Wildfire simulation model based on cellular automata and stochastic rules

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Abstract. A significant increase in the occurrence of large wildfires has been observed in the last decades. Several works seek ways to attenuate the side effects of these events. In this work, it is proposed a simulation model for wildfires propagation based on stochastic cellular automata. Its main objective is to understand the dynamics of these wildfires in order to speed the decision-making on the main actions to be taken by firefighter forces. The model presents different states, fire intensities and wind currents that redirect the flames. In addition, a non-linear vegetation recovery function is proposed, which brings the model closer to the real characteristics of natural systems. According to the results obtained, it was possible to conclude that the model achieves the expected objectives, satisfactorily simulating the analysed phenomenon.

Keywords: Cellular automata · Stochastic rules · Wildfire simulation · Complex phenomena · Firefighting efficiency

1 Introduction

Spontaneous wildfires occur in nature and are part of the natural cycle necessary for the conservation of some biomes [13]. However, the occurrence of these events has increased throughout the planet in the last decades due to the impacts of climate changes, indiscriminate exploitation and extraction [9]. Since this increase is not part of its natural cycle, in most cases these environments end up collapsing. In addition to the loss of the fauna and the flora, which are irreparable, these wildfires can advance to areas of human occupation [11], especially those of marginalised populations (e.g., indigenous tribes, *quilombolas*, riverside dwellers and *favelas*) where there is no ideal physical infrastructure.

In order to mitigate negative effects, many works propose wildfire simulation models [12], seeking to understand the behaviour of the flames as a means to recommend countermeasures, strengthening the capacity to prevent and suppress wildfires while protecting human lives, nature itself and property.

Cellular Automata (CA) [4] stand out as a simulation technique due to their simplicity of implementation and high correspondence with natural behaviour.

Among the several dynamic models that use CA, we can highlight models for urban growth [1], pedestrian evacuation [3], coordination of swarm of robots [16], epidemiology [14], and disease vector spreading [6]. Considering that a wildfire can be categorised as a complex natural phenomenon, the application of CA facilitates its simulation, since they are discretised both in time and in space [5]. On the other hand, the implementation of continuous systems for the spread of fire would demand a greater computational processing. Furthermore, since the cells evolve independently, it is easily adaptable for multiprocessing, allowing the exploration of high-performance simulations.

Therefore, considering the points raised, this work proposes a computational model to simulate wildfires as a way to speed the decision-making process and, thereby, enabling a greater efficiency for management and firefighting forces. The model is based in CA with stochastic rules for fire propagation. Applied in areas of vegetation, the model does not only take into account the burning time, but other important characteristics during a wildfire, such as the fire intensity, the presence of wind currents and obstacles. Furthermore, this work also contributes from an experimental perspective, since it performs a set of experiments in order to analyse how different parameters influence the evolution of wildfires.

2 Related Works

This section describes a brief literature review including some works related to the application of cellular automata in wildfires simulation. At the end of this review, a table (Table 1) is presented in order to compare key characteristics of the models described by these works with our proposed model.

One of the seminal works proposing CA models to simulate fire spreading is [5]. The model employs three states and stochastic transition rules to recover burnt cells and provide spontaneous combustion. In order to enhance simulations with wildfires, the application CA with hexagonal tessellation spaces was proposed in [20]. Experiments with artificial and real data allowed to conclude that the model can be useful in managing wildfires with heterogeneous characteristics. In [19], it was proposed the integration of CA and Geographic Information Systems for the simulation of forest fires. Focusing on modelling the environment, the system presents different options for terrain, vegetation and weather. According to the authors, the results showed that the proposed model can be adapted to other spatiotemporal modelling applications based on CA. Bringing the models closer to reality, a case study related to a forest fire (Spetses Island, 1990) was carried out in [2]. The authors proposed a simulation model using a non-linear optimisation approach to approximate its behaviour to that of the analysed event. The simulation results were promising in terms of the predictive capacity of the model. More recent works still present CA as an important tool for fire simulation models. In [8] is proposed a model for the simulation of forest fires based on CA that applies a numerical optimisation approach to find values that correlate the model parameters. Simulations showed promising results, bringing the proposal closer to the classical methods. In [18], the authors evaluated a set of factors that influence the spread of flames in forest fires. Among the analysed factors, the authors highlight combustible materials, wind, temperature, and terrain. Implemented through CA rules, the model demonstrates to be able to satisfactorily simulate the flame spread trends under different conditions. Finally, a model for simulating forest fires was proposed by combining different techniques, including CA, in [15]. The main objective of the authors was to improve the accuracy of the model in relation to the spread speed of the flames. According to the results, the model was able to simulate and predict the spread of forest fires, ensuring accuracy in the simulations.

Table 1: Detailed comparison between CA-based wildfire simulation models

Authors	Year	CA States				Prblty.	Wind	Topog.	Veg. recover
		Veg.	Fire	Obst.	Total				
Chopard et al. [5]	1998	1	2	0	3	Yes	No	2D	Linear
Yongzhong et al. [20]	2004	1	2	0	3	No	Yes	3D	No
Yassemi et al. [19]	2008	1	[0.0...1.0]	0	∼	Yes	Yes	3D	No
Alexandridis et al. [2]	2008	1	2	1	4	Yes	Yes	3D	No
Ghisu et al. [8]	2015	1	2	0	3	No	Yes	3D	No
Xuehuaet al. [18]	2016	1	2	1	4	No	Yes	3D	No
Sun et al. [15]	2021	1	4	0	5	No	Yes	3D	No
Our Model	**2022**	**1**	**4**	**1**	**6**	**Yes**	**Yes**	**2D**	**Non-linear**

3 Model Description

Inspired by the works presented in Section 2, we propose a wildfire simulation model based on CA. Applying a stochastic evolution, the model is characterised by the composition of a combustion matrix with wind currents. Furthermore, in order to maintain the environment cycle realistic, it is also proposed a non-linear recovery function based on an exponential probability for burnt cells.

Figure 1 shows the possible states for each CA cell. The state “vegetation” (in green) represents the cells that have fuel material. It is a state that does not influence others, but can be influenced by the fire states. States “initial-fire”, “stable-fire” and “ember” (orange, red and dark-red, respectively) represent the fire states, where each one has a different local fire intensity (defined later). When a fire is over, the cells change to the state “ash” (grey). In this state, there is no likelihood of spreading fire to other cells or catching fire again, unless fuel material in this position recovers. Finally, the state “water” (blue), is a state defined at the beginning of the simulation, and does not interact with any other state, but it can serve as a barrier if a fire takes its direction.

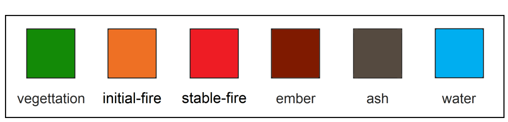
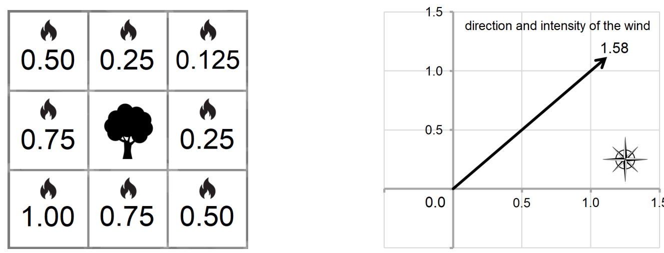


Fig. 1: Possible states for the cells of the CA described by different colours.

Cells change state according to transition rules, which here we call fire propagation rules. These rules use a combustion probability matrix that defines the probability of the central cell to ignite through the propagation of fire from its closest cells (Moore's Neighbourhood), whether they are already in some state of fire. The proposed combustion probability matrix can be seen in Figure 2a. The figure shows a central cell in the state "vegetation", i.e., capable of igniting. Each cell in the neighbourhood of the central one has a probability of propagating the fire. For example, the cell to the right of the central cell has a probability of 25% of propagation. Furthermore, the total burning time of a cell lasts a few time steps and the central cell is influenced by all the cells in its neighbourhood, increasing the probability of ignition when accumulated.



(a) Combustion matrix (b) Wind force vector

Fig. 2: Combustion probability considering a northeast wind: (a) combustion matrix and (b) force vector with the direction and intensity of the wind.

It is known that certain factors can influence how the flames spread in a wildfire [18]. In our work, the wind was defined as an influencing factor. In the combustion matrix (Fig. 2a), one can see that the lower-left cell has a higher probability of propagation (100%) in comparison to the upper-right cell (12.5%). This difference in the probability is due to the composition of the combustion matrix and wind currents. In order to facilitate the visualisation, Figure 2b presents the wind influence as a force vector. This vector constitutes the influence composition of all cells that are in the neighbourhood of the central cell. As a result, we have the wind direction and its intensity.

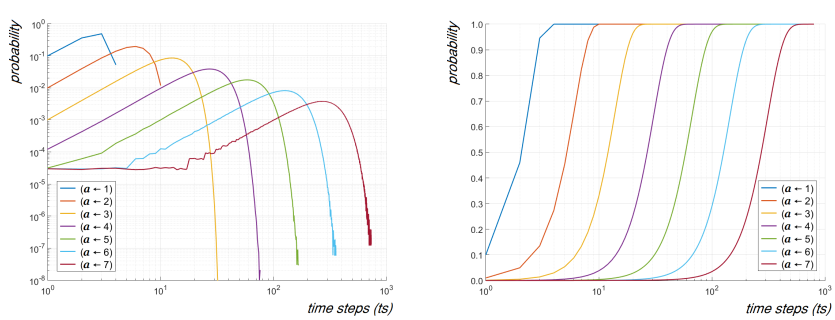
The model has two coefficients to adjust the fire behaviour: the calorie (λ) and the wind factor (δ). The calorie λ is used to produce different scales of wildfires, i.e., it represents the global fire intensity. For its implementation, the coefficient is applied to each cell of the combustion matrix (Fig. 2a). In turn, the wind factor δ represents a cardinal/collateral value that indicates the direction of the wind. For instance, considering Figure 2b, the value of δ would be "northeast". From this coefficient, it is possible to rearrange the combustion matrix (done by means of rotations) in such a way that its values represent the specified direction. Since the combustion matrix represents a predefined proportionality of fire propagation, both coefficients, λ and δ, modifies these values maintaining the same proportion. Furthermore, from these coefficients, the model derives all parameters used in the simulation, including the CA rules.

In addition to the fire propagation rules, our model also implements a transition rule for the recovery of burnt vegetation. That is, unlike the other models of the literature presented in Section 2, in our model, a cell that is burnt, i.e., in the state "ash", can return to be a cell in the state "vegetation". Vegetation recovery is an important process to consider, as some biomes are highly resilient to wildfires and have a rapid recovery capacity. Described by the Generating Function (GF) in Equation 1, it defines the probability of recovering P_r of a cell x_{ij} of the 2D lattice. If a time of idleness is defined, i.e., a period after the burn where no recovery occurs, then the probability is zero. Otherwise, the probability is equal to the square of the counting of time steps since the cell x_{ij} turn to ash (ts_r) over a power of 10. Defined by the variable a, this exponential represents the longitudinal extent of the probability distribution.

$$P_r(x_{ij}) = \begin{cases} 0.0, & \text{if } \textit{idle} \\ {(ts_r)^2}/{10^a}, & \text{otherwise, such that } ts_r \geq 1 \textit{ and } a \geq 1 \end{cases} \tag{1}$$

In order to take the model closer to reality, the GF is defined as an exponential, in which the applied probability is proportional to the number of time steps, i.e., cells that have been burnt for a long time are more likely to change state. Other types of functions would not print the desired behaviour. On the one hand, a constant probability function would not have a temporal effect on the recovery of the flora, i.e., it would not imply that the longer a cell is burnt, the more likely it is to be reborn. On the other hand, using a linear probability function, although the temporal characteristic is present, would imply an accentuated probability of recovery for cells that have just been burnt.

Figure 3 illustrates examples of Probability Density Functions (PDF) (Fig. 3a) and Cumulative Distribution Functions (CDF) (Fig. 3b), obtained through the GF (Eq. 1). The PDF and CDF curves were computed using a process derived



(a) Relative Probability (b) Cumulative Probability

Fig. 3: Probability distribution for the recover of cells after a complete burning.

from the Monte Carlo method [10] (each curve with a sample size of 100m). The variable a affects the height of the PDF curve, i.e., it increases the distribution of data over more time steps. According to the data obtained, the value of a equal to six ($a = 6$) presented the best behaviour intended. In this case, the PDF shows that the highest probability of a cell being reborn is reached around the time step 160. In turn, in CDF, from the time step 300, the probability of a burnt cell being reborn is almost 100%, considering that the $\lim_{x\to\infty} CDF = 1.0$.

CA Rules: Taking into account the characteristics and parameters of the model presented, the fire propagation rules can be described as follows:

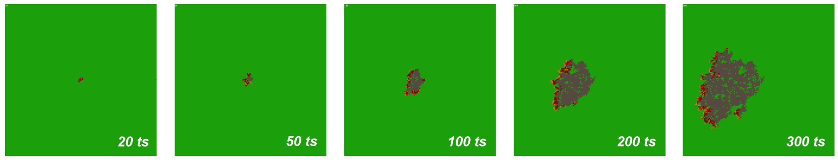
- If the central cell is in the state *"vegetation"* and there are no cells in a fire state in the neighbourhood: maintain the same state;
- If the central cell is the in state *"vegetation"* and a cell cl in the neighbourhood is in a fire state: there is a probability to change to the state *"initial_fire"*; $\{P($*"initial_fire"*$) =$ *combustion-matrix(cl)* $\times$ *local-fire-intensity* $\times (\lambda)\}$
- If the central cell is in the state *"initial_fire"*: it is not influenced by other cells, maintains this state for 3 time-steps and switches to the state *"stable_fire"*;
- If the central cell is in the state *"stable_fire"*: it is not influenced by other cells, maintains this state for 3 time-steps and switches to the state *"ember"*;
- If the central cell is in the state *"ember"*: it is not influenced by other cells, maintains this state for 10 time-steps and switches to the state *"ash"*;
- If the central cell is in the state *"ash"*: it is not influenced by other cells. It can change to the state *"vegetation"* according to the recovery function (Eq. 1);
- If the central cell is in the state *"water"*: there is no interaction with others states.

Model Parameters (values obtained by preliminary experiments): calorie ($\lambda = \{0.08, 0.16, 0.24\}$); wind factor ($\delta = \{\{cardinal\} \cup \{collateral\}\}$); local fire intensity (*"initial_fire"* $= 0.6$; *"stable_fire"* $= 1.0$; *"ember"* $= 0.2$); dwell time of states with active fire (*"initial_fire"* $= 3ts$; *"stable_fire"* $= 3ts$; *"ember"* $= 10ts$); recovery time step ($ts_r = \{1..\} \parallel ts_r \in \mathbb{N}^*$); and, the exponent ($a = 6$).

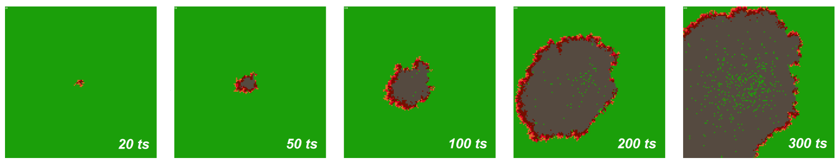
4 Simulations and Analyses

This section describes the simulations and analyses performed with the proposed model. It was implemented in the GameMaker [7] engine and in the C programming language, where the former was used for visualisation and the latter for mass processing. All simulations have run for 300 time steps, while the mass experiments consist of 100 executions per simulation, using different seeds to avoid outliers. Screenshots are composed of a CA lattice (1024×1024) in the same time step intervals $ts = \{20, 50, 100, 200, 300\}$.

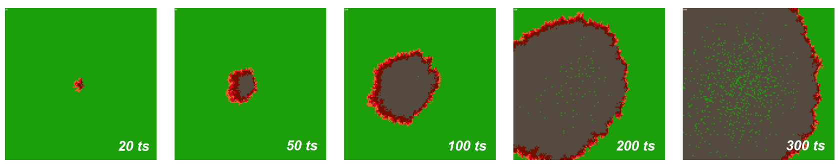
Figure 4 presents three scenarios (S1, S2 and S3) of wildfires using our proposed model. Each scenario implements a different caloric coefficient: $\lambda_1 = 8\%$ (Fig. 4a); $\lambda_2 = 16\%$ (Fig. 4b); and $\lambda_3 = 24\%$ (Fig. 4c), respectively. The evaluation of different calories is very important, since some biome and climate characteristics (e.g., type of vegetation, seasonality, humidity, temperature) can



(a) Scenario S1: ($\lambda_1 = 0.08$)



(b) Scenario S2: ($\lambda_2 = 0.16$)



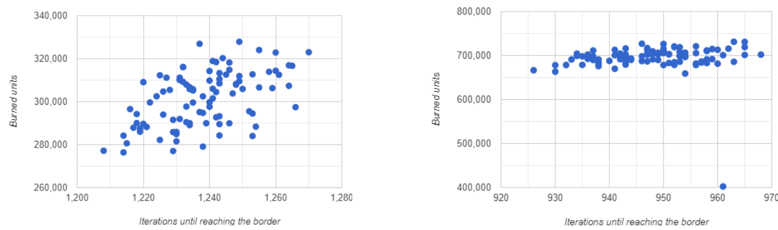
(c) Scenario S3: ($\lambda_3 = 0.24$)

Fig. 4: Evolution of the model in three different scenarios, in which there is the presence of wind currents from east to west and different calorie coefficients.

influence how the flames behave whether a wildfire occurs. Thus, the main objective of these simulations is to, empirically, observe the evolution of the flames in relation to the caloric coefficient, so that it would be possible to calibrate the model and bring its behaviour closer to the characteristics of real wildfires.

In the beginning, all cells are in the state *"vegetation"*. Intentionally, a spark is placed in the centre of the lattice to start the fire. In the scenario S1, one can observe that the propagation of the fire is slower compared to the other two scenarios. In S2 and S3, all cells within the wildfire radius went into combustion, differently from scenario S1. This is due to the fact that the coefficient calorie was weakened in S1. Observing Figure 4a ($ts = 300$), there are several intact green areas within the burnt area, not resulting from the recovery of the vegetation (depending on environmental conditions, a part of the vegetation may not be affected in real wildfires). In the scenarios S2 and S3, in which the coefficient calorie is stronger, all cells ignited within the radius of the wildfire. In S3, in addition to the burning of all cells, the speed of fire propagation was faster. For instance, in S3 with 200 time steps, the burn radius is close to that of S2 with 300 time steps. Finally, it is worthy to highlight the recovery of cells in the state *"ash"*, from the centre (older burnt cells) to the edges (recently burnt cells), which characterises the proposed recovery function (see Eq. 1).

This analysis is even more evident by observing the charts of Figure 5, which show the total number of burnt cells and time steps required for the fire to



(a) S2 ($\lambda_2 = 0.16$) (b) S3 ($\lambda_3 = 0.24$)

Fig. 5: Simulations performance in the scenarios S2 and S3.

reach one of the lattice edges in all simulations, considering scenarios S2 and S3 (Figures 5a and 5b, respectively). As it can be noticed, the increase of 50% in the combustion coefficient resulted in an increase upper than 100% in the number of burnt cells (300,000 vs. 700,000) and a reduction of approximately 33% in the time steps needed to reach the lattice edge (950 vs. 1,240).

In a second experiment, an obstacle was built in the direction of the fire (southwest). Figure 6 presents a scenario (using $\lambda = 0.16$ and $a = 6$) where the fire goes towards a lake (cells in blue representing state *"water"* [5]). From 100 time steps, it is possible to notice that the flames reach the lake and, in that direction, the fire propagation is interrupted. However, the flames manage to go around the lake and reach the opposite shore. Despite being an initial experiment, this is an important variable to be considered in wildfires, to understand which factors would influence the blocking of the flames. For instance, although water flows are obstacles, in some real wildfires, flames are able to cross rivers, depending on their width, through the dispersion of sparks by the wind.

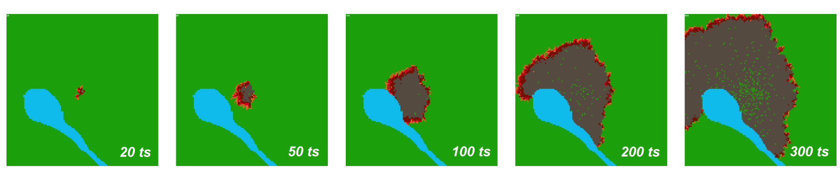
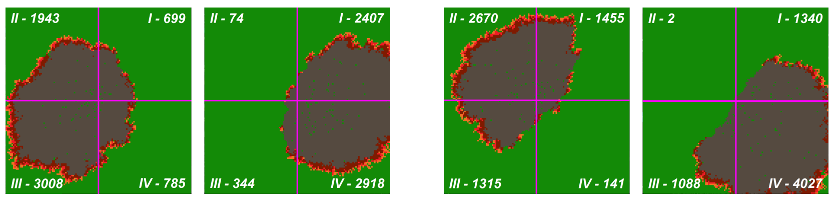


Fig. 6: Propagation of the wildfire towards a lake as an obstacle.

In order to better visualise the influence of wind currents, Figure 7 shows two scenarios where the wind force (δ) is opposite. In the first one (Fig. 7a) the wind current is cardinal *east* $\leftrightarrow$ *west*, whereas in the second one (Fig. 7b) it is collateral *northwest* $\leftrightarrow$ *southeast*, both using ($\lambda = 0.16$) and ($a = 6$). Besides, the figures were divided into Cartesian quadrants, making it possible to compare and quantify burnt cells (state *"ash"*). Figure 7a, in which the wind current is from *east* $\rightarrow$ *west*, has a total of 6435 burnt cells, where 76.93% (4951 cells) are in quadrants II and III, and 23.06% (1484 cells) in quadrants I and IV. On the other hand, when the wind current from *west* → *east*, the fire spreads in the opposite direction. From 5743 burnt cells, 92.72% (5325 cells) are in quadrants I and IV, while 7.27% (418 cells) are in quadrants II and III. The same behaviour is observed in Figure 7b. Applying a wind current from *southeast* → *northwest*, from 5581 burnt cells, 47.84% (2670 cells) are just in quadrant II, while 52.15% are distributed over the others. When the wind current is from *northwest* → *southeast*, from 6457 burnt cells, 62.36% (4027 cells) are in quadrant IV, while 37.63% are distributed. These results are consistent with the expected influence of wind currents, since the fires have started exactly at the centre of the lattice.



(a) West ⟷ East (b) Northwest ⟷ Southeast

Fig. 7: Assessment of the influence of wind currents through Cartesian planes.

5 Conclusion and Future Work

This work proposed a model for wildfire simulation through the application of cellular automata. Among its main characteristics, one can highlight (i) the presence of different states for the fire, which makes it possible to simulate different intensities of flames; (ii) the presence of wind currents that influence the fire direction; and, (iii) a non-linear recover function for the burnt vegetation.

According to the preliminary analyses, it was possible to conclude that our model achieves the expected behaviour. It was able to satisfactorily simulate, considering the characteristics presented, the fire behaviour in the event of a wildfire. The spreading of the flames presented clear characteristics of a stochastic model, and the wind currents were able to direct these flames. Moreover, the proposition of a recovery function allowed to print more realistic characteristics, mainly, compared to a random function, which, in turn, gave a high probability to the vegetation to grow in the time step subsequent to its burning.

Regarding future works, we intend (i) to add more states to the vegetation, bringing it closer to the characteristics of the Cerrado, a biome in our location that frequently suffers from wildfires; (ii) to compare our model with other wildfire simulation models present in the literature; (iii) to evaluate the construction of a three-dimensional model, which would allow the implementation of fire propagation by roots and wind; (iv) to make a deep study of the sensitivity of the model's parameters; and (v) to apply evolutionary computation in the optimisation this parameters [17], taking into account real data.

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