



A novel agent-based model for forest fire prediction

Saeed Behzadi^{1*}, Zahra Mousavi²

¹ Department of Survey Engineering, Faculty of Civil Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran

² Department of Natural Resources and Environment, Islamic Azad University, Science and Research Branch, Tehran, Iran

Article history:

Received: 8 February 2019, Received in revised form: 26 August 2019, Accepted: 10 September 2019

ABSTRACT

In recent years, forest fires have increased drastically due to global warming. Forest fire prediction is the best way to control the spread of fire. Therefore, several studies have focused on developing models that predict the behavior of forest fires. Predicting fire spread and its behavior is crucial to mitigate the adverse effects on weather conditions, environment, and human activities. Improving forest fire prediction using higher quality data can be expensive. In some cases, obtaining or even precise estimation of these data is difficult. On the other hand, using prediction models are more reasonable and feasible to increase prediction accuracy. In this paper, we introduced a novel Belief-Desire-Intention (BDI) agent-based model to predict the behavior of forest fires in the Mazandaran region in the north of Iran. This paper attempted to map the concepts of BDI agent architecture into generic GIS. A novel BDI-GIS model was then proposed in which an agent's belief, desire, and intention were defined based on spatial or non-spatial data and GIS functions. Therefore, an agent-based model was developed to determine the prediction of forest fires and implemented it on a real dataset. The experimental results showed that the proposed model could be successfully applied to the real-world scenarios with a Kappa Coefficient of more than 68.2%.

KEYWORDS

GIS
Agent-based model
Forest fire prediction
Belief
Intention
Optimization

1. Introduction

Fire agencies aim to prevent forest fires before they have an impact on the environment. Forest fires impose severe problems in this area. Forests are the primary resource for providing oxygen and clean weather in the world. Protecting forests is an important task especially in regions that have lightning or are burning out of control due to the dry conditions as the major reasons for forest fire ignition. Annually, about 1-4 billion tons of carbon is released into the atmosphere by forest fires all over the globe (Andreae and Goldammer, 1992). The prediction of fire propagation across landscapes is necessary for safe and effective fire management. Fire simulation provides a valuable tool for handling fires and consequent contaminations.

Forest fires usually spread at high speeds from their originating point. Their direction unexpectedly changes, and they are capable of passing the barriers such as roads, rivers, and fire-breaks. The ignition can be initiated by lightning,

sparks from rock-falls, spontaneous combustion, volcanic eruptions, coal seam fires, extreme heat in the environment, and human negligence. The fire can be prevented by isolating the spread by trenches in the ground, spray of sand, water, and chemicals. The hazards include loss of human and animal lives and forest resources. Smoke, ash, and dust damage the lungs and respiratory systems.

Recently, humans are facing the risk of increasing population density, creeping urban sprawl from the incursion into the wild-land urban interface (WUI), and from changes in land-use patterns that conflict with societal and ecological protection. Climatic and weather condition changes are exacerbating these problems (Tedim et al., 2015).

The main reasons causing uncontrolled fires are a combination of severe drought, destructive logging practices, and slash-and-burn agriculture. During protracted dry seasons, drought stress causes evergreen trees to shed their leaves, particularly in logged-over areas (Heyer et al., 2018;

* Corresponding author

E-mail addresses: behzadi.saeed@gmail.com (S. Behzadi); mousaviz881@gmail.com (Z. Mousavi)

DOI: 10.22059/eoge.2020.283932.1051

Young et al., 2019). In general, if the precipitation falls below 100 mm/month, and if there is no precipitation for two or more weeks, the forest vegetation sheds its leaves progressively with increasing drought stress. Besides, the remnants of the deadwood left after felling this accumulated dry litter lead to a rapid spread of an uncontrolled fire (Goltenboth et al., 2006).

Forest fire prediction has been the focus of many studies in various countries since its inception in the 1920s. Chen and Chen (2015) used a given day's highest temperature, temperature variation, the accumulated period without rainfall, and drought index as weather factors for deriving forest fire in Hsiao. In that study, they also considered space and time variations in weather factors using the GIS system to conduct temperature and rainfall space-time estimates and also to rate forest fire hazards for forests in Taiwan. The methodology used in (de Groot et al., 2015) and (Herrera, 2016) were also similar but with different case studies.

Forest fires have influenced the contemporary physical, chemical, and biological properties of streams and lakes. The increases in sulfate and nitrate and hydrological outputs from streams in burned areas persist from a few to several years, depending on fire severity, weather and climate (ROSENBERG et al., 2005).

There are several ways of modeling forest fires. Recently, machine learning algorithms have helped researchers to model the problem. The methodologies introduced by (Thach et al., 2018) and (Bui et al., 2018) are some examples that are based on machine learning for forest fire prediction. For instance, a new machine learning method, named as DFP-MnBpAnn, was developed based on Artificial Neural Network (ANN) for spatial modeling of forest fire hazards (Bui et al., 2018). The study conducted by (Hodges et al., 2019) was another case that used ANN for fire prediction. Hodges et al. (Hodges et al., 2019) presented a data-driven approach to predict spatially resolved temperatures and velocities within a compartment based on zero-dimensional zone fire modeling using a transpose convolutional neural network (TCNN).

With the advent of remote sensing, forest fire data and analysis have been modified. (Schroeder et al., 2016), (Vidal and Devaux-Ros, 1995), and (Nurdiana and Risdiyanto, 2015) are among some researchers who used Landsat images for forest fire prediction. Furthermore, Reddy and Satish (2018) used multi-temporal Landsat and Indian Remote Sensing satellite data to quantify burnt forest areas. In China, ground-based data of forest fires at the county level have been used to study forest fires and five relevant factors: climate, fuel, topography, human activity, and firefighting facilities at regional and local scales. The results provided a first ground-based snapshot of forest fire patterns in China at a high spatial resolution, revealed different features of natural- and human-caused forest fires, and highlighted the

spatial variation of fire drivers (Ying et al., 2018). Murthy et al. (Murthy et al., 2019) tried to understand a wildfire in the Himalayan foothills through fine-scale analysis of fire incidences. They built a temporal model with spatially explicit information on anthropogenic, bio-physical, and climatic variables to develop a fire risk map.

Cellular Automaton (CA) is one of the new algorithms which is widely used in spatial issues such as forest fire prediction (A Hernández Encinas et al., 2007a; Ghisu et al., 2015; L Hernández Encinas et al., 2007b). By integrating the Extreme Learning Machine (ELM) with the CA framework, a new cellular automaton modeling approach was proposed for the simulation of forest fire spreading. In that research, CA was used to simulate complex mechanisms of fire spreading (Zheng et al., 2017). In order to predict the behavior of wildfires, a two-dimensional mathematical model was considered, which was derived by averaging the three-dimensional equations over the thickness of the forest fuel material layer (Kuleshov et al., 2013). At a local scale, a 3D multi-physical model referred to as "FireStar3D" was developed for forest fire (Morvan et al., 2018). Moreover, Iudin et al. (Iudin et al., 2015) applied new arithmetic to a CA forest-fire model connected to the percolation methodology, and in some sense, integrated the dynamic and the static percolation problems, which would exhibit critical fluctuations under certain conditions. They discovered that both instantaneous forest combustion and stepwise firing could be revealed by using the same cellular automaton forest-fire model. In another study, Hamilton–Jacobi equations were used to model wildfire spread (Fečkan and Pačuta, 2018). Besides, a new fuzzy-based model was introduced for the calculation of plant growth potential in the context of forest development simulation, which has become an important tool for prediction and monitoring of forest biodiversity. The enhanced expressiveness about the tolerance of tree species for deviation of growth conditions allows fuzzy models to improve the accuracy of forest composition prediction concerning the crisp model (Strnad et al., 2018).

The accuracy of the predicted model was analyzed by calculating error statistics and compare model predictions with observed spread rates of field observations of wildfires and prescribed fires. Comparing the changes in error metrics of older models to newer ones showed the new one to be better (Cruz et al., 2018).

Ager et al. (2018) developed and applied a wildfire simulation package in the Envision agent-based landscape modeling system. They said that the Wildfire package combines statistical modeling of fire occurrence with a high-resolution, mechanistic wildfire spread model. This package can capture fine-scale effects of fire feedbacks and fuel management, and replicate restoration strategies at scales that are meaningful to forest managers. Their study revealed

that the potential for fire-on-fire feedbacks was higher for human versus natural ignitions due to human ignition hotspots within the study area (Ager et al., 2018).

Agent-based modeling (ABM) is a powerful simulation modeling technique that has been frequently used in the last few years, including its applications to real-world business problems. In ABM, a system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions based on a set of rules. Agents may execute various behaviors appropriate for the system they represent (Bonabeau, 2002). For example, Niazi et al. (2010) presented the verification and validation of an agent-based model of forest fires. By using a combination of a Virtual Overlay Multi-Agent System (VOMAS) and a Fire Weather Index (FWI), the forest fire Simulation was validated. In this study, each virtual "sensor" agent uses FWI to calculate fire probability and compares it with the simulation model. They concluded that VOMAS verification and validation methodology for agent-based models would allow for interactive design of Agent-Based Models involving both the Simulation Specialists as well as the Subject Matter Experts (Niazi et al., 2010).

Furthermore, a designing of fire suppression simulation can be conducted using a discrete event agent model based on a discrete cellular space (Hu and Sun, 2007). Hu and Sun (2017) presented a framework of wild-land fire suppression simulation and described how firefighters' direct attack, parallel attack, an indirect attack were modeled. Experimental results were also provided to demonstrate the agent models and to compare them in different fire suppression scenarios.

The behavior of a system can be estimated by simulating

the actions of each entity within the system, including how these entities interact with each other or how they are affected by physical and social factors of the surrounding environment. Thus, in the current study, this method is used for modeling forest fire and estimating the behavior of broadcasting fire in an area.

In this paper, an agent-based model is proposed to handle forest fire prediction. In this architecture, agents try to understand the conditions of the problem by generating and arranging some cells, and then they use these cells to solve the problem. This paper first reviews and identifies the basic concepts of agents. All concepts of spatial-agents are then translated to the spatial domain. Section 3 of this paper is devoted to a case study - prediction of forest fire spread- in which a detailed implementation of the newly introduced architecture is elaborated. The final section of this paper is discussing the obtained results.

2. The Proposed Method

Figure 1 shows the proposed Agent-Based method, which handles spatial problems. The agent observes spatial data and generates its specific database. This procedure is planned based on the structure of the problem. Then, the agent's belief is produced based on its action and its database. A combination of the agent's belief and the goal is used to generate the agent's desire. The agent's intention is also important in generating its desire. An optimization operator such as a genetic algorithm (GA) can be used to generate such an intention. Finally, the intention generated by the agent is converted to action based on the agent's commitment. The followings are a detailed description of our proposed architecture.

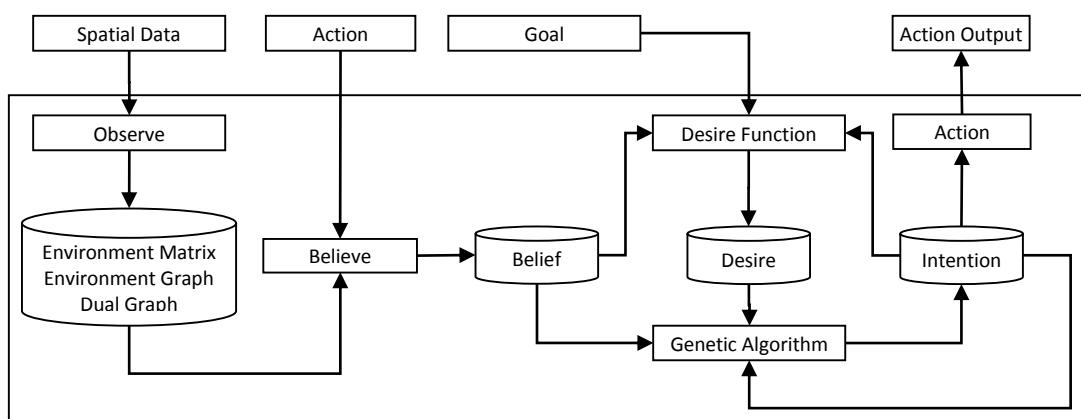


Figure 1. The proposed architecture for handling spatial problems.

2.1. Environment

Environment (E) is a space in which agents are present. The environment can be sensed by agents and modified by their actions. Time, position, and attributes are the three fundamental components of a GIS entity. In the proposed

architecture, the spatial dataset forms the environment. Such an environment is a set of sub-environments (e_i) that varies in time. Each sub-environment consists of one or more layers of data (L_j^i), having one positional (Pos^j) and one or more information attributes ($att_{m_j}^j$). Therefore, each layer is

shown as a set of positions and attributes.

2.2. Agent

An agent is an entity that is put in the environment to do some action based on its perceptions to achieve its goal (Arend Ligtenberg et al., 2010). In an agent-based model, a set of agents are working in the environment, each of which is trying to attain its goals based on the competition and cooperation with others (Tweedale et al., 2007). To define agents in the environment, it is necessary to specify the perception, action, competition, and cooperation of the agent.

- **Agent’s Actions**

Agents make some changes (in this paper, referred to as *actions*) in positions and attributes. The changes are made to reach the goals. Agents try their best to satisfy their predefined goals. Actions also play an effective role in defining the number of agents – more actions require more agents. In his paper, actions are classified into two general categories: 1) changes in the attribute information ($att_{m_j}^j$), and 2) changes in position (Pos^j). When an agent is put in an environment, the class of agent’s action (one of the above two cases) must be specified.

- **Agent’s Goals**

The outcome expected from the whole system is called the

goals. These goals are divided into several sub-goals which the agent wants to accomplish in the environment. In practice, the goal is used in two different parts of the package: 1) in environment evaluator - it is part of the package which assesses the action of agent performed on the environment, and 2) in generating the agents.

- **Agent’s Observation**

To achieve the goals, an agent needs to sense the environment. In this method, the set of information on the environment and the determined actions is considered as a set of tuples. In each epoch of time (e_i), information is put in a matrix named “*Environment Matrix*,” therefore, the number of environment matrices is equal to the number of time epochs. Environment matrix is a square matrix with its dimension equals to the total number of position and attribute information in set E . For instance if there are n layers in the environment and each layer (L_j^i) of information includes m_i attributes of information considering one position for each layer - the dimension of the matrix will be equal to $\sum_{i=1}^n (1 + m_i) \times \sum_{i=1}^n (1 + m_i)$. Figure 2 shows the environment matrix driven from a sample of the data layer in one epoch of time. The environment consists of four information layers; each layer has a varying number of attributes.

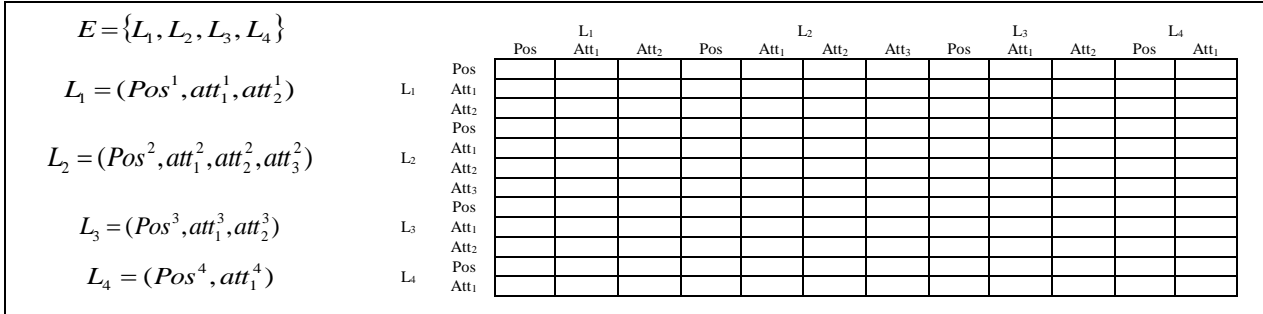


Figure 2. An environment matrix.

Each cell of the environment matrix represents the relationship between positions and attributes information. “*Environment Graph*” is presented to visualize the flow of the information, and the sequences of spatial analysis. The environmental graph is generated based on the environment matrix. If the environment matrix is considered as an adjacency matrix of a graph, then the position and attributes parts of a layer in the environment are regarded as nodes. Edges of this graph can show the relations among all nodes; therefore, each edge in the environment graph plays the role of each cell of the environment matrix. Environment matrix and graph are two different representations of the same phenomenon. The environment matrix shows the process done for solving the problem, while the environment graph represents the flow of the data among the component of the environment. Figure 3 shows the environment graph of a

sample environment matrix.

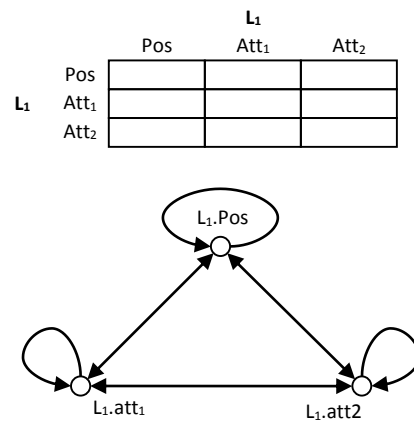


Figure 3. An environment matrix, and its environment graph.

• **Agent’s Belief**

In the geospatial information field, an agent’s belief is considered as the current state of the environment (A. Ligtenberg, Wachowicz, M., Bregt, AK., Beulens, A., Kettenis, DL, 2004). Therefore, an environment matrix can be considered as one part of agents' beliefs. The matrix is the same for all agents. The second part of agents' beliefs is about their actions, and therefore, this part varies. As assumed earlier, each agent can only do one action which can be the changes in position or attribute information of the environment. If the environment matrix is considered as an adjacency matrix of a graph, then the part of the data which

is supposed to be changed is considered as the end node and its associated position information is regarded as the start node. It is possible that the start and end nodes to be the same in the environment matrix. It happens when the agent wants to change position. In summary, the agent’s belief is the environment matrix plus the start and terminal nodes of the environment graph. Due to the differences in the start and end nodes of agents' actions, their beliefs are different. Each cell in the belief matrix has a specific name, and it is obtained from the name of its related row and column. Figure 4 shows the name of each cell in a sample belief matrix.

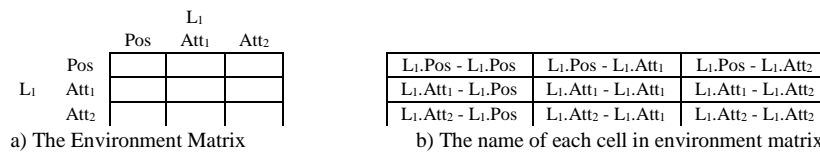


Figure 4. the name of each cell in the environment matrix of the Belief.

Each cell stores the current state of the environment related to its row and column. The cells of the belief matrix are categorized into four groups: cells which show the relation between position and position, position and attribute, attribute and attribute, and attribute and position. The structures of data stored in these groups are different from each other.

The existing spatial data are stored in cells related to position-position. In cells related to position-attribute, the current state between position and attribute is stored. In this case, if the cell in the belief matrix is related to the position and attribute of the same layer, the layer itself can show the relationship. However, if the cell is related to the position and attribute of different layers, a pattern recognition algorithm such as Neural Network (NN) plays the role of belief in the cell.

In cells related to attribute-attribute, the current relationship between these two attributes is considered as the belief. If both attributes are from the same layer, the probability of occurring the second attribute (related to the column) is obtained based on the first attribute (related to the row). If both attributes are from two different layers, the occurrence probability of the second attribute (regardless of the first attribute) is considered as the belief.

In cells related to attribute-position, the distribution of each type of attribute in the area is considered as the belief.

• **Agent’s Desire**

In the concept of the agent, desire is defined as option generation (Hall et al., 2005; Tweedale et al., 2007; Behzadi and Alesheikh, 2013), namely:

$$\wp(\text{Bel}) \times \wp(\text{Int}) \rightarrow \wp(\text{Des}) \tag{1}$$

Equation 1 states that an agent has different intentions (Int) based on the current state of the environment (Bel); the agent

assesses the results of its intentions on the belief concerning its goal (Des). The intention is defined as the processor of the agent; it tests different actions on the environment. This determines the behavior of the agent's desire based on the action. Intention function is defined based on some parameters (Int = I (P)). Equation 1 indicates that the desire of an agent is a function of its intention; therefore, the desire of an agent is a function of the parameters of intention (Des = D (P)). Therefore, both intention and desire functions are related to each other by an intermediate value of parameters. The intention is implemented on belief, more specifically, on the structure of belief. The belief is represented in the cells of the environment matrix; thus, the intention must be represented as the structure of the cells. Accordingly, the intention is also considered as a matrix with the same dimension of the belief matrix. The structure of the intention matrix is stemmed from the belief matrix. Each cell in the intention matrix has a specific name similar to those defined in the belief matrix. Each cell also has a definite state.

• **Agent’s Intention**

Numerous intentions have resulted from the previous section. This section is to determine the one that the agent selects. The intention of the agent is defined as (Casali, 2005):

$$\wp(\text{Bel}) \times \wp(\text{Des}) \times \wp(\text{Int}) \rightarrow \wp(\text{Int}) \tag{2}$$

Equation 2 shows that the agent must intend to the intention on the environment (belief) that successfully passes through the desire function. In our proposed architecture, the following process must be executed on the desire function to find acceptable intention values. The highest values of desire are the most favorable values of parameters for intention. The agent must consider other values of parameters as alternatives to work on if the highest values are not practical.

Based on the values obtained from desire functions, the values of parameters are prioritized using an optimization algorithm. Since each agent has only one goal, a single-objective genetic algorithm (SOGA) can be a useful optimizer. The optimizer estimates the value of parameters that has the highest desire. To specify the other values of parameters with less desire, it is important to determine the relative maximums of the desire function. These points are determined through rerunning the optimizer in the domain except for the highest values location. Therefore, the second maximum value of desire is obtained and the related parameters of this maximum value are considered as the second priority of the agent's intention.

- **Agent's Commitment and action**

The priorities of intention are known to the agent, but the type of commitment that each agent has specifies the preferences of the agent. Three types of commitments are: blinded, single-minded, and open-minded (Guerra-Hernández et al., 2009; Guerra-Hernández et al., 2008), each of which must be defined based on the structure of desire and intention of the agent in our proposed architecture. In blind commitment, the agent focuses only on the intention that has the highest desire. Single-minded commitment makes the

agent commit to the highest intention if achievable. Otherwise, the agent searches in the area around the highest intention. In open-mind commitment, the agent is allowed to drop an intention when it finds out the intention is unattainable, so it can intend to each of the intentions it wants. When the agent commits to the specific intention, it obtains the preference which must intend to do as an action.

3. Experimental Results

In this part, the main problem of forest fire is tried to be solved based on the structure of the proposed BDI-GIS. In this study, programming was accomplished using the MATLAB® package. Preliminary model validation was performed on a real forest fire case happened in the Mazandaran region in Northern Iran, on 12th of August, 2001. The fire began around 13:00 and lasted 14 hours. The region selected for this study is located between 53°47' to 53°52' E, and 36°34' to 36°37' N and has an area of about 36 km². At first, Alexandridis' model was calibrated using the available data, and then three different scenarios were generated. Three burned areas were considered: the first one was used for calibrating agents and the other two were used for prediction.

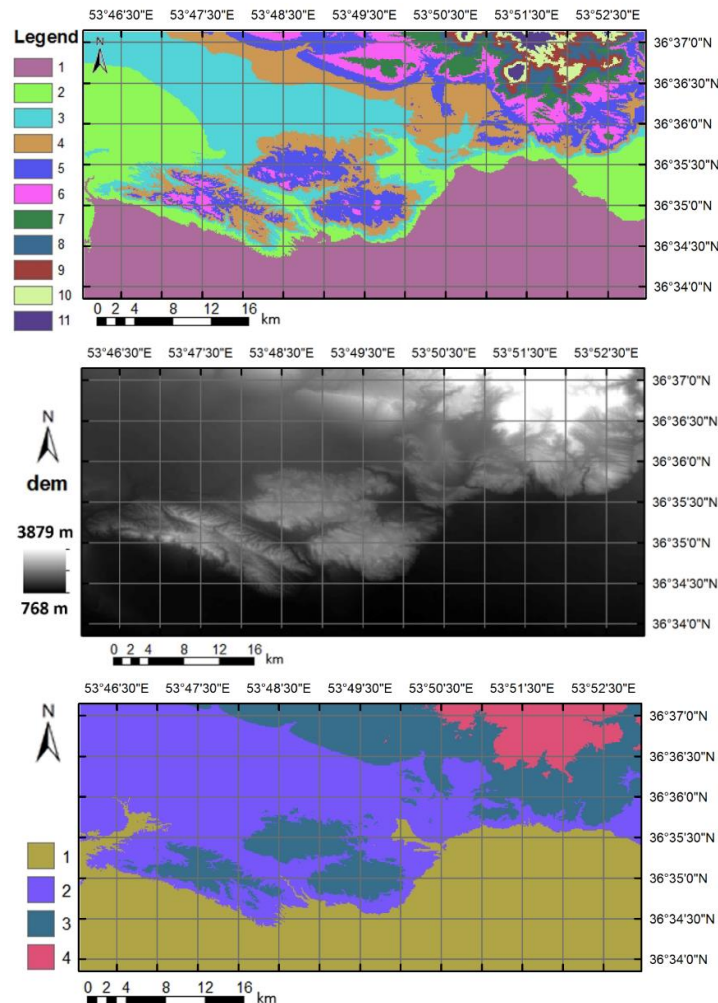


Figure 5. The case study for forest fire prediction, a) Density of vegetation, b) Elevation, and c) Types of vegetation cover.

Forest fire spread prediction was investigated by taking into account factors such as elevation, as well as the type and the density of vegetation. Each layer was considered as a two-dimensional grid tessellation. The structure of input data that the agent wanted to assess was composed of three layers. They included the states of altitude, vegetation density, and vegetation type (Figure 5). Vegetation density was categorized into eleven groups; the value of a cell showed its density. These values showed the desire for burning; the higher the value, the greater the tendency for burning. The vegetation type was also categorized into four groups based on burnability. The topography of the area (elevation) is a type of data that the agent needs for the process. Therefore, the environment is shown as:

$$\begin{aligned}
 E &= \{e_1\} \\
 e_1 &= \{Elevation, Vegetation, Density, BurnArea\} \\
 Elevation &= \{Pos, att\} \\
 Vegetation &= \{Pos, att\} \\
 Density &= \{Pos, att\} \\
 BurnArea &= \{Pos, att\}
 \end{aligned}
 \tag{3}$$

The action of the agent was defined as changing the attribute of one layer to a finite number: (N=1: there was no related data, N=2: The cell had not burned, N=3: The cell was burning, N=4: The cell had been burned). The similarity between the agent's action and the ground truth was considered as the goal of the agent; if the differences were slight, the agent would obtain more profit from the evaluator of the environment. Since only one action and one goal were defined for this problem, only one agent was generated.

The agent observed the environment, and the environment matrix was generated (Figure 6a) as the result of the observation. Based on the environment matrix, the environment graph is generated (Figure 6b). The environment matrix shows the computation, while the flow of the data is better seen in the environment graph. The action of the agent (BurnArea.Att) determined specific nodes in the environment graph and also specific row and column in environment matrix (as seen in Figure 6).

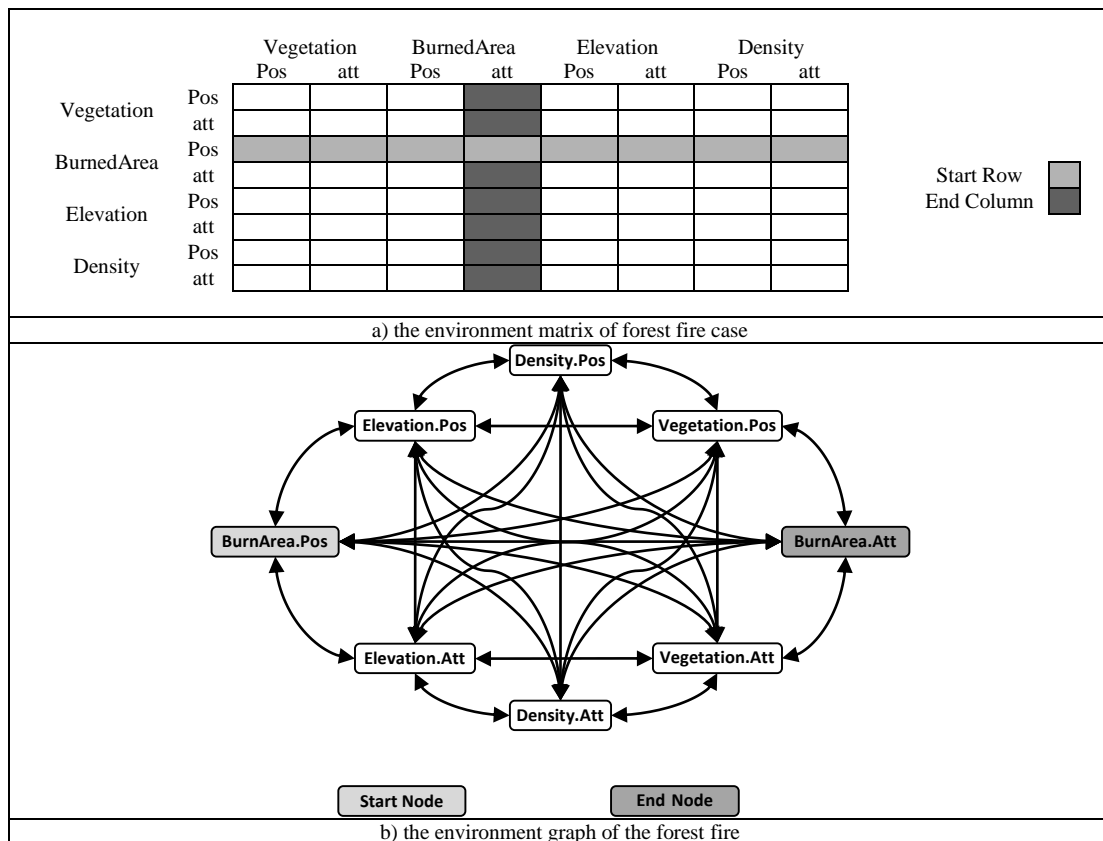


Figure 6. a) The environment matrix, and b) The environment graph of forest fire prediction.

Three different events of forest fire were investigated. In the first event, the agent recognized the structure of the environment parameters, and then the other events were used to assess the behavior of the agent for forest fire prediction. In the first event, the belief of agent

(Figure 7) and the best value of parameters that made the highest desire for the agent were obtained; these parameters generated the specific intention for the agent (Figure 8).

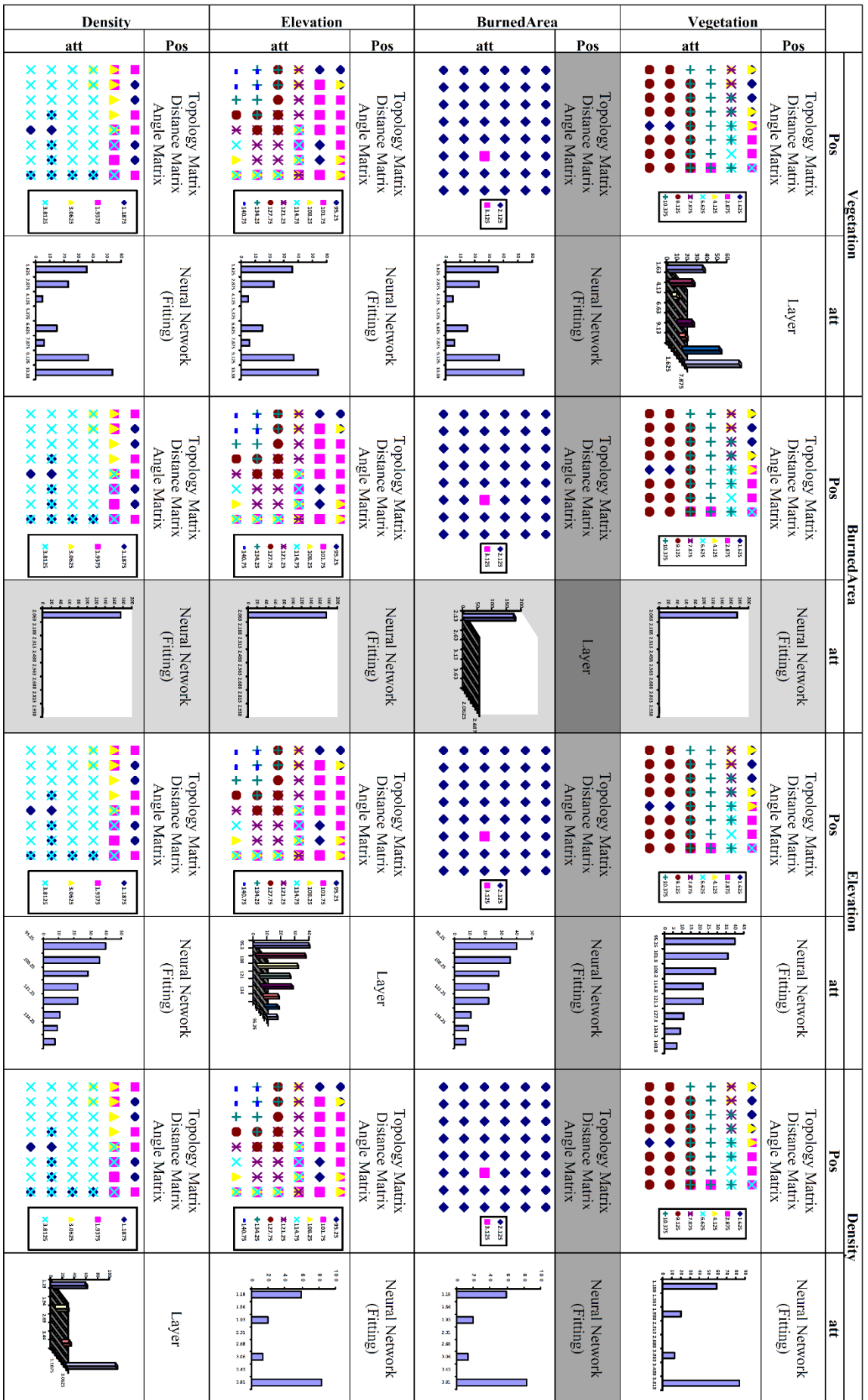


Figure 7. The belief of an agent.

		Vegetation		BurnedArea		Elevation		Density	
	Pos	att	Pos	att	Pos	att	Pos	att	Pos
Density	att			att			att		
	Pos	 Distance = 11.08 Topology: 'meet'	 Distance = 8.24 Topology: 'disjoint'	 Distance = 8.31 Topology: 'meet'	 Distance = 7.35 Topology: 'containdly'	Pos	 Distance = 5.79 Topology: 'overlap'	 Distance = 7.63 Topology: 'meet'	 Distance = 11.08 Topology: 'meet'
Elevation	att			att			att		
	Pos	 Distance = 5.52 Topology: 'meet'	 Distance = 8.12 Topology: 'disjoint'	 Distance = 11.08 Topology: 'containdly'	 Distance = 7.14 Topology: 'disjoint'	Pos	 Distance = 5.33 Topology: 'contain'	 Distance = 5.33 Topology: 'contain'	 Distance = 3.09 Topology: 'meet'
BurnedArea	att			att			att		
	Pos	 Distance = 5.36 Topology: 'meet'	 Distance = 5.33 Topology: 'contain'	 Distance = 5.33 Topology: 'contain'	 Distance = 3.09 Topology: 'meet'	Pos	 Distance = 7.63 Topology: 'meet'	 Distance = 7.63 Topology: 'meet'	 Distance = 11.08 Topology: 'meet'
Vegetation	att			att			att		
	Pos	 Distance = 5.79 Topology: 'overlap'	 Distance = 7.63 Topology: 'meet'	 Distance = 11.08 Topology: 'meet'	 Distance = 11.08 Topology: 'meet'	Pos	 Distance = 5.33 Topology: 'contain'	 Distance = 5.33 Topology: 'contain'	 Distance = 3.09 Topology: 'meet'

Figure 8. The intention of the agent that obtained the highest desire.

The representation of the agent's belief can be categorized into four groups: the belief about position-position, position-attribute, attribute-position, and attribute-attribute relationships (Figure 7). The agent's belief about the position-position relationship is defined as the agent's perception of the spatial relationship between entities. In this case, topological relationship, distance, and angle among entities are obtained and stored in the agent's database. So, the components B_{ij} ($i=1, 3, 5, 7; j=1, 3, 5, 7$) of the belief matrix show the agent's belief between the position of one layer to the position of another layer. In this case, the topological relationship, distance, and angle of all entities in the first group related to the entities of the second group were calculated and considered as the current state of the environment for those parts of the data. The belief of the agent about position-attribute cells clarifies how the current relationship between position and attribute is. In this case, if the position and attribute were from the same layer, that layer can be the best way for expressing the current state as seen in $B_{12}, B_{34}, B_{56},$ and B_{78} components of belief matrix. But, if the attribute and position are from different layers, a model which exposes the distribution of attribute in the area is needed. A neural network model was used in the rest of the position-attribute cells of the belief matrix. The agent's belief toward attribute-position presents the distribution of each value of the attribute in the area. Thus, the current state of the relationship between attribute and position was obtained (B_{ij} components of the belief matrix ($i=2, 4, 6, 8; j=1, 3, 5, 7$) showed such a relationship). The attribute-attribute cells of the belief matrix show how much the attributes of different layers are related to each other. If both attributes are from the same layer, that layer can be used for extracting the frequency of occurrence each value of the first attribute to the ones of the second attribute. But if both attributes are not from the same layer, the frequency of occurrence of the values of the second attribute is regarded as the belief of the

agent for attribute-attribute cells.

Figure 8 shows the intention of the agent for achieving its goal. The value of the matrix can be categorized into four groups: the intention related to position-position, position-attribute, attribute-position, and attribute-attribute. For each part of the matrix, based on the type of the cells, and the calculation is done by the agent, the best value for intention parameters are estimated. The value for position-position cells in intention matrix shows the type of topology, distance, and angle which the agent selects as its intention to define the relationship of the second part of the data (column part) to the first part of the data (row part) in the matrix. Based on these values, the entities of the second layers (entities related to the column) are selected based on the entities of the first layer (layer related to the row of the matrix). The intention of the agent toward position-attribute is shown by a two-dimensional polynomial, so the magnitude of the value of the attribute in each position is shown by bubbles in Figure 8. The intention of the agent for attribute-position cells is defined as $F(x, y, att)$ function. In these cells, each layer of the function shows the distribution of the value of the attribute. Therefore, the cells of the intention matrix related to attribute show the distribution of each value of the attribute in the area. The intention of the agent for attribute-attribute cells is a table whose values show the frequency of synchronous occurrence of the values of both attributes. The histogram of values of this table is shown as the intention of the agent for attribute-attribute cells.

This intention is considered as the intention of the agent for the other two events of forest fire prediction. The resulting action of this intention was performed on the environment for these two events, and then the burned area that the agent predicted was obtained.

The result of the agent's prediction and the actual-observed results were compared as shown in Figure 9, and Table 1.

Table 1. A comparison between agent prediction and actual-observed data.

Event 1				
		Actual-observed data		
		Burned cell	Unburned cell	Total
Agent prediction	Burned cell	164553	97797	262350
	Unburned cell	192	884652	884844
	Total	164745	982449	1147194
Event 2				
		Actual-observed data		
		Burned cell	Unburned cell	Total
Agent prediction	Burned cell	183501	187188	370689
	Unburned cell	6	776499	776505
	Total	183507	963687	1147194
Event 3				
		Actual-observed data		
		Burned cell	Unburned cell	Total
Agent prediction	Burned cell	85281	42948	128229
	Unburned cell	5880	1013085	1018965
	Total	91161	1056033	1147194

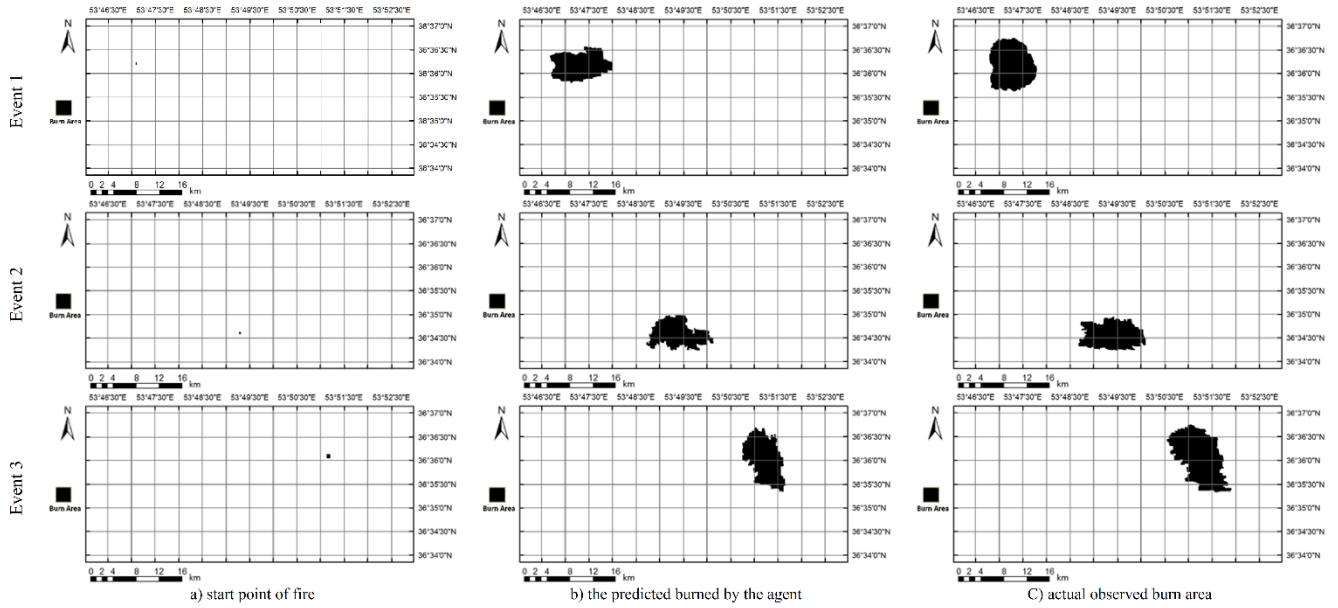


Figure 9. a) The starting point of fire b) The burned area estimated by the agent c) The burned area in reality.

4. Discussion

Table 1 shows that the burned area predicted by our agent is quite close to the actual one. To assess the result of the agent's prediction more accurately, a boundary box was drawn around the burned area, and the states of pixels in that area were compared. At first, the agent understood the structure of forest fire by using the data in the first event. So, the results were the same. The three events of forest fire were used for accuracy assessment. As seen in Table 1, in event 1, the state of 1049205 pixels of the area was predicted correctly, but the model specified the state of 97797 pixels as unburned while in reality those pixels were burned. On the other hand, the model determined 192 pixels as burned while those were not burned in reality. The Kappa Coefficient for prediction in event 1 was 72.1%. In Event 2, while 960000 pixels were predicted accurately, 187194 pixels predicted was wrong, as unburned and burned pixel respectively. The Kappa Coefficient for this Event was 57.0%. In event 3, the state of 1098366 pixels of 1147192 pixels was predicted correctly while agent predicted 42948 pixels as unburned pixels which were burned and it predicted 5880 pixels as burned which was unburned. In this event, the Kappa Coefficient for predicting the burned area was 75.5% and also the Kappa Coefficient for all predictions were 68.2%.

5. Conclusion

In this paper, at first, all concepts of the agent-based model such as observation, belief, desire, and intention, were modified to the spatial domain, and a new type of spatial analysis architecture was introduced. In our architecture, the agent perception of the spatial environment generated two matrixes called belief and intention matrixes. The belief matrix stored the environment data, while the intention matrix contained some processors. The cells of an intention

matrix play the roles of processors for analyzing the problem to reach the goal defined for the agent. In this architecture, the information such as layers, spatial relation among entities of layers, and statistical information among attributes were considered as the current state of the environment (believe).

In this paper, a general architecture was presented to address spatial issues. In such a general model there was no need to know how many agents were needed. Additionally, the number of goals and also the changes in the environment (actions) were unknown for each problem. Therefore, the problem was divided into some sub-problems based on the goals and actions. One goal and one action were assigned to each agent. Each agent had only one goal, so a single objective optimizer could be easily used by the agent to satisfy the goal. Therefore, the main advantage of this model is generality. To illustrate the capability of the proposed model, forest fire prediction presented an agent's desire and intention defined based on the common action used in GIS. To solve forest fire prediction based on the proposed architecture, one agent was generated to extract the current state of the spatial and non spatial information, then considered the goal and selected the tools based on its intention.

In forest fire prediction, at first, agent understands the structure of the environment, together with the impact of different data layers on each other. Then, the agent starts to predict the forest fire spread. To assess the result of the agent's prediction, a comparison between the predicted values and actual-observed were made. The Kappa coefficient was obtained at around 68.2%. The reason for the errors was attributed to the lack of adequate information. In reality, forest fire spread does not only depend on the type and density of vegetation and elevation, but also to other

factors such as wind speed and direction. Another reason for the dissimilarity between the results was that the agent needed more forest fire events to understand the structure of the problem more correctly.

References

- Ager, A. A., Barros, A. M., Day, M. A., Preisler, H. K., Spies, T. A., & Bolte, J. (2018). Analyzing fine-scale spatiotemporal drivers of wildfire in a forest landscape model. *Ecological Modelling*, 384, 87-102.
- Andraea, M. O., & Goldammer, J. G. (1992). Tropical wildland fires and other biomass burning: Environmental impacts and implications for land use and fire management. *Conservation of West and Central African Rainforests* (K. Cleaver et al., eds.), 79-109.
- Behzadi, S., & Alesheikh, A. A. (2013). Introducing a novel model of belief–desire–intention agent for urban land use planning. *Engineering Applications of Artificial Intelligence*, 26(9), 2028-2044.
- Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(suppl 3), 7280-7287.
- Bui, D. T., Van Le, H., & Hoang, N.-D. (2018). GIS-based spatial prediction of tropical forest fire danger using a new hybrid machine learning method. *Ecological Informatics*, 48, 104-116.
- Casali, A. (2005) Extension of the BDI Agent Model: Representing and Reasoning using Graded Attitudes. UNIVERSITY OF GIRONA
- Chen, J.-C., & Chen, C.-T. (2015). Discourse on Taiwanese Forest Fires. *Wildfire Hazards, Risks and Disasters* (pp. 145-166). Elsevier.
- Cruz, M. G., Alexander, M. E., Sullivan, A. L., Gould, J. S., & Kilinc, M. (2018). Assessing improvements in models used to operationally predict wildland fire rate of spread. *Environmental Modelling & Software*, 105, 54-63.
- de Groot, W. J., Wotton, B. M., & Flannigan, M. D. (2015). Wildland fire danger rating and early warning systems. *Wildfire Hazards, Risks and Disasters* (pp. 207-228). Elsevier.
- Encinas, A. H., Encinas, L. H., White, S. H., del Rey, A. M., & Sánchez, G. R. (2007a). Simulation of forest fire fronts using cellular automata. *Advances in Engineering Software*, 38(6), 372-378.
- Encinas, L. H., White, S. H., Del Rey, A. M., & Sánchez, G. R. (2007b). Modelling forest fire spread using hexagonal cellular automata. *Applied mathematical modelling*, 31(6), 1213-1227.
- Fečkan, M., & Pačuta, J. (2018). Existence of solution of a forest fire spread model. *Applied Mathematics Letters*, 83, 227-231.
- Ghisu, T., Arca, B., Pellizzaro, G., & Duce, P. (2015). An improved cellular automata for wildfire spread. *Procedia Computer Science*, 51, 2287-2296.
- Goltenboth, F., Timotius, K. H., Milan, P. P., & Margraf, J. (2006). Ecology of insular Southeast Asia: the Indonesian archipelago. Elsevier.
- Guerra-Hernández, A., Castro-Manzano, J., & El-Fallah Seghrouchni, A. (2008). Toward an AgentSpeak (L) theory of commitment and intentional learning. *MICAI 2008: Advances in Artificial Intelligence*, 848-858.
- Guerra-Hernández, A., Castro-Manzano, J., & El Fallah Seghrouchni, A. (2009). CTL AgentSpeak (L): A specification language for agent programs. *Journal of Algorithms*, 64(1), 31-40.
- Hall, D., Guo, Y., Davis, R. A., & Cegielski, C. (2005). Extending unbounded systems thinking with agent-oriented modeling: conceptualizing a multiple perspective decision-making support system. *Decision support systems*, 41(1), 279-295.
- Herrera, G. V. (2016). Mexican forest fires and their decadal variations. *Advances in Space Research*, 58(10), 2104-2115.
- Heyer, J. P., Power, M. J., Field, R. D., & van Marle, M. J. (2018). The impacts of recent drought on fire, forest loss, and regional smoke emissions in lowland Bolivia. *Biogeosciences*, 15(14), 4317-4331.
- Hodges, J. L., Lattimer, B. Y., & Luxbacher, K. D. (2019). Compartment fire predictions using transpose convolutional neural networks. *Fire Safety Journal*, 102854.
- Hu, X., & Sun, Y. (2007) 'Agent-based modeling and simulation of wildland fire suppression' *Proceedings of the 39th conference on Winter simulation: 40 years! The best is yet to come*. IEEE Press, pp. 1275-1283.
- Iudin, D., Sergeev, Y. D., & Hayakawa, M. (2015). Infinity computations in cellular automaton forest-fire model. *Communications in Nonlinear Science and Numerical Simulation*, 20(3), 861-870.
- Kuleshov, A., Chetverushkin, B., & Myshetskaya, E. (2013). Parallel computing in forest fires two-dimension modeling. *Computers & Fluids*, 80, 202-206.
- Ligtenberg, A., van Lammeren, R. J., Bregt, A. K., & Beulens, A. J. (2010). Validation of an agent-based model for spatial planning: A role-playing approach. *Computers, Environment and Urban Systems*, 34(5), 424-434.
- Ligtenberg, A., Wachowicz, M., Bregt, AK., Beulens, A., Kettenis, DL (2004). A design and application of a multi-agent system for simulation of multi-actor spatial planning. *Journal of environmental management*, 72(1-2), 43-55.
- Morvan, D., Accary, G., Meradji, S., Frangieh, N., & Bessonov, O. (2018). A 3D physical model to study the behavior of vegetation fires at laboratory scale. *Fire Safety Journal*, 101, 39-52.
- Murthy, K. K., Sinha, S. K., Kaul, R., & Vaidyanathan, S. (2019). A fine-scale state-space model to understand drivers of forest fires in the Himalayan foothills. *Forest ecology and management*, 432, 902-911.
- Niazi, M. A., Siddique, Q., Hussain, A., & Kolberg, M. (2010) 'Verification & validation of an agent-based forest fire simulation model' *Proceedings of the 2010 Spring Simulation Multiconference*. Society for Computer Simulation International, p. 1.
- Nurdiana, A., & Risdiyanto, I. (2015). Indicator determination of forest and land fires vulnerability using Landsat 5 TM data (case study: Jambi Province). *Procedia Environmental Sciences*, 24, 141-151.

- Reddy, C. S., Satish, K., & Rao, P. P. (2018). Significant decline of forest fires in Nilgiri Biosphere Reserve, India. *Remote Sensing Applications: Society and Environment*, 11, 172-185.
- ROSENBERG, D. M., CHAMBERS, P. A., CULP, J. M., FRANZIN, W. G., NELSON, P. A., SALKI, A. G., et al. (2005). Nelson and Churchill river basins. *Rivers of North America* (pp. 852-901). Elsevier.
- Schroeder, W., Oliva, P., Giglio, L., Quayle, B., Lorenz, E., & Morelli, F. (2016). Active fire detection using Landsat-8/OLI data. *Remote sensing of environment*, 185, 210-220.
- Strnad, D., Kohek, Š., & Kolmanič, S. (2018). Fuzzy modelling of growth potential in forest development simulation. *Ecological Informatics*, 48, 80-88.
- Tedim, F., Xanthopoulos, G., & Leone, V. (2015). Forest fires in Europe: Facts and challenges. *Wildfire Hazards, Risks and Disasters* (pp. 77-99). Elsevier.
- Thach, N. N., Ngo, D. B.-T., Xuan-Canh, P., Hong-Thi, N., Thi, B. H., Nhat-Duc, H., et al. (2018). Spatial pattern assessment of tropical forest fire danger at Thuan Chau area (Vietnam) using GIS-based advanced machine learning algorithms: A comparative study. *Ecological informatics*, 46, 74-85.
- Tweeddale, J., Ichalkaranje, N., Sioutis, C., Jarvis, B., Consoli, A., & Phillips-Wren, G. (2007). Innovations in multi-agent systems. *Journal of Network and Computer Applications*, 30(3), 1089-1115.
- Vidal, A., & Devaux-Ros, C. (1995). Evaluating forest fire hazard with a Landsat TM derived water stress index. *Agricultural and forest meteorology*, 77(3-4), 207-224.
- Ying, L., Han, J., Du, Y., & Shen, Z. (2018). Forest fire characteristics in China: Spatial patterns and determinants with thresholds. *Forest Ecology and Management*, 424, 345-354.
- Young, D. J., Werner, C. M., Welch, K. R., Young, T. P., Safford, H. D., & Latimer, A. M. (2019). Post-fire forest regeneration shows limited climate tracking and potential for drought-induced type conversion. *Ecology*, 100(2), e02571.
- Zheng, Z., Huang, W., Li, S., & Zeng, Y. (2017). Forest fire spread simulating model using cellular automaton with extreme learning machine. *Ecological Modelling*, 348, 33-43.