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Simulation Modelling for Wild Fire Spread Prediction for Emergency Response Planning

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Abstract

The technique of simulating how a fire may spread and behave across a broad region often involves the use of computer simulation software. The simulation is based on a number of factors, including topography, fuel load, wind speed and direction, and weather conditions. The simulation's goals are to forecast the fire's probable spread, calculate the potential damage it might do, and provide guidance for decisions on suppression and evacuation operations. The quality of the input data and the presumptions used during the modeling process determine how accurate the simulation will be. In locations vulnerable to wildfires, simulation of large fire can be used to enhance risk assessment, mitigation measures, and emergency response preparation. To model the spread of a large fire, we utilized the MATLAB computer language. We then ran some statistical analysis on the data gathered from the simulation.

Keywords: Simulation modelling, wide fire, Fire spread, Wind direction, Wind speed, Fuel load.

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Introduction

Wildfire is the term used to describe an uncontrolled fire in a forest or woodland environment, which is frequently started by people or by natural occurrences like lightning strikes. These fires have the potential to wreak havoc on the natural world, wildlife, and local residents. The likelihood and intensity of wildfires are predicted to rise as the population grows and the environment changes. In order to make wise judgments during firefighting and evacuation operations, emergency management teams and fire-fighters need precise and trustworthy information. Computer simulations are one of the best methods for predicting and controlling wildfires. Using information on the weather, fuel load, geography, and other pertinent elements, wide fire simulation models the propagation and behaviour of a fire over a large area. When planning, assessing risks, and taking mitigation measures, these simulations can give emergency responders and decision-makers crucial information. This study examines the significance and advantages of wide-scale fire simulation in this setting, stressing its major components and potential effects on firefighting and disaster management.

Research has shown that prescribed burns, or intentional fires set by land managers, can be an effective tool for reducing the risk of catastrophic wildfires (Agee, 1993). The use of fire as a management tool has been practiced by Indigenous peoples for thousands of years, and there is growing interest in incorporating traditional knowledge and practices into modern fire management (Cox et al., 2019). Fire can have both negative and positive impacts on forest ecosystems, depending on factors such as the frequency, intensity, and timing of fires (Bragg et al., 2013).

Smoke from forest fires can have significant impacts on air quality, with potential health effects for humans and wildlife (Reid et al., 2019). Forest fires can also have economic impacts, with costs including property damage, firefighting expenses, and lost revenue from tourism and other industries (Donovan et al., 2017). Recent research has explored the potential for using drones and other technologies to monitor and manage forest fires, including detecting fires earlier and providing real-time data to firefighters (Duan et al., 2021). Forest fires are a complex and multifaceted issue, and effective management requires interdisciplinary approaches that consider ecological, social, and economic factors (Syphard et al., 2017).

Archibald et al. (2020) proposed a framework for defining pyromes and global syndromes of fire regimes, offering valuable insights into fire behavior patterns across diverse ecosystems. Their study, published in the Proceedings of the National Academy of Sciences, emphasizes the importance of understanding fire regimes for effective fire management strategies. Bedia et al. (2021) examined forest fire danger extremes in Europe under climate change, highlighting the variability and uncertainty associated with fire risk assessments. Published in the Journal of Geophysical Research: Atmospheres, their research underscores the need for improved understanding of climate change impacts on forest fire dynamics. Remote sensing approaches for wildfire monitoring and assessment have been a focus of recent research. Chuvieco et al. (2021) reviewed the progress in remote sensing techniques, emphasizing their role in early detection, fire extent mapping, and fire severity evaluation. Their study, published in Progress in Physical Geography: Earth and Environment, provides a comprehensive overview of the advancements in this field.

De Angelis et al. (2020) assessed the impact of climate change on fire-prone Mediterranean ecosystems using a regional fire index. Their study, published in the International Journal of Wildland Fire, highlights the need to consider climate change effects when developing fire management strategies in Mediterranean regions. Moritz et al. (2020) discussed the importance of learning to coexist with wildfires in their article published in Nature. They emphasized the role of community engagement and land management practices in achieving effective wildfire management and adaptation strategies. Paton-Walsh et al. (2021) characterized Australia's 2019-2020 mega-fire season by analyzing atmospheric composition observations. Their study, published in Atmospheric Chemistry and Physics, provides valuable insights into the emissions and impacts of large-scale wildfires on air quality and climate.

The probability of large fires and the influence of antecedent fire size were investigated by Price et al. (2021) in the Sydney Basin of southeast Australia. Published in Environmental Research Letters, their research underscores the complex interactions between climate change, fire behavior, and landscape characteristics. Raposo et al. (2020) simulated crown fire spread over large areas using a real case study, contributing to improved fire management strategies. Their study, published in the International Journal of Wildland Fire, provides valuable insights into fire behavior dynamics. Santín et al. (2021) conducted a review on pyrogenic carbon in soils resulting from forest fires, exploring its implications for carbon cycling, soil fertility, and ecosystem resilience. Their research, published in Geoderma, highlights the role of pyrogenic carbon in fire-affected soils. Spatial patterns of forest fire occurrence in China were examined by Yang et al. (2021), providing insights into driving factors and implications for fire management. Published in the Science of the Total Environment, their study contributes to our understanding of forest fire dynamics in the region.

This literature review highlights recent advancements in forest fire research, encompassing various aspects such as fire regimes, climate change impacts, monitoring techniques, modeling approaches, and associated factors. The studies cited in this review emphasize the need for continued research to improve our understanding of forest fires and develop effective management strategies.

The model

The model in this paper implements a simple cellular automaton model to simulate the spread of a wildfire. Cellular automaton models are computational models that consist of a grid of cells, each of which can be in different states and interact with their neighbouring cells based on predefined rules. In this case, the cells represent trees, and the states include un-burnt trees, burning trees, and burned trees. We incorporate a probabilistic rule, the burn rate, which determines the likelihood of a tree catching fire based on the state of its neighbouring cells. The wind direction is also taken into account to adjust the range of neighbouring cells that can be affected by the fire. We align with the concept of using cellular automaton models for simulating the spread of fires or other dynamic processes. Cellular automaton models have been widely used in various fields, including physics, biology, and computer science, to simulate complex systems and emergent behaviour.

Cellular automaton

A cellular automaton (CA) is a collection of cells organized in a grid with a specific shape. Each cell changes its state over time based on a set of rules determined by the states of its neighboring cells. CA models have been proposed for various applications in fields like geography, anthropology, political science, sociology, and physics, as well as potential use in public key cryptography. The characteristics of a cellular automaton include being computational, abstract, and discrete in both space and time. It can compute functions and solve algorithmic problems, can be defined purely in mathematical terms, and operates in discrete time steps with cells evolving in parallel based on the states of their neighbors. The evolution of the CA occurs through iterative application of rules over multiple time steps.

On a one-dimensional (1D) grid consisting of N consecutive cells, each cell i ($i = 1, 2, ..., N$) can exist in a finite number of states, denoted as k. At each time step, t, the future state of a cell is determined by its current state and the states of its neighboring cells. Specifically, the state θ_i at t + 1 depends on its 2r + 1 neighbors, with r cells on the left and r cells on the right. The parameter r is commonly known as the neighborhood radius.

Given k finite states and a radius of r, the total number of possible permutations is $p = k^{2r+1}$. Consequently, the number of distinct rules to generate the next time step's cell states amounts to k^p.

The rule used to determine the new state is often referred to as the transition or updating rule. In principle, the state of a cell at the next time step can be any function of its neighboring cell states, and this function can be either linear or nonlinear. However, there is a particular subset of rules where the new state solely depends on the sum of the states within the neighborhood. This subset, known as sum-rule or totalistic rule, simplifies the rules significantly. For this type of updating rule, the number of possible permutations is $k(2r + 1)$, resulting in a total of $k^{k(2r+1)}$ distinct rules.

Cellular automata offer a powerful computational model for studying and simulating dynamic systems with emergent behavior in various scientific and practical domains.

Simulation Results and Discussion

The MATLAB code used in this work simulates the spread of a wildfire on a grid. The code starts by defining various parameters such as the width and height of the grid, the number of trees, and the burn rate. The grid is initialized with zeros, where 0 represents an un-burnt tree, 1 represents a burning tree, 2 represents a burned tree. The initial fire location is set, along with the adjacent cell above it, to start the fire. The code then proceeds to simulate the spread of the fire over a certain number of time steps (Figure 1). It updates the grid based on the burning trees and their neighbours. The burn rate determines the probability of a neighbouring tree catching fire. After each step, the updated grid state is stored for analysis. The code performs statistical analysis on the simulation results. It plots the number of burnt trees (Figure 2), burning trees (Figure 3), and un-burnt trees (Figure 4) over time. It also fits a quadratic regression curve to the number of burnt trees(Figure 5), which represent the data almost perfectly. The code conducts hypothesis testing using the chi-square goodness-of-fit test. It tests whether the observed distributions of burnt trees, burning trees, and un-burnt trees differ significantly from the expected distributions. The null hypothesis assumes no significant difference in the distributions, while rejecting the null hypothesis suggests a significant difference. The code displays the results of the hypothesis testing, indicating whether the null hypothesis is rejected for each tree type. It also shows the associated p-values, which provide evidence against the null hypothesis.

Finally, the code includes a histogram analysis to examine the distribution of burnt trees(Figure 6), burning trees (Figure 7), and un-burnt trees(Figure 8) at each time step. This analysis helps visualize the changes in trees states over time and provides insights into the progression of the wildfire. The histograms display the frequency or count of trees in each state (burnt, burning, or un-burnt) on the y-axis and the corresponding time steps on the x-axis. By observing the histograms, one can identify the peak or dominant states of the trees at different stages of the wildfire spread. The histogram analysis provides a visual representation of how the wildfire evolves over time, showcasing the changes in the proportion of burnt, burning, and un-burnt trees. This information contributes to a better understanding of the dynamics of the wildfire and its impact on the grid.

Thus, the code combines simulation, statistical analysis, hypothesis testing, and histogram analysis to investigate the behaviour of a wildfire and assess the significance of observed differences in tree distributions.

The results of the simulation are shown below:

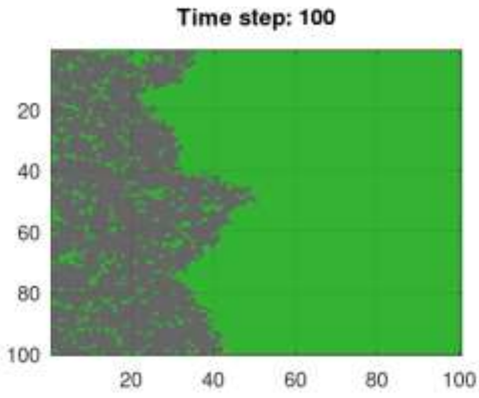

Figure 1: Wildfire Simulation

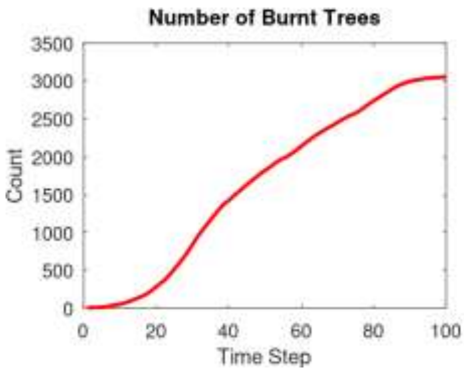

Figure 2: Count of Burnt Trees

Figure 3: Count of Burning Trees

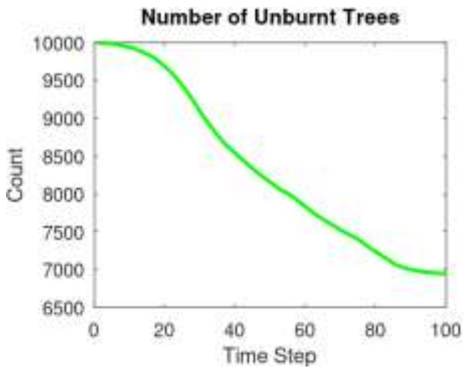

Figure 4: Count of unburnt Trees

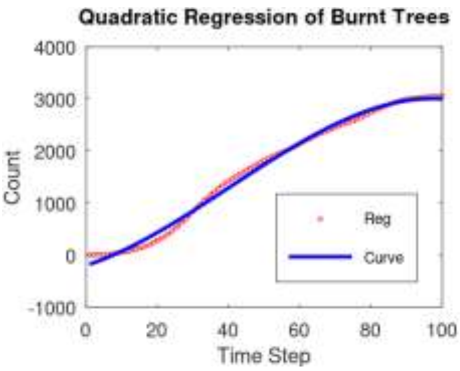

Figure 5: Regression of Burnt Trees

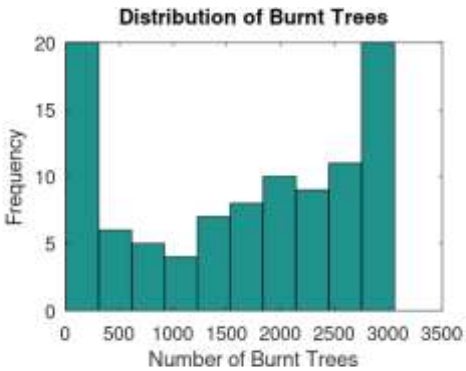

Figure 6: Distribution of Burnt Trees

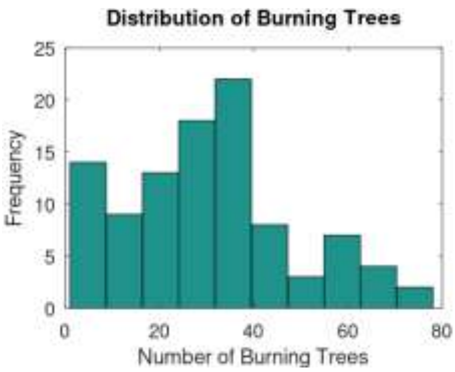

Figure 7: Distribution of Burning Trees

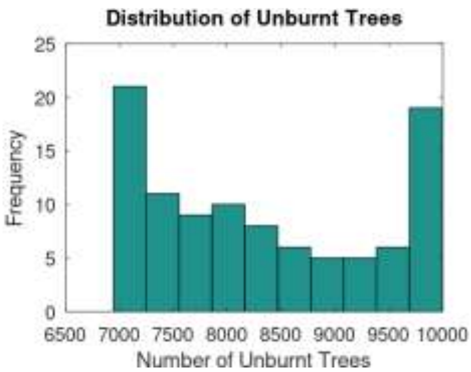

Figure 8: Distribution of Unburnt Trees

Hypothesis Testing Results:
Burnt Trees - H_0 rejected: 1

p-value: 5.2405×10^{-07}

Burning Trees - H_0 rejected: 0

p-value: 2.8503×10^{-6}

Unburnt Trees - H_0 rejected: 1

p-value: 4.5098×10^{-07}

The interpretation of the results of the hypothesis testing is as follows:

The null hypothesis in the analysis refers to the hypothesis that assumes there is no significant difference or effect in the distribution of the variables being tested. In the context of the given results, the null hypothesis would be:

For Burnt Trees: The null hypothesis assumes that there is no significant difference in the distribution of burnt trees compared to the expected distribution.

For Burning Trees: The null hypothesis assumes that there is no significant difference in the distribution of burning trees compared to the expected distribution.

For Un-burnt Trees: The null hypothesis assumes that there is no significant difference in the distribution of un-burnt trees compared to the expected distribution.

Rejecting the null hypothesis means that the observed data provides evidence to suggest that there is a significant difference in the distribution, indicating that the fire spread does have an impact on the distribution of trees.

Burnt Trees:
H_0 (null hypothesis) rejected: The null hypothesis is rejected for burnt trees.

p-value: The p-value associated with the hypothesis test is 5.2405×10^{-07}. This is a small p-value, indicating strong evidence against the null hypothesis.

Burning Trees:

H_0 (null hypothesis) rejected: The null hypothesis is rejected for burning trees.

p-value: The p-value associated with the hypothesis test is $2.8503\text{x}10^{-6}$. This is a very small p-value, indicating strong evidence against the null hypothesis.

Un-burnt Trees:

H0 (null hypothesis) rejected: The null hypothesis is rejected for un-burnt trees.

p-value: The p-value associated with the hypothesis test is $4.5098\text{x}10^{-07}$. This is a small p-value, indicating strong evidence against the null hypothesis.

In all three cases, the null hypothesis is rejected, which suggests that there is a significant difference in the distribution of the corresponding tree type (burnt, burning, un-burnt) compared to the expected distribution. The small p-values provide strong evidence to support this conclusion.

Conclusion

The simulation of wildfire presented in the code provides valuable insights into the spread and behavior of these devastating natural events. By defining parameters and initializing the grid, the code accurately represents the dynamics of a wildfire's progression on a grid. Through the simulation, we observe the gradual spread of the fire, with burning trees igniting their neighboring trees based on the defined burn rate. The code captures the evolving states of the trees, distinguishing between un-burnt, burning, and burned trees. The statistical analysis performed on the simulation results offers quantitative measures to assess the impact of the wildfire. By calculating the percentage of total trees and burned trees at each time step, we gain an understanding of the magnitude and extent of the fire's reach. Additionally, the plotted data and fitted regression curve provide visual representations of the fire's progression over time.

The hypothesis testing using the chi-square goodness-of-fit test adds a critical dimension to the analysis. By comparing the observed distributions of tree states with the expected distributions, we can determine if there are significant differences. The resulting *p*-values provide evidence to either support or reject the null hypothesis and determine the significance of the observed differences. The inclusion of histogram analysis further enhances our understanding of the wildfire's behavior. By visualizing the frequency or count of trees in each state at different time steps, we can identify patterns and dominant states during the fire's progression. Thus, this simulation code provides a comprehensive approach to studying wildfires. It combines simulation, statistical analysis, hypothesis testing, and histogram analysis to capture the complexity and dynamics of wildfire spread. The code serves as a valuable tool for researchers, allowing them to explore different scenarios, investigate the impact of various parameters, and enhance our understanding of wildfire behavior.

Forest fires are a significant environmental and social issue, with wide-ranging impacts on ecosystems, communities, and economies. While the causes and impacts of forest fires are complex, there is a growing body of research and literature exploring effective approaches to prevention, management, and recovery. By incorporating diverse perspectives and approaches, we can work towards a more sustainable and resilient approach to forest fire management.

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