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Research Article

# Intelligent Agent-Based Simulation of Fire Propagation in Multiple Environments

**Mailyn Moreno-Espino[1*], Lázaro Michel Reyes-Valdés[2], Robert Ruben Benitez[2], Ariel López-González[3], Cornelio Yáñez-Márquez[4], Yahima Hadfeg-Fernández[5]**

[1] Computer Research Center, National Institute of Technology, Mexico City, Mexico
[2] Jose Antonio Echeveria, School of Computer Science, Havana Technical University, Havana, Cuba
[3] Department of Computer Science and Engineering, Carlos III University, Madrid, Spain
[4] Computer Research Center, National Institute of Technology, Mexico City, Mexico
[5] School of Economics and Administration, North Catholic University of Antofagasta, Chile
E-mail: mmorenoe2022@cic.ipn.mx

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**Abstract:** Wildfire propagation in urban and forest environments poses significant challenges, particularly in regions like Cuba, where the interplay of diverse environmental factors amplifies the risks. This study develops an agent-based simulation model integrated with Geographic Information Systems (GIS) using the GAMA platform to analyze fire dynamics under varying conditions. The model evaluates critical environmental variables, including wind speed, fuel types, and humidity, and identifies their impact on fire behavior. A multi-phase experimental approach was employed, incorporating sensitivity analysis, a screening experiment, and a full factorial design. The results highlight that wind speed and the number of fire outbreaks are the most influential factors, with high wind speeds doubling the rate of fire spread. Notably, the strategic use of firebreaks reduced the affected areas by up to 40%. Additionally, interactions between factors, such as wind speed and the number of outbreaks, demonstrated significant effects on burned area and fire intensity. This research advances the state of fire propagation modeling by incorporating real-time meteorological data, adapting the model to the Cuban context, and enabling realistic scenario testing. The insights gained provide actionable recommendations for disaster management, urban planning, and firefighter training, offering a robust tool for mitigating fire-related risks in tropical and subtropical environments.

***Keywords*:** intelligent agents, agent-based simulation, fire

**MSC:** 65L05, 34K06, 34K28

## 1. Introduction

A model is an abstract and simplified representation of a real-world object or system, focusing exclusively on the aspects pertinent to a specific research context. Computational simulation employs the model to replicate real-world behavior, simulating its dynamics and providing analyzable results. This process permits the emulation of actual systems within a controlled setting, thereby mitigating the risks associated with the construction or modification of such systems [1, 2].

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The value of simulation in disaster prevention is twofold. Firstly, it enables the analysis of complex processes, thus facilitating the anticipation of potential outcomes before they occur [3, 4]. Secondly, it allows for the examination of scenarios that may otherwise be difficult to simulate in real time. One particular form of simulation, designated as agent-based modeling and simulation (ABMS), has been demonstrated to be particularly efficacious for the investigation of systems wherein individual entities (agents) interact within an environment, resulting in the emergence of behaviors that may not be explicitly programmed [5].

Agents in ABMS are autonomous entities that act in accordance with specific rules, engaging in interactions with both other agents and their surrounding environment. These interactions give rise to patterns and behaviors that mirror real-world dynamics, rendering this method highly applicable across a range of fields, including disaster management, social sciences, and logistics [6, 7].

In the context of fire propagation, simulations provide invaluable insights that can inform decision-making and disaster mitigation efforts. Nevertheless, accurately simulating fire behavior remains a significant challenge due to the extensive range of influencing factors, including fuel types, oxygen availability, weather conditions, and terrain. The current models are inadequate for addressing the specific environmental characteristics of regions like Cuba, where both urban and forest fires present a significant threat [8–10].

The objective of this paper is to develop an intelligent agent-based simulation system for fire propagation in diverse environments, with a particular focus on the specific conditions present in Cuba. The proposed system integrates Geographic Information Systems (GIS) with agent-based models, thereby enhancing the capacity for informed decision-making in disaster prevention. The practical value of this research lies in its potential to facilitate disaster preparedness and the training of firefighters and forest rangers, thereby reducing the impact of fire-related disasters.

## 2. Simulation and fire

### 2.1 *Fire*

Fire is a complex and dynamic natural phenomenon influenced by an interplay of chemical, physical, and environmental factors. The rapid and often unpredictable spread of fire poses significant challenges for ecological management and human safety. A comprehensive understanding of fire behavior is imperative for effective disaster management, urban planning, and enhancing infrastructure resilience. The study of fire involves the analysis of ignition, spread, and intensity under diverse conditions, which form the foundation for effective fire control strategies. Fire is defined as a chemical reaction involving incandescent particles that emit heat and light. The visible manifestation of this reaction is referred to as flames, while the non-luminous particles are collectively termed smoke. Uncontrolled combustion of materials can result in structural damage, harm to living organisms, and, in some cases, death due to smoke inhalation or severe burns [9, 10].

#### 2.1.1 *Chemical factors and environmental influence on fire behavior*

The chemical behavior of fire is determined by the interaction of three key elements: fuel, oxygen, and a heat source. The interplay among these components initiates a sequence of reactions that culminates in the production of flames and heat. This fundamental understanding is imperative for effective fire behavior analysis and management. Fuels, classified as solid, liquid, or gas, play a pivotal role in this process. Solid fuels undergo gradual combustion, characterized by the inward penetration of heat. In contrast, liquid fuels generate vapors that serve to intensify flames, thereby elevating the risk of explosion [9, 11].

Fire is a chemical reaction that is commonly described by the hydrocarbon combustion equation:

$$\mathrm{CH_4} + 2\mathrm{O_2} \rightarrow \mathrm{CO_2} + 2\mathrm{H_2O} + \text{energy}$$

This reaction produces heat and light, which characterizes the flame visible in fires. In addition, incomplete combustion can result in the formation of carbon monoxide **CO** and other hazardous by-products.

The characteristics of the fuel, including its type, size, surface area, and moisture content, have been shown to have a significant impact on the behavior of the fire. Hydrocarbons, which are composed of carbon and hydrogen, combust readily when combined with oxygen, producing carbon dioxide and water vapor. The presence of larger fires has been demonstrated to provide more heat to the fuel, thereby accelerating combustion. Fuels with higher moisture content have been shown to be less likely to ignite, as more energy is required to evaporate the water before combustion can occur [12–14].

Environmental conditions further modify these dynamics:

• Wind speed: Influences the direction and rate of fire spread by supplying oxygen and displacing flames.

• Humidity: Higher humidity suppresses fire spread by increasing moisture in the fuel.

• Temperature: Warmer conditions often result in lower ignition thresholds and more rapid combustion.

It is imperative to consider the availability of oxygen, as its presence directly impacts the intensity of combustion. Each material possesses a distinct ignition temperature, defined as the minimum heat required to ignite in the absence of an external heat source. By disrupting the “fire triangle” (fuel, oxygen, and ignition temperature), effective mitigation of fire risks can be achieved. Strategies employed for fire extinguishment include the application of moisture to dampen fuels, the reduction of oxygen levels, and the direct application of water to the fire.

The behavior of fires in different environments, such as forests and urban areas, varies significantly due to differences in meteorological conditions, topography, and the availability of fuels. In forest environments, the spread of fire is influenced by factors such as relative humidity, wind speed, and terrain characteristics. Conversely, in urban environments, the unique characteristics of building structures, materials, ventilation systems, and the proximity of structures can substantially influence fire intensity and risk. This underscores the necessity for a customized approach to fire management in each distinct environment [15].

## 2.2 *Process simulation*

The utilization of simulation provides a virtual laboratory environment, thereby enabling the examination of fire behavior under controlled and repeatable conditions. Process simulation involves the construction of models that replicate the intricate interactions between chemical reactions, environmental factors, and fire spread. The integration of diverse data sources, including satellite imagery, meteorological records, and ecological surveys, enables the recreation of real-world conditions with a high degree of fidelity. These models facilitate scenario testing, such as evaluating the effectiveness of firebreaks or assessing the impact of climate change on fire frequency and intensity [5].

A model is defined as a simplified representation of a system, designed to exhibit the same structure and behavior as the real system it aims to replicate. The model must achieve a balance between realism and simplicity, incorporating key characteristics while remaining facile to comprehend and manipulate. The employment of specialized software facilitates the examination of system behavior under diverse configurations, thereby providing valuable insights into performance over time. The employment of simulation as a tool is particularly beneficial in contexts involving randomness in systems, where analytical solutions are either too complex or too costly to implement [5].

## 2.3 *Agent-based simulation*

Agent-based modeling and simulation (ABMS) employs a bottom-up approach to modeling fire behavior, emphasizing the actions and interactions of individual agents within the system. In the context of fire modeling:

• Agents may represent individual flames, particles of fuel, or environmental features such as wind or terrain.

• Each agent operates according to predefined rules, such as combustion rates or wind-driven movement, allowing for emergent phenomena like spot fires or rapid directional shifts.

ABMS has been demonstrated to be particularly effective in simulating localized interventions and understanding how small-scale actions influence larger systemic outcomes. A salient benefit of ABMS is its aptitude for emulating the erratic and stochastic behaviors frequently observed in real-world systems, particularly in complex environments. ABMS models enable the spontaneous emergence of patterns without the necessity of explicit programming. However, validating these models can be challenging, particularly in areas where data is limited. To enhance the precision of these models, there has been an increasing adoption of calibration methodologies that leverage empirical data, expert insights, machine learning, and big data. Furthermore, the integration of Geographic Information Systems (GIS) with specialized simulation platforms offers valuable features, such as realistic environmental modeling [6, 16].

#### 2.3.1 *An overview of the main agent-based simulation platforms*

Agent-based modeling and simulation (ABMS) platforms are a vital tool for modelling complex systems. Some of the most prominent examples include [7, 17–20]:

AgentPy [21] is a Python library that streamlines the development of models with Jupyter Notebooks, enabling parallel simulations without the need for additional programming. AnyLogic [5], a multi-method platform, provides tools for both discrete events and dynamic systems, making it an ideal choice for users without advanced programming skills. Evoplex [22], which is modular and written in C++, separates the graphical interface from the core, thereby facilitating interaction with the visual environment. GAMA is particularly adept at handling large volumes of data and agents, making it an ideal choice for large-scale simulations integrated with GIS systems [23].

Jade [24], implemented in Java, is a popular choice in academic and industrial environments thanks to its scalability and ease of use in distributed systems. KrABMaga, in Rust, is optimized for parallel simulations, while MASON is a flexible option for computationally demanding simulations. Mesa, also in Python, is notable for its extensibility and active community. Finally, NetLogo is an accessible tool with a vast library of models, although it is limited in complexity. Repast, with more than 20 years of development, is a robust and modular platform ideal for advanced simulations.

### 2.4 *Fire simulation systems*

The field of fire simulation encompasses a range of widely utilized computational solutions within the scientific and engineering communities. One of the most prominent tools is the Fire Dynamics Simulator (FDS) [25–27], a computational model based on fluid dynamics developed by the National Institute of Standards and Technology (NIST). FDS solves Navier-Stokes equations adapted for thermally driven, low-speed flows, making it an effective tool for modeling heat and smoke transport in fires, as well as studying fire behavior in relation to structures and surfaces. The simulator has been enhanced with new algorithms, enabling more accurate predictions of phenomena such as smoke concentration and flame spread.

Another notable tool is Prometheus [28, 29], a deterministic model based on the Fire Weather Index (FWI) and the Canadian Forest Fire Danger Rating System. This vector-based system models fire growth in heterogeneous landscapes, considering fuel, topography, and weather conditions. Its precision makes it an invaluable tool for planning prescribed burns, evaluating fuel management strategies, and simulating fires under different climate scenarios.

The Cell2Fire [30] simulator, based on cells, divides the landscape into small, homogeneous areas, enabling efficient prediction of fire propagation thanks to its parallel computing capabilities. In comparative simulations with other leading models like Prometheus, Cell2Fire has demonstrated high accuracy, exceeding 90%.

It should be noted that FARSITE and Visual Behave are two of the most widely used systems in the field of forest fire management [29, 31]. FARSITE is a deterministic simulator that calculates fire behavior in various scenarios, including the simulation of fire suppression actions. Meanwhile, Visual Behave [32, 33], a Cuban adaptation of BehavePlus, is a flexible system that generates models of fire behavior and is used for planning controlled burns and assessing fuel hazards. Both tools provide valuable capabilities for analyzing fire growth and impact in a range of environments.

### 2.5 *Integration of geographic information systems (GIS) in fire simulations*

Geographic Information Systems (GIS) play a transformative role in enhancing the accuracy and relevance of fire simulations. GIS provides spatially explicit data on terrain, vegetation types, and weather patterns, which are critical inputs for modeling fire dynamics. For example:

• High-resolution topographic maps help predict how fire spreads across varying slopes.

• Vegetation indices derived from remote sensing data indicate the fuel availability and flammability.

• Real-time weather data enables dynamic adjustments to simulation models to reflect current conditions.

By combining GIS with simulation tools, researchers can create geographically accurate models that improve risk assessments and inform proactive fire management strategies.

# 3. Multi-environment fire spread simulation model

The multi-environment fire spread simulation model is an advanced approach to capturing the dynamics of fire propagation across diverse landscapes, including forests, grasslands, and urban areas. By integrating environmental variability, such as differing fuel types, topographical features, and weather conditions, the model simulates fire behavior under various scenarios. This comprehensive approach enables researchers to analyze the influence of specific environmental factors on fire spread, assess the effectiveness of intervention strategies, and provide insights into potential risks and mitigation measures. The incorporation of multi-environment considerations ensures a realistic and adaptable framework for understanding fire dynamics and supporting decision-making in fire management.

## 3.1 *GAMA platform: simulation environment*

The GAMA platform is a robust and versatile simulation environment specifically designed for complex multi-agent systems. It offers a flexible and user-friendly interface, enabling the integration of geographic information, advanced modeling techniques, and real-time scenario testing. Key features of the GAMA platform include:

• Scalability: Supports simulations ranging from small-scale environments to extensive geographic regions, making it ideal for both localized and large-scale studies.

• Visualization tools: Provides real-time graphical representation of simulation processes and outcomes, including detailed spatial and temporal dynamics of fire spread.

• Interoperability: Facilitates the integration of external data sources, such as GIS datasets, remote sensing imagery, and meteorological data, ensuring that simulations are informed by accurate and comprehensive inputs.

These characteristics render GAMA particularly well-suited for simulating fire dynamics in diverse and complex environments. Its capacity for detailed agent-based modeling enables researchers to represent intricate interactions within the simulation framework.

### 3.1.1 *Analysis of the architecture and programming model of GAMA*

The architecture of GAMA is modular and extensible, allowing users to customize simulations to meet specific research needs. Its programming model includes [23]:

• Agent-based modeling: Enables the definition of individual agents with specific behaviors, interactions, and environmental responses. These agents can represent entities such as fire cells, vegetation, and weather systems.

• Layer-based design: Supports the overlay of geographic, environmental, and behavioral data to create comprehensive simulation environments. This facilitates the visualization of spatial interactions and the assessment of environmental impacts.

• Scripting language: GAMA's integrated scripting language simplifies the creation and modification of simulation models, enabling rapid prototyping, iterative development, and the incorporation of complex algorithms.

This architecture ensures that the platform is adaptable to a wide range of research applications, including fire propagation studies, environmental management, and disaster response planning.

## 3.2 *Simulation model proposal*

The proposed simulation model leverages the capabilities of the GAMA platform to create a detailed and adaptable framework for studying fire behavior. Key elements of the model include:

• Agent definitions: Agents represent fire cells, vegetation, and environmental factors, each with specific attributes and interaction rules. For example, fire cells are modeled with attributes such as intensity and direction, while vegetation agents include flammability and moisture content.

• Dynamic interactions: Simulations account for changes in wind speed, humidity, and temperature, enabling realistic fire spread scenarios. These dynamic interactions ensure that the model reflects the variability of real-world conditions.

• Scenario testing: The model allows researchers to test the effectiveness of firebreaks, controlled burns, and other intervention strategies under various conditions. This capability is crucial for evaluating potential management practices and mitigation measures.

The model's flexibility and granularity provide valuable insights into fire dynamics and management practices, making it a powerful tool for research and decision-making.

### 3.2.1 *Geographic information*

Geographic information plays a central role in the simulation model, providing spatial context and enhancing the accuracy of fire spread predictions. Key geographic data inputs include:

• Topographic maps: Capture elevation changes, slope gradients, and terrain features, which significantly influence fire behavior and propagation.

• Land cover classifications: Identify vegetation types, fuel availability, and urban infrastructures across the simulation area, enabling a detailed representation of the environment.

• Weather data: Incorporate real-time and historical weather patterns, including wind direction, temperature, and humidity, to model dynamic environmental conditions.

• Hydrological data: Include water sources and drainage patterns that can act as natural firebreaks or influence fire dynamics.

By integrating these data sources, the simulation model ensures that predictions are both geographically accurate and contextually relevant, supporting informed decision-making and risk assessment. To increase the realism of the model, Geographic Information Systems (GIS) are integrated, focusing on a forested area, in this case in Cuba, the area near Sagua de Tánamo, in the province of Holguín. This region, characterized by plains interrupted by mountains, provides an accurate representation of Cuban topography and vegetation, making it ideal for simulation. Google Earth satellite imagery was used to obtain accurate data, as shown in Figure 1.

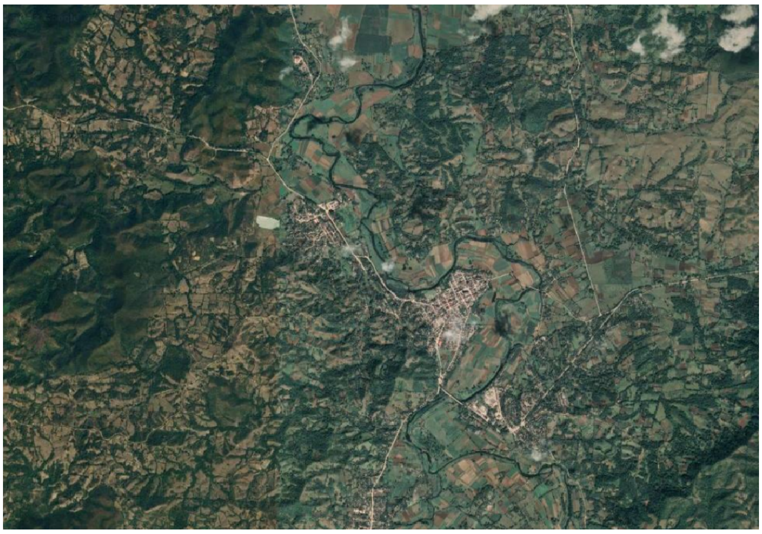


**Figure 1.** Area selected for simulation

The selected area was incorporated into the GAMA platform using a .tif file, which allowed the simulation to use detailed geographic features. Figure 2 illustrates the successful integration of the geographic data into the platform, allowing for more accurate modeling of the environment.

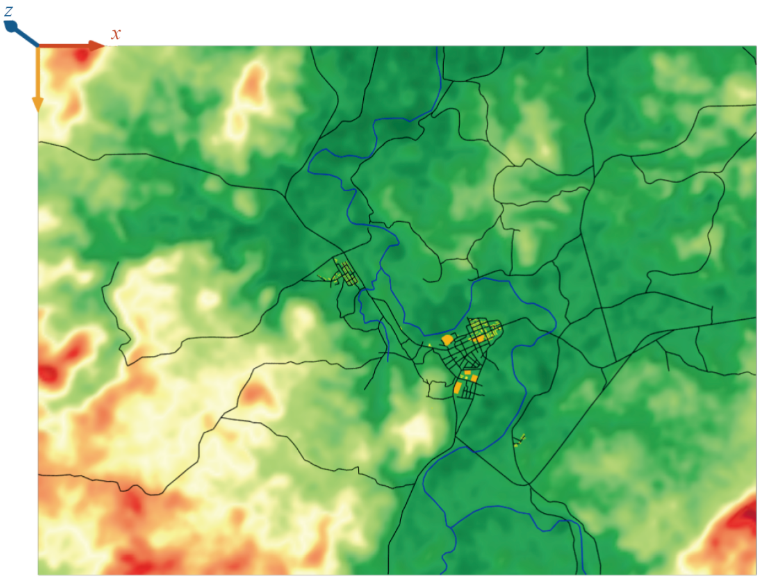



**Figure 2.** Areas of interest are already included in the GAMA platform

### 3.2.2 *Mathematical model for simulation*

The mathematical model underlying the simulation integrates principles of physics, ecology, and fire science to represent fire behavior quantitatively. Key components include:

• Rate of Spread (ROS): Calculated using empirical formulas that account for fuel type, moisture content, wind speed, and slope. The ROS is a critical parameter for determining the speed and direction of fire propagation.

• Heat transfer mechanisms: Include conduction, convection, and radiation to model energy propagation within the fire and its surroundings. These mechanisms are essential for understanding how fire spreads through different materials and environments.

• Probabilistic elements: Introduce stochastic factors to account for variability in environmental conditions and fuel characteristics. These elements enhance the model's realism by capturing the inherent unpredictability of fire behavior.

• Environmental feedback loops: Incorporate interactions between fire dynamics and environmental factors, such as how burning vegetation alters local humidity and temperature, influencing subsequent fire spread.

The mathematical framework ensures that the simulation model is grounded in scientific principles, providing reliable and reproducible results. This foundation supports the development of effective fire management strategies and enhances the model's applicability to real-world scenarios.

By unifying these elements, the multi-environment fire spread simulation model establishes a comprehensive methodology for analyzing and managing fire dynamics, offering robust tools and insights for diverse scenarios. A model is proposed that focuses on expressing the simulation process of fire dynamics in forest fires according to a set of parameters [34].

$M_{mxn}$: matrix representing the simulation area.

$E_{mxn}$: matrix containing the values associated with the terrain elevation.

$C_{mxn}$: matrix containing the values associated with the CUBA19 fuel models.

$T$: ambient temperature. It is in the range of 0 °C and 40 °C. This is in response to the minimum and maximum records registered in Cuba.

$H_r$: relative humidity of the environment. It is in a range between 50-100%.

$Vv$: wind speed. It is in a range from 0 to 60 km/h. This responds to the average values of winds that can be registered in a day with relatively normal weather conditions.

$Dv$: wind direction. It is represented by a text string indicating where the wind comes from. The accepted values are: N, NE, E, SE, S, SW, W, NW.

If $(M_{ij})$: intensity of the fire in cell $M_{ij}$. It expresses the intensity with which the fire burns in a given area. It is the conjunction of the above factors.

Pp $(M_{ij})$: probability that the fire spreads to the cell $M_{ij}$.

After defining these variables, it is time to propose how the system will act in each step of the simulation. We propose the division of the geographical environment into a grid of cells with the same area.

For a cell $M_{ij}$ that is on fire:

$$\text{If } (M_{ij}) = \frac{C_{ij}}{max(C_{mxn})} + T \tag{1}$$

For a cell $M_{ij}$ that is on fire, the probability that the fire spreads to a neighboring cell, considering that Moore's topology is used in the distribution of cells, i.e., those 8 surrounding cells are considered neighbors of a cell is defined as follows:

$$Pp(M_{kl}) = \text{If } (M_{ij}) + E_{kl} - E_{ij} + Vv \tag{2}$$

### 3.2.3 *Controllable process parameters*

To simulate this model, there are several parameters that can be controlled within the simulation environment. These increase the level of dynamics of the model with the aim of representing different situations to be analyzed. Factors classified as "controllable" in the model were those that could be directly adjusted within the simulation environment to represent different scenarios. For instance, temperature, wind speed, and the number of fire outbreaks were selected due to their ability to be manipulated in virtual experiments. The values reflected correspond to the average meteorological data from Cuba in the area used as a reference for the simulation.

It should be noted that there may be other controllable elements that were not included in the model due to their complexity and scope. The controllable elements within the simulation process are shown in Table 1.

**Table 1.** Controllable parameters of the process

| Parameter | Definition | Type | Initial value |
|---|---|---|---|
| Fuel | File with fuel models | Continuous | - |
| Temperature | Ambient temperature | Continuous | 20 °C |
| Relative humidity | Ambient relative humidity | Continuous | 75% |
| Wind directio | Direction from which the wind blows | Nominal | N |
| Wind speed | Wind speed | Continuous | 30 km/h |
| Initial focus | Location where the fire starts | Nominal | - |
| Number of outbreaks | Number of fire outbreaks | Discrete | - |

Figure 3 shows the Model Parameter Configuration Menu.

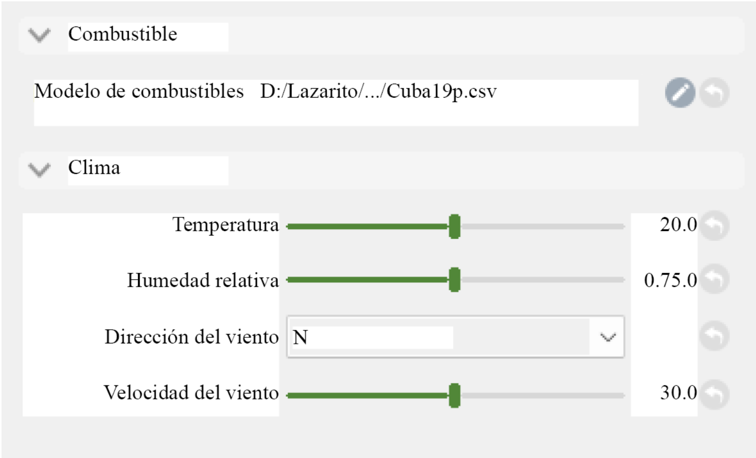



**Figure 3.** Parameter configuration menu

### 3.2.4 *Geographical representation of the forest area and the urban area*

Figure 4 shows a three-dimensional perspective of the terrain elevation. It has a color scale from green to red representing the elevation of the terrain.

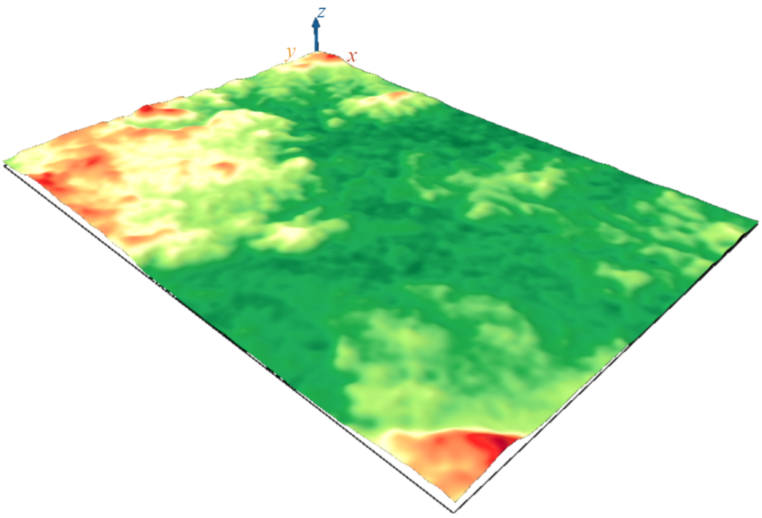



**Figure 4.** Three-dimensional representation of the forest environment

Figure 5 shows a three-dimensional view of the urban environment. It shows roads in black, water bodies in blue, buildings in yellow, and landmarks in orange.

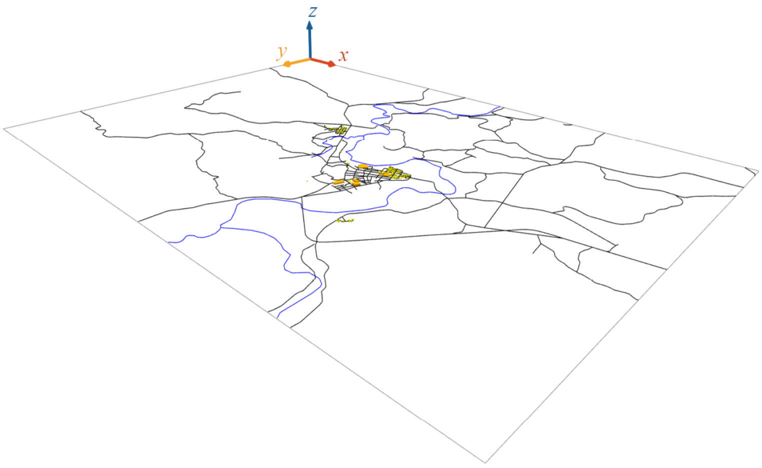



**Figure 5.** Three-dimensional representation of the urban environment

### 3.2.5 *Geographical representation of the forest area and the urban area*

Figure 6 shows the main areas of interest around which the simulation revolves:

• Grey cell: natural, unburned area.

• Red cell: area being burned with a scale of fire intensity.

• Yellow cell: area already burned and extinguished (the fire in this area is negligible because all available fuel has been consumed).

• Blue line: river.

• Black line: road.

• Red line: road damaged by fire.

• Yellow polyhedron: building.

• Orange polyhedron: point of interest.

• Red polygon: building or point of interest damaged by fire.

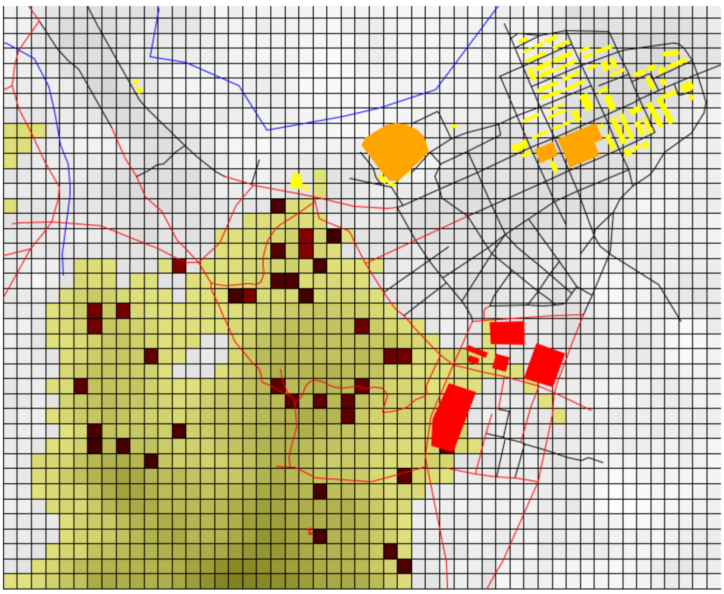
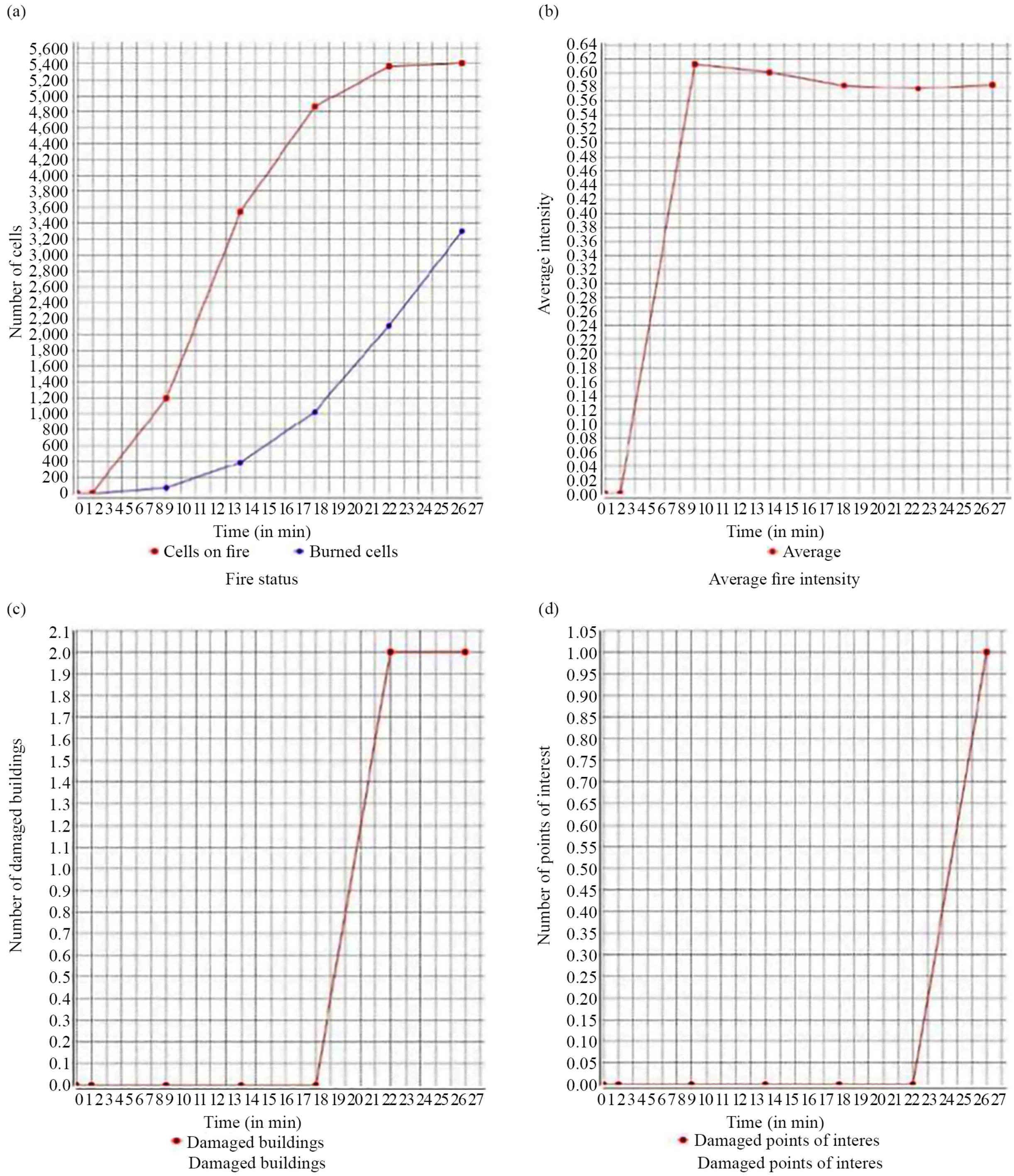


**Figure 6.** Simulation area

## 4. Results

### 4.1 *Relevant information extracted from the simulation*

Relevant information is presented in two main ways: with time series plots and pie charts. Time series plots allow the evaluation of variables over time. They provide the analyst with the ability to know a state of the simulation for a given time. Figure 7 below groups these plots according to the associated output variable.



(e)

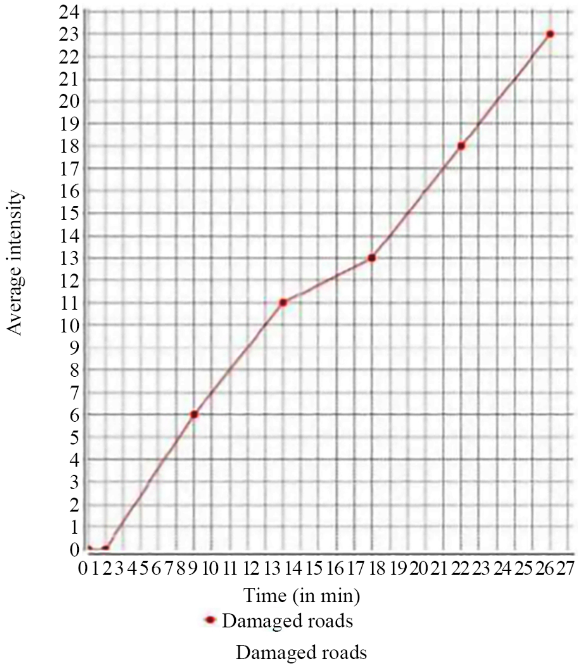



**Figure 7.** Weather-relevant information

Figure 7a shows the state of the fire from the analysis of the number of cells burned and the number of cells in flame over time. Figure 7b shows the average intensity of the fire over time, allowing the analyst to identify peaks where the fire has the highest intensity and make decisions accordingly. Figure 7c-e shows the number of damaged buildings, landmarks, and roads as a function of time.

On the other hand, Figure 8 is a group of pie charts designed to analyze the relationship between two output variables. They allow the analyst to estimate in a percentage way the damage that could be caused by the fire. Figure 7 shows the ratio between burning cells and burned cells. Figure 8b-d shows the number of damaged buildings, points of interest and roads and the ratio between them and the undamaged ones.

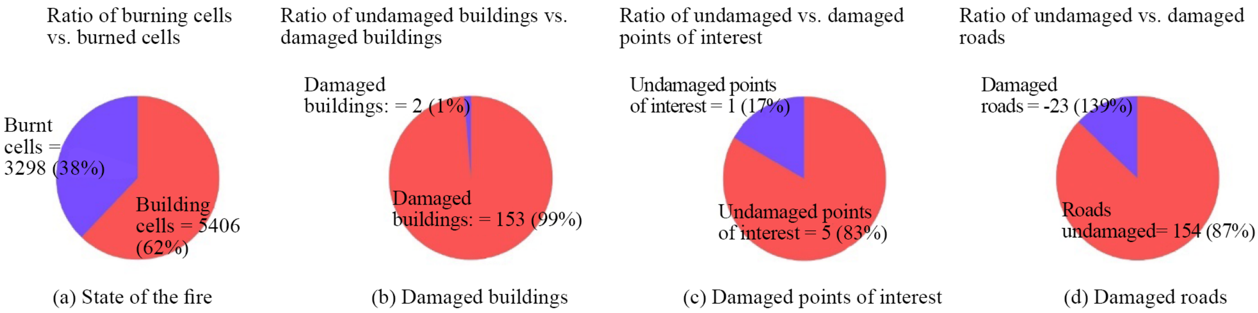



**Figure 8.** Relevant percentage information

## 4.2 *Experimentation*

In the absence of data on fires in Cuba, a sensitivity analysis was conducted to corroborate the simulation model's responsiveness to the identified influencing factors. Firstly, a screening experiment was conducted to analyse the influence of each input variable separately, as detailed in Table 1.

Subsequently, a full factorial experiment was conducted based on the results of the screening experiment. This was done to demonstrate the influence of the simulation parameters, considering not only the separate influence of each input variable, but also the interactions that may occur between them. Table 2 shows the performance variables that will be used to evaluate the response of the simulation model, along with their respective units of measurement.

**Table 2.** Performance variables

| Variable | Unit of measurement |
|---|---|
| Simulation duration | minutes |
| Burnt area | cells |
| Maximum average intensity | - |
| Damaged buildings | number of buildings |
| Damaged points of interest | number of points of interest |
| Damaged roads | number of roads |

### 4.2.1 *Final screening experiment*

**Planning**

The process begins with the identification and articulation of the problem. The objective is to analyze the impact of each factor separately in the simulation. The model includes eight controllable factors and one non-controllable factor. The controllable factors are listed as simulation parameters in Table 1. The non-controllable factor, slope, is calculated automatically and progressively based on the GIS file used and the specific cell from which its value is required.

The Pareto diagrams were generated using Minitab software. In this analysis, performance response variables were evaluated against the controllable factors listed in Table 3. Statistical significance for each factor was determined using a significance level of $\alpha = 0.05$, with the Bonferroni correction applied to minimize cumulative errors resulting from multiple testing. This methodological approach ensures statistically robust conclusions.

**Design**

The configuration for each controllable factor and the corresponding values for each level are presented in Table 3. The results of this experiment are presented in Table 4.

**Table 3.** Controllable factors and levels for the final screening experiment

| ID | Factor | Level | | Unit |
|---|---|---|---|---|
| | | Low | High | |
| A | Fuel | *p*-file | *q*-file | - |
| B | Temperature | 10 | 30 | °C |
| C | Relative humidity | 72.5 | 87.5 | % |
| D | Wind direction | N | SW | - |
| E | Wind speed | 15 | 45 | km/h |
| F | Initial focus | [109, 91] | [189, 77] | - |
| G | Number of foci | 1 | 2 | - |
| H | seed (seed of the random number generator) | 1 | 2 | - |

**Table 4.** Final screening experiment setup

| Configuration parameter | Value |
|---|---|
| Factors to analyse | 8 |
| Replicas | 3 |
| Number of blocks | 1 |
| Central points | 6 |
| Base runs | 18 |
| Total runs | 54 |

**Conduction of the experiment**

The 54 runs were conducted in accordance with the corresponding treatments, forming part of the conduct phase. The statistical software *Minitab* was employed as a support tool. The results are presented in the form of Pareto diagrams, as illustrated in Figure 9.

**Analysis**

The interpretation of the Pareto plots in Figure 9 is explained by considering an alpha ($\alpha$) significance value, which allows us to assert with confidence that a given factor directly influences the model and is not the result of random chance. For instance, in Figure 9c, the factors exceeding the $p$-value threshold for a significance level of $\alpha = 0.05$ are relative humidity and temperature, indicating a strong relationship between these factors and the average intensity yield variable. This analysis can be extended to each of the remaining Pareto charts. To mitigate the risk of cumulative error from multiple testing, the Bonferroni correction was applied to adjust $p$-values. This ensures that the derived conclusions are statistically robust.

The Pareto diagram (Figure 9) identifies wind speed and fuel type as the most influential factors in fire propagation, with relative impacts of 45% and 30%, respectively. For example, under moderate wind conditions (10-15 km/h), the propagation rate doubled compared to weak winds ($<$ 5 km/h). This finding corroborates previous observations emphasizing the pivotal role of wind speed in fire escalation. Moreover, the interaction between fuel type and wind speed reveals a multiplicative effect, highlighting the importance of incorporating these parameters into predictive simulations.

As shown in the Pareto diagram for average fire intensity (Figure 9c), the effects of relative humidity and temperature are particularly significant. At relative humidity levels above 85%, average intensity decreased by 60%, indicating a critical threshold for fire propagation. Conversely, temperature exhibited a synergistic effect with wind speed, with fire spread accelerating significantly at temperatures above 30 °C. These findings underscore the importance of including these environmental variables in model calibration to enhance the accuracy of fire behavior predictions.

Table 5 ranks each factor based on its influence on the yield variables, as determined by the analysis of the Pareto diagrams. The four controllable factors with the highest degree of influence on the model are fuel, wind speed, initial focus, and the number of fire outbreaks.

**Table 5.** Analysis of the results of the final screening experiment

| Input variable | Duration | Area | Intensity | Buildings | POIs | Roads | FA |
|---|---|---|---|---|---|---|---|
| Fuel | 5 | 4 | - | 3 | 4 | 4 | 5 |
| Temperature | - | - | 2 | - | 5 | - | 2 |
| Relative humidity | - | - | 1 | - | - | - | 1 |
| Wind direction | 4 | - | - | - | - | - | 1 |
| Wind speed | 1 | 1 | - | 1 | 2 | 1 | 5 |
| Initial focus | 2 | 3 | - | 4 | 3 | 3 | 5 |
| Number of foci | 3 | 2 | - | 2 | 1 | 2 | 5 |
| seed | - | - | - | - | - | - | 0 |

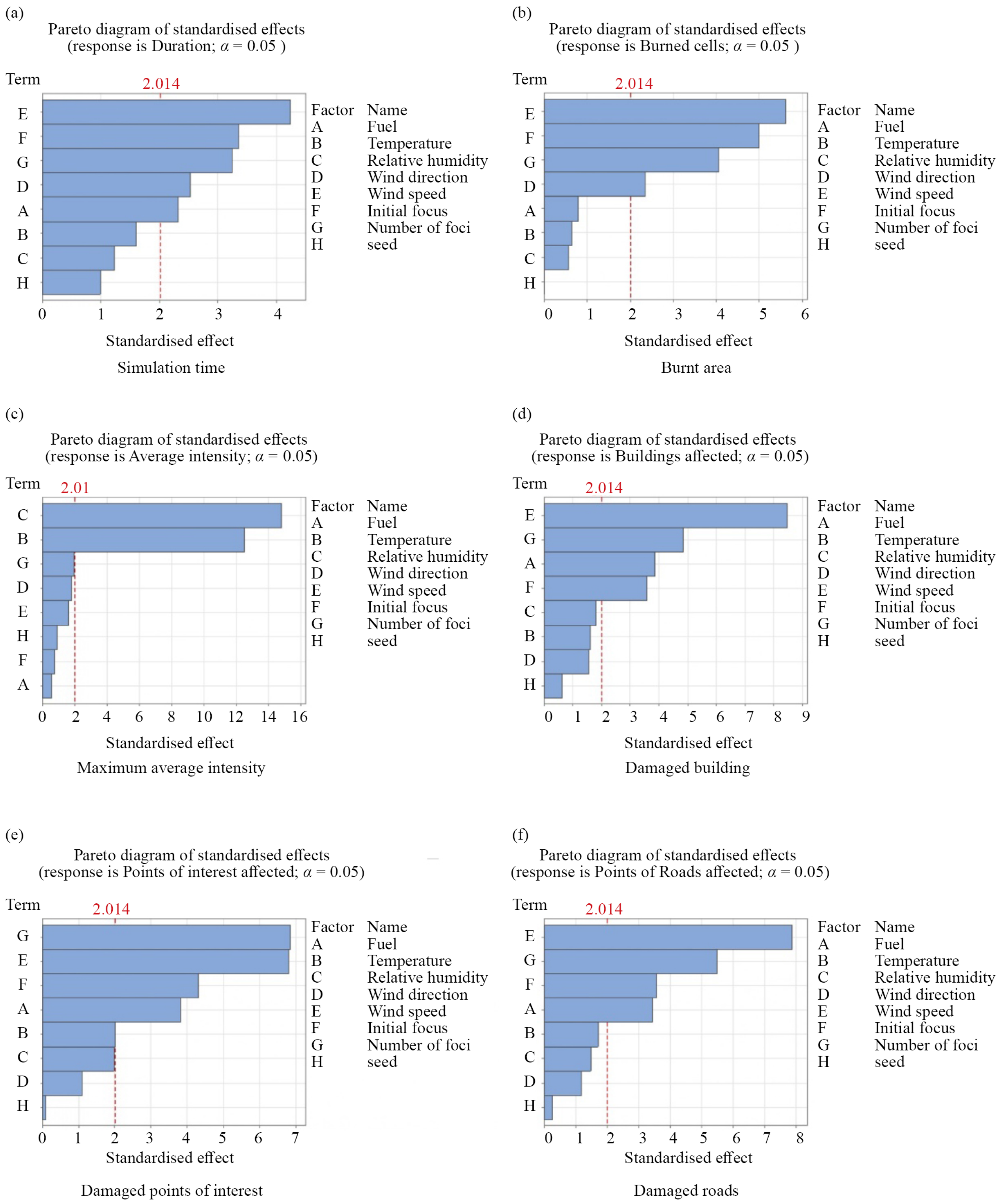



**Figure 9.** Pareto plots for each variable in the screening experiment

### 4.2.2 *Full factorial experiment*

Considering the final screening experiment already performed, i.e., the results shown in Table 5, we can deduct from the absolute frequency of each factor which factors alone have a greater influence on the model. It is then necessary to carry out a full factorial experiment to see if the interactions between these factors could influence the performance of the model.

**Planning**

On this occasion, four of the eight controllable factors will be analysed. The same design will be used as in the final screening experiment, as shown in Table 3.

The selection of the four controllable factors-fuel type, wind speed, initial focus, and number of fire outbreaks-was informed by the results of the screening experiment (Table 5), which ranked the factors based on their influence on performance variables. These factors demonstrated the highest impact across multiple metrics, such as burned area and fire intensity. This focused approach ensures computational efficiency while maintaining relevance to the key variables driving fire behavior. Other factors, such as temperature or relative humidity, were considered less impactful under the experimental conditions and were thus fixed at constant values during the factorial experiment. This decision minimizes complexity while still capturing the dominant effects in the simulation.

**Table 6.** Controllable factors and levels for the full factorial experiment

| ID | Factor | Level | | Unit |
|---|---|---|---|---|
| | | Low | High | |
| A | Fuel | *p*-file | *q*-file | - |
| B | Wind speed | 15 | 45 | km/h |
| C | Initial focus | [109, 91] | [189, 77] | - |
| D | Number of foci | 1 | 2 | - |
| - | Temperature | 20 | | °C |
| - | Relative humidity | 75 | | % |
| - | Wind direction | N | | - |
| - | seed (seed of the random number generator) | 1 | | - |

**Design**

The configuration for each controllable factor and the values corresponding to each of the levels are shown in Table 6. Italics indicate the fixed values for the controllable factors that will not be analysed in this experiment.

The number of controllable factors is four, with three replicates and 16 centre points, which, according to Equation (3), implies that the total number of treatments is 64. The resolution of this experiment is shown in Table 7. The most important benefit of this design resolution is that the different configurations of controllable factors in the process are fully explored.

$$\text{cant\_treatments} = \text{cant\_levels}^{\text{cant\_factors}} * \text{repetitions} + \text{centre\_points} = 2^4 * 3 + 16 = 64 \,\ldots\ldots\ldots \tag{3}$$

**Table 7.** Full factorial experiment setup

| Configuration parameter | Value |
|---|---|
| Factors to analyse | 4 |
| Replicas | 3 |
| Number of blocks | 1 |
| Central points | 16 |
| Design of the base | 4; 16 |
| Total runs | 54 |

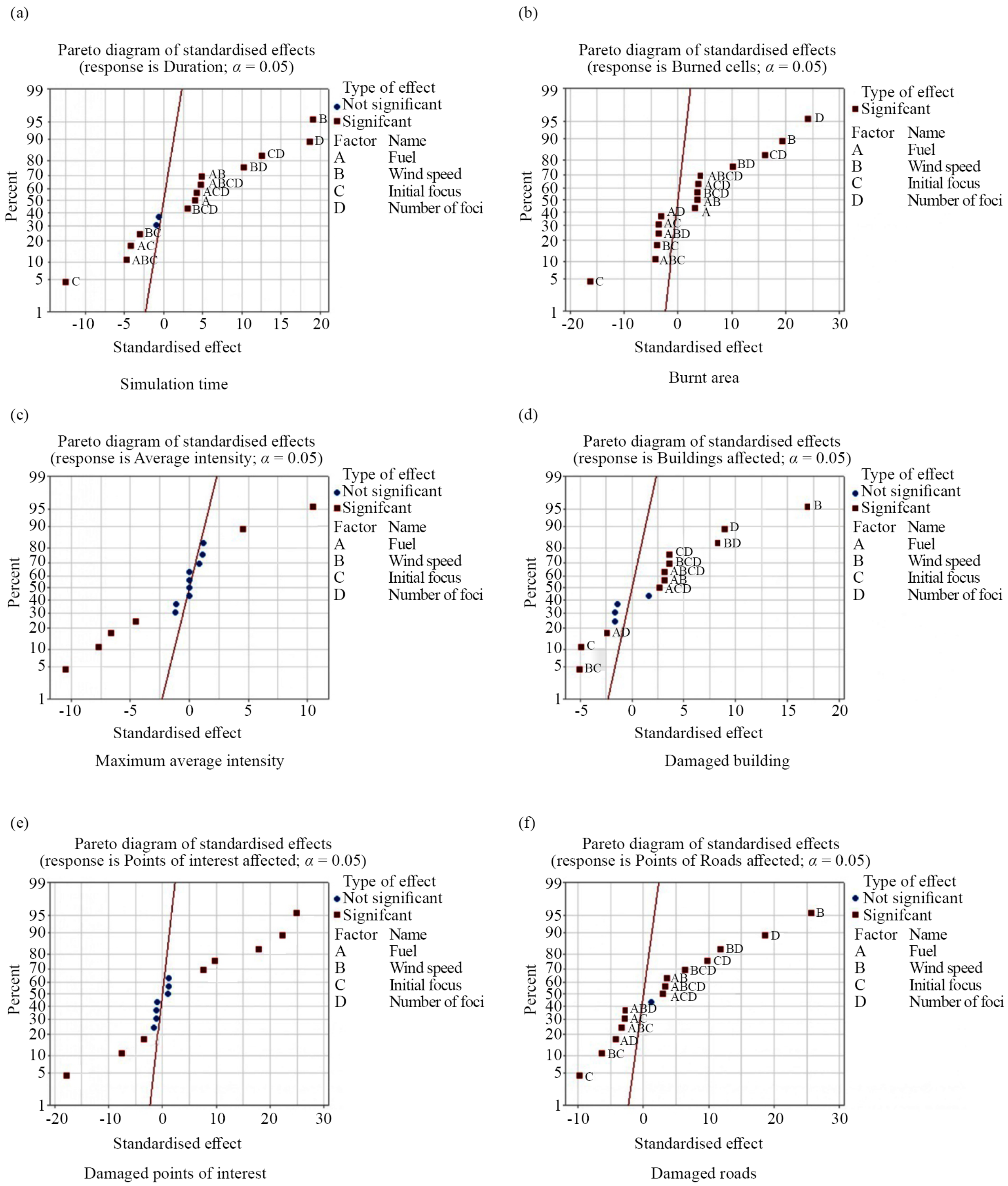



**Figure 10.** Standardised normal effects plots of the full factorial experiment

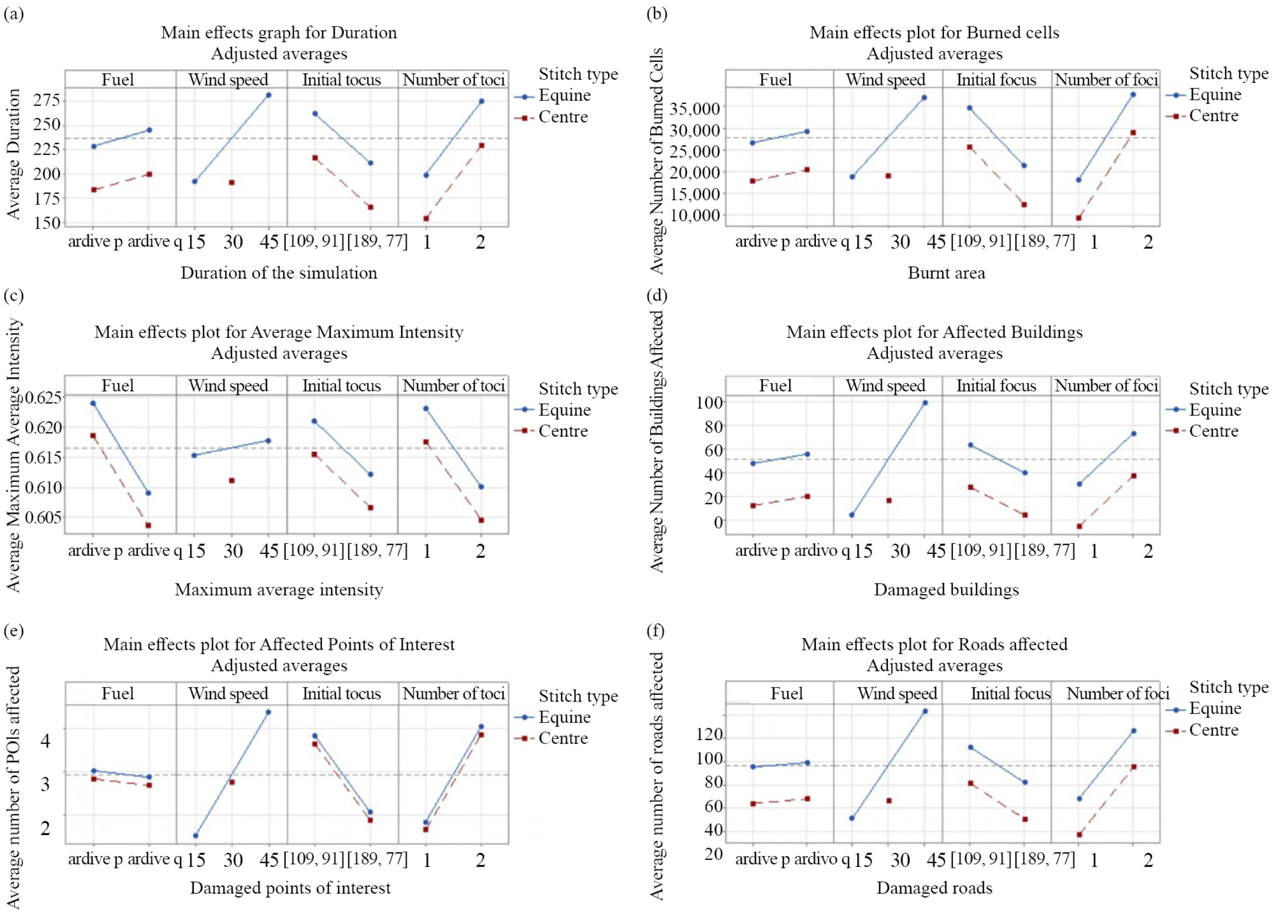



**Figure 11.** Main effect plots for each variable in the full factorial experiment

**Conduction of the experiment**

The 64 runs, corresponding to the designated treatments, were conducted during the experimental phase. The statistical software Minitab was employed as a support tool. The results are presented in Figures 10 and 11, grouped according to the relevant categories. The former illustrates the standardised effects associated with each controllable factor and their interactions for each performance variable. The factors that exert a significant influence on the model's behaviour are indicated in red. The second set of results provides an overview of the primary influencing factors for the analysed yields across all treatments, with a particular focus on those that fall outside the central range, i.e., the low and high levels.

**Analysis**

Analysing the interactions shown in Figure 10, we can see for example that the interaction between the initial focus and the number of foci is close, which is to be expected. Furthermore, the interaction between wind speed and the number of foci is close and has a significant effect on all the performance variables analysed, except for average intensity.

The interactions between factors were quantified using a full factorial design, with statistical analysis conducted using Minitab. Significant interactions were observed, particularly between wind speed and the number of fire outbreaks. For example, Figure 10 shows that the interaction between these two factors strongly influences all performance variables except average fire intensity. Additionally, the interaction between initial focus and the number of fire outbreaks exhibited a substantial impact on burned area, highlighting the sensitivity of the model to spatial dynamics. Unexpected results included the diminished effect of the initial focus at high wind speeds, suggesting a nonlinear dependency requiring further investigation.

Figure 11 shows the main effects of each variable separately. For example, looking at the straight line describing wind speed, it can be seen that it has a steeper slope for each yield variable except area burnt. This suggests that this is the most influential main effect. In the case of area burnt, Figure 11b shows that the number of foci has an even steeper slope than that of wind speed and therefore has a greater effect.

### 4.2.3 *Conclusion of the experiment*

The final screening experiment provided a comprehensive analysis of the individual influence of each controllable factor and allowed for a reduction in the number of factors to four for a full factorial design. The four most influential factors identified were fuel type, wind speed, initial focus, and the number of fire outbreaks.

The factorial experiment enabled an in-depth exploration of both the individual effects of these factors and their interactions on the model's performance variables. Notably, a strong interaction was observed between the initial focus and the number of fire outbreaks, significantly influencing the model's behavior. Similarly, the interaction between wind speed and the number of fire outbreaks emerged as a critical factor, except in the case of mean intensity.

Wind speed demonstrated a dominant influence on the model's behavior across all performance metrics. This pronounced impact suggests that recalibration of the simulation may be necessary to balance its effect with that of the other controllable factors.

The combined results from the screening and factorial experiments confirmed that fuel type, wind speed, initial focus, and the number of fire outbreaks are the primary drivers of fire behavior in the model. The factorial design also revealed significant dependencies between these factors, such as the interplay between wind speed and the number of fire outbreaks. These findings validate the simulation model's design and underscore the importance of accounting for such interactions when applying the model to real-world scenarios.

Finally, the Pareto diagram analysis reinforced that fuel type and wind speed are the most influential factors in fire propagation. These variables, alongside initial focus and the number of fire outbreaks, exhibited significant impacts on multiple metrics, including average fire intensity and burned area. This highlights the necessity of prioritizing these parameters in future studies to enhance predictive accuracy.

## 5. Conclusions

This study proposes an agent-based simulation model for investigating the spread of fires across diverse environments, with a particular focus on conditions specific to Cuba. The model integrates Geographic Information Systems (GIS) and utilizes the GAMA platform, facilitating the creation of a more accurate and detailed terrain representation, thereby enhancing decision-making processes for fire prevention and mitigation. The experimental analysis identified fuel type, wind speed, and the number of fire outbreaks as the most influential factors driving fire behavior. Additionally, a strong interaction between the initial fire location and the number of outbreaks was observed, underscoring the importance of accurately modeling these spatial dynamics. Among all factors, wind speed exhibited a dominant influence across performance metrics, except for average fire intensity, suggesting the need for recalibration to better balance its effect with other factors.

Compared to previous studies, this research introduces a novel approach by integrating real-time meteorological data and tailoring the model to Cuba's unique environmental context. These advancements facilitate realistic scenario testing and provide actionable insights for disaster management, urban planning, and firefighter training. Furthermore, the model demonstrates its potential for broader applications, such as improving fire brigade training and disaster response planning, making it a valuable tool for mitigating the impacts of natural fires on human lives and ecological resources.

The findings emphasize that wind speed and fuel type are the most critical factors influencing fire propagation, with relative impacts of 45% and 30%, respectively. These variables, in conjunction with initial focus and the number of fire outbreaks, ought to be prioritized during model calibration. The substantial interaction between initial focus and the number of fire outbreaks further underscores the importance of incorporating spatial dynamics in fire propagation simulations. In summary, the results of this study offer significant insights that can be used to improve the model's accuracy and its applicability to real-world scenarios.

While this study provides valuable insights and a novel approach to modeling fire propagation, it is important to acknowledge that the practical applications of the model in its current form remain limited. To achieve its full potential, further refinements are necessary, particularly in recalibrating the influence of wind speed and validating the model across diverse real-world scenarios. It is imperative for users of the model to exercise caution when interpreting its results and applying them to decision-making processes.

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Mailyn Moreno-Espino, Centro de Investigacion en Computacion, Instituto Politecnico Nacional, Ciudad de Mexico, Mexico; Lazaro Michel Reyes-Valdes, Facultad de Informatica, Universidad Tecnologica de La Habana "Jose Antonio Echeverria", La Habana, Cuba; Robert Ruben Benitez, Facultad de Informatica, Universidad Tecnologica de La Habana "Jose Antonio Echeverria", La Habana, Cuba; Ariel Lopez-Gonzalez, Computer Science and Engineering Department, Universidad Carlos III de Madrid, Madrid, Spain; Cornelio Yanez- Marquez, Centro de Investigacion en Computacion, Instituto Politecnico Nacional, Ciudad de Mexico, Mexico; Yahima Hadfeg-Fernandez, Facultad de Economia y Administracion, Universidad Catolica del Norte, Antofagasta, Chile.

## Conflict of interest

The authors confirm that there is no conflict of interest to declare for this publication.

## References

[1] Macal CM. Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*. 2016; 10(2): 144-156.

[2] Rossetti MD. *Simulation Modeling and Arena*. Hoboken, NJ, USA: Wiley & Sons; 2021.

[3] Law AM, Kelton WD, Kelton WD. *Simulation Modeling and Analysis*. 3rd ed. New York, NY, USA: McGraw-Hill Education; 2014.

[4] Maria A. Introduction to modeling and simulation. In: *Proceedings of the 29th Conference on Winter Simulation-WSC '97*. USA: IEEE Computer Society; 1997. p.7-13.

[5] Borshchev A. *The Big Book of Simulation Modeling: Multimethod Modeling with Anylogic 6*. Wilmington, DE, USA: AnyLogic North America; 2013.

[6] Macal CM, North MJ. Tutorial on agent-based modelling and simulation. *Journal of Simulation*. 2010; 4(3): 151-162.

[7] Antelmi A, Cordasco G, D'Ambrosio G, Vinco DD, Spagnuolo C. Experimenting with agent-based model simulation tools. *Applied Sciences*. 2023; 13(1): 13.

[8] Úbeda X, Francos M. Incendios forestales, un fenómeno global [Forest fires, a global phenomenon]. *Biblio 3w: Revista Bibliográfica de Geografía y Ciencias Sociales*. 2018; 23(21): 742-798.

[9] Drysdale D. *An Introduction to Fire Dynamics*. Hoboken, NJ, USA: John Wiley & Sons, Ltd; 2011.

[10] ISO. *Seguridad Contra Incendios*. Vocabulario. Geneva, Switzerland: ISO; 2008.

[11] Segumar L. *Química del fuego [Fire Chemistry]*. Universidad Nacional del Centro de la Provincia de Buenos Aires, Facultad de Ingeniería: Buenos Aires, Argentina; 2015.

[12] Muñoz RV. *La Defensa Contra Incendios Forestales*. New York: McGraw-Hill; 2000.
[13] Pūtaiao PA. *Fire Behaviour*. Science Learning Hub Pokapu Akoranga Putaiao; 2009. Available from: https://www.sciencelearn.org.nz/resources/763-fire-behaviour [Accessed 10 April 2023].
[14] Julio G, Giroz G. Notas sobre el comportamiento del fuego y su aplicación en el control de incendios forestales [Fire behavior and its application in forest fire prevention]. *Bosque*. 1975; 1(1): 18-27.
[15] Barowy A, Madrzykowski D. *Simulation of the Dynamics of a Wind-Driven Fire in a Ranch-Style House-Texas*. Gaithersburg, MA, USA: National Institute of Standards and Technology, Fire Research Division Engineering Laboratory; 2012.
[16] Wooldridge MJ. *An Introduction to Multiagent Systems*. 2nd ed. Hoboken, NJ, USA: John Wiley & Sons; 2009.
[17] Cenani Ş. Emergence and complexity in agent-based modeling: Review of state-of-the-art research. *Journal of Computational Design*. 2021; 2(2): 1-24.
[18] Pal CV, Leon F, Paprzycki M, Ganzha M. A review of platforms for the development of agent systems. *Information*. 2020; 14(6): 348.
[19] Abar S, Theodoropoulos GK, Lemarinier P, O'Hare GM. Agent based modelling and simulation tools: A review of the state-of-art software. *Computer Science Review*. 2017; 24: 13-33.
[20] Kravari K, Bassiliades N. A survey of agent platforms. *Journal of Artificial Societies and Social Simulation*. 2015; 18(1): 11.
[21] Foramitti J. AgentPy: A package for agent-based modeling in python. *Journal of Open Source Software*. 2021; 6(62): 3065.
[22] Cardinot M, O'Riordan C, Griffith J, Perc M. Evoplex: A platform for agent-based modeling on networks. *SoftwareX*. 2019; 9: 199-204.
[23] Taillandier P, Gaudou B, Grignard A, Huynh QN, Marilleau N, Caillou P, et al. Building, composing and experimenting complex spatial models with the GAMA platform. *GeoInformatica*. 2019; 23(2): 299-322.
[24] Caire FBG, Poggi A, Rimassa G. JADE A white paper. *Telecom Italia Lab*. 2003; 3: 1-14.
[25] McGrattan K, Hostikka S, Floyd J, Baum H, Rehm R, Mell W, et al. *Fire Dynamics Simulator (Version 5) Technical Reference Guide*. Gaithersburg, MD: NIST Special Publication; 2010.
[26] McGrattan K, Hostikka S, McDermott R, Floyd J, Weinschenk C, Overholt K. *Fire Dynamics Simulator User's Guide*. Gaithersburg, MD: NIST Special Publication; 2013.
[27] Smardz P, Novozhilov V. *Validation of Fire Dynamics Simulator (FDS) for Forced and Natural Convection Flows*. Northern Ireland, UK: University of Ulster; 2006.
[28] Tymstra C, Bryce RW, Wotton BM, Taylor SW, Armitage OB. *Development and Structure of Prometheus: The Canadian Wildland Fire Growth Simulation Model*. Information Report NOR-X-417. Edmonton, AB, USA: Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre; 2010.
[29] Hagelin H, Cluzel M. *Applying FARSITE and Prometheus on the Västmanland Fire, Sweden (2014): Fire Growth Simulation as a Measure Against Forest Fire Spread: A Model Suitability Study*. Lund University Sweden: Student Thesis Series INES; 2016.
[30] Pais C, Carrasco J, Martell DL, Weintraub A, Woodruff DL. Cell2Fire: A cell based forest fire growth model. *arXiv:190509317*. 2019. Available from: https://doi.org/10.48550/arXiv.1905.09317.
[31] Finney MA. *FARSITE: Fire Area Simulator-Model Development and Evaluation*. Fort Collins, CO, USA: US Department of Agriculture, Forest Service, Rocky Mountain Research Station; 1998.
[32] Pacheco AP, Claro J, Fernandes PM, de Neufville R, Oliveira TM, Borges JG, et al. Cohesive fire management within an uncertain environment: A review of risk handling and decision support systems. *Forest Ecology and Management*. 2015; 347: 1-17.
[33] Silva FRy, Molina-Martínez JR. Modeling mediterranean forest fuels by integrating field data and mapping tools. *European Journal of Forest Research*. 2012; 131(3): 571-582.
[34] Rodríguez RG. Estrategia y Programa Nacional de Gestión y Manejo del Fuego en los bosques de la República de Cuba para el período 2018-2025 [National strategy and program for forest fire management and management in the republic cuba from 2018 to 2025]. *Biodiversidade Brasileira*. 2019; 9(1): 262.