Wildfire Spread Modeling in Pau Furado State Park Using Cellular Automata and Genetic Algorithms

Maria Eugênia A. Ferreira[1], Danielli A. Lima[2], Luiz Gustavo A. Martins[3]

[1]Federal University of Uberlândia (UFU) Campus Santa Mônica,
Electrical Engineering Faculty (FEELT), Uberlândia, MG, Brazil

[2]Laboratory of Intelligent Computating, Robotics and Optimization (LICRO)
Federal Institute of Triângulo Mineiro (IFTM) Campus Patrocínio, Patrocínio, MG, Brazil.

[3]Federal University of Uberlândia (UFU) Campus Santa Mônica,
Computer Faculty (FACOM), Uberlândia, MG, Brazil

maria.eugenia@ufu.br, danielli@iftm.br, lgamartins@ufu.br

Abstract. *Wildfire spread has intensified in Brazil, particularly in biomes such as the Cerrado, due to climate change and environmental degradation. This study proposes a heterogeneous wildfire spread model based on cellular automata (CA), optimized using genetic algorithms (GA), to simulate fire propagation in areas with different vegetation types, such as Pau Furado State Park. The model accounts for the interaction between wind, vegetation, and soil conditions, and employs the GA to adjust parameters such as fire intensity and wind direction, aiming to align the simulations with reference data. The results showed that the model accurately reproduced fire spread dynamics, demonstrating the effectiveness of GA in parameter optimization.*

1. Introduction

The spread of wildfires is a phenomenon that can result in substantial environmental, social, and economic damage. In Brazil, wildfires have intensified in recent years, particularly in biomes such as the Amazon, the Cerrado, and the Pantanal [Mota et al. 2019]. The increasing frequency of fires is closely linked to climate change, which leads to longer drought periods and rising temperatures. Additionally, environmental degradation caused by human activities further hinders the maintenance of ecological balance and biodiversity preservation [Ramos-Neto and Pivello 2000]. This scenario aligns with the Sustainable Development Goals (SDGs), particularly SDG 15, which "aims to protect, restore, and promote the sustainable use of terrestrial ecosystems, combat desertification, halt and reverse land degradation, and halt biodiversity loss." Effective wildfire modeling and monitoring are key strategies for achieving this objective, enabling a more assertive approach to fire prevention and control.

The Cerrado biome, in particular, is naturally fire-prone due to its vegetation and climatic regime. Although fire is a natural component in many ecosystems, including the Cerrado, uncontrolled and unscheduled burning leads to irreversible habitat destruction and species loss [Brasiel and Lima 2024]. Therefore, computational modeling of fire spread becomes essential to predict and mitigate such damage, providing valuable information for fire prevention and management.

Within this context, cellular automata (CA) have emerged as an effective tool for modeling natural phenomena, including wildfire spread [Tinoco et al. 2019]. CAs are dynamic systems that use a grid of interactive cells to simulate evolutionary and propagation processes in complex systems [Oliveira et al. 2001]. In the case of wildfires, they can represent the interaction between fire, wind, vegetation type, and soil conditions, allowing the simulation of fire evolution across different scenarios [Alexandridis et al. 2008]. However, to ensure the reliability of such models, effective parameter calibration is crucial. This task is particularly challenging due to the complexity and high dimensionality of the factors involved. Genetic algorithms (GAs), a class of bioinspired optimization techniques, have shown promise in automatically tuning CA parameters to improve the consistency between simulations and target scenarios [Martins et al. 2019], [Ferreira et al. 2022a], [Murilo et al. 2025].

In this paper, we propose a heterogeneous wildfire spread model based on cellular automata, designed to simulate fire behavior in areas with four distinct vegetation types. Unlike studies focused on reproducing real wildfire data, our primary goal is to evaluate the effectiveness of genetic algorithms in calibrating the parameters of the CA model. To this end, we generate synthetic reference scenarios and assess whether the GA is capable of recovering the original parameter configurations that produced them. The study is contextualized in the region of Pau Furado State Park, located in Uberlândia, Minas Gerais, whose environmental characteristics inform the construction of the synthetic scenarios used for model evaluation.

2. Related Work

In the field of evolutionary computation, several researchers have investigated the use of GAs to calibrate the parameters of CA models for the spread of insects and disease vectors [Fraga et al. 2021] [Monteiro et al. 2020]. The results demonstrated that the evolutionary approach can significantly enhance simulation accuracy by automatically and efficiently tuning model parameters. Similarly, GAs have been applied to calibrate homogeneous wildfire models [Ferreira et al. 2022a, Ferreira et al. 2022b, Murilo et al. 2025].

However, many existing studies still focus on homogeneous or simplified scenarios, and the application of GAs in heterogeneous contexts — such as those found in biomes like the Cerrado — remains a challenge. The present work aims to advance in this direction by proposing a heterogeneous model incorporating four types of vegetation and using GAs to optimize the CA parameters, thereby more accurately representing fire spread in a realistic environment, such as the Pau Furado State Park.

3. Methods

The main objective of this study is to develop a wildfire spread model based on probabilistic cellular automata, using genetic algorithms to optimize the model parameters. The model is designed to simulate heterogeneous scenarios with different vegetation types and is applied to study wildfire propagation in the Pau Furado State Park. The following sections describe the main components of the model, the optimization methodology, and the scenarios used to evaluate model performance.

3.1. Heterogeneous Cellular Automata Model for Wildfire Spread

The CA model used in this study is two-dimensional and probabilistic, representing a terrain area subdivided into cells. Each cell can assume one of two states: vegetation or fire. Fire spreads from cells currently burning to neighboring vegetation cells, depending on factors such as wind direction and intensity.

A key feature of the model is the wind matrix $W_{3\times3}$, which defines wind direction and intensity in each terrain cell. Wind is one of the main factors influencing the speed and direction of fire spread, as fire tends to propagate more quickly in the direction of the wind and in areas with stronger wind intensity. The wind matrix is dynamically configured and can be adjusted to represent different climatic and geographic conditions. Each cell of the $W_{3\times3}$ matrix contains information about wind direction (e.g., north, south, east, west) and its intensity (wind strength). This matrix plays a crucial role in the model's behavior, allowing fire propagation to be influenced by changing wind conditions, resulting in a more realistic and locally adaptable simulation. The model also includes two essential parameters to control fire spread and vegetation recovery:

`LQ` (Burning Limit): This parameter determines the fire spread rate in vegetation cells. The higher the `LQ` value, the greater the probability of fire spreading to neighboring cells. This parameter reflects vegetation characteristics such as density and fire resistance. High `LQ` values represent highly flammable vegetation, while lower values indicate more fire-resistant vegetation.

`LR` (Recovery Limit): The `LR` parameter controls the speed of vegetation recovery after a fire. Once a cell has burned, the vegetation regeneration time is determined by `LR`. A higher `LR` value implies faster recovery, whereas lower values indicate slower recovery or an inability to regenerate.

3.2. Genetic Algorithm

The purpose of the GA is to optimize the CA model parameters by tuning the `LQ`, `LR`, and the wind matrix $W_{3\times3}$, in order to improve the accuracy of fire spread simulations, aligning them with reference data. In this study, $W_{3\times3}$, `LQ`, and `LR` are calibrated by the GA to test its ability to recover model parameters from synthetic scenarios.

In a GA, each individual represents a potential solution to the optimization problem. In this case, the individual is a parameter vector describing fire behavior in a specific scenario, considering the different vegetation types in the model. Each individual consists of 10 genes per vegetation type, totaling 40 genes for the model with four vegetation types. For each vegetation type, the chromosome includes: LQ, represented by an integer value between 1 and 10; `LR`, represented by an integer between 1 and 100; and the $W_{3\times3}$ matrix, represented by 8 real values between 0 and 1, with each value indicating the probability of fire propagation in the cardinal (north, south, east, west) and intercardinal directions. With four vegetation types, the chromosome is represented as a 40-gene vector: 8 integers and 32 real values.

The initial population is randomly generated with 100 individuals. Parent selection is performed via simple tournament selection with a tournament size of 2. The crossover operator is two-point crossover, with a 90% crossover rate. The mutation rate is 20%, randomly altering genes. Two techniques are employed to determine which genes are mutated: applying a mutation mask and randomly selecting a gene to mutate. Additionally, the top 25% of individuals from each generation are preserved. The GA evolves over 100 generations. The GA parameters used in this study (mutation rate, crossover probability, and population size) were adopted from a previous sensitivity analysis [Ferreira et al. 2022a].

Each individual's fitness is calculated based on the difference between fire cells generated by the simulation and those in the reference dataset. To account for the spatial dispersion of fire cells, the grid is divided into nine parts, and the differences in the number of fire cells are computed for each part. The sum of these differences is then calculated. To reduce the effect of simulation stochasticity, cell values are recorded at each time step of a complete simulation. A total of 10^2 executions are performed for each scenario, recording the average number of fire cells in each of the nine grid regions. Each individual is evaluated over five different simulations using the parameters defined in its chromosome. For each simulation, the average number of fire cells across the nine grid regions is calculated. In heterogeneous vegetation scenarios, each vegetation type is evaluated separately. Fitness values are normalized using the min-max method, and the simple average of the fitness values for each vegetation type is computed.

At this stage of the study, synthetic datasets generated through wildfire simulations with varying parameters were used to create diverse scenarios. The goal was to evaluate the GA's ability to identify appropriate parameters for representing fire spread. Temporal sequences of grids were generated, with 50 grids representing the temporal evolution of fire. These reference datasets were used to optimize the model parameters. To reduce stochasticity and bias, 100 executions were carried out for each scenario, recording the average number of fire cells in each grid region. Differences between the simulations and the reference dataset were calculated by comparing the average values of the 100 executions with the individual simulation values.

4. Results

In this section, we present the main results obtained from the simulations. First, we describe the simulations using a heterogeneous model with four distinct vegetation types, followed by the simulation of a wildfire scenario in the Pau Furado State Park.

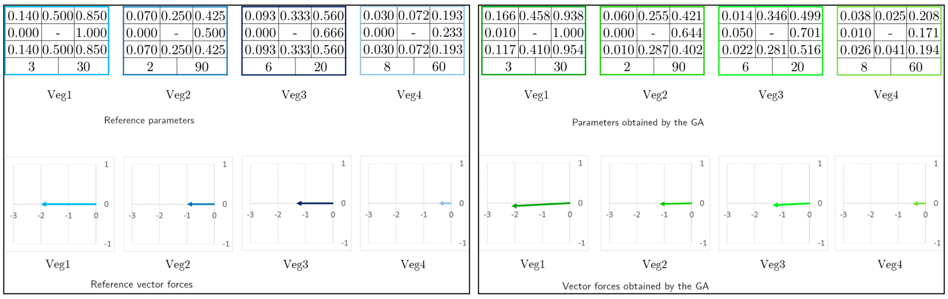
4.1. Heterogeneous Model with Four Vegetation Types

Figure 1 compares the reference parameters with those adjusted by the GA for the four simulated vegetation types. The `LQ` and `LR` parameters adjusted by the GA closely match the reference values, ensuring efficient fire propagation while maintaining intensity control. The $W_{3\times3}$ matrix obtained through the GA indicates that fire propagation occurs predominantly westward, with slight variations in vector forces, especially in Veg1 and Veg3. This suggests that the GA successfully captured subtle differences in propagation conditions.

Figure 2 illustrates the temporal evolution of the wildfire, highlighting the burned areas over time. The propagation behavior across different time steps reflects the fire dynamics, taking into account both vegetation type and wind influence. Variations in fire spread are most evident in `Veg1` and `Veg3`, with fire remaining confined to a single vegetation type in the third and fourth simulations. Despite these variations, the overall propagation behavior follows the expected pattern, realistically capturing fire dynamics, which is essential for effective wildfire prevention and control.

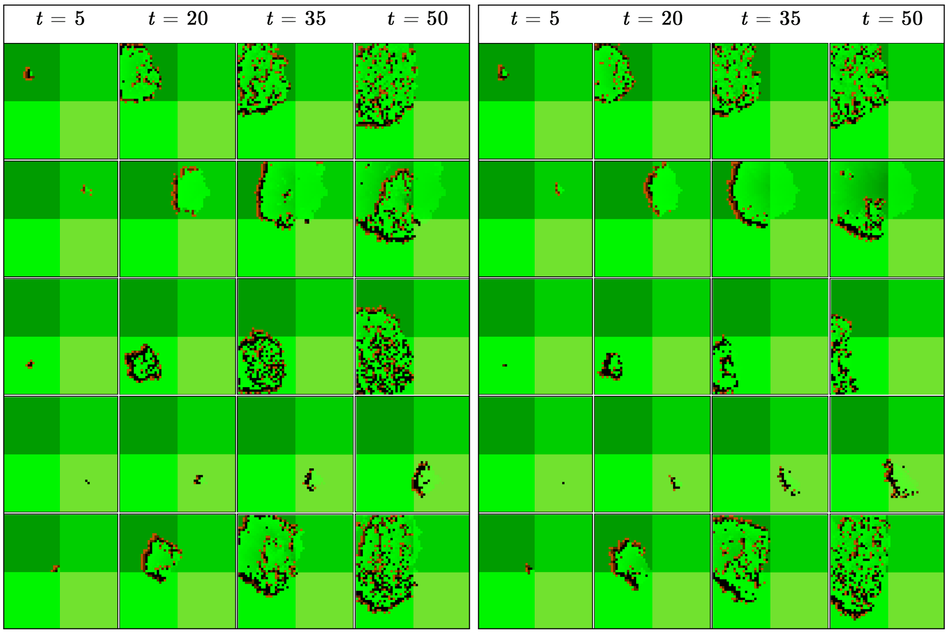
4.2. Pau Furado State Park

Validating a CA model in real-world scenarios is essential to ensure its practical applicability, particularly for wildfire spread simulations. In the context of Pau Furado State Park,



(a) Reference Model. (b) Genetic Algorithm.

Figure 1. Parameter sets and force vectors used in the heterogeneous scenario with four vegetation types: (a) reference; and (b) obtained by the genetic algorithm based on simulations with different fire ignition points.



(a) Reference model. (b) Genetic Algorithm.

Figure 2. Temporal evolution of the cellular automata in a heterogeneous scenario with four vegetation types (in shades of green), where columns represent time steps and rows represent different ignition points: (a) reference model; and (b) model configured by the GA.

the application of the model enabled the observation of its response to natural variations, such as vegetation types and wind direction, contributing to improving model robustness by adapting it to unforeseen real-world conditions.

To construct this scenario, specific vegetation segments were extracted from the park's vegetation map, which was generated using satellite imagery. Due to the unavailability of official georeferenced vector data for the region, a conceptual representation of the landscape was created manually using Adobe Photoshop, for the purpose of a proof of concept. This approach allowed the simulation to proceed despite data limitations, and does not aim to reproduce exact geographic accuracy.

These segments were represented using distinct RGB colors, each corresponding to a vegetation type, forming a gridded matrix processed in MATLAB. The final configuration included four vegetation types represented by green, yellow, purple, and brown, simulating a heterogeneous area, as shown in Figure 3. To adjust the wildfire propagation, a genetic algorithm (GA) was employed to optimize the CA model parameters, including wind direction and intensity. The parameters LQ and LR were adjusted to optimize the model and better match real conditions, using specific values represented by the pairs: $(3, 30)$, $(2, 90)$, $(6, 20)$, and $(8, 60)$. Additionally, the preference matrices were adjusted

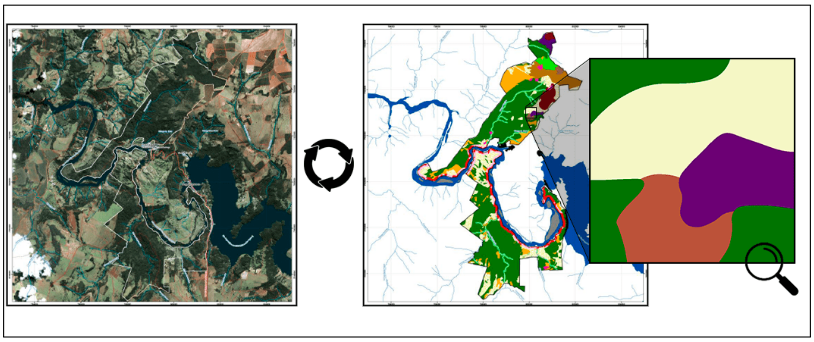
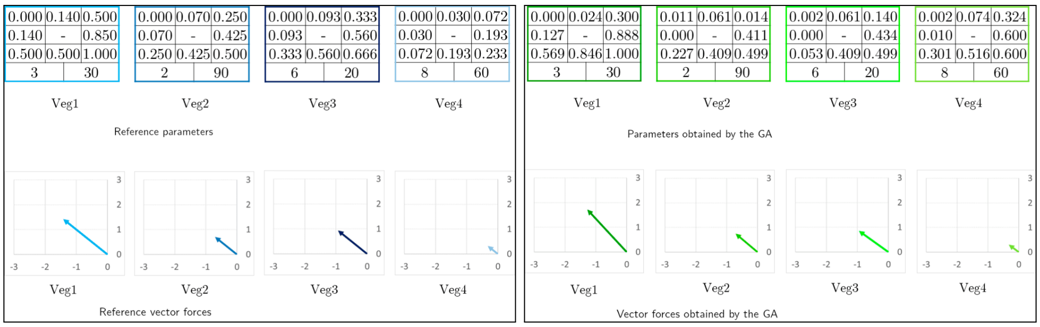


Figure 3. Region of Pau Furado State Park represented in the first evaluated scenario.

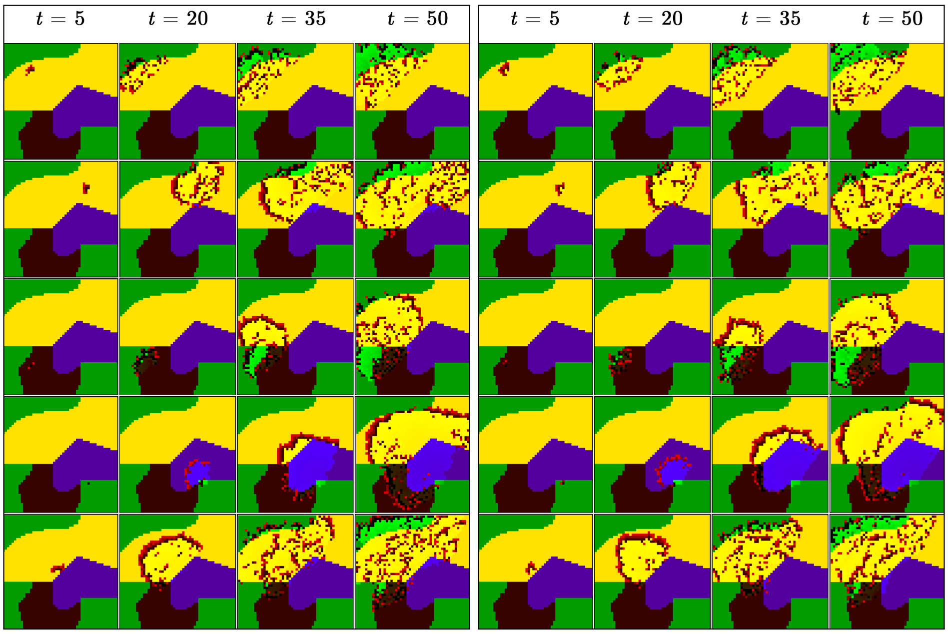
with a clockwise rotation, maintaining the same wind intensities but changing the direction to northwest. The objective of the GA was to automatically tune these parameters to improve the fire spread simulation, making it as close as possible to real-world observations. When compared to the reference parameters, the GA-adjusted vectors exhibited very similar intensities and directions (Figure 4), indicating that the algorithm effectively calibrated the parameters. The best individual found by the GA achieved a fitness value of 0.093, while the average fitness across runs was 0.094 ± 0.0009, suggesting a good model fit.



(a) Reference model. (b) Genetic Algorithm.

Figure 4. Parameter sets and force vectors used in the first scenario representing Pau Furado State Park: (a) reference; and (b) obtained by the genetic algorithm based on simulations with different fire ignition points.

In the temporal evolution simulation, fire spread was observed to verify how it developed within the scenario. Initially, the fire spread consistently from the ignition point toward the northwest. Figure 5 shows that the fire propagated through all vegetation types proportionally, with intensity variations depending on vegetation characteristics. The GA-adjusted model presented behavior very similar to the reference model, with the exception of a slight discrepancy in `Veg3` (brown), where the fire spread with less intensity. This difference was more pronounced when fire started near the edges of the mapped area.



(a) Reference model. (b) Genetic Algorithm.

Figure 5. Temporal evolution of the cellular automaton considering different ignition points in the first scenario representing Pau Furado State Park: (a) reference model; and (b) model configured by the GA.

Overall, the CA model adjusted by the GA was able to satisfactorily simulate fire behavior in a heterogeneous vegetation area, validating its capacity to represent fire spread in more complex and realistic environments, such as those found in Pau Furado State Park. Despite minor discrepancies, the general propagation behavior was preserved, demonstrating the GA's effectiveness in tuning the model parameters.

The second scenario, shown in Figure 6, was designed to test the CA model under a configuration different from the previous one, involving horizontal and vertical reflection of the preference matrices. This change altered the wind direction to southeast while keeping the intensity unchanged. Additionally, the second scenario introduced the presence of a river in the mapped area, modeled as a natural barrier to fire spread. The river served as a containment line in the simulated area, which was important to assess the model's ability to handle natural obstacles and how these affect fire behavior. For this scenario, the GA was again used to calibrate the CA model parameters under the new conditions. While the preference matrices were adjusted, slight differences were observed when compared to the reference model (Figure 7).

For instance, in `Veg1`, the center-right cell of the preference matrix had a lower value than in the reference, resulting in a vector with a slightly larger angle. In `Veg2`, the center-bottom cell had a lower value, resulting in a weaker and slightly misaligned vector. For `Veg3`, the left-side cells had lower values, producing a vector with a flatter angle. In `Veg4`, the top-right cell had a slightly higher value than in the reference, causing a minor

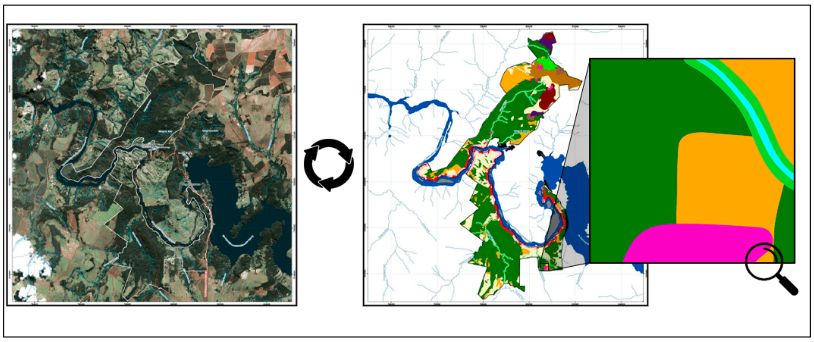
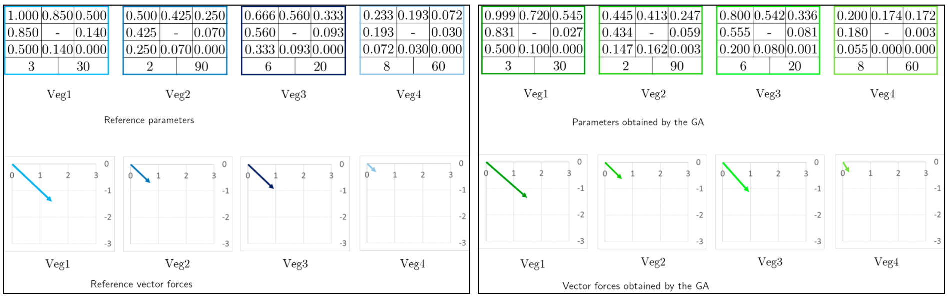


Figure 6. Region of Pau Furado State Park represented in the second evaluated scenario.

increase in vector intensity while maintaining a similar direction.



(a) $Ref.$ (b) $GA.$

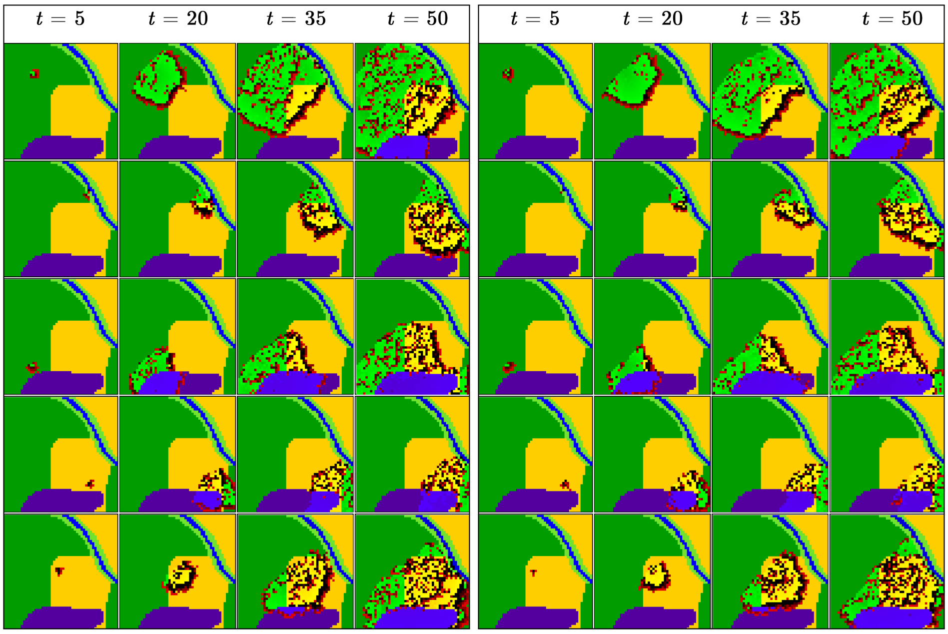
Figure 7. Parameter sets and force vectors used in the second scenario representing Pau Furado State Park: (a) reference; and (b) obtained by the genetic algorithm based on simulations with different fire ignition points.

Despite these small differences in the parameters, results showed that fire propagation in the GA-adjusted model followed the same direction and intensity as the reference model, with fire spreading southeast and being contained by the river. The overall propagation behavior was adequately replicated, with the river acting as a containment barrier and preventing fire from crossing to the other side. However, some discrepancies were observed in `Veg2`, where the fire spread more discretely in the GA-adjusted model compared to the reference, especially in simulations where the fire started in central or lower regions of the grid, as shown in Figure 8.

In terms of performance, the best GA individual achieved a fitness value of 0.124, and the average fitness across runs was 0.125 ± 0.0002, indicating that the algorithm effectively adjusted the parameters, albeit with slight differences from the reference model. Overall, this second scenario validated the CA model's ability — when adjusted by a GA — to simulate fire propagation in an environment with natural obstacles, such as rivers, and heterogeneous vegetation, maintaining consistency with the reference model's behavior, except for minor variations in the simulations involving `Veg2`.

5. Final Considerations

Wildfire spread modeling is an essential tool for understanding and mitigating the environmental, social, and economic impacts caused by such events, particularly in vulnerable



(a) Reference Model. (b) Genetic Algorithm.

Figure 8. Temporal evolution of the cellular automaton considering different ignition points in the second scenario representing Pau Furado State Park: (a) reference model; and (b) model configured by the GA.

biomes like the Cerrado. This study proposed a heterogeneous CA model, optimized using GAs, to simulate fire propagation in realistic scenarios, with a focus on Pau Furado State Park.

The results demonstrated that the GA - adjusted model was capable of satisfactorily reproducing wildfire propagation behavior, accounting for environmental variables such as vegetation type and wind direction. Although minor discrepancies were observed — especially in specific vegetation types — the overall fire propagation behavior was preserved, validating the model's potential to realistically represent fire dynamics.

These findings underscore the importance of using computational models to predict and monitor wildfires, enabling more effective approaches to fire prevention and suppression. Furthermore, the ability to automatically calibrate model parameters using GAs offers a powerful tool to deal with dynamic and complex scenarios, such as those found in biomes like the Cerrado.

Future work should include comparisons with other fire models — such as 3D simulations — and incorporate additional variables like topography and soil moisture. Validation with real-world data (e.g., satellite imagery, remote sensing, field measurements) is also essential for assessing model accuracy under different climatic conditions and improving its generalizability across seasons and landscapes.

Acknowledgment

The authors MEAF, DAL and LGAM would like to thank CNPq for the financial support provided under the call Chamada CNPq/MCTIC/FNDCT No. 18/2021 (Grant number: 423105/2021-3), within the scope of the project "Cerrado Resiliente: Computação Bio-inspirada e Monitoramento por VANTs na Prevenção e Combate a Incêndios Florestais e

Urbanos".

References

Alexandridis, A., Vakalis, D., Siettos, C. I., and Bafas, G. V. (2008). A cellular automata model for forest fire spread prediction: The case of the wildfire that swept through spetses island in 1990. *Appl. Mathematics and Computation*.

Brasiel, H. and Lima, D. (2024). Parameter analysis in probabilistic cellular automaton model for fire spread simulation in sete cidades national park. In *Anais do XV Workshop de Computação Aplicada à Gestão do Meio Ambiente e Recursos Naturais*, pages 101–110, Porto Alegre, RS, Brasil. SBC.

Ferreira, M. E. A., Lima, D. A., Martins, L. G. A., and Oliveira, G. M. B. (2022a). Refining a parameter setting evolutionary approach for fire spreading models based on cellular automata. In *2022 International Conference on Computational Science and Computational Intelligence (CSCI)*, pages 480–486.

Ferreira, M. E. A., Quinta, A. L. M. P., Lima, D. A., Martins, L. G. A., and Oliveira, G. M. B. (2022b). Automatic evolutionary adjustment of cellular automata model for forest fire propagation. In *ACRI*.

Fraga, L. M., Oliveira, G. M. B., and Martins, L. G. A. (2021). Multistage evolutionary strategies for adjusting a cellular automata-based epidemiological model. In *IEEE CEC*.

Martins, L. G., Franca, T. P., and de Oliveira, G. M. (2019). Bio-inspired algorithms for many-objective discrete optimization. In *2019 8th Brazilian Conference on Intelligent Systems (BRACIS)*, pages 515–520. IEEE.

Monteiro, L., Fanti, V., and Tessaro, A. (2020). On the spread of sars-cov-2 under quarantine: A study based on probabilistic cellular automaton. *Ecological Complexity*, 44:100879.

Mota, P. H. S., da Rocha, S. J. S. S., de Castro, N. L. M., Marcatti, G. E., de Jesus França, L. C., Schettini, B. L. S., Villanova, P. H., dos Santos, H. T., and dos Santos, A. R. (2019). Forest fire hazard zoning in mato grosso state, brazil. *Land use policy*, 88:104206.

Murilo, L. V., Oliveira, G. M. B., and Martins, L. G. A. (2025). Evolutionary adjustment of a cellular automata-based model for wildfire spreading. In *Intelligent Systems*, pages 260–275, Cham. Springer Nature Switzerland.

Oliveira, G. M. B., De Oliveira, P., and Omar, N. (2001). Improving genetic search for one-dimensional cellular automata, using heuristics related to their dynamic behavior forecast. In *IEEE CEC*.

Ramos-Neto, M. B. and Pivello, V. R. (2000). Lightning fires in a brazilian savanna national park: rethinking management strategies. *Environmental management*, 26(6):675–684.

Tinoco, C. R., Lima, D. A., and Oliveira, G. M. (2019). An improved model for swarm robotics in surveillance based on cellular automata and repulsive pheromone with discrete diffusion. *Int. Journal of Parallel, Emergent and Distributed Systems*, 34(1).