of the actual fire on December of 2010. Whereas the fire start point in actual fire had been located in the North of study area, the fire start point in simulation model was also selected in the same location. In addition, the wind direction in simulation model was also considered just like the wind direction in actual fire (Southeast). Thus, fire in simulation model was fronted from the North to the South of study area after selecting of the fire start point. Notice that the increasing elevation and slope toward the South of study area (Fig. 9) which had been accompanied with the wind direction (Southeast), strengthened the fire front to the South of study area; because in all of the fire front models, if the dominant wind exists, wind direction will determine the fire front direction. Otherwise, topography will determine the fire front direction. In addition, vegetation type and density have the important roles in the fire permanence. In simulation of the fire front in this research, topography and wind direction had the most important roles in determination of fire front direction. In addition, the dense vegetation and sensitive vegetation to fire (Figs. 7 and 8) was provided the suitable conditions for fire front to the South of simulation confine. On the other hand, the actual fire on December of 2010 was also fronted to the South of study area based on some reports (MNRA 2011). Therefore, the results of CA-based model to predict the fire front direction seem satisfactory. This can confirm the high efficiency of cellular automata model in simulation of fire front in Hyrcanian forests of Iran. The capability of this model in fire front simulation has already been proved in other studies (Karafyllidis and Thanailakis 1997; Bodrožic 2006; Encinas et al. 2007a; Encinas et al. 2007b; Yassemi et al. 2008; Alexandridis et al. 2008; Almeida and Macau 2010; Pak and Hayakawa 2011; Innocenti and Cancellieri 2013).

The simulation results of the fire front have been shown in Fig. 10. In our simulation, the fire burned a total area of 618.23 ha in 11 h. The actual fire burned a total area of 443.69 ha in 11.5 h. The simulated fire front polygon (CA-based model output) was overlaid on the actual fire polygon to compare the simulated fire shape with the actual one (Fig. 11). Results showed that the shape of simulated fire is very similar to the shape of actual fire. This confirms that the CA-based model has had the satisfactory results in fire front simulation. In addition, Kappa index and total accuracy were used to evaluate the quantitative accuracy of the CA-based model. Results showed that Kappa index and total accuracy of CA-based model are 0.74 and 0.88, respectively. It can show the acceptable accuracy of the CA-based model to predict the fire front in Hyrcanian forests of Iran.

Finally, it is suggested that effect of the cell size would be investigated on the shape and process of fire front in the next studies. In addition, the effect of other factors such as temperature, relative humidity, and fuel moisture content (FMC) can be evaluated in fire front simulation in the next researches. Further, if the aforementioned factors show the important effects in fire front, they can be imported to the fire front simulation model in the future studies. In addition, the results of this study can be compared with the results of other fire front models (such as FARSITE) in the study area to find out the most proper model in the fire front prediction.

Conclusion

The results of this study showed that the CA-based model has the acceptable efficiency in prediction of the fire front in Hyrcanian forests of Iran. However, there were some limitations in this work. Unfortunately, there is not a complete database of fires data in Hyrcanian forests of Iran at present. In this research, we tried to use the data of a wildfire in the study area which its data was available for testing of capability of CA-based model. In addition, modeling of fire front based on effect of the wind speed and direction was one of the challenges of fire front modeling in the current study. So far, a proper model which can model the wind effect in fire front has not been presented, because wind as a fluid has a complex behavior especially in the gradient terrains. For this purpose, the wind modeling to consider its effect in fire front models should be done in the separate studies.

The capability of CA-based model in this study should be further evaluated by implementing it in different actual fires (in case of fire data availability) in Hyrcanian forests of Iran. It is noted that further improvements in this model may result the better predictions in fire front simulation. In this case, this model can present a good monitoring pattern for predicting of fire front direction in these forests. This pattern can be used as a decision support system for firefighting and allocating of facilities and human forces in the proper locations at the fire time in Hyrcanian forests of Iran.

References

Alexandridis A, Vakalis D, Siettos CI, Bafas GV (2008) A cellular automata model for forest fire front prediction: the case of the wildfire that swept through Spetses Island in 1990. Appl Math Comput 204: 191–201

Almeida RM, Macau EEN (2010) Stochastic cellular automata model for wildland fire front dynamics. Proceedings of the 9th Brazilian Conference on Dynamics Control and their Applications, Serra Negra, 249–253

Beer B (1989) The Australian national bushfire model. Proceedings of the 8th Biennial Conference and Bushfire Dynamics Workshop, Canberra, Australia, 568–572

Berjak SG, Hearne J (2002) An improved cellular automaton model for simulating fire in a spatially heterogeneous Savanna system. Ecol Model 148:133–151

Bodrožic L (2006) Forest fires front modeling using cellular automata approach. M.Sc. Thesis, University of Split, Split, Croatia, p 80

Encinas LH, White SH, del Rey AM, Sanchez GR (2007a) Simulation of forest fire fronts using cellular automata. Adv Eng Softw 38:372–378

Encinas LH, White SH, Rey AM, Sánchez GR (2007b) Modelling forest fire front using hexagonal cellular automata. Appl Math Model 31(6):1213–1227

Eskandari S, Chuvieco E (2015) Fire danger assessment in Iran based on geospatial information. Int J Appl Earth Obs Geoinf 42:57–64

Filippi JB, Mallet V, Nader B (2014) Evaluation of forest fire models on a large observation database. Nat Hazards Earth Syst Sci 14:3077–3091

Good RB, McRae RHD (1989) The challenges of modeling natural area ecosystems. Proceedings of the 8th Biennial Conference and Bushfire Dynamics Workshop, Canberra, Australia, 475–484

Innocenti E, Cancellieri D (2013) Randomizing activity in fire fronting simulations. ITM Web of Conferences 1, published by EDP Sciences, 1–16

Iudin DI, Sergeyev YD, Hayakawa M (2015) Infinity computations in cellular automaton forest-fire model. Commun Nonlinear Sci Numer Simul 20(3):861–870

Karafyllidis I, Thanailakis A (1997) A model for predicting forest fire fronting using cellular automata. Ecol Model 99(1):87–97

Kessell SR, Beck JA (1991) Development and implementation of forest fire modeling and decision support systems in Australia. Proceedings of GIS/LIS '91, Atlanta, USA, 2: 805–816

Li X, Magill W (2001) Modeling fire front under environmental influence using a cellular automaton approach. Complex Int 8:1–14

Mazandaran Natural Resources Administration (MNRA) (2010) Forestry plan of district three of Neka-Zalemroud forests. Iran's Forests, Rangeland and Watershed organization, Mazandaran, Iran

Mazandaran Natural Resources Administration (MNRA) (2011) Statistics and data of fire in 2010 in Mazandaran, Sari. Protection unit of MNRA, Mazandaran, Iran

McRae RHD, Sharples JJ, Fromm M (2015) Linking local wildfire dynamics to pyroCb development. Nat Hazards Earth Syst Sci 15:417–428

Ohgai A, Gohnai Y, Ikaruga S, Murakami M, Watanabe K (2004) Cellular automata modeling for fire fronting as a tool to aid community-based planning for disaster mitigation. In: Van Leeuwen JP, Timmermans HJP (eds) Recent advances in design and decision support systems in architecture and urban planning. Kluwer Academic Publishers, Dordrecht, pp. 193–209

Pak SI, Hayakawa T (2011) Forest fire modeling using cellular automata and percolation Threshold Analysis. Proceedings of American Control Conference, San Francisco, USA, 293–298

Pastor E, Zarate L, Planas E, Arnaldos J (2003) Mathematical models and calculation systems for the study of wildland fire behaviour. Prog Energy Combust Sci 29:139–153

Rochoux MC, Emery C, Ricci S, Cuenot B, Trouvé A (2015) Towards predictive data-driven simulations of wildfire front—part II: Ensemble Kalman Filter for the state estimation of a front-tracking simulator of wildfire front. Nat Hazards Earth Syst Sci 15:1721–1739

Von Neumann J (1966) The theory of self-reproducing automata. University of Illinois Press, Urbana, p. 388

Yassemi S, Dragicevic S, Schmidt M (2008) Design and implementation of an integrated GIS-based cellular automata model to characterize forest fire. Ecol Model 210:71–84

Yongzhong Z, Feng ZD, Tao H, Liyu W, Kegong L, Xin D (2004) Simulating wild fire fronting processes in spatially heterogeneous landscapes using an improved cellular automaton model. Proceedings of Geoscience and Remote Sensing Symposium IGARSS '04, Anchorage, AK, USA, 3371–3374

Yongzhong Z, Youhao E, Tao H, Songbing Z, Jihe W (2005) A CA-based information system for surface fire fronting simulation. Proceedings of Geoscience and Remote Sensing Symposium IGARSS '05, Seoul, South Korea, 3484–3487