

Analyzing Wildfire Dynamics: an Agent-Based Model of the 2025 Wolf Wildfire

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Abstract

The 2025 Wolf Wildfire near Denare Beach, Saskatchewan was one of the most severe wildfires in Western Canada, contributing to one of the worst fire seasons in Canadian history. This project utilizes Agent-Based Modelling to simulate wildfire spread dynamics using historical environmental data and geographical information as inputs, with the goal of reproducing the behaviour of the Wolf Wildfire, and analyzing how varying conditions and interventions influence the spread of the fire. In particular, the model employs rasterized geospatial data in three layers, woodland, water, and saturated soil, in addition to hourly climate observations such as temperature, wind speed, wind direction, relative humidity percent, and precipitation. Agents in the model are cells, representing areas of land, and are organized in discrete space. Each cell incorporates various exogenous factors, such as moisture, and endogenous factors, such as fuel levels. Overall, the model utilizes 22,500 agents in a 150 by 150 grid, allowing cells to ignite neighbours based on directionality and moisture, and fire spreads at a rate given by employing equations from the McArthur's fire danger meters for forests. Calibration and sensitivity analysis were conducted to evaluate model behaviour and assess the influence of various parameters, particularly moisture and fuel consumption rate, on fire spread dynamics. These revealed how the model reflects unrealistic effects based on moisture variations. Furthermore, various scenarios fortified the current understanding of forest fires relating to seasonal climates. Overall, the model establishes a foundation for understanding wildfire spread dynamics and provides a framework for future development in order to support retrospective wildfire analysis and inform fire management strategies.

Background

2025 has marked the second-worst wildfire season in Canadian history, with more than 6,000 fires occurring across nearly every province and territory and burning over 8.3 million hectares [1]. These fires have caused extensive environmental and societal damage, displacing communities, threatening infrastructure, and placing immense strain on emergency response systems. One of the most severe and fast-moving fires in Western Canada was the Wolf Wildfire near Denare Beach, which began on May 19, 2025 [2]. Its rapid expansion forced large-scale evacuations, pushed families from their homes, and required responders to work under extreme conditions to protect lives and property [3,4]. Motivated by the scale and urgency of this event, this project develops a modelling framework capable of simulating wildfire behaviour under varying geographic and environmental conditions. The broader objective is to deepen the understanding of the key drivers of fire spread and to support retrospective analysis of how different conditions or earlier interventions might have influenced the progression of the Wolf Wildfire.

To achieve this, the Wolf Wildfire model is built using an Agent-Based Modelling (ABM) approach to represent fire dynamics at the cell level, supplemented with Java-based data handling for environmental and geographic inputs. The model is designed to capture how both

endogenous factors, such as fire spread rate, burn duration, and interactions between neighbouring cells, and exogenous factors, such as wind speed and direction, influence the evolution of a wildfire. By incorporating real spatial data where available, the model aims to replicate the fire spread dynamics of the Wolf Wildfire and explore how fire behaviour changes under different environmental scenarios. The main goal of the model is to replicate wildfire behaviour while accounting for key endogenous and exogenous factors such as environmental conditions, fuel properties, and topography. Although the modelling framework is designed to be flexible and adaptable to different regions, this project is specifically focused on characterizing the 2025 Wolf Wildfire near Denare Beach, Saskatchewan. By recreating the spread of this fire under varying environmental and geographic conditions, the model aims to provide insights into how the fire progressed and how damage might have been mitigated.

Data

To support the development of a realistic wildfire simulation, the model incorporates several forms of geospatial data describing the landscape affected by the Wolf Wildfire. Geographic information was obtained from the Geospatial Data Extraction service provided by the Government of Canada [5]. The data was originally supplied in GeoPackage vector format, which required preprocessing before it could be used within the model. Using QGIS, the vector layers were rasterized and exported as TIFF files so that they could be read by the AnyLogic model. The data layers used in the model include woodland areas, representing regions containing forest fuel, water bodies, such as lakes and rivers that may act as natural barriers, and saturated soil, indicating areas where moisture levels could influence fuel availability and fire behaviour. Since the model processes TIFF raster data, each cell in the simulation grid determines its land classification based on local pixel values. Specifically, a cell assigns itself a type (e.g., woodland, water, saturated soil) if at least half of the pixels within a surrounding ten by ten neighbourhood correspond to that land category. This approach smooths local variation and helps create more continuous spatial patterns suitable for agent-based simulation. At present, the model's data reader accepts only TIFF files, and all raster layers must share the same pixel resolution to ensure correct alignment. The area of interest for the Wolf Wildfire is defined by a latitude range of 54.5064 to 55.7469 and a longitude range of -103.0120 to -99.8974 (Figure 1). These bounds correspond to a spatial region approximately 197.7 km in longitude and 137.9 km in latitude, which is approximately 2,726,283 hectares. This defined region serves as the spatial foundation for integrating real-world geographic features into the model.

Regarding environmental data, the model utilizes historical data available by the Meteorological Service of Canada [6]. Specifically, the model accesses hourly climate observations in a CSV format via a url of the form:

“https://dd.weather.gc.ca/today/climate/observations/hourly/csv/{provTerr}/climate_hourly_{provTerr}_{climateID}_{year}_P1H.csv”

Where *provTerr*, is the specified province or territory of the climate station of interest, *climateID* is a specific ID number for the climate station, and *year* is the year of interest [6]. For the given time and area of interest for the Wolf Wildfire, a climate station in Manitoba, near Flin Flon, specifically climate station 5050919 is accessed for its 2025 data. Specifically, climate station 5050919 is the closest climate station to the point given by a latitude, longitude of 55.1280, -101.4547, which is the center of the geographic region of interest. The model reads data from the given csv data using a *getClimateData* function which was implemented. More precisely, the function accesses the data from the url, parses the file, creates a *ClimateRecord* object for the specific hour of data, and then adds it to the list of *ClimateRecord* objects. The *ClimateRecord* class is defined to store the date and time of the data, temperature, relative humidity percent, precipitation, wind direction, and wind speed based on its index in each line of the CSV file, replacing missing data with the data from the previous hour. Importantly, the specific index of each climate factor has changed over the years; since the model implements the indexing used in 2025, the indexing may need to be adjusted if data from many years ago is used. The implementation of the *ClimateRecord* class allows for the model to only store environmental data that is used in the model design, and is easily adaptable if more types of data is needed. Currently, the model utilizes the initial model date and time to create a starting index for the data, which is updated hourly, however, the index loops back to the start of the climate data list once the end is reached, rather than accessing the next available CSV file, or the previous year's data for that time.

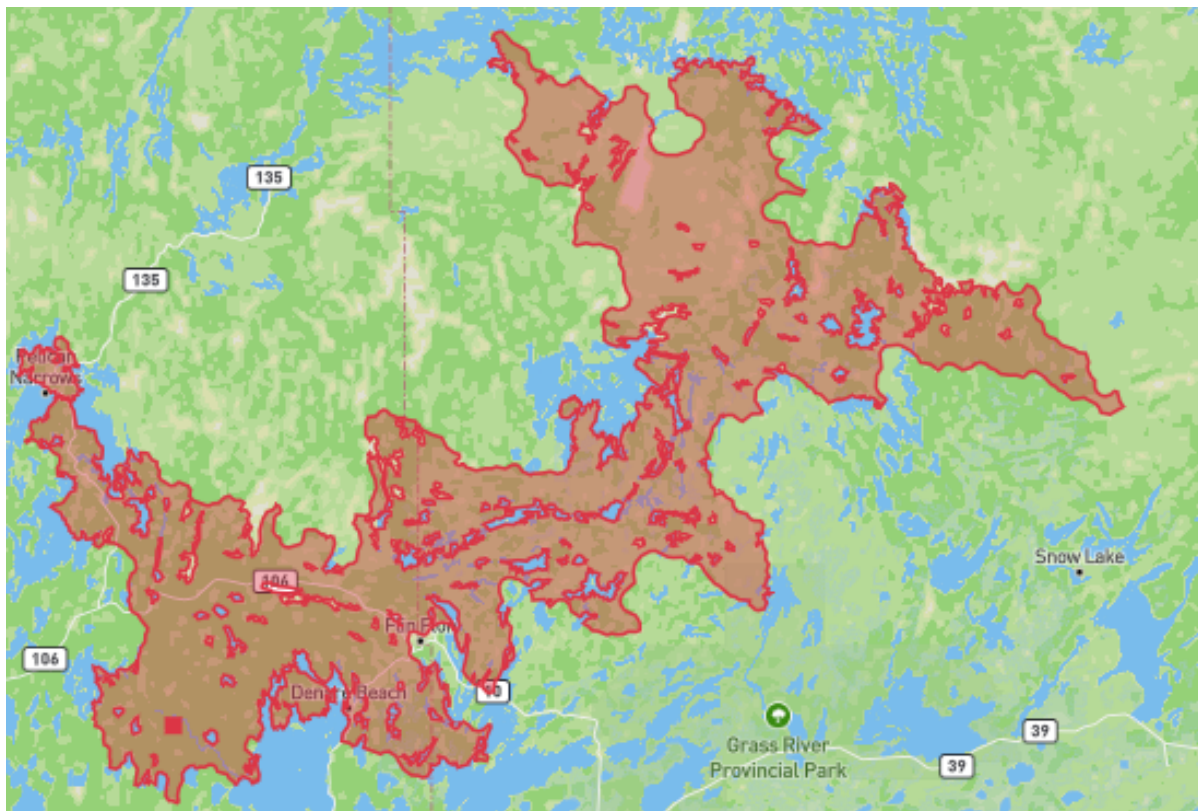


Figure 1. Geographic region used in our model. The red region indicates the area burned by the Wolf Wildfire [2].

Model

For the model, the prospective scope was to simulate wildfire behaviour given geographic and environmental data as inputs, with the goal of replicating known wildfires. This will then allow for the examination of different intervention plans and how they would have affected the spread of the fire, such as location and timing of blockages. Specifically, the model will focus on the Wolf Wildfire to determine if different locations and timings of interventions would have mitigated the spread of the fire. The model utilizes a square grid of 150 by 150 agents, in discrete space, to represent areas of land. The model has time units of days, and utilizes calendar dates for start and end times. Each agent is called a cell and is able to be ignited by neighbours, then burn and ignite their neighbours based on a probability related to the moisture level, and then transition into states of being burnt or charred. Once in the charred state, cells are able to be reignited, as they still have fuel remaining, and return to the burning state. However, once the cell is burnt, no further state transitions can occur. In order to adopt a more precise directionality of the fire spread, each cell is given eight evenly spaced points with fuel being equally divided among them (Figure 2). When a cell is then ignited, the fire originates from the point first touched by the fire spread of a neighbouring cell. From the originating point, the fire then spreads out in a circle; however, the inclusion of wind speed and direction changes the shape and direction of the spread. The rate at which the spread occurs is given by a fire spread rate, which is calculated hourly for each burning cell as climate data and fuel consumption updates occur.

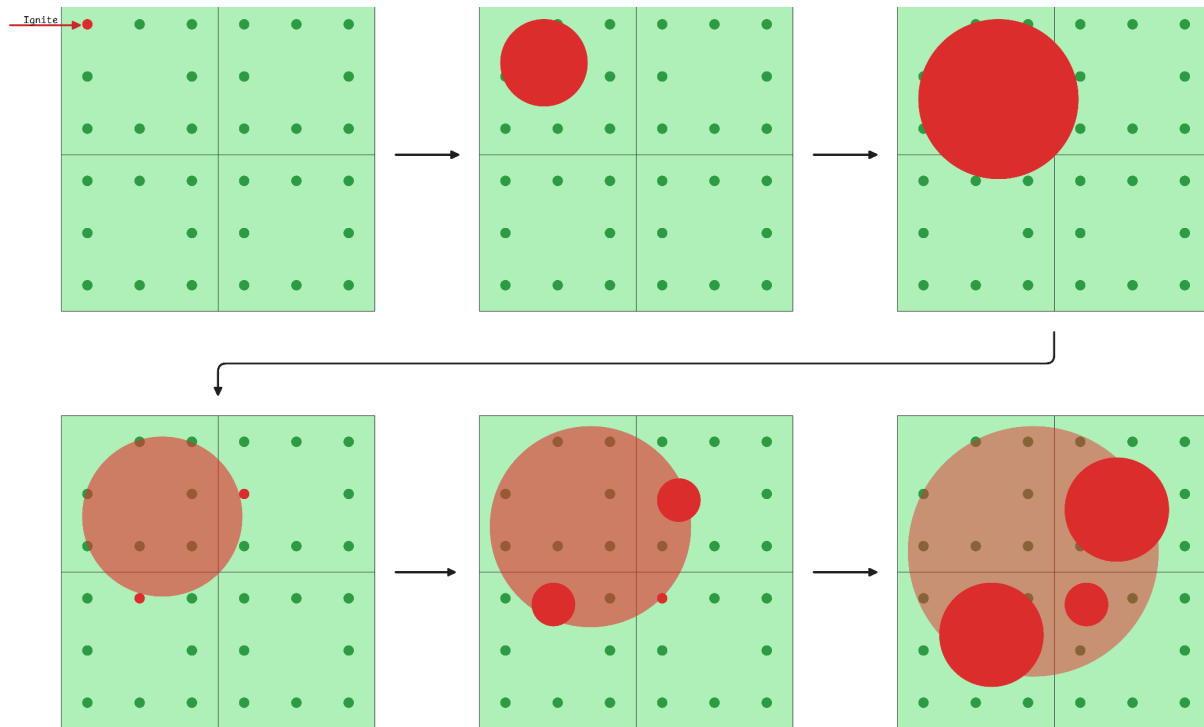


Figure 2. Diagram of fire spread between four cells with eight sub points each. The diagram considers a wind direction in the south east direction, however the rate of growth and specific shape is illustrative only.

Each cell carries different parameters, indicating exogenous values, and variables, indicating endogenous values (Figure 3). A key exogenous factor utilized is fuel ratio, which is the ratio of fuel that is usable within a cell, that is, the ratio of land area to total cell area. When geographical data is not used, all fuel for each cell is usable, however, the incorporation of geographical data changes the fuel ratio based on if the cell is water, in which case the fuel ratio is set to zero, partially water, or completely land. Another exogenous factor is the parameter local moisture specified by the moisture ratio of the fuel. At the moment this value is the same for each cell, specified to be 0.3, by taking the average moisture of Balsam fir, White birch, Trembling aspen, and Black spruce, four trees commonly found in boreal forests [7]. Additionally, parameters, such as Neighbours, posX, and posY contain each cell's spatial information as set upon startup of the model.

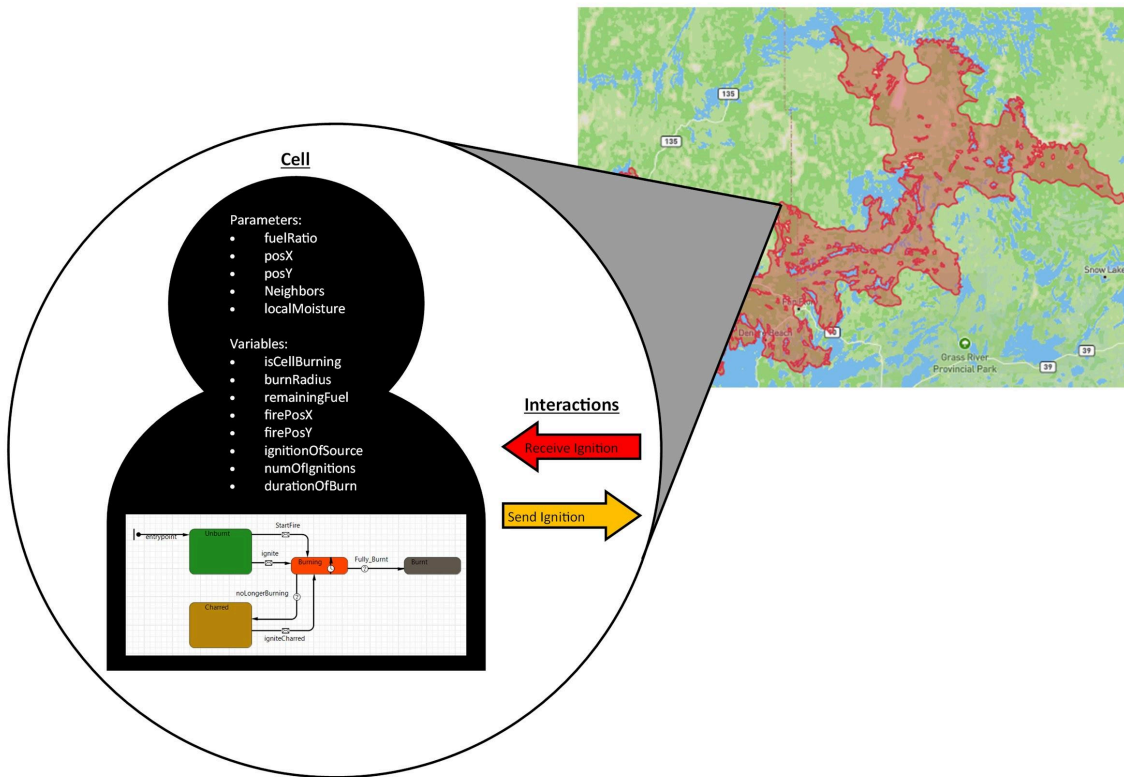


Figure 3. Model mapping illustrating cell agents on geographic region of interest for the Wolf Wildfire [2].

The primary endogenous factor for each cell is the fireSpreadRate. This is a value calculated hourly based on the McArthur's fire-danger meters for forests, composed of the following equations:

$$\bullet \quad F = 1.25 * D * e^{(T-H)/30.0 + (0.0234 * V)} \quad (1)$$

$$\bullet \quad D = 0.191 * (I + 104) * (N + 1)^{1.5} / (3.52 * (N + 1)^{1.5} + P - 1) \quad (2)$$

$$\bullet \quad R = 0.0012 * F * W \quad (3)$$

Where F is the Fire danger index, D is the Drought factor, R is the rate of forward spread of fire on level ground (km/h), T is the air temperature ($^{\circ}\text{C}$), H is the relative humidity percent, V is the wind velocity (km/h), I is the Ketch-Bryam drought index, N is the number of since rain, P is the Amount of precipitation (mm), and W is the Fuel weight (tonnes/ha) [8].

Overall the values used in equations 1, 2, and 3 are the same for all cells, except for W , which changes based on how long a cell has been burning for. Additionally, since the Ketch-Bryam drought index is not used in Canada, the Drought code multiplied by two was used. This is because the Ketch-Bryam drought index is a scale from 0 to 800 and the Drought Code is a value typically from 0 to 400 [9]. However, this introduces an assumption in the model that the Ketch-Bryam drought index is linearly related to the Drought Code. The value for the Drought Code was taken to be 200, based on historical data from the time and region of the Wolf Wildfire. The value of N is initialized to nineteen, and increases by one each day. The value of nineteen was chosen based on the precipitation history accessed from the Flin Flon climate station used to access environmental data and all other values involved in the equation, as previously mentioned. The McArthur's fire-danger meters for forests were chosen based on its alignment with the scope of the model, however, other more complex mathematical models were considered, such as the Canadian Forest Fire Behavior Prediction (FBP) System [8,10,11].

Each cell also records information on whether is is currently burning, the radius of its burn spread, the originating point of fire spread, the number of subpoints containing fuel, the amount of fuel remaining, the number of ignitions the cell has undergone, which cell(s) ignited the cell, the colour of the cell, as well as the number of days the cell was burning for, all of which are endogenous to the the model. The initial fuel per point in a cell is given by the `baseFuelPerCelPt` parameter in main. This value is calculated based on a base fuel load of 3.5 kg/m^2 , and the cell area divided by eight. The value of 5 kg/m^2 is chosen based on the fuel loads of different types of fuel present in a boreal forest [12].

The value of fuel changes as a cell burns, given by the equation:

$$\bullet \quad f = (1 - m_l) * b * f_0 * R_f \quad (4)$$

Where f is the remaining fuel, m_l is the local moisture, b is the fuel ratio, f_0 is the previous fuel amount, and R_f is the rate of fuel consumption set to a fixed value of 0.5 kg/hr to represent an baseline exponential decay when fuel is completely dry. Equation 4 does present a new assumption into the fire spread dynamics of our model since the equation comes from modelling an exponential decay, rather than a specific wildfire equation, thus the relationship between the values may be different in reality.

Furthermore, in main, the model records the number of cells in any given state and outputs it to a time plot. Additionally, the wind speed, temperature, precipitation, and relative humidity percent are presented in text, and the wind direction is shown, as they are all updated hourly. The hourly

updates of the environmental data, as well as the recalculation of the fire spread rate, occurs through a cyclic event. Similarly, a daily update occurs for burn duration values, overall and per cell, and a histogram for burn duration per cell is updated. An event is also utilized to end the simulation once the number of burning cells is zero. Upon startup of the model, climate data for a given year is accessed and put in a list. Then the index for the list is calculated based on the starting date of the model. Next, the fire spread rate is calculated for each cell using the relevant climate data. Finally, the initial ignition message is sent to a cell which is not water.

When a cell is burning, the burn radius grows every hour by the equation:

- $r = r_0 + R_f * 10 \quad (5)$

Where r is the new fire radius, r_0 is the previous fire radius, and R_f is the rate of fire spread (km/h). The value of ten is used as a multiplier because ten pixels equals about one kilometer, based on the scaling of the model. Additionally, fuel is consumed from each of the eight points in the cell within the cell's fire spread region, as calculated by equation 4, and ignition messages are sent to all neighbours within the fire spread. If all fuel in a given point is consumed before the fire is able to consume the fuel from the other points, the cell enters the charred state, where the cell may be reignited via a point containing fuel. If all fuel is consumed from all eight points within a cell, it then enters the burnt state.

The direction of the fire spread region is also specified by the equations:

- $X = X_0 + V * \sin(W) \quad (6)$

- $Y = Y_0 + V * \cos(W) \quad (7)$

Where X and Y are the new x and y positions of the fire origin, X_0 and Y_0 are the previous positions of the fire origin, V is the wind speed (km/h), and W is the wind direction (radians). Equations 6 and 7 also present assumptions as the equations assume the center of the originating flame will move entirely based on the wind direction. However, this is mitigated by not scaling the wind speed to pixels, which results in a less drastic movement of the x and y points.

Apart from the values considered, the model does not include some factors which play a role in fire spread dynamics. The main factor which was ignored was topography. The slope of ground plays a role in all fire prediction models, including the McArthur's fire-danger meters for forests, but was excluded in the current version of the model [8,10,11]. Additionally, our model does not take into account different types of fuel and moisture levels, but rather considers general values given the region of interest is a boreal forest. The model also does not currently take into account interventions in the fire, infrastructure, different stages of burn, specific starting locations of the fire, or specific reason for the fire starting.

Calibrations

For the model, initially, each factor was added and arbitrary relationships were created between these factors to roughly replicate fire spread dynamics. This was done to ensure the model progressed forward as data was being prepared and more concrete equations and values were found to better fit the scope of our model. When these arbitrary relationships were created, the goal was to create fire which spread in a circular fashion, but still affected by wind direction and speed. Thus, as each parameter was added to the model, it was incorporated into the model and the baseline simulation over flat grassland and uniform fuel load would be run to ensure the behaviour of the fire spread is as expected. Once geographical data was implemented, similar calibrations were done to ensure each cell had the proper colour, that cells burned differently depending on moisture, and that water cells did not burn at all. Similarly, the implementation of the historical environmental data involved calibrations to ensure updates were occurring properly within the system behaviour and reporting. This was done by cross referencing the values in the model at a given time with the CSV file of the data, as well as by changing climate stations and dates within the model.

Once the McArthur's fire-danger meters for forests were implemented, calibrations were done by hand to ensure the fire spread was more similar to the spread of the Wolf Wildfire. Specifically, as the Wolf Wildfire burned 164,583 hectares from May 19th, 2025 to August 13th, 2025 [2], and the geographic region considered in the model is roughly 2,762,83 hectares, the calibrations aimed to see a fire spread and burn of around 15-25% in the same time frame. The reason the aimed area is more than twice the area of the Wolf Wildfire is because the model does not currently implement slope or interventions, which are a factor that would play a significant role in the fire spread dynamics, and slow down the spread of the fire. These calibrations were done by visual inspection and calculating the percentage of area burned. One specific value that was adjusted during the calibrations was the multiplier in equation 5, since the geographic region considered is a rectangle scaled to a square. In doing so ten pixels aligned best with the expected output, and aligns with the scaling since each cell is eight pixels by eight pixels, representing approximately 0.9 kilometers.

Sensitivity

Structurally, the main sensitivity analysis done is the comparison of the fire spread on a geographical area and the fire spread on dry, uniform land. When comparing these two situations, it was observed that when geographical data was considered, the average duration of burn per cell was higher due to the presence of moisture and water (Figure 4). This led to the fire typically burning a greater percentage of the area before going out when geographical data was used (Figure 4). However, there was more variability in the results of when geographical data was used, because if the starting position was blocked in many directions with water, the fire would go out more quickly. Despite the differences, overall, both situations had relatively similar

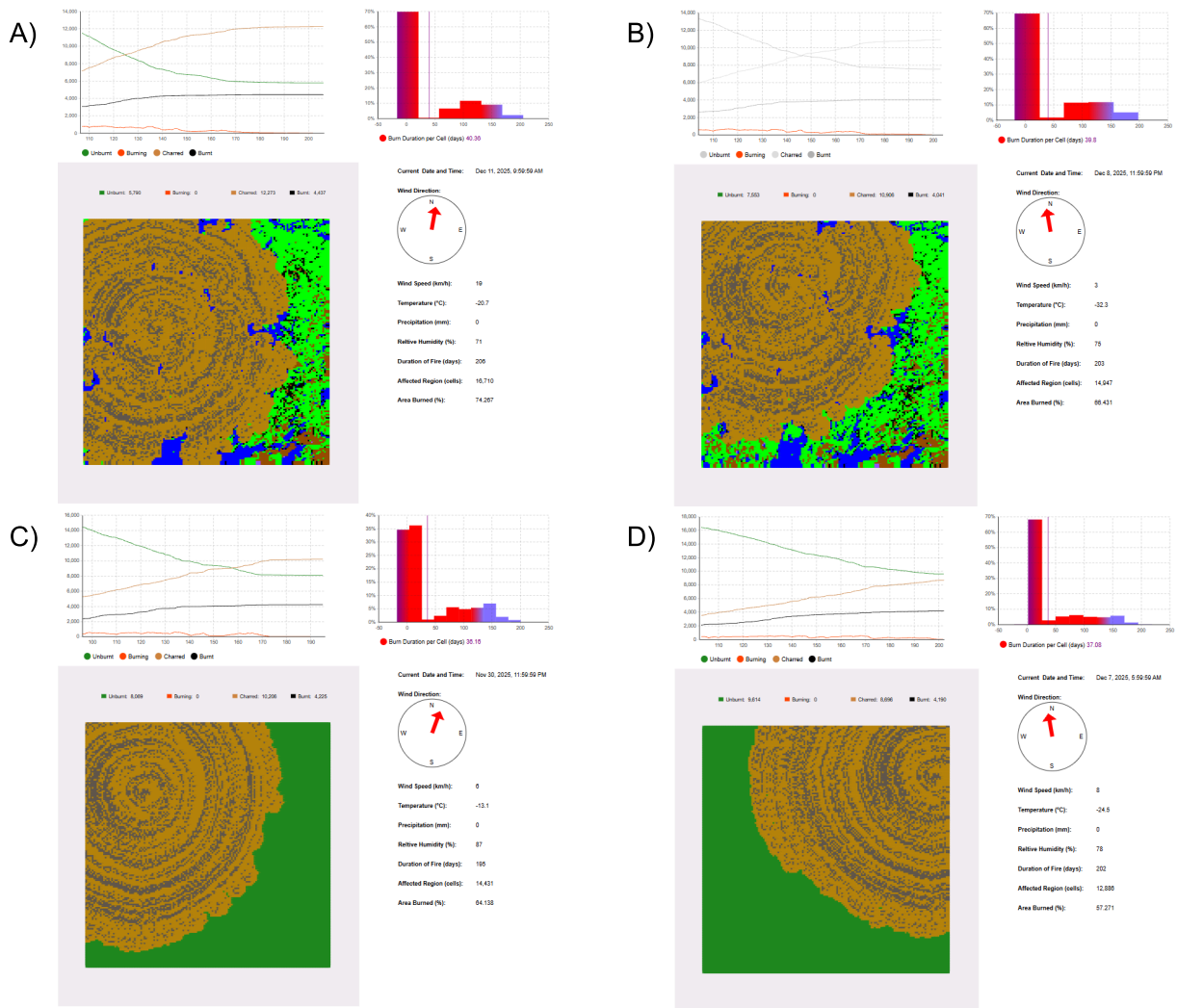


Figure 4. A) and B) show outputs from two separate runs of the model considering geographical data. C) and D) show outputs from two separate runs of the model not considering geographical data.

results, which is likely due to the effects of water bodies blocking the fire being negated to an extent by the presence of moisture, in the case of geographical data.

Two parameters were selected to perform sensitivity analysis experiments to find out how likely they influence the behaviour of the wildfire simulation when we vary their values. They are moisture and fuel consumption rate. The base moisture is inversely proportional to the wildfire's ability to spread. Drier fuels, smaller moisture values, will ignite more easily and burn more intensely, increasing the rate of fire spread. Conversely, wetter fuels, high moisture values, will require more energy to ignite and sustain combustion, slowing down the wildfire's progression, while burning for longer. A high value of 0.5 for the *moisture* parameter showed that the fire would spread and reach a state of equilibrium where the fire front would burn out, but patches of fire would remain in the burned/charred region (Figure 5A). A low value of 0.1 for *moisture* showed that the fire would go out very quickly (Figure 5B). These results indicate some issues in the model logic as dry fuels should burn more quickly over the region. This issue is believed to

be due to the universal *moisture* parameter, since in reality each cell will have differing moisture levels.

The fuel consumption rate is inversely proportional to the wildfire's ability to spread. It represents the rate in which the combustible material is consumed by the fire. A high value for *fuelConsumptionRate*, 0.9 kg/hr, showed that the burning material changes state more quickly, as the fuel is quickly consumed to change from burning to charred, not allowing the fire to spread (Figure 6A). A low value for *fuelConsumptionRate*, 0.1 kg/hr, showed that the burning state retains longer within a particular area before changing into completely burnt or charred (Figure 6B). The result of these sensitivity analysis experiments regarding the two specified parameters gives insights into the simulation model's behaviour and potential issues or effects of assumptions. A wider range of scenarios can be tested by adjusting their values, which eventually serves to increase comprehension of the real-world wildfire dynamics.

Scenarios

Our model has two baseline scenarios, *BaselineWithGeoData* and *BaselineWithoutGeoData*. These scenarios have input values and assumptions that are the same as outlined in the model formulation section, the only difference being *BaselineWithGeoData* utilizes geographical data to initial each cell. These baselines were chosen as one incorporates a real scenario and the other an

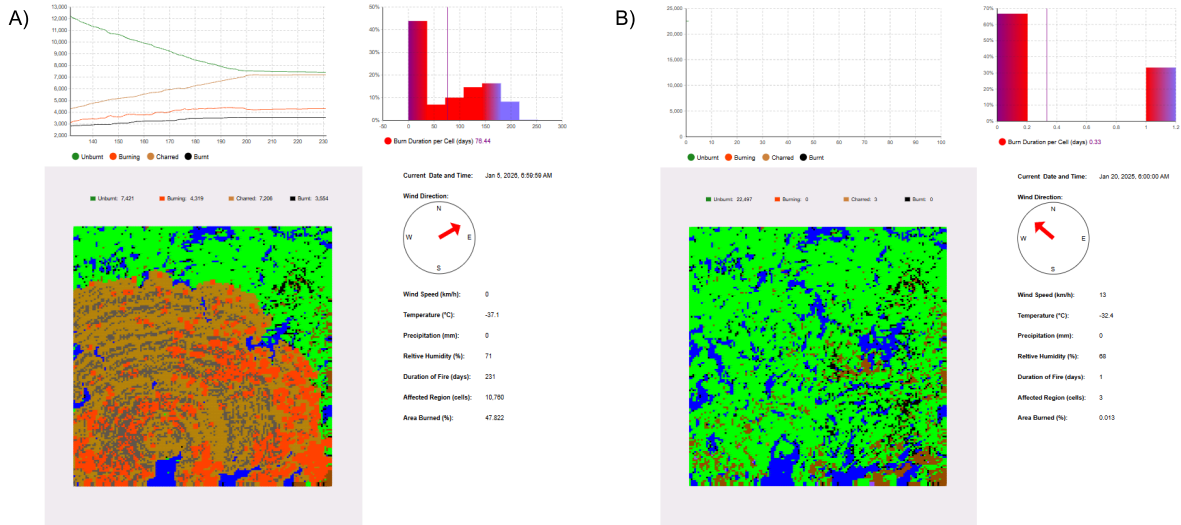


Figure 5. A) Fire reaches an equilibrium state when *moisture* is high. B) Fire does not expand far when moisture is very low.

arbitrary one. Figure 4 shows how outputs compare visually for each of these baselines. However, *BaselineWithoutGeoData* functions more as a calibration scenario, as other scenarios are built on *BaselineWithGeoData*.

Experiments were conducted by varying the value of moisture and fuel consumption rate. The model's simulation process revealed that the fire behaviour is sensitive to changes in these parameters as discussed in the sensitivity analyses. Specifically, high moisture resulted in the

wildfire retaining intensity over a longer duration (Figure 5A). Meanwhile, scenarios with low moisture caused the fire to progress slower than the baseline scenario (Figure 5B). The observation process revealed a few interesting scenarios regarding the fuel consumption rate. When the fuel consumption level is elevated, the fire's material consumption substantially exceeds that of the baseline scenario. This condition drives rapid depletion of the fuel across the simulation area, resulting in the immediate and complete cessation of burning of newly ignited cells (Figure 6A). When the fuel consumption level is minimized, the slow rate of material

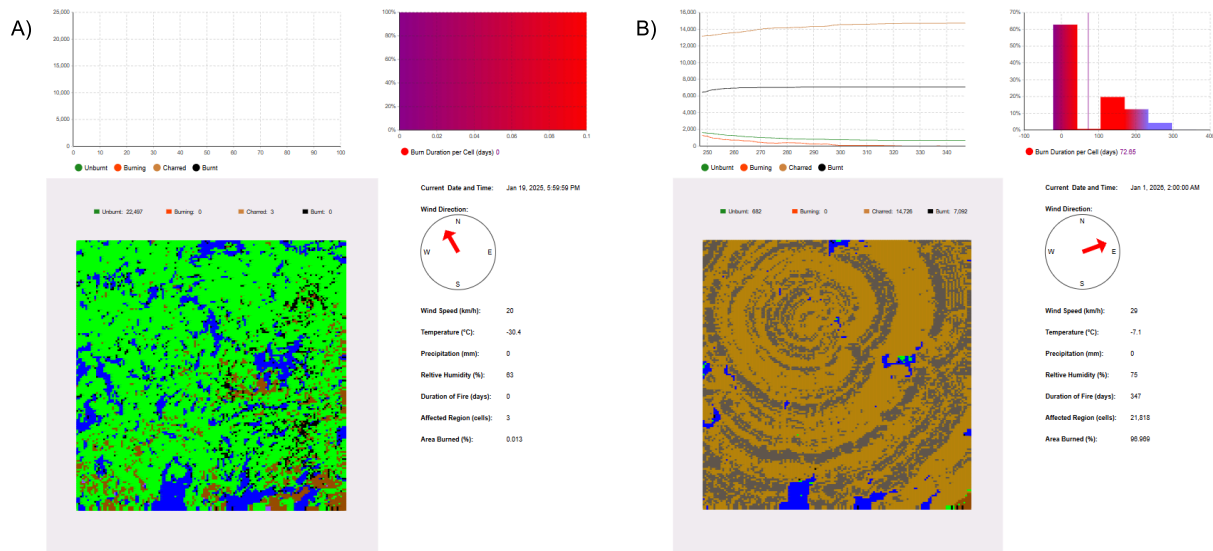


Figure 6. A) Fire does not expand far when *fuelConsumptionRate* is high.. B) Fire spreads far when *fuelConsumptionRate* is low.

consumption lets the combustion process persist longer than the baseline scenario (Figure 6B). This results in the fire maintaining a wider active front, characterized by greater number of simultaneously burning cells relative to the total number of burnt cells.

Additionally, three scenarios were considered with varying starting dates. The first scenario started on January 1st, 2025, the second on May 1st, 2025, and the third on September 1st, 2025. All assumed values remained the same as the baseline, other than the starting dates. For the January fire scenario, the fire ceased very quickly compared to the baseline, likely due to the low temperatures (Figure 7B). The results from the May fire scenario showed similar results to the results of the baseline scenario, as expected, since the baseline utilizes May 19th, 2025 as the starting date (Figure 7C). Finally, the results from the September fire scenario revealed the fire burning out more quickly than the baseline scenario, but lasting longer than the January fire scenario (Figure 7D). These results align with what is expected of the model, as in reality forest fires are able to persist during summer months, rather than the winter or fall. As a result, these scenarios verify the current understanding of wildfires and how they relate to seasonal climates.

The domain area is determined by the integrated geospatial data to simulate the region affected by the Wolf Wildfire. Initial findings in the model indicate a strong influence of environmental factors, specifically fuel consumption rate of the wildfire and fuel moisture, based on conducted

experiments. Many observations demonstrate that the fuel consumption rate of the wildfire mainly dictates the residence time, the duration required for complete burnout of a cell, whereas the moisture acts as a factor that prolongs the fire spread. The model utilized various geospatial raster data to construct the simulation environment in the wildfire incident. Through data integration, each cell can determine its land classification. Consequently, this standardized structure ensures the simulation logic is applied consistently and correctly, allowing different geographical areas presented in the model to exhibit comparable behaviours under identical scenario parameters.

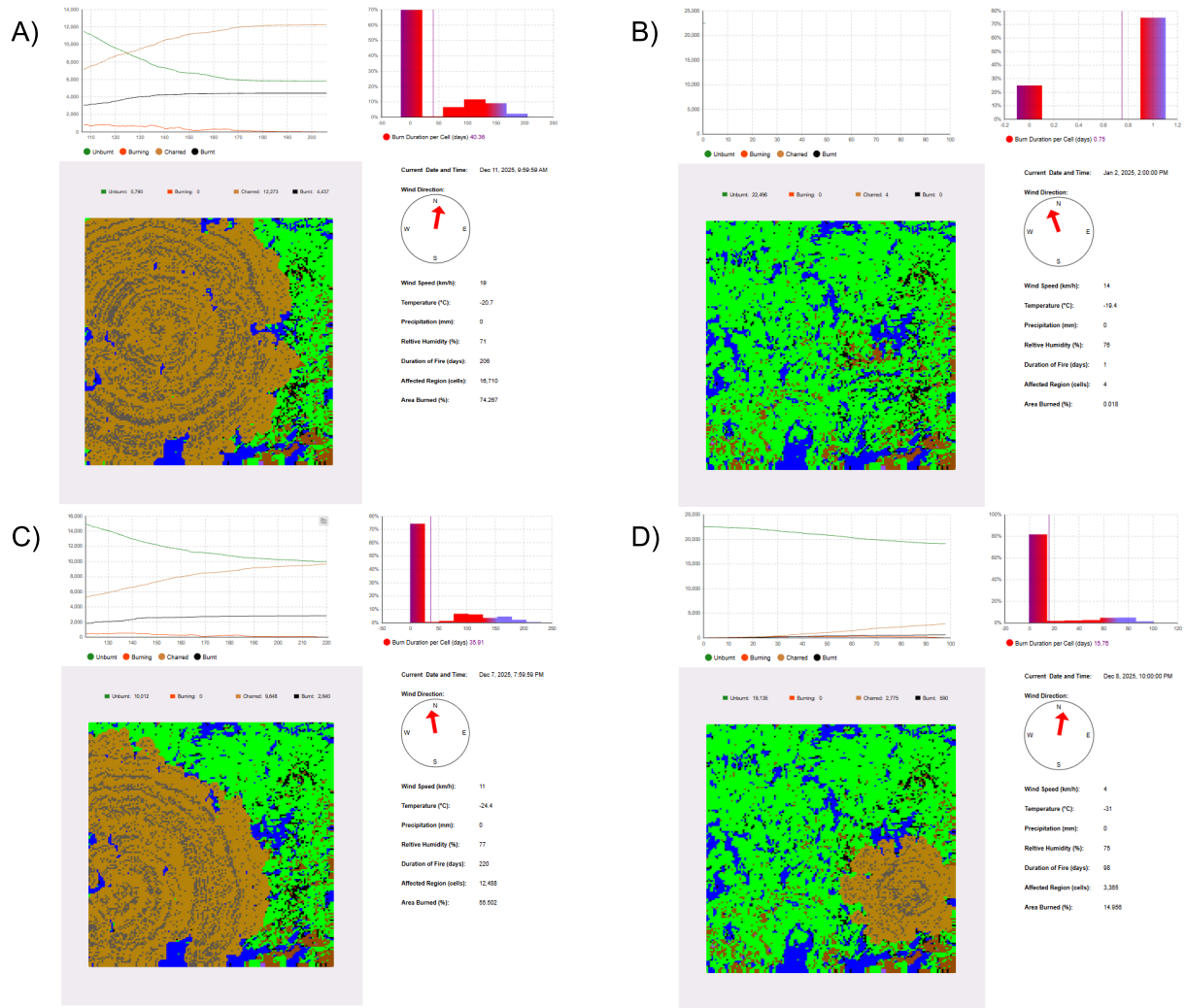


Figure 7. A) Output from the baseline scenario, where the fire starts on May 19th, 2025. B) Output from scenario where fire starts on January 1st, 2025. C) Output from scenario where fire starts on May 1st, 2025. D) Scenario where fire starts on September 1st, 2025.

Learning

If we were to undertake this project again, we would restructure the development process and follow a more deliberate incremental approach. One of the challenges we encountered early on

was that we over-scoped the model, attempting to include too many features at once. As the project progressed, we were required to reduce the scope due to time constraints and data availability. A more gradual, step-by-step development process would have allowed us to validate each component before adding more complexity. The most difficult part of the project involved converting environmental and geological data into a format that AnyLogic could process. If we were to revise the model scope in the future, we would begin by focusing on a small number of essential factors influencing fire spread, and then expand to include additional data layers once the foundational model was validated.

Another major learning outcome concerned the choice of modelling architecture. While Agent-Based Modelling (ABM) was well-suited for capturing spatially explicit fire spread and local interactions between cells, we realized that some components particularly intervention scheduling and environmental data handling might have been better represented through Discrete Event Simulation (DES) or System Dynamics (SD). This highlighted a key architectural tradeoff: ABM provides strong spatial realism but can become complex when managing large datasets and inter-agent communication. In retrospect, a hybrid approach using ABM for spatial propagation and DES for time-based interventions would have improved model structure and made certain processes more transparent.

We also encountered significant technical challenges with GIS integration. Handling GeoPackage vector data, converting it into TIFF layers, and interpreting those layers inside AnyLogic required more time and effort than expected. This reinforced the importance of selecting data formats compatible with the modelling environment and verifying data compatibility early in the project. From a domain perspective, we learned that wildfire behaviour emerges from the combined influence of several interacting factors wind speed, humidity, moisture levels, vegetation density, and topography. This understanding emphasized the necessity of performing sensitivity analyses, as effective wildfire modelling must account for uncertainty rather than relying solely on average conditions.

One of the biggest technical challenges was fitting converted data into the grid structure in a way that preserved realistic fire-spread patterns. To address this, team members developed a generalized grid-processing approach that allowed fire to spread based on aggregated environmental characteristics. Interestingly, the first half of the project was easier because the initial model—without real geographic data allowed us to focus purely on fire dynamics. Once real data was introduced, complexity increased substantially.

Using ABM as our modelling technique was a collective decision, as it initially provided a convenient and intuitive way to build a simple fire-spread model. However, as the project progressed, we realized that certain aspects of the system such as scheduling interventions and handling environmental data could have been implemented more effectively using additional

modelling approaches. Techniques such as Discrete Event Simulation (DES) and System Dynamics (SD) would have offered greater clarity for time-based processes and high-level fire dynamics. This experience demonstrated that no single modelling technique is sufficient on its own for capturing all aspects of wildfire behaviour. For future developers working with wildfire simulation, we would strongly recommend adopting a hybrid modelling approach that combines ABM for spatial propagation with DES or SD structures to handle interventions, resource flows, and system-level dynamics more efficiently.

The modelling process itself becomes significantly easier when it follows a small, incremental workflow. Throughout our project, incremental development, regular testing, and teamwork helped simplify the modelling tasks and made the overall experience both manageable and engaging. The main challenge we encountered was the conversion and preparation of geospatial data; beyond that, the step-by-step modelling approach allowed us to build confidence in each component before introducing additional complexity. Practices such as extreme value testing, performing checks after every modification, and creating small test grids were crucial for identifying issues early. These strategies revealed problems with message passing, timing, or state transitions long before the model was applied to real-world geographic data.

Ultimately, the modelling process taught us that a disciplined, incremental workflow combined with continuous validation, scenario testing, and early error detection is essential for building a reliable and meaningful simulation. These practices not only improved the quality of our wildfire model but also deepened our understanding of both the modelling techniques and the strengths and limitations of AnyLogic as a simulation platform.

Future Work

While the current model provides a foundational framework for simulating wildfire behaviour, several promising directions for future work could significantly enhance its accuracy, flexibility, and practical usefulness. Future work on the model would need to work on addressing potential issues observed regarding moisture. Specifically, one primary area for future development is the incorporation of more detailed and higher-resolution environmental and geographical data. Although the model currently uses rasterized layers to represent features such as woodland and water bodies, its realism could be improved by integrating additional datasets. These may include vegetation types, soil moisture and saturation levels, tree species characteristics, such as fuel type and internal moisture content, and dynamic weather conditions, including winter snowfall and seasonal water-level variations. Additionally, more detailed outputs can be made, such as a graphic showing the spread of the fire, akin to a vector field, by utilizing the information on which cell ignited another, as well a heatmap showing duration of burn, to analyze how fires burned differently in different regions.

Another important avenue for development lies in improving the intervention logic of the model. Future versions could incorporate specific fire-management strategies, including both fire

suppression and fire-enhancing scenarios. Suppression interventions could be designed to analyse which techniques such as aerial water drops, firebreak construction, or controlled backburning are most effective at particular moments, enabling the fire to be contained early and minimizing overall damage. Conversely, factors that intensify fire behaviour, such as spark travel and increased fuel density, could also be modelled to better understand extreme wildfire scenarios. Together, these enhancements would allow the model to function as a decision-support tool for emergency management teams.

Finally, future work could focus on developing a hybrid modelling architecture to more efficiently represent real-world wildfire dynamics. Combining multiple modelling approaches, along with systematic model calibration, would enable more reliable testing and improved predictive accuracy. Additionally, the development of a user-friendly interface allowing easy parameter adjustment, data upload, and result visualization would make the model more accessible to external stakeholders, including emergency planners, researchers, and government agencies.

Conclusion

The Wolf Wildfire model successfully establishes a foundational understanding of wildfire behaviour and fire spread by incorporating key environmental and geographical factors. The model uses an agent-based modelling (ABM) structure along with some hard-coded JavaScript logic to simulate wildfire dynamics. Although there is clear scope for future enhancements, time constraints limited the current implementation. Nevertheless, the model effectively simulates fire spread in the Denare Beach, Saskatchewan region based on the available data. Additionally, sensitivity analysis was performed, and multiple scenarios were explored to examine variations in fire spread behaviour. While the current implementation captures essential aspects of wildfire propagation, it also highlights the limitations of relying on a single modelling approach and relatively coarse input data. With further calibration, validation, and the development of a user-friendly interface, this model has the potential to evolve into a robust decision-support system capable of assisting emergency responders, planners, and researchers in predicting wildfire behaviour and minimizing potential impacts.

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