Parameter analysis in Probabilistic Cellular Automaton model for fire spread simulation in Sete Cidades National Park

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Abstract. *This study investigates forest fire dynamics in Sete Cidades National Park, a Cerrado Biome area, using cellular automaton models. We examine how varying wind speeds and vegetation scenarios affect fire spread, analyzing their impact on burned area expansion. By simulating fire spread across varied landscapes, we analyze the impact of wind velocities* $\vec{w} = \{5, 20\}$ *on the expansion of burned areas over successive iterations, roughly doubling the burned area* (b) *rate. Heterogeneous vegetation varies in fire susceptibility, with certain scenarios, like Rupestrian Cerrado and Clean Camps, suffering more damage. Our simulations can aid wildfire management, emphasizing the importance of considering environmental factors to effectively mitigate fire risks in the Cerrado biome.*

1. Introduction

The Cerrado biome, known for its rich biodiversity and unique ecosystems, faces the ongoing threat of forest fires, exacerbated by urban expansion and global warming. As a resilient biome, the Cerrado plays a crucial role in preserving life by providing habitats for diverse flora and fauna species, many of which are endemic and endangered [Alvarado et al. 2019, Castro et al. 2002]. However, the increasing frequency and intensity of forest fires pose significant challenges to the preservation of this vital ecosystem. Urgent action is needed to address the root causes of forest fires, including deforestation, agricultural expansion, and climate change, in order to protect the Cerrado and its invaluable contributions to biodiversity conservation, ecosystem services, and human well-being [Eloy et al. 2019].

In this context, Sete Cidades National Park, located in the northern region of Piauí state, Brazil, spans Brasileira and Piracuruca municipalities over 7,700 hectares, with 26.21% in Brasileira and 73.77% in Piracuruca [Castro et al. 2002]. The park is surrounded by the Serra da Ibiapaba Environmental Protection Area, covering 1,592,550 hectares, established in 1996 [Matos and Felfili 2010]. It hosts the Cerrado Biome's arid savannas, babassu forests, and transitional zones, providing sanctuary for diverse wildlife and vital water resources. Geological formations, cave paintings, and prehistoric inscriptions enhance its natural and cultural significance [Araújo et al. 2020].

Taking this into consideration, modeling forest fires in the Cerrado biome is crucial for enhancing security measures and implementing effective strategies to mitigate the impact of wildfires on both human populations and the environment. There are various methods to simulate forest fire propagation, including the use of differential equations and cellular automata (CA). In our study, we will employ a probabilistic two-dimensional cellular automaton to model forest fires. This approach builds upon a previous model that utilized CA to simulate fire spread. Here, we present a practical application of forest fire spread within the Sete Cidades National Park.

In this context, our objective is to evaluate three distinct scenarios within Sete Cidades National Park using cellular automata on a grid of 200×200 cells, enhancing the precursor model [Brasiel and Lima 2023] for application with real images. This evaluation will take into account the heterogeneous vegetation, which significantly influences fire behavior. Specifically, we will consider six different vegetation types, with fire behavior being altered accordingly. Additionally, we will examine the impact of varying wind directions, as they play a crucial role in shaping fire spread patterns and the geometry of fire fronts. Finally, we will analyze the effect of different wind velocities on fire propagation dynamics within the park, as these factors can either slowly or rapidly destroy vegetation during the simulation iterations.

2. Theoretical foundation

In this theoretical foundation section we will present the definitions related to the topic in question, with the aim of clarifying the concepts and foundations necessary for understanding the subject.

2.1. Cerrado biome

The Cerrado biome, renowned for its vast array of species (approximately 12,300) and significant endemism, stands out globally as a biodiversity hotspot within savanna ecosystems. However, rapid development since the 1960s has caused alarming destruction (50% loss), mainly due to agriculture [Alvarado et al. 2019]. Despite lacking national heritage status, the Cerrado's value is undeniable. Encompassing diverse vegetation types, it showcases distinct cerrado subtypes. The northwestern "distal marginal cerrados" act as a biodiversity hotspot. Conservation efforts (covering 9.4% of the biome) prioritize ecological conditions and species survival through protected areas. Plant ecology research plays a crucial role in informing effective conservation planning. Building on Castro's characterization [Castro et al. 2002] of a Cerrado biome in Sete Cidades National Park, we present a fire propagation model to aid conservation efforts. Fires in the Cerrado, natural or human-caused, threaten biodiversity. Frequent fires degrade the ecosystem and worsen climate change [Oliveira et al. 2007]. The Cerrado's unique species and vulnerability to fires necessitate urgent action for prevention and management.

2.2. Cellular automata

Cellular automata (CA) are computational systems based on sets of cells interacting with each other according to predefined rules, where each cell is represented by a state [Lima and Lima 2014]. Proposed as mathematical models to simulate the complexity of natural systems, CA are widely used in various scientific fields to model complex systems characterized by numerous local interactions and unpredictable behavior, such as robotics, disease modeling, and forest fire modeling [Brasiel and Lima 2023]. CA can be represented by a vector or matrix L and are classified based on the number of dimensions in which cells are arranged, such as one-dimensional (1D), two-dimensional (2D), or three-dimensional (3D).

One well-known CA is the Game of Life proposed by John Conway in 1970, which exhibits emergent complexity as live and dead cells interact according to predefined rules [Brasiel and Lima 2023]. These rules are applied simultaneously to every cell in the grid, generating dynamic patterns of live and dead cells over successive generations [Ferreira et al. 2022].

Cellular automata serve as valuable computational tools for modeling dynamic and complex systems, offering a realistic alternative to numerical simulations from differential equations. By simulating state transformations through transition rules, CA can effectively capture the dynamic behavior of various systems across different domains, including fire propagation modeling and pedestrian evacuation simulations in panic scenarios [Ferreira et al. 2022]. In our study, we focus on 2D cellular automata applied to fire modeling, a complex task influenced by variables like topography, climate, vegetation type, region, and wind.

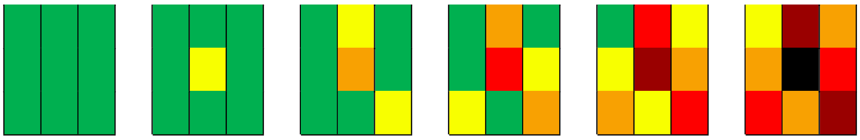
2.3. Related works

In our model, we incorporated six vegetation types with unique propagation probabilities linked to humidity and dryness, similar to [Brasiel and Lima 2023]. Additionally, we integrated a wind preference matrix derived from an evacuation matrix designed for pedestrian movement [Schadschneider et al. 2011]. Rooted in the real-world context of Sete Cidades National Park, our model enhances the authenticity and applicability of our simulation by employing machine learning clustering algorithms, specifically k-means, to group pixels with similar colors in real maps [Zheng et al. 2018]. The first analyzed study [Jellouli and Bernoussi 2022] improved real-world integration by introducing a wind flow model that accurately calculates wind parameters based on topography and land use, demonstrating dynamic wind effects on fire spread. In paper of [Ferreira et al. 2022] proposed genetic algorithms for adjusting fire propagation model parameters, enhancing parameter optimization in fire spread models. [Zan et al. 2022] proposed a data-driven approach to derive cell burning probabilities from historical forest fire data, enabling varied fire spread speeds under diverse geographical conditions.

In the paper proposed in [Brasiel and Lima 2023], it is important to note that the authors introduced a model based on cellular automata (CA), building upon the model described in [Lima and Lima 2014]. However, they did not consider real scenarios. In our paper, we applied these models in a real scenario by adapting them to the context of Sete Cidades National Park. To achieve this, we combined the CA-rule update from precursor models with a machine learning clustering algorithm, specifically k-Means. This adaptation ensures that real scenario images from biomes such as the Cerrado can be effectively evaluated using the CA model.

3. Materials and methods

Initially, as depicted in Figure 1, the cellular automata (CA) states are initialized at T_A ($t = 0$). Subsequently, a fire focus is introduced into the 5×5 grid, igniting fires at lattice points T_{B_i}, where $1 \leq i \leq 4$. These fires exhibit varying intensities represented by different colors, reflecting the duration of vegetation burning. In this example, the burning time (t_{b_i}) is set to 2 time steps, indicating that the fire's intensity changes every $t = 2$ steps. If a cell x_{ij} has neighboring cells on fire, it has a non-zero probability ($p(x_{ij})$) of catching fire ($T_A \to T_B$) at a later time, with a probability of ignition ($p(x_{ij})$) typically set to 0.6 in homogeneous forest scenarios. Eventually, as the fire progresses to a certain burning state,



100	55	35
100	x_{ij}	35
100	55	35

Figure 1. Squares (1-6): CA transitions depicting states between cells: (T_A) alive (green), (T_{B_i}) burning (light yellow to red), and (T_D) dead (black). Last square (7): Burning probabilities per neighboring cell, with $\vec{w} = 20$.

the trees are completely destroyed (dead) and transition to state T_D. The evolution of the CA is depicted using lattice representations at various time points $t = \{0, 2, 4, 6, 8, 10\}$, illustrating the spread of flames throughout the forest over time.

When creating 2D CA wildfire models, considering wind's effect is crucial. It dictates fire's behavior, influencing its direction, speed, size, and shape. Integrating wind speed and direction boosts simulation accuracy and realism. A fixed matrix field denotes wind speed and direction for each cell throughout the simulation. This wind field matrix informs the probability of cell ignition and fire spread based on wind direction and speed. The wind preference matrix, derived from previous studies [Schadschneider et al. 2011, Lima and Lima 2014, Ferreira et al. 2022], is depicted in Figure 1, with $\vec{w} = 20$. Cells downwind from burning cells are more likely to ignite, while those upwind are less likely. Moreover, wind direction can influence the shape and size of the fire front, with perpendicular winds causing elongated spreads and parallel winds leading to circular spreads. Wind's role in fire propagation is crucial, particularly in heterogeneous landscapes where different vegetation types interact. Therefore, integrating wind effects into CA models is imperative for accurate wildfire simulations, facilitating a deeper understanding of fire behavior and aiding in the development of effective wildfire prevention and control strategies.

Forest fire spread hinges on vegetation types, especially fire-prone ones like dry grasslands and wood-rich forests, heightening ignition risk and rapid spread. Additional factors like fuel, temperature, humidity, and wind also play key roles. When using CA models for wildfire simulation, considering vegetation type is crucial. Models may be homogeneous [Lima and Lima 2014], ideal for studying uniform vegetation fire behavior, or heterogeneous [Brasiel and Lima 2023], offering realistic scenarios with diverse vegetation and landscape interactions. In heterogeneous models, diverse vegetation types and landscape features, like rivers as barriers or varying flammability levels, influence fire behavior. Including vegetation diversity, such as the 6 types in Sete Cidades National Park, improves simulation accuracy and aids in wildfire prevention and control strategy development. Vegetation diversity, influenced by topography and water availability, requires considering transitional states where vegetation shows characteristics of multiple types. Incorporating these factors in CA modeling enables more accurate simulations for specific environments, aiding in wildfire management strategies.

The chosen image of Sete Cidades National Park was utilized to construct a matrix representing the cellular automata (CA) lattice L, with each pixel collected in RGB (red, green, blue) format. Subsequently, clustering was conducted to assign each cell x_{ij} in the matrix to a distinct state, representing different vegetation types. Six vegetation categories were identified, including mesophytic cerrado (evergreen forest), flooded gallery forest (riparian), semideciduous dry forest (savanna), typical cerrado, rocky cerrado (rupestrian), and open grassland (clean camp), as depicted in Figure 2. This analysis is crucial for grasping the heterogeneity of the Cerrado's characteristic vegetation, essential for modeling real scenarios using stochastic two-dimensional cellular automata.

Regarding territorial extension, typical savanna covered the largest proportion (37.6%), followed by mesophytic savanna (24.3%) and open camp (14.3%), confirming the predominance of savanna formations in the park. However, as only three parts of the park were utilized in the simulation, depicted in Figure 2, these proportions may have varied. In Figure 2, numbered 1 through 5, a flowchart outlines the process of clustering image pixels representing the Sete Cidades National Park maps. This includes matrix and vegetation state initialization, fire focus creation, burning probability calculation, cell state updating, and fire evaluation. The k-means clustering process assigns pixels to vegetation type states, forming the initial input for the 2D-CA representing the park map. Euclidean distance is used for pixel clustering and reference color attribution. Six vegetation types are identified, and the process iterates until all pixels are assigned a state.

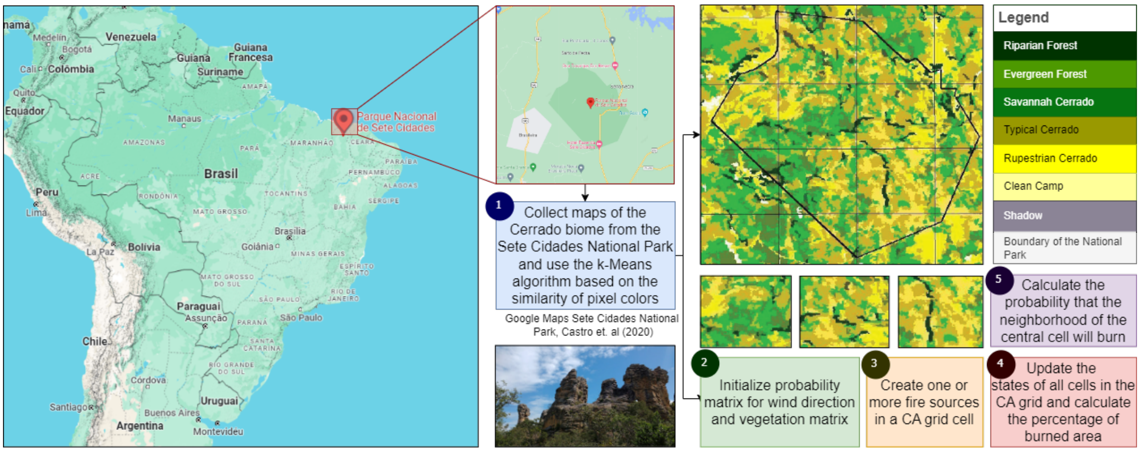


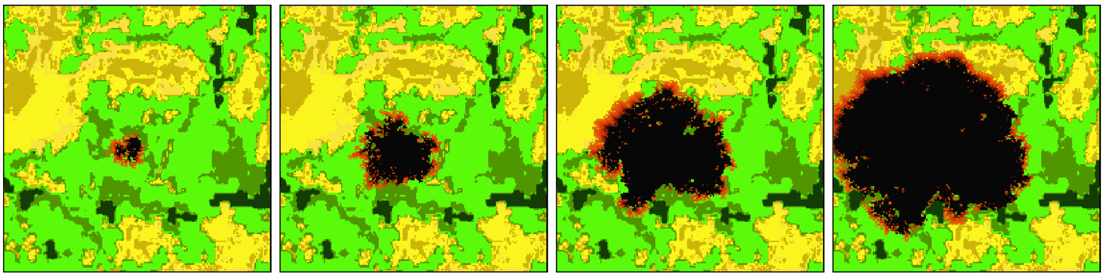
Figure 2. Algorithm proposal considering image clustering and cellular automata rule update for modeling fire propagation.

In this study, we utilize CA techniques to simulate forest fire propagation in the Cerrado biome, capable of modeling complex systems. We conduct various experiments considering different vegetation types, including homogeneous and heterogeneous forests. The simulation algorithm begins by selecting a real Cerrado map and performing vegetation clustering based on RGB colors. This process creates a realistic simulation using Euclidean distance between map pixels p and RGB reference colors (centroids) q. The process iterates until all pixels are assigned distinct states. Then, a CA lattice matrix $L_{m\times n}$ is initialized, representing vegetation areas, with each cell x_{ij} initially set to state 0 for $t = 0$. Fire starts (state 1) are placed in the forest. Neighboring cells then have a chance to ignite based on wind, vegetation, and surrounding fire. Cell states are updated for the next iteration, incrementing burning cells' states by 1 and marking fully burned cells as T_D. Establish distinct fire probabilities for various land cover types: ($T_{D_{11}}$) Rupestrian cerrado with $p(x_{ij}) = 80$, ($T_{D_{12}}$) Clean camp with $p(x_{ij}) = 65$, ($T_{D_{13}}$) Typical cerrado with $p(x_{ij}) = 40$, ($T_{D_{14}}$) Dense cerrado with $p(x_{ij}) = 25$, ($T_{D_{15}}$) Evergreen forest with $p(x_{ij}) = 10$, and ($T_{D_{16}}$) Riparian forest with $p(x_{ij}) = 0$. These steps are repeated for defined iterations, updating L states according to the CA probabilistic rule. Finally, fire propagation and affected area metrics are evaluated.

4. Results

In this section, we present a visualization of our model's performance using a grid of 200×200 cells and 6 vegetation types, as shown in Figure 2. Different probabilities are considered for each vegetation type, represented as $p(x_{ij}) = \{80, 65, 40, 25, 10, 0\}$. These visualizations offer valuable insights into the interaction between wind dynamics and fire spread, as well as the resulting vegetation loss. Understanding environmental factors like wind velocity (herein we used $\vec{w} = \{5, 20\}$) is essential for developing effective strategies for wildfire management and mitigation.

Figure 3 depicts the evolution of Scenario 1 experiments with a wind velocity of $\vec{w} = 5$ across multiple iterations ($t = 20$, $t = 40$, $t = 60$, and $t = 80$). Each subfigure provides a snapshot of the landscape at a specific time step, illustrating the propagation of forest fires within the Cerrado biome. The percentage of burned area (b) is annotated for

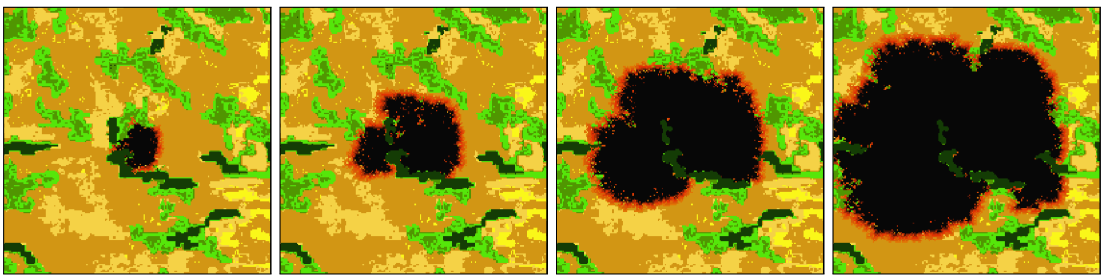


(a) $t = 20, b = 1.11\%$. (b) $t = 40, b = 5.83\%$. (c) $t = 60, b = 17.03\%$. (d) $t = 80, b = 36.46\%$.

Figure 3. Scenario 1 experiments with wind ($\vec{w} = 5$).

each iteration, offering quantitative insight into the extent of fire spread over time. Notably, the burned area increases dramatically over the simulation period; for instance, at $t = 0$, the burned area was 1.11% of the CA grid representing Sete Cidades National Park, whereas at $t = 80$, it escalated to 36.46%, reflecting a more than 30-fold increase. This exponential growth underscores the rapid expansion of wildfires as they advance across the landscape.

Figure 4 presents the progression of Scenario 2 experiments with a wind velocity of $\vec{w} = 5$ across successive iterations ($t = 20$, $t = 40$, $t = 60$, and $t = 80$), with each subfigure showcasing the landscape at a specific time point. The b (%) percentage is also indicated for each iteration. For instance, at $t = 20$, the burned area covered 2.23% of



(a) $t = 20, b = 2.23\%$. (b) $t = 40, b = 10.79\%$. (c) $t = 60, b = 27.07\%$. (d) $t = 80, b = 51.85\%$.

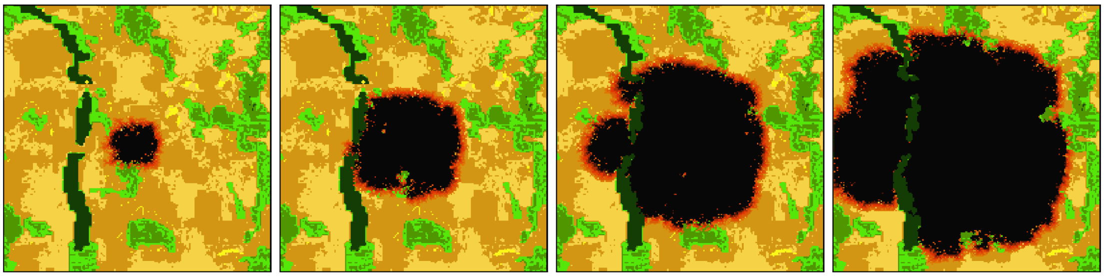
Figure 4. Scenario 2 experiments with wind ($\vec{w} = 5$).

the CA grid representing the Sete Cidades National Park, and this proportion increased to

51.85% by $t = 80$.

Figure 5 illustrates the progression of Scenario 3 experiments with wind ($\vec{w} = 5$) over consecutive iterations. Each subfigure corresponds to a specific iteration ($t = 20$, $t = 40$, $t = 60$, and $t = 80$), providing visual representations of the evolving forest fire dynamics within the Cerrado biome. The images depict the temporal evolution of fire spread and its impact on vegetation cover, highlighting the critical role of wind direction and intensity in influencing the behavior of wildfires. As the iterations advance, the extent of burned areas increases, demonstrating the escalating nature of fire propagation under the influence of east-to-west wind.

Figure 5 illustrates the progression of Scenario 3 experiments with wind velocity $\vec{w} = 5$ over successive iterations ($t = 20$, $t = 40$, $t = 60$, and $t = 80$), each accompanied by the corresponding percentage of burned area (b). At $t = 20$, the burned area stands at

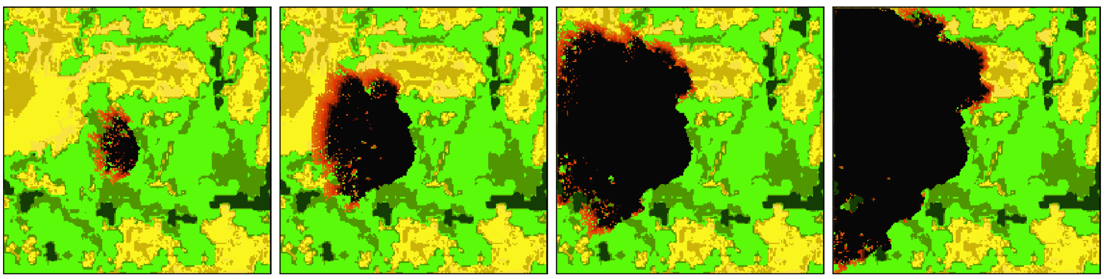


(a) $t = 20, b = 3.52\%$. (b) $t = 40, b = 14.90\%$. (c) $t = 60, b = 32.95\%$. (d) $t = 80, b = 58.29\%$.

Figure 5. Scenario 3 experiments with wind ($\vec{w} = 5$).

3.52%, indicating moderate fire spread within the Cerrado biome. By $t = 40$, the burned area has significantly expanded to 14.90%, suggesting a notable increase in fire propagation. Subsequently, at $t = 60$, the burned area has nearly doubled to 32.95%, indicating a substantial escalation in fire severity and extent. Finally, at $t = 80$, the burned area reaches 58.29%, reflecting a significant portion of the landscape affected by the wildfire.

Figure 6 presents the progression of Scenario 1 experiments with a wind velocity of $\vec{w} = 20$, highlighting the burned area (b) at each iteration ($t = 20$, $t = 40$, $t = 60$, and $t = 80$). Initially, at $t = 20$, the burned area covers 2.99% of the cellular automaton grid representing Sete Cidades National Park, indicating the early stages of fire spread.

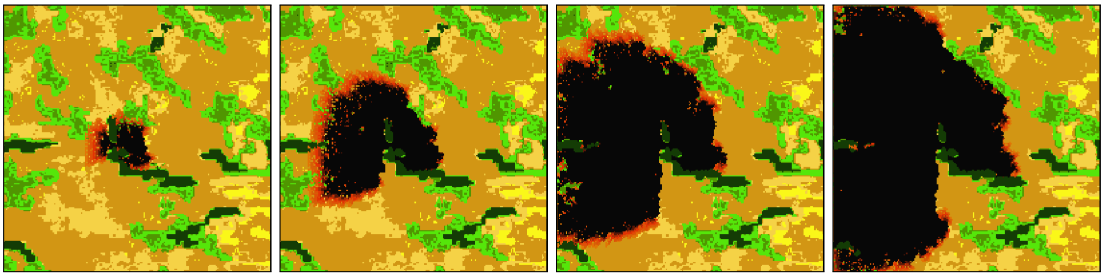


(a) $t = 20, b = 2.99\%$. (b) $t = 40, b = 14.16\%$. (c) $t = 60, b = 30.57\%$. (d) $t = 80, b = 40.17\%$.

Figure 6. Scenario 1 experiments with wind ($\vec{w} = 20$).

By $t = 40$, the burned area has expanded to 14.16%, demonstrating a significant increase in fire propagation. Subsequently, at $t = 60$, the burned area further escalates to 30.57%, illustrating the rapid advancement of the fire front. Finally, at $t = 80$, the burned area encompasses 40.17% of the landscape, indicating substantial vegetation loss and highlighting the heightened severity of the wildfire.

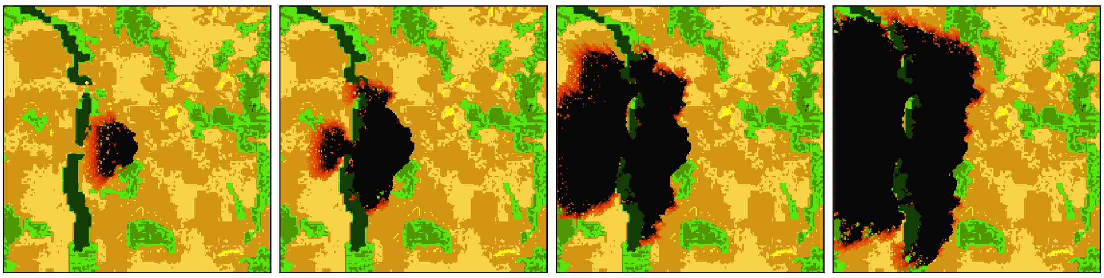
Figures 7 and 8 present the progression of Scenario 2 and Scenario 3 experiments, respectively, with a wind velocity of $\vec{w} = 20$ across multiple iterations ($t = 20$, $t = 40$, $t = 60$, and $t = 80$). Each subfigure in both figures showcases the landscape at a specific



(a) $t = 20, b = 3.19\%$. (b) $t = 40, b = 15.87\%$. (c) $t = 60, b = 35.32\%$. (d) $t = 80, b = 47.46\%$.

Figure 7. Scenario 2 experiments with wind ($\vec{w} = 20$).

time step along with the corresponding percentage of burned area (b). At $t = 20$, the burned areas were 3.19% and 3.85% for Scenarios 2 and 3, respectively. As the simulation progresses, the burned areas increase, reaching 15.87% and 10.51% at $t = 40$ for Scenarios 2 and 3, respectively. By $t = 60$, the burned areas further escalate to 35.32% for Scenario 2 and 26.40% for Scenario 3. Finally, at $t = 80$, the burned areas peak at 47.46% for Scenario 2 and 39.56% for Scenario 3. These visual representations offer a



(a) $t = 20, b = 3.85\%$. (b) $t = 40, b = 10.51\%$. (c) $t = 60, b = 26.40\%$. (d) $t = 80, b = 39.56\%$.

Figure 8. Scenario 3 experiments with wind ($\vec{w} = 20$).

step-by-step depiction of the expansion of forest fires over time, providing valuable insights into the dynamics of fire spread and the resulting vegetation loss under varying wind conditions.

To summarize the results for visual step-by-step observations, we created Figure 9, which is a line graphic comparing all experiments described above. The graphic depicts burned area progression across scenarios and wind velocities at iterations $t = 20, 40, 60, 80$. In Scenario 1 with $\vec{w} = 5$, the burned area rises from 1.11% at $t = 20$ to 36.46% at $t = 80$, whereas with $\vec{w} = 20$, it starts at 2.99% and reaches 40.17% by $t = 80$. Similar trends occur in Scenarios 2 and 3, where higher wind velocities lead to larger burned areas. Notably, Scenario 3 consistently exhibits the highest burned areas. Ramping up the fire intensity to $\vec{w} = 20$ results in its spread beyond the grid boundaries,

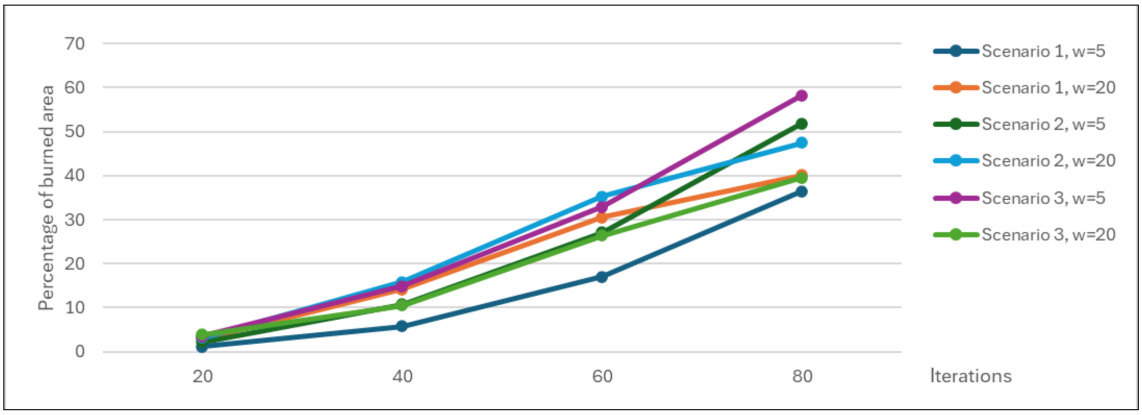


Figure 9. Comparison of burned areas between different scenarios and wind velocities.

significantly accelerating propagation compared to $\vec{w} = 5$. For instance, in Scenario 1, the burned area reaches $b = 17.03\%$ at $t = 60$ with $\vec{w} = 5$, whereas it surges to $b = 30.57\%$ at the same time with $\vec{w} = 20$.

Finally, it is worth mentioning that Scenario 3 spreads more fire along the grid due to the presence of open fields, which allow for greater wind propagation. Following that is Scenario 2, characterized by a riparian forest near water bodies. Lastly, Scenario 1, with more green areas and higher humidity, presents greater difficulty in fire spread. Therefore, it is crucial to calculate the optimal strategies for fire management and mitigation based on the specific environmental conditions and characteristics of each scenario.

5. Conclusion and future works

In conclusion, this study sheds light on the dynamics of forest fire spread in the Cerrado biome, particularly within the context of Sete Cidades National Park. Through the utilization of cellular automaton models and exploration of wind $\vec{w} = \{5, 20\}$ velocities and 3 vegetation scenarios, we have uncovered valuable insights into the factors influencing fire propagation. Our findings underscore the significant impact of wind velocity on the extent of burned areas, as well as the varying susceptibility of heterogeneous vegetation compositions to fire.

Moving forward, future research endeavors could focus on refining the models used in this study to incorporate additional environmental variables and improve the accuracy of fire spread predictions. Furthermore, exploring the efficacy of different wildfire management strategies in mitigating fire risks in the Cerrado biome would be a pertinent avenue for further investigation. By continuing to deepen our understanding of the complex interplay between environmental factors and fire dynamics, we can develop more effective measures for wildfire prevention and control, ultimately safeguarding the biodiversity and ecological integrity of the Cerrado biome.

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