Modeling Wildfires' Spread Based on Low-cost Sensors Measuring Real-time Moisture Content

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Abstract

This study addresses the growing challenge of accurate wildfire prediction by integrating low-cost, real-time sensors into fire spread simulations. Traditional models, which often rely on static data, tend to underestimate risks, particularly concerning plants' moisture content, a crucial factor in fire dynamics. Our research enhances an existing cellular automata model by incorporating real-time data from dense networks of low-cost sensors that monitor environmental variables such as temperature, humidity, and plant moisture levels. The simulations reveal that lower moisture conditions significantly accelerate fire spread and increase the total burned area. These findings underscore the importance of real-time data integration in wildfire management, improving the precision of predictions and enabling more effective prevention and response strategies. By deploying these low-cost sensors, especially in remote and high-risk areas, fire management teams can better anticipate and mitigate the impact of wildfires. This approach has the potential to significantly enhance wildfire resilience in the face of increasing fire incidents driven by the climate crisis.

Keywords

Wildfire prediction, Wildfire modeling, Low-cost system, Real-Time Sensors

1. Introduction

Fires have significant ecological and human impacts, causing biodiversity loss, habitat destruction, and long-term soil changes that hinder vegetation recovery [1]. Smoke from wildfires poses health risks, while economic losses in sectors like forestry, agriculture, and tourism can be severe [1]. The destruction of infrastructure and homes further adds to the financial and social burden [1].

A key factor in fire behavior is plants' water content. Plants with higher moisture resist ignition and slow fire spread, while those with low water content burn more easily, accelerating wildfires [6]. Monitoring vegetation's moisture is essential for predicting and managing fire risks [16].

Current fire prediction models combine empirical data and computational techniques, incorporating meteorological data, soil moisture, and vegetation types to estimate plant water content's impact on fires [1, 12]. Remote sensing, such as satellite imagery, offers real-time monitoring, improving fire spread predictions [8].

Sensors are also vital, measuring temperature, humidity, soil moisture, and plants' water content in real-time. These sensors are affordable, easy to deploy, and particularly useful in remote areas, enhancing fire risk assessments and response strategies. Integrating sensor data into fire models improves fire management [14].

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1.1. Motivation and Contribution

Supporting firefighting and prevention is vital due to the rising frequency and severity of wildfires from climate change and human activity. Current simulation systems struggle with real-time data, especially dynamic variables such as Live Fuel Moisture Content (LFMC), which are crucial for accurate wildfire predictions. These models often use static data, leading to underestimated and/or outdated risks. Integrating advanced, low-cost sensors and real-time data into these systems is essential for better accuracy, faster responses, and improved fire resilience [6, 14].

In wildfire modeling, accurately simulating fire spread is essential for effective management. Combining static data (like topography and vegetation) with dynamic data (such as real-time weather and plant moisture) can greatly improve predictions' accuracy. The cellular automata approach, as detailed in the literature [3, 7, 8, 12, 15, 16], is a powerful framework for integrating these data sources. By incorporating both static and real-time information at the cell level, this model better captures the complex interactions driving wildfires' spread [12]. This optimization involves calibrating the model to adjust for variations in fuel moisture, wind speed, and other environmental conditions that influence fire behavior.

Advances in affordable humidity sensors now allow for dense networks to monitor plant moisture in real-time across vulnerable areas. These durable sensors, part of a broader environmental system, collect and analyze data continuously [14]. Real-time updates on weather, moisture, and wind can be integrated into simulations, ensuring they reflect current conditions and help fire management agencies make well informed decisions. This requires advanced algorithms to dynamically process and apply data throughout the simulation [12].

2. Background – Related Work

In the realm of wildfire management, the integration of advanced technologies has significantly improved early detection and monitoring capabilities. Modern systems employ a variety of methods, including ensemble learning, geographic information systems (GIS) [1, 2], intelligent vision-based systems, and Internet of Things (IoT) technologies to enhance the accuracy and speed of detection [4, 5, 17].

Additionally, the use of drones equipped with sensors and cameras introduces a mobile and flexible approach to monitoring, capable of covering large and inaccessible areas. These drones can quickly detect smoke and other indicators of wildfires, providing real-time data that is vital for timely intervention [18].

Cellular Automata (CA) models are highly effective in simulating the complex dynamics of wildfire spread. These models represent the landscape as a grid, where each cell evolves based on rules influenced by the state of its neighboring cells. Noteworthy implementations include Alexandridis's et al. [3,7,12] application of CA integrated with GIS and meteorological data, which significantly enhances the ability to predict fire evolution across mountainous and heterogeneous forest landscapes.

The balance between internal and external moisture is crucial for plant survival, especially in areas with variable water availability. Internal moisture, stored in plant tissues, helps buffer against short-term water shortages during high transpiration periods. This internal reserve is linked to external moisture sources, such as soil water and atmospheric humidity, which affect how plants replenish their reserves. For shallow-rooted herbaceous species, internal moisture closely correlates with upper soil moisture, as indicated by the Keetch-Byram Drought Index (KBDI) [6, 10, 11, 13].

3. Proposed Methodology

In this study, we propose a novel approach to wildfire simulation by elaborating the cellular automata model developed by Alexandridis et al. [3, 7] which simulates wildfires' spread across heterogeneous vegetations landscapes and incorporating real time measurements. Each cell interacts with its neighbors based on factors such as vegetation type, topography, and environmental conditions such as wind speed, thereby effectively capturing fire dynamics. Our methodology highlights the importance of incorporating real-time plants' moisture measurements to enhance the accuracy and timely responsiveness of wildfire simulations. Although real-time data integration is planned for future work, we currently use varying moisture levels in our simulations to illustrate its potential impact.

We conducted simulations across three distinct scenarios to explore how varying moisture levels influence wildfires' behavior:

- **Uniform Moisture Content (Low or Normal):** The entire field has uniform moisture content, allowing us to assess the impact of consistent moisture levels on fire spread. Moving forward, this will be referred to as *Uniform (Low or Normal)*.
- **Central Ellipse of Higher Moisture (Low or Normal):** The field has lower overall moisture, with a central elliptical area of higher moisture content. This scenario demonstrates how variations within a field affect fire's dynamics, particularly in interactions with areas of differing moisture and thus flammability. This will be referred to as *Ellipse (Low or Normal)*.
- **Three Smaller Ellipses with Higher Moisture (Low or Normal):** The central ellipse is divided into three smaller ellipses with higher moisture content, within an otherwise lower-moisture field. This setup provides insights into how dispersed varying moisture patches influence fire's progression and direction. This will be referred to as *Small Ellipse (Low or Normal)*.

In each scenario, we conducted 10 simulations using two moisture levels—normal and low—and calculated the averages to assess how moisture variability influences wildfire behavior.

Although real-time moisture data integration is not yet implemented, these controlled simulations focus on the importance of such data for accurate fire modeling. Our results provide a foundational understanding of how plants' moisture content affects fire dynamics, paving the way for future models that incorporate real-time sensor data to enhance wildfire predictions and inform fire management

4. Results

From the simulation scenarios, we recorded metrics on the average percent burned over time and final percent burned.

Figure 1 and **Figure 2.** highlights that low moisture scenarios generally lead to a steeper increase in percent burned over time, indicative of a more aggressive and sustained spread. This is particularly evident in the Small Ellipses Low and Uniform Low scenarios, where the percentage burned increases sharply as the fire progresses. Conversely, Normal scenarios show a more gradual increase, with some, like Ellipse Normal, reaching a plateau, suggesting the fire may have naturally limited its spread.

Finally, **Figure 3** shows that low moisture conditions consistently result in a higher final percent burned across all shapes (Ellipse, Small Ellipses, and Uniform). This indicates that fires under low moisture, despite possible variability in spread rate, ultimately consume a larger area. The Ellipse Low and Small Ellipses Low scenarios exceed their normal counterparts in final percent burned, reinforcing the conclusion that lower moisture contributes to a more extensive spread. Notably, Uniform Low achieves the highest final percent burned, underscoring that uniform landscapes vegetation shapes under low moisture are particularly susceptible to widespread fire.

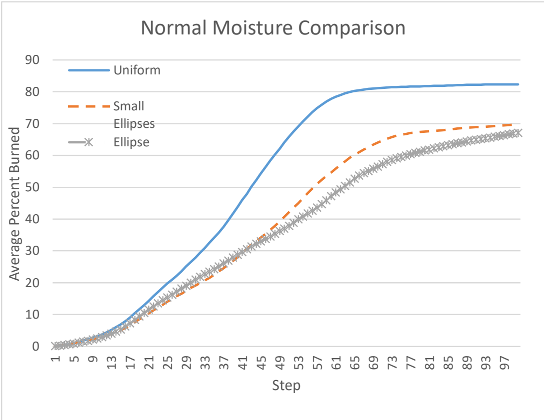

Figure 1: Average percent burned over time under normal moisture conditions

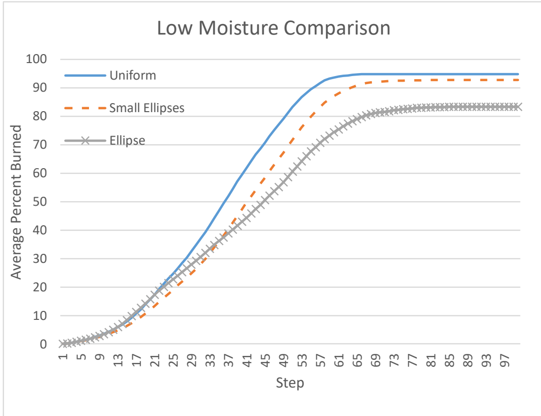

Figure 2: Average percent burned over time under low moisture conditions

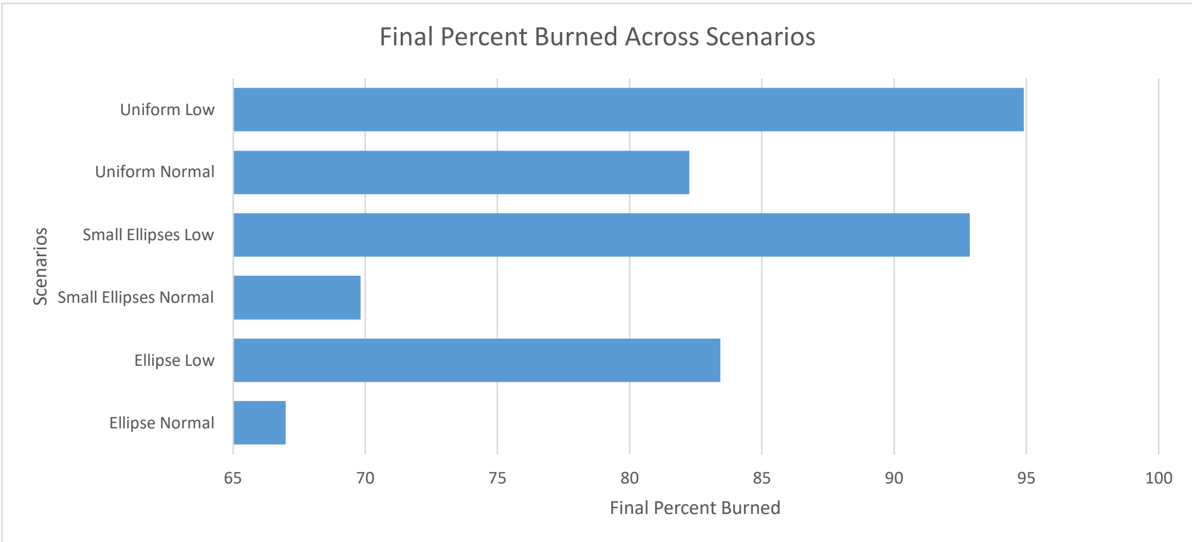

Figure 3: Final percent burned across all scenarios

5. Discussion

The analysis of wildfire simulations across different landscape vegetation shapes and moisture conditions underscores the critical importance of accurately predicting wildfire behavior to inform effective fire prevention strategies. The findings highlight how a low-cost system that can accurately monitor and model these conditions is essential for mitigating the risks associated with wildfires. Low Moisture Conditions were found to lead to more sustained and, in some cases, faster fire spread. This suggests that real-time monitoring of moisture levels using a low-cost system could be crucial in predicting and responding to wildfire threats before they become unmanageable. The ability to detect and model these conditions in advance allows for better allocation of resources and quicker response times. The simulations show that Low Moisture Conditions result in a significantly larger area being burned. By utilizing a low-cost system to continuously track environmental factors like moisture levels, fire prevention teams can anticipate areas at higher risk. This proactive approach enables targeted prevention efforts, such as controlled burns or resource pre-/re-positioning, to minimize the potential impact of wildfires.

The rapid increase in the average percent burned over time under low moisture conditions illustrates the need for accurate, ongoing data collection. A low-cost system capable of providing this data in real-time can help predict the trajectory of a fire more effectively. This information is vital for developing dynamic fire management strategies that adapt to changing conditions, reducing the likelihood of fires spreading uncontrollably.

6. Conclusion

The increasing frequency of wildfires due to climate change highlights the need for improved fire prediction models. A key factor in fire dynamics is plants' moisture content, as plants with lower moisture burn more easily and intensify fire spread. Traditional models using static data often underestimate this risk, making real-time data integration crucial. By using low-cost sensors to measure environmental variables like plant moisture, temperature, and humidity, we aim to enhance fire simulations for more accurate predictions.

Our simulation results show that low moisture conditions significantly accelerate fire spread, leading to faster velocities, larger burned areas, and more sustained fire behavior. These effects are particularly evident in uniform-shaped areas, where the lack of natural barriers increases vulnerability. This underscores the importance of monitoring both moisture levels and terrain characteristics to improve wildfire risk assessment. Variations in moisture distribution also dramatically impacted fire dynamics, with lower moisture levels consistently causing faster and more widespread fire spread across all scenarios.

In the future, we plan to conduct field experiments by deploying our proposed low-cost sensors in high-risk wildfire areas. These sensors will continuously monitor moisture and environmental conditions in real time, allowing us to integrate this data into our model. This real-world experiment will test the system's ability to improve fire predictions and enhance wildfire management strategies, providing more timely and effective prevention and response measures.

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