FUEL TYPE AGGREGATION FOR WILDFIRE SIMULATION OPTIMIZATION.

GOSSE LUURT VAN DER MEER
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SUPERVISORS:
dr. ir. T. A. Groen
dr. M. Huesca Martinez

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GOSSE LUURT VAN DER MEER
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SUPERVISORS:
dr. ir. T. A. Groen
dr. M. Huesca Martinez

THESIS ASSESSMENT BOARD:
prof.dr.ir. L.L.J.M. Willemen (Chair)
drs. R.G. Nijmeijer (Procedural Advisor)

ABSTRACT

Wildfire behaviour modelling plays an important role in the field of wildfire management and in conducting fire risk assessments. This research is focused on the influence fuel type aggregation on the accuracy of wildfire simulations outcomes, by using the Flammap fire behaviour modelling software. The FBFM40 fuel type classification (Scott & Burgan, 2005) has been systematically aggregated based on the following fire behaviour characteristics: fuel load, rate of spread, and flame lengths or no specific characteristic. The River Road East Fire, 2023, in the Lolo National Forest, Montana (USA), has been selected as the study area. This due to its representative boreal forest ecosystem and recent fire occurrence. This study uses the Minimum Travel Time (MTT) fire spread model to analyse changes in simulation accuracy across multiple levels of fuel type aggregation. The Sørensen Similarity Index (SSI) has been used to quantify the under- and over-simulation, while entropy levels have been calculated to evaluate the fuel type diversity left within the input data. The results indicate that fuel type aggregation mainly impacts the over-simulation, especially after the 6 aggregation steps and or when the entropy levels reached < 0.61. The rate of spread showed the greatest influence on the simulation accuracy.
The findings suggest that maintaining an optimal level between the amount of unique fuel types left in the simulation and the fuel type diversity (entropy) is essential to balance the computational efficiency and simulation accuracy. This study shows potential risks of oversimplification for the input fuel type classification to use in fire behaviour modelling Future research should explore dynamic aggregation methods with more focus on small-scale differences as well as fire suppression efforts. Recommended would be further validation of entropy-based thresholds across diverse wildfire-prone regions or complete ecosystems.

Key words: Wildfire simulation, fuel type aggregation, Flammap, FBFM40, fire behaviour characteristics, entropy, Minimum Travel Time (MTT), Sørensen Similarity Index (SSI), fire spread modelling, Boreal Forest fires, producer accuracy, computational efficiency, wildfire management

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On a personal note, I feel a sense of relief and accomplishment in completing this thesis and reaching the finish line of my academic studies. It has been a challenging journey to combine my studies with a professional sports career for the last 11 years. Looking back now, I am proud of my athletic and academic achievements. Both of these books have been closed in 2025, I am no longer a professional athlete nor a university student.

But learning never stops, as I embark on the next chapter in my life. Cadet van der Meer is reporting for flight training. Looking forward to the new challenges and experiences that await me in the skies. A good pilot is one that wants to improve with every flight, and therefore I value the lessons learned in the past decade through combining sports and studies.

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1. Introduction

The annual burned areas by wildfires in the United States is expected to increase by a factor of five by 2039 based on observations from 1961-2004 (Kitzberger et al., 2007). On top of that the length of the fire seasons will increase by 2-3 months in comparison with the last decades (Jolly et al., 2015). Being able to predict and simulate possible scenarios and outcomes in the event of a wildfire can greatly increase the safety of people and property involved. By using the forecasting possibilities of fire behaviour simulations, the results of these simulations prior- and post-fire, can gain valuable insights to the fire (risk) management. Prior to fires, risk assessments can be made helping to guide firefighters to focus areas, as well as giving insight into potential danger zones in case of a fire event. During the event of a fire, simulations can be of great help in adjusting firefighting strategies or evacuation plans (Šerić et al., 2005). Wildfire- and forest management strategies regarding restoration and recovery of past-, as well as resilience to future fire events are gaining useful insights by using wildfire simulations (Barros et al., 2018).

Boreal forests are known to be housing an ecosystem which is critical for the storage of global carbon resources. In recent studies (Zhao et al., 2021a), it has been shown that a third of the total global emissions of fossil fuels are being absorbed by boreal forests. The soils of these ecosystems are a long-term storage for a significant amount of the global carbon household. Wildfires in this type of ecosystem will therefore also be able to contribute to a significant change in the regional, national and even global carbon household (Deluca and Boisvenue, 2012; Zhao et al., 2021).

1.1 The Wickedness in Wildfire Management

Wildfire management is a great example for a scenario of a "wicked problem"—a term for issues that are complex, multifaceted, and resistant to straightforward resolution (Rittel & Webber, 1973). Wicked problems are characterized by their lack of clear solutions, conflicting stakeholder interests, and high levels of uncertainty. Looking from the field of wildfire management, the wickedness is found in the connection between the ecological, social, economic, and political dimensions. Each of these dimensions are playing their part in creating a complex environment for decision-making and long-term planning. The complexity of each theme is described below.

Ecological Dimension

Wildfire management must constantly adapt to the ecological complexity of landscapes which are prone to wildfires. Wildfires are not only destructive but also essential for many ecosystems. For example, with regards to plant regeneration and maintaining biodiversity(He et al., 2019). However, decades of fire suppression efforts have resulted in a change in vegetation and caused an increase in fuel loads, making forests more vulnerable to wildfires (Steel et al., 2015).Climate change is a major factor regarding the frequency and intensity of wildfires, increasing temperatures, longer periods of droughts, and changing weather patterns can all be traced back to climate change (Goss et al., 2020).

At the same time, human activities, like increased housing density along the boundaries of a forest, the frequency in wildfires is rising due to human pressure on such area (Stein et al., 2007). Within the ecological dimension there are natural and manmade factors that contribute to the complexity in achieving appropriate and effective wildfire management strategies.

Social and Economic Dimensions

Balancing human community protection and allowing the ecological benefits of natural wildfires is a contentious issue. Over the past two decades, the effects of wildfires have increased to impact human lives. Losses and damage of assets like houses, cars and other property. Besides the direct loss of assets the loss of life of pets, cattle, wildlife and humans come on top of that (Moritz et al., 2014).

Indirect costs such as increased healthcare expenses for smoke-related illnesses arise. As well as long-term ecological damages which have an impact on industries like forestry and agriculture as well slowing regional economies as many businesses cannot continue to operate as usual (Thomas et al., 2017). Allocating resources effectively is challenging, especially when economic interests conflict with ecological interests. Or when ecological interests are conflicting with other ecological interests.

Wildfire prevention is often more cost-effective than wildfire suppression (e.g., fuel load management, rural development changes), but prevention does require upfront investments and long-term planning(Wunder et al., 2021). Policies that prioritize areas of high risk for specific interventions can reduce overall economic and social costs (Al Abri & Grogan, 2021). A consensus among all stakeholders within the economic and social dimension would be needed, which is often difficult to achieve due to the wickedness of such cases.

Political and Policy Dimension

Wildfire management is politically influenced by political dynamics. Research has shown a correlation between the belief in climate change and political identity in the United States (Hartter et al., 2020). Finding bipartisan support for long-term policy changes has proven too complicated due to opposing beliefs with regard to climate change and therefore adding complexity to the effectiveness of wildfire policies (Hazlett & Mildenberger, 2020).

This brings more challenges to the table as policymakers navigate a landscape of competing interests, including those of environmental groups, industry representatives, tribal and local communities as well as governmental agencies (Abreu, 2021).

The difference in priorities among these stakeholders often leads to divided, short-term policy strategies instead of consistent and long-term plans.

Future directions in wildfire management

To address the wickedness in wildfire management, it is important to first recognize the connection between the dimensions involved. Policies and actions including all crucial stakeholders in developing a futureproof strategy to balance fire suppression with ecological restoration and socio-economic interests. A conceptual diagram is provided in figure 1 to visualize the following connections.

- Climate change strengthens ecological vulnerability, which results in an increased risk and intensity of wildfires.
- These wildfires increase social and economic loss, resulting in political pressures for immediate, short-term focused action.
- As a result of these political decisions, resource allocation may either reduce or increase ecological and social vulnerabilities.
- With the help of wildfire simulation and modelling capabilities increase the identification of areas of high risk.

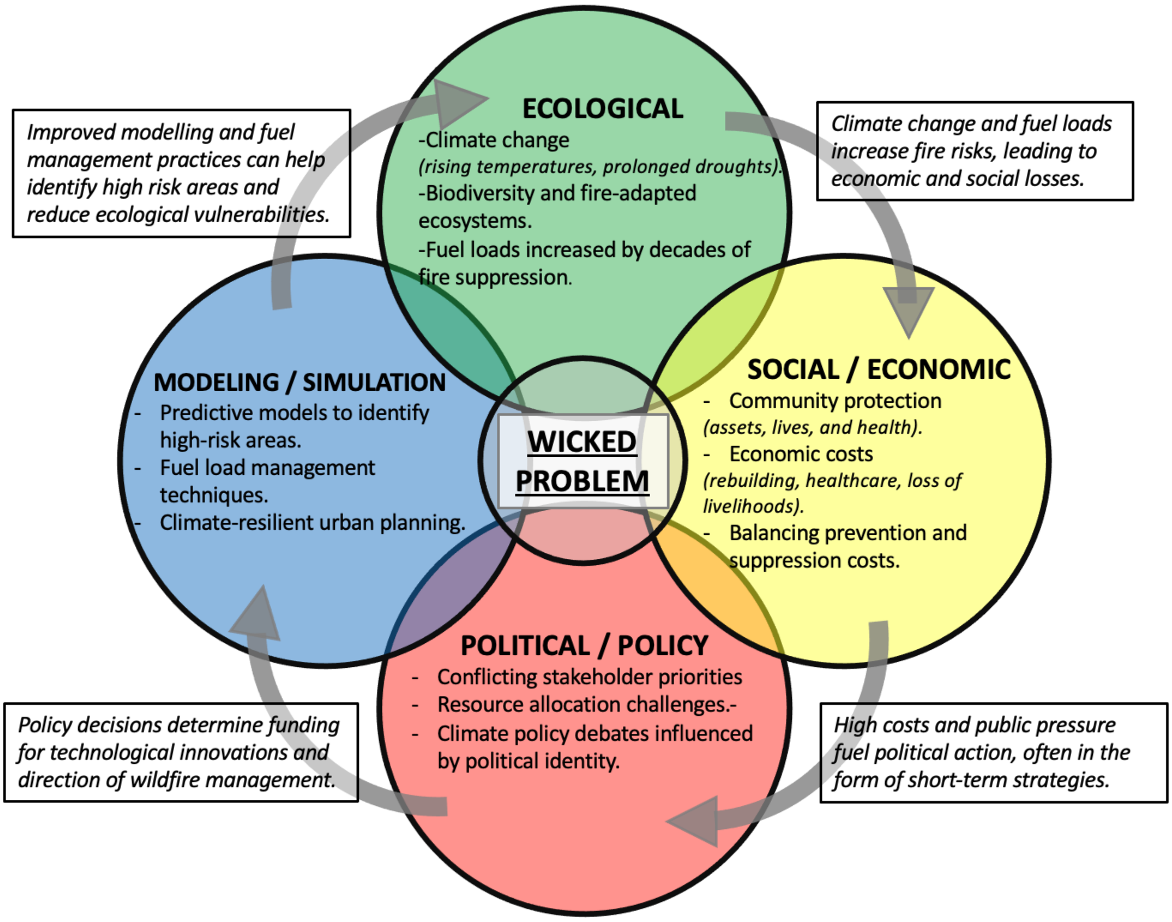


Figure 1: **Conceptual diagram for wildfire management as a wicked problem.**

Aims to reduce wickedness

Being able to improve predictive capabilities, wildfire management is using advanced simulation models to identify areas of high risk and incorporate this into the policy- and decision-making process. These wildfire simulations give insights into potential risk areas as well as supporting suppression efforts in prioritizing specific areas in the event of a fire (Pham et al., 2020).

By integrating the perspectives of the stakeholders involved, future policies could be developed which balance the community protection by ecological restorations through a transparent long-term decision-making process (Vogler et al., 2015).

Promoting proactive management aims to shift practices from fire suppression efforts as a reaction to wildfires to a proactive approach in preventive measurements(Molina et al., 2019). Policies can be created towards active fuel load management, creating landscapes adapted to a certain level of fire risk as well as developing more resilient urban planning (Halofsky et al., 2020; Schoennagel et al., 2017).

New forest management practices are needed in the recovery process of a burned area and its surroundings after the event of a wildfire (Halofsky et al., 2020; Mansoor et al., 2022). Implementing policies to strengthen the post-fire recovery and to improve the long-term resilience of ecosystems can be achieved by restoring degraded landscapes and or replanting more fire-resistant vegetation (Chuvieco et al., 2010).

These aims are in line with the overall goal to reduce the wickedness involved with wildfire management practices. Creating strategies which have a higher adaptation to specific situations and increase inclusivity of stakeholders involved which are looking further ahead in the future.

1.2 Fire behaviour simulations, developments over the years

Wildfire simulations started with the usage of mathematical models to calculate trends in fire spread. Early models only seemed to exist in the literature and were hardly used in practice. Models like the Fons model for light forest fuels (1946), the Thomas and Simms (1963), the Hottel, Williams and Stuward model (1965) were published before Anderson (1969) and Rothermel (1972) published their models. The Rothermel model was considered the most comprehensive and up to date in 1976 (Albini, 1976). These early models were basic and only focussed on the fire spread based on simple fuel type classifications and weather data (Bakhshaii & Johnson, 2019; Johnson & Wagner, 1985). Towards the 1980s a more specific approach was introduced which used wind patterns and fuel type classifications. With '' *A Mathematical Model for Predicting Fire Spread in Wildland Fuels''* (Finney, 2023) it was Richard Rothermel who became a founding father in 1972 and a known name in what we now know as wildfire simulations as Mark Finney, a leading fire behaviour researcher at the Missoula Fire Sciences laboratory, stated. He sat down with Richard Rothermel during an interview in 2022 to discuss the 50-year milestone of the publication of Rothermel's paper, *''A Mathematical Model for Predicting Fire Spread in Wildland Fuels''* from 1972 (Finney, 2023).

The introduction of Geographical Information Software (GIS) in an era in which computer capabilities rapidly increased around the turn of the century, made significant improvements in wildfire simulation capabilities (Andrews & Queen, 2001). More focus has been aimed towards accuracy and predictions in more specific and complex environments (Loehman, Keane, and Holsinger 2020). The increase in computational power also increased the complexity of the simulation models as more specified input data could be used. With weather forecast models increasing in quality as well, these new forecasting methods were introduced in the fire simulations (Loehman et al., 2020).
Nowadays, complex models are being used in wildfire management and are used to help the decision-making process in this field (van Hees 2013). The current state of the field of wildfire simulations has made it possible to make accurate predictions in complex environments. This is mainly used in making risk assessments as well as supporting the decision-making process during active fire events.

Management strategies have been shifting away from maintaining historical forest structures. Wildfire simulations therefore offer valuable guidance for forest managers to maintain a fire-prone landscape. The ability to create a more resilient ecosystem is important as these ecosystems are continuing to adapt to a changing climate as well (Schoennagel et al., 2017). Adapting the management strategies, which include an increase in prescribed fires, a reduction in fire suppression and to recognize the limits in which a regional fire pattern can be changed. (Loehman et al., 2020; McKenzie & Perera, 2015).
The increase in the frequency of high severity burns in North American boreal forests have shown to be a large source of carbon emissions. In the last 40 years, the total burned area as well as the frequency of large fire (>1000km^2) events in Canada has doubled. A positive correlation has been shown between the increase in wildfires and the global climate change. With boreal forests storing a third of the global terrestrial carbon, fire events in these ecosystems only speed up the combustion of these carbon emissions in the atmosphere (Zhao et al., 2021a).

1.3 Components of fire behaviour modelling

In the field of wildfire simulation sciences, there are concepts that play a key role. After a brief run-over of the history and developments of this field, an introduction will be given into the fundamentals on which wildfire simulations stand. For successful simulations, several input models are needed, as well as validation and accuracy models to assess the model outcomes. These models use the input data and are used mainly for wildfire management purposes which will be explained further in this chapter as well.

Input data

The different input data needed to run successful simulations can be divided into fire behaviour, weather- and fuel data. For each of these input data types, there are several different possible data input models, the exact description for the ones used in this research can be found in the methods chapter.

Behaviour Models are used to simulate how fires behave based on factors such as weather, landscape, fuel types, and their ignition source. These models aim to predict the flow of fire spread, the rate of spread, and the fire intensity, as fire characteristics in a simulation. (Cardil et al., 2021).

The rate of spread and the length of the flames are crucial outputs of the fire behaviour models for emergency response teams to set up a suitable approach (Cardil et al., 2021).

There are a few fire behaviour or so-called simulation models, with the following models being used the most, Farsite (Finney, 1998), Flammap (Finney, 2006), Wildfire Analyst (Ramírez et al., 2011), and Behave Plus (Andrews, 2013). In short, *Farsite* uses the Huygens' principle as it looks at the fire perimeter based on a series of points that spread independently in response to the fire environment of the other points. *Farsite* is designed for maximum simulation precision, prioritizing accuracy over processing speed. It is effective for simulating the growth and behaviour of a single fire over a period of up to a few weeks.

Flammap is a geospatial simulations system that calculates potential fire behaviour characteristics across the entire extent of a Landscape (LCP file). Flammap generates geospatial data on potential fire behaviour, such as spread rate, fire line intensity, flame length, and crown fire activity. *Flammap* lacks a temporal component, it uses spatial information on topography and fuels to compute fire behaviour characteristics for a single set of environmental conditions(Scott & Burgan, 2005).

Wildfire Analyst is known for fast processing speeds (>60sec. for simulations) for multiple simulation modes. To be able to run large-scale forecasting analyses there is a cloud-based High Performance Computing version available. The software runs on an API (Applications Programming Interface) to combine to use multiple applications together. Technosylva is the commercial company behind the Wildfire Analyst software and works with a license and subscription platform for usage.

The *Behave Plus* fire simulations system is a collection of models that describe fire behaviour, fire effects, and the fire environment. *Behave Plus* generates tables, graphs, and diagrams, making it useful for various fire management planning and wildfire incident management applications (Scott & Burgan, 2005).

The second inputs are the ***weather data***. Integrating weather data helps to improve the accuracy of fire behaviour predictions. Advanced weather data can provide accurate forecasts of winds, temperature, and humidity, which are important components for wildfire simulations (Alley et al., 2019). The rate of spread of fire depends for a big part on the winds, and therefore accurate weather models and forecasting are important in achieving accurate fire behaviour predictions. The weather data collection is running on observed weather data, this data has been recorded for decades (Herrera et al., 2017), which results in the availability of a lot of input data to be used in these datasets. As these weather models make predictions based on input data, the prediction accuracy increases if there is observational weather data available which has been collected for over decades in certain areas. The rise of the availability of small sensor weather stations adds real-time measurements and improves area-specific data to be used in weather forecasting models (Illingworth et al., 2015; Schauberger et al., 2020). Making observational weather data increase in spatial accuracy.

Finally, the ***fuel data***, these datasets are used to show the characteristics of fuel types that are burning in the event of a wildfire. Data on the spatial distribution of the fuels is crucial in the process of running a fire simulation (Arroyo et al., 2008a). Fuel models can be sub-categorized into *surface fuel model*, *canopy base heights*, and the *bulk density* of the *canopy*. Each of these sub-categories influences the behaviour of the fire spread. The surface fire will transform into a passive crown fire as soon as the intensity of this surface fire passes a specific threshold. This threshold depends on the canopy base height. The fire intensity depends on the bulk density of the canopies once the surface fire has turned into a crown fire (Hall & Burke, 2006). Increasing the accuracy and spatial resolution of the fuel type modelling will increase the accuracy of the fire behaviour simulations, by considering the different influences that each fuel type has on the fire behaviour (Burgan et al., 1998).
Outdated fuel data, when used as input for the fire behaviour simulations, can lead to inaccurate simulation outcomes(Benali et al., 2016). These inaccurate results can have a negative impact on the operational firefighting, fire mitigation efforts, and eventually the severity of the fire event. Understanding the fuel treatments is important to be able to suppress the fire and to be able to limit the severity of the fire (Shang et al., 2004) (Taneja et al., 2021). *Fuel Load, Rate of Spread* and *Flame Length* are characteristics which are essential in fire behaviour modelling. These characteristics can differentiate substantially between the individual fuel types and, therefore, often show different impacts on fire behaviour. The fuel load is often used as the main factor for a fuel type classification. It refers to the amount of burnable materials available and is often measured in weights like kilos per m^2 or tons per km^2. Fuel loads can be alive or dead vegetation and can range from pine needles to complete trees or from grasses to dead logs. With regard to fire behaviour, higher fuel loads tend to lead to a higher intensity in the fires (McNorton & Di Giuseppe, 2024).

The rate of spread refers to the speed in which a fire moves over the surface. As different fuels burn at different rates, fire spread often increases when fuels are dry. Topography plays an important role in the rate of spread as well as fire tends to move faster uphill than downhill. This is due to the pre-heating of fuels uphill, which increases their ignition and therefore the rate or spread. Lastly, the weather conditions and mainly the wind conditions are an important element in the rate of spread (Cardil et al., 2019). The flame length is an indicator of the fire intensity and refers to the length of the base of the fire to the tip of the flames. Dense and dry fuels tend to create longer flames, winds are able to stretch the length of the flames as well. Longer flames are showing higher-intensity fires and long flames are also harder to control during suppression efforts (Barboni et al., 2012; Kreider et al., 2024).

1.4 Validation and Accuracy

After introducing the input data, running a simulation would be possible based on these previously introduced models and data. To be able to determine the quality of the simulation outputs a validation method must be used as well as an accuracy determination of the simulation outputs.
By validating the wildfire simulations with real-world and/or real-time data, researchers aim to increase the accuracy of the predictions. Rochoux (2013) has been able to validate their simulation with real-world data by running small-scale, prescribed fires (Rochoux et al., 2013). By using a ***validation method,*** researchers are trying to decrease the uncertainties in the simulation outputs. These validations help to improve the reliability of the simulation results which results in better-informed decision-making around wildfires.

Two commonly used validation methods are focussed on either, the arrival time of the fire or the burned perimeter (Filippi et al., 2013). For the burned vs unburned perimeter, the Sørensen similarity index is often used. This index calculates the inter-agreement between the simulated and the observed (burned) perimeters. The intersection of the two areas is then divided by the total area and the outcome value will be between 0 and 1. This will be further explained in the *methods* section. Often, this index is approached as a hit-or-miss analysing method to determine the level of agreement between the simulated and observed areas (Perry, 1999).
The second validation method has been developed more recently. The arrival time agreement finds its base in the simulated arrival times versus the observed arrival times. The observed arrival time is often unknown because of the low availability of observations, in cases there is only one observation possible at the moment the fire has stopped. In practice, the observed arrival time is often chosen for a more generally used score to use in the calculation (Filippi et al., 2013).
With fuel types and their spatial distribution being one of the key drivers of wildfire simulations, detailed data products in this field are of great importance (Arroyo et al., 2008b). Classification of fuels and fuel types is often difficult due to the complex structures and large variations in vegetation which can be present in an aera (Stefanidou et al., 2022). Individual tree mapping has produced high-resolution spatial data on fuel distribution (Young et al., 2022). However, the size of these study areas is still relatively small in comparison with wildfires which can quickly spread over several hectares.
Detailed fuel type distribution maps are essential to improve fire behaviour modelling and assessing fire risk (Penman et al., 2022), unfortunately large-scale application often remains limited by data availability and computational constraints.
Eventually, the accuracy of a simulation output is one of the key parameters to be able to determine the quality and usefulness of the model (Penman et al., 2022).

Accurate simulation outputs ensure that the model can effectively predict fire behaviour. Those predictions help in supporting the decision-making processes and wildfire management (Zimmerman, 2011). When a complex and accurate model is run with low-quality input data, the simulations outputs will be low in accuracy. Finding the right balance between the quality of the simulation outputs versus the (computing) costs and challenges of generating high-quality input (Schwerdtner et al., 2024)data has always been a key research focus within this field.

Lowering the complexity of the simulation process can be achieved in multiple ways, for example, by simplification of the total model used for the simulations (Robinson, 2023). A reduction in variables used, scenario reduction (limiting possibilities of less likely behaviour) and hierarchical modelling (providing intermediate results during the process). These options are mainly based on the model itself. Another possibility for simulation simplification can be found in (spatial) data aggregation. This approach is aimed

at the input data, smaller data fields are aggregated to create larger data fields and reduce the number of individual data units (Bian & Butler, n.d.).
It is essential to validate and verify the model's accuracy while aggregating fuel types to ensure the simulations can provide meaningful and useful insights for wildfire management purposes. Previous studies have shown great results in aggregating underrepresented fuel type classes. Cutting the training dataset in half has shown a model accuracy loss of 7.2% in a recent study conducted by using the LANDFIRE surface fuel model with the usage of the FBFM40 classification (Alipour et al., 2023).

1.5 Limitations in current research

Wildfire behaviour simulation uncertainties largely stay unmeasured in the literature due to the lack of computing power. While many improvements have been made in the field of wildfire simulations, a changing climate will bring new challenges to the table. Extreme weather behaviour, for example, will bring new challenges (Aparício et al., 2022). As stated before, an increase in the frequency of high-severity burns in North American boreal forests have shown to be a large source of carbon emissions (Zhao et al., 2021a). With an increasing amount of fuel loads burning, as well as more and larger areas becoming prone to wildfires, the need for abilities to simulate larger wildfires faster increases (Cardil et al., 2021).

In recent years, a big part of the research in this field has been evolving around increasing the spatial resolutions of fuel-type data, intending to increase the accuracy in wildfire simulations (Bakhshaii and Johnson, 2019; Rwanga and Ndambuki, 2017; Syifa, Panahi, and Lee, 2020). However, computational power has been a limiting factor, often resulting in decreasing the size of the research area that can be effectively studied. Parallel Processing Capability and Data Flow showing to be the biggest load on the computational power (Bakhshaii & Johnson, 2019).
One of the oldest publications used in this research pointed already towards these struggles when published in 1976, *''limitations could be found in the model not being applicable for the research area, the accuracy could be at fault and, or, the input data may be inaccurate''* (Albini, 1976).

Alipour et al., (2023) have published great results in their research to decrease the input datasets, for their study area a hot and dry ecosystem has been used. The study area was the entire state of California, which has a Mediterranean ecosystem. Therefore, opportunities for research within boreal forest ecosystems stay untouched.

1.6 Research problem statement

Maintaining the predictive capabilities of wildfire simulation outcomes, while simplifying input data, is crucial for their practical and efficient usability.
A big challenge in this process is to maintain the accuracy of the fire behaviour simulations while lowering the complexity when simplifying the input data needed.
One way to approach this challenge is by proposing a method focussed on the aggregation process of fuel types. Aggregating fuel types can take place in many ways, with different rule sets for each proposed aggregation step. Understanding the individual influence of fire characteristics on the simulation process and outcomes is crucial. This ensures that the simulations after aggregation maintain their essential predictive qualities.
Therefore, this research focuses on the individual influence of fire characteristics of the different fuel types to develop an effective aggregation strategy.

1.7 Research goal

This research aims to develop a systematic fuel type aggregation method for wildfire simulations that balances accuracy with lowering input data complexity.
Identifying the key fire behaviour characteristic which shows the most influence on the wildfire simulation outcomes is an important topic. This research will follow aggregation rules which will simplify the input data needed, while maintaining the predictive reliability. The goal is to broaden the usability of wildfire simulation modelling. And to provide a more efficient and simplified process to provide potential wildfire scenarios to support the decision-making process in wildfire management and response operations.

2. Research Questions

Main-Hypothesis:

Aggregating fuel types, based on the most influential fire behaviour characteristics is a way to simplify the input data without a substantial loss of simulation accuracy.

Analysing the output-accuracy levels based on wildfire simulation performances by using various aggregation processes to simplify the input data.

Research Question one:

How does aggregating fuel type classes, based on the fire behaviour characteristics of each class or only based on presence, affect the accuracy for fire simulation outputs based on similar and under- and over-simulation?

Hypothesis one:

Aggregating fuel type classes, based on the fire behaviour characteristics of each class or only based on presence, will result in a clear loss of accuracy in fire simulation outputs.

This implies aggregating fuel type classes based on a ruleset with regards to the specific fire behaviour characteristics or only by looking at the fuel type presence. Therefore, stopping the aggregation process when no individual fuel types which hold similar fire behaviour characteristics are left within the input data.

Research Question two:

How do the individual fire behaviour characteristics, fuel loads, rate of spread, flame length or no specific characteristic, impact the accuracy of wildfire simulation outcomes under different levels of fuel type aggregation?

Hypothesis two:

Based on the fire behaviour characteristics, the rate of spread has the greatest influence on wildfire simulation outcomes, shown in the trendlines representing the producer accuracy for under- and over-simulation during the aggregation process.

The rate of spread is expected to show the greatest influence on wildfire simulation accuracy, as it directly affects fire movement. Therefore, analysing trendlines for producer accuracy based on under- and over-simulation, will show if the rate of spread has the most influence on accuracy compared to fuel load, flame length or no characteristics.

3. Method

A reference dataset was created based on a historical fire event to compare fire simulations with differing levels of fuel type aggregations. In a systematic approach, we aggregated fuel-type input maps and simulated fires in a study area. These simulations were compared against a reference simulation of a historical fire event which was used to compare the simulations results under different aggregation levels (figure 2).
The simulation software does not take any suppression efforts into account which have taken place during the historical fire events. This will show an accuracy difference between the simulated data for the burned area of the reference dataset and the observed burned area (figure 3). Therefore, the simulated data of this first run (with an unaggregated fuel type classification) has been used as the reference data instead of the observed burned area from the historical fire event (figure 3).

After setting all parameters for the simulations, the model was run based on a constructive data aggregation method. This method focused on the presence and characteristics of the available fuel type classes within the study area. Validating the simulated burned areas with a produced reference dataset has been the approach to determine accuracy values of different levels of fuel type aggregation. Eventually assessing the quality and effect of the individual aggregation steps. The reference dataset used is the result of the initial simulation outcome before starting the aggregation process, therefore the producer accuracy for the model has been used to validate the simulation outcomes.

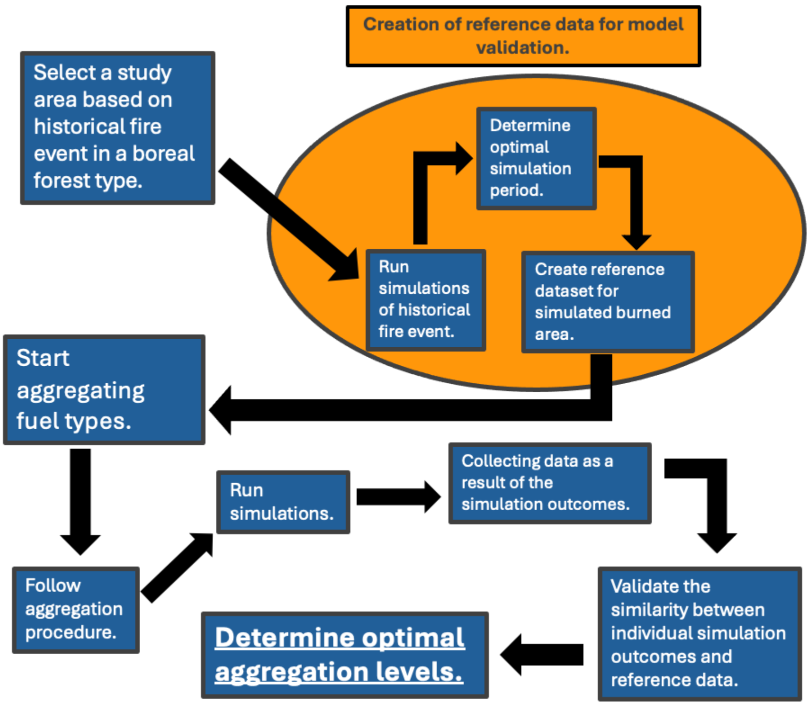


Figure 2: flowchart of the proposed method.

3.1 Study area: River Road East fire

The 2023 River Road East Fire in the Lola National Forest in the state of Montana, is a relevant case study for boreal wildfire research. This is due to the similarity in fuel composition, topography, and fire behaviour found in boreal forests. The Lola National Forest can be found in the Northwest of Montana, directly on the border with the state of Idaho. This region contains a mixed conifer forest and surface fuel loads similar to those found in boreal ecosystems (Walker et al., 2020).

Boreal forests typically feature flat lowlands, rolling hills, and mountain ranges. Slow draining soils, permafrost, and peatlands can be found at lower elevations. Steep slopes and a network of streams, rivers and lakes further characterize these mountainous regions(Laamrani et al., 2014).

With the terrain being identified by the Bitterroot and the Rocky Mountains ranges, there are valleys and basins in the region. The elevation levels range from 700 up to 2,100 meters and the Lolo National Forest shares similarities with mountainous boreal regions such as the Boreal Cordillera.

The Boreal Cordillera is an ecozone located in northern British Columbia up until the southern Yukon. Forests dominate the lower elevations and other characteristics are mountain ranges, plateaus, deep valleys and lowlands (Demarchi, 2011)

The FBFM40 fuel type classification contains of 40 classes (see Appendix A, organized according to presence in the study area). The most distinctive classes for the study area, according to Scot and Burgan (2005), for the boreal forests are:

TL8: (Long-Needle Litter): *'' Long needle litter, moderate load long needle pine litter, may have small amounts of herbaceous fuel, spread rate moderate and flame low''*(Scott & Burgan, 2005).

GR2: (Low Load Grass): *"Low load, dry climate grass primarily grass with some small amounts of fine, dead fuel, any shrubs do not affect fire behaviour''*(Scott & Burgan, 2005).

TU5: (Very High Load Timber-Shrub): *''Very high load, dry climate timber shrub, heavy forest litter with shrub or small tree understory, spread rate and flame moderate''*(Scott & Burgan, 2005).

Besides the TU5 fuel type class the TU2 is also commonly found in boreal forests which are defined as mountainous and dry forests conifer-dominated forests.

TU2: (Moderate Load, Dry Climate Timber-Shrub): *''moderate litter load with some shrub, spread rate moderate and flame low''*(Scott & Burgan, 2005).

The TU2 has lower fuel loads and fire intensity versus the TU5 as it is often found in a more open and dry forest (Scott & Burgan, 2005).

The fire season in boreal forests runs from May to September. The peak activity occurs during the July and August months, often as a result of lightning strikes, high temperatures and periods of drought (Clelland et al., 2024). The fire was discovered on August 18th, 2023, roughly 10 kilometres southeast of the small town of Plains in Montana. In total, the burned area grew to around 7 hectares. The fire event took place in the Lola National Forest and was 100% contained on September 15th, 2023.

The information provided to the public around this fire has been of high quality with daily updates (figure 4) on the burned area, fire behaviour and suppression efforts. The fire event and its suppression operation have been documented well which provides good input data to set parameters to run simulations. The ecological characteristics of the study area, like the topography, fuel types and the time of occurrence of the River Road East Fire, these factors make it a suitable case to use as study area for this research.

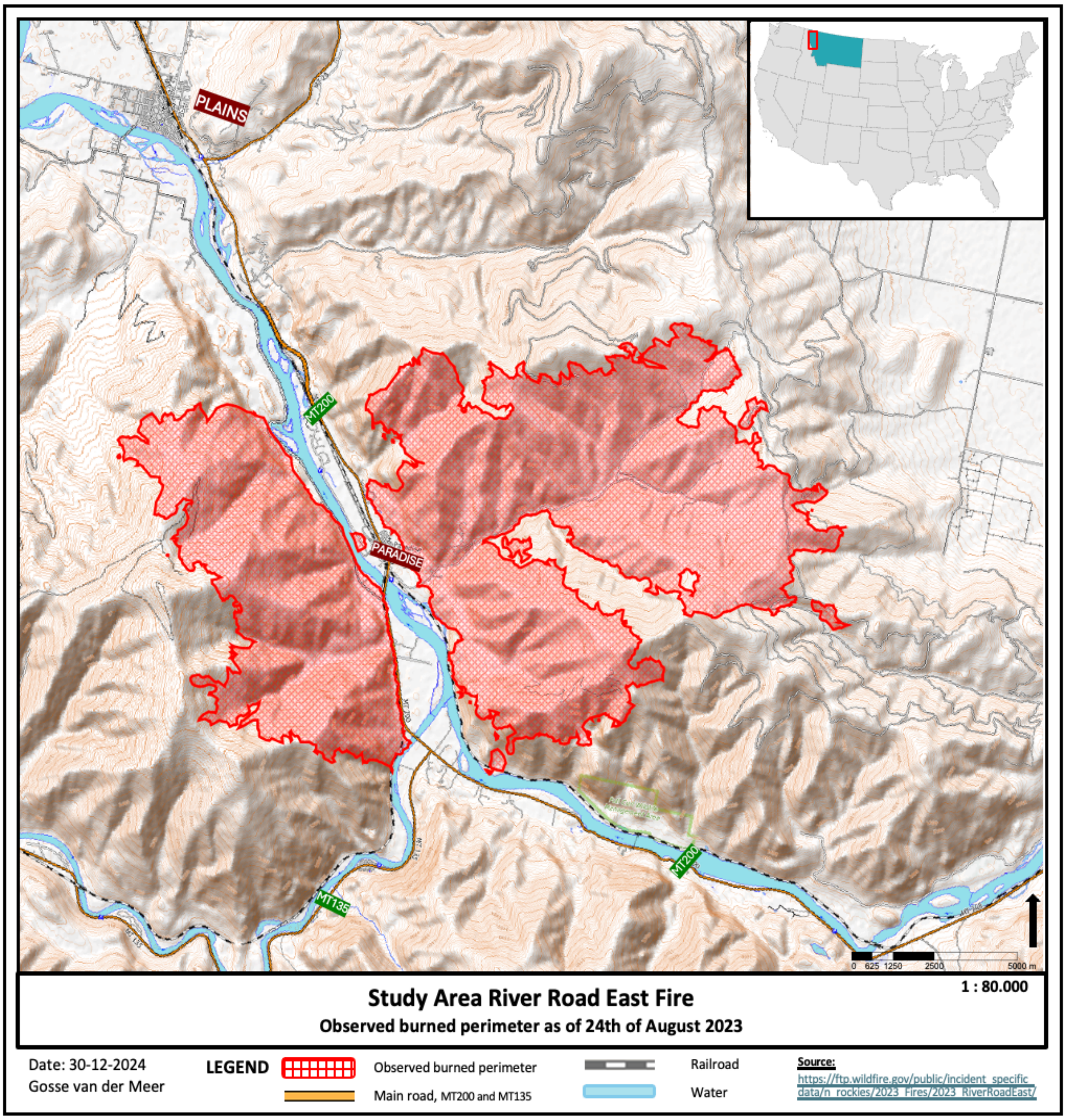


Figure 3: **Study area: River Road East fire.**
Including the observed burned perimeter as of 24th of August 2023.

Aerial photograph of the burned slope during the River Road East fire.

Source: Brent Olson, fire department commander, posted in the River Road East Facebook group.

Slope burning seen from the main road through the valley.

Image credits of InciWeb.

Figure 4: **Imagery published to the public during the River Road East Fire.**

3.2 Flammap

Flammap is a fire behaviour simulation software package. The project is set up by Charles McHugh and Mark Finney from the Missoula Fire Sciences Laboratory. The current software version is 6.2 (February 2024), the first version was launched in 2013. Flammap is a fire mapping and analysing program. The model simulates fire behaviour under set environmental conditions, including weather and fuel moisture, using predefined weather files which are introduced later in this chapter. Fire behaviour is calculated for each pixel within the landscape file (study area), included here are fire spread dynamics and changes in fire types. The simulations consider both surface and crown fires. A surface fire is spreading through ground-based fuels, and it may turn into a crown fire if an ignition takes place based on flame length, canopy base height, and weather condition

Flammap includes several fire behaviour models. Surface and fire spread are based on Rothermel's (1972 and 1991) models and the spread from ground into canopy is modelled with Scott and Reinhardt's (2001) model. This results in a realistic representation of fire behaviour under different fuel and weather conditions.

Flammap is running on a *landscape file* (.LCP) which can be accessed through the LANDFIRE program. This landscape file is built up by the following geospatial data layers:

1. Topographic layer (Elevation, Slope, Aspect)
2. Fire Behaviour Fuel Models
3. Forest canopy cover,
4. Canopy Height,
5. Canopy base height,
6. Canopy Bulk density.

Keeping environmental conditions constant, the Minimum Travel Time (MTT) algorithm calculates the fastest path of fire spread along the grid based on the cell corners (nodes) (Finney, 2006).

MTT is the minimum time a fire takes to travel between nodes in a two-dimensional network (Finney, 2002). The MTT is an algorithm used to compute the fire growth over the cells in the simulation grid, and it exposes the effects of topography and arrangement of fuels on fire growth (Ager & Finney, 2009; Kalabokidis et al., 2014).

The required steps to run the algorithm are setting: the ignitions (points, lines or polygons), the desired resolution as well as pre-determining the simulation period (Finney, 2002). Flammap inputs and outputs are visually represented in figure 5.

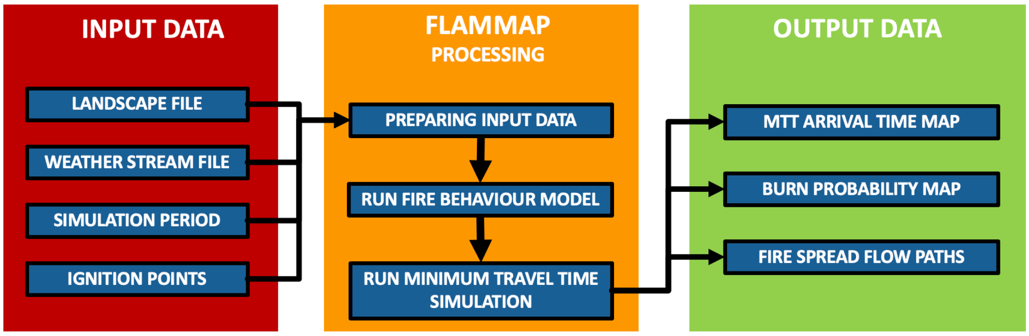


Figure 5: **Flammap processing visualization.**

Flammap uses an internal tool to create a Weather Stream File (.WXS). This typically contains hourly observations of temperature, humidity, precipitation, wind speed, wind direction, and cloud cover. This weather stream file is based on hourly averages, as it aims to provide a practical amount of weather information for modelling usage. The wind grid has been created within Flammap by using the *WindNinja* Plugin.
WindNinja uses data from weather observation stations and or user-defined wind conditions. These inputs are being combined with terrain data to create a gridded wind file which contains wind directions, speed and local turbulences and or venturi effects as a result of local terrain variations (Firelab, 2017).
All weather data used has been obtained from the weather observation post with *station ID:* 241206 located in Plains Montana, coordinates: 47°27'57.0"N 114°52'45.0"W.

By keeping the weather conditions equal for all simulations, by using the same Weather Stream File, any change in simulation outcome is the result of aggregation of fuel types.

Outputs

MTT arrival time output will be used to determine the performance of the simulations by looking at under- and over-simulation relative to a reference simulation. The MTT arrival time shows the simulated burned area in combination with the arrival times of the fire during the simulation process.
The total simulated burned area sizes are being used for further assessment of the aggregation steps. This process will be explained in further detail in the *validation method* chapter (3.6).

3.3 Datasets

Flammap input data.
To simulate fires with Flammap data on the landscape, weather, and fuel condition (table 1) is needed.

Dataset	Title	Attributes	Format	Link
Landscape	Landscape	Elevation, Slope, Aspect, Fuel Model, Canopy Cover, Stand Height, Canopy Base Height and Canopy Bulk Density.	GeoTIFF Spatial resolution: 30 meters.	https://www.landfire.gov/viewer/
Weather observation posts	NFDRS16	Station ID Location	RAW FW13 file	https://cefa.dri.edu/raws/index.php
Weather and fire data.	Wildland Fire Application Information Portal	Date, Time, Temperature, windspeed, wind direction, precipitation relative humidity, cloud cover	Weather Observation Data Transfer Format, 2013 (WxObs 13)	https://www.wildfire.gov/application/fire-and-weather-data
Fuel Moistures	FireFamily Plus	Soil and vegetation moistures levels, drought levels and fire risks.	Software Plugin	https://www.firelab.org/project/firefamilyplus

Table 1: **Input datasets used for Flammap.**

Reference data
The observed fire perimeter (the actual fire) used for the burned area was obtained from the U.S. Wildland Fire Open Data system. This publicly open portal provides geospatial information specific to past and current fire incidents in the Northern Rockies. The spatial data for the observed fire perimeter for August 26th, 2023, has been used, as this was the first available data following the ignition of the fire.

Publicly available spatial data for the River Road East fire incident can be accessed through the following link:
https://ftp.wildfire.gov/public/incident_specific_data/n_rockies/2023_Fires/2023_RiverRoadEast/

3.4 Fuel type classification

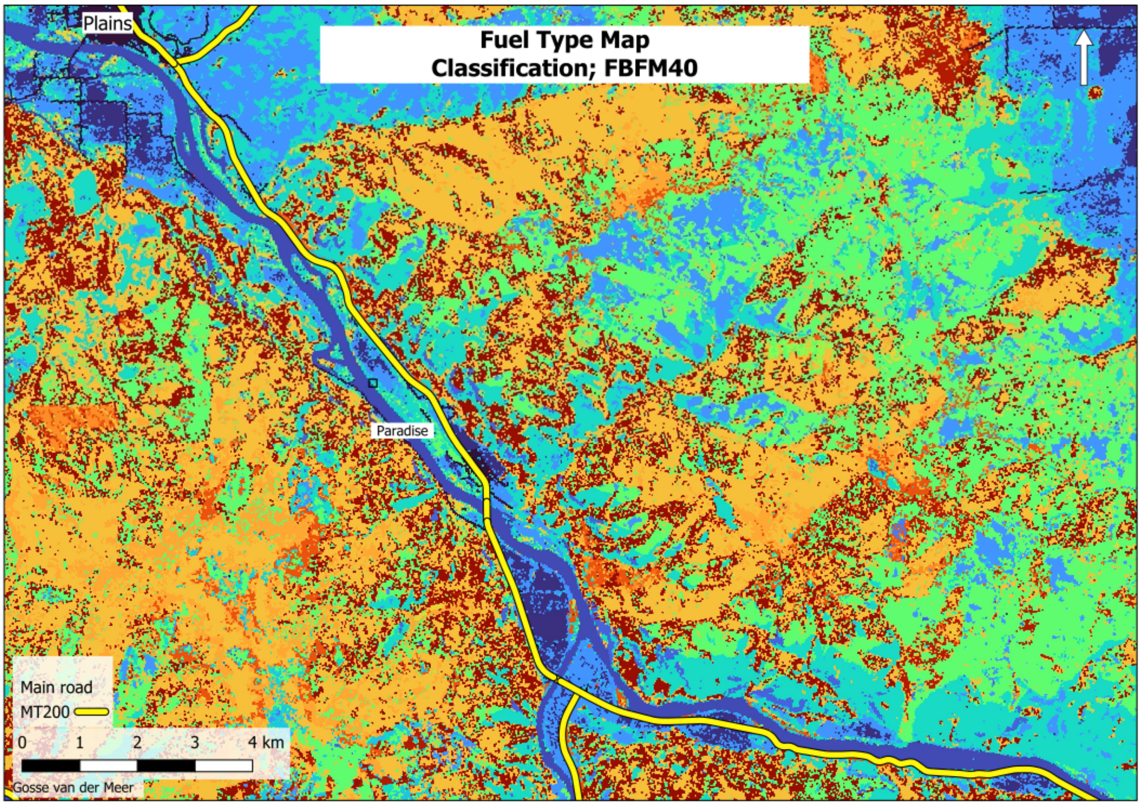
Four of the five commonly used fuel type classifications have been created in, and for North America. In Mediterranean Europe, the often used classification is the Prometheus System (García-Cimarras et al., 2021). In the USA the Northern Forest Fire Laboratory, (*NFFL)* system from Anderson (1982) and the Fire Behaviour Fuel Model, *FBFM40* from Scott and Burgan (2005) (Aragoneses et al., 2022) is commonly used.

With the study area being located within North America and containing an ecosystem that holds a boreal forest, this research used a classification created and commonly used in North America. The NFFL classification has been commissioned by the US Forest Services for the Northern parts of the United States. The main fuel type classes are grasses, brush, timber, and slash. These 4 classes can be subdivided into 13 subclasses in total. (Anderson, 1982).

The Fire Behaviour Fuel Model, *FBFM40,* is an extended version of the NFFL model, having 40 individual classes which are grouped into seven main classes mainly focused on surface fuels. Each class is grouped by letter combinations instead of numbers. The model contains the following 7 fuel type groups: GR = grass, GS = grass-shrub, NB = non-burnable, SH = shrub, SB = slash-blowdown, TL = timber litter and TU = timber-understory. The non-burnable fuels are Urban/ Developed, Snow/Ice, Agricultural, Open Water and Bare Ground. Despite mainly focusing on surface fuels the FBFM40 influences canopy fire spread and ignitions (Scott & Burgan, 2005). The canopy layer is included in the LANDFIRE (table 1) data which has been obtained to create the Landscape file which has been introduced earlier.

The FBFM40 model opens the possibility to model forest-litter, but also combinations of grasses, shrubs and forest-litter. To model on a wider range of humidity levels, where litter affects surface fuel behaviour, a wider range of modelling options for humidity levels becomes available. Increasing the possibilities to model fuel loads with relatively high dead fuel moistures (Scott & Burgan, 2005). The classes within this classification can almost all be found in any large boreal forest, which makes this classification suitable for this ecosystem.

Upon generating the Fuel Type Map (figure 6) the available fuel types within the study area were identified (table 2).



Datasource	**Landfire 2022 (LF2_30).**
Product name	Conterminous U.S. LANDFIRE - LF 2022 (LF_230) - Fuel - Surface and Canopy - us_230 40 Fire Behavior Fuel Models-Scott/Burgan
Layer name	Us_230 40 Fire Behavior Fuel M
Spatial resolution	30m
Download / location /date	https://www.landfire.gov/viewer/ 05-06-23

Figure 6: **fuel type classification map of the study area (colours explained in table 2).**

Fuel ID	Color	Fuel Group	Fuel Code	Frequency	Exact Matches	Hectares	Frequency %
91		*Non-burnable*	*NB1*	*9113*	*9113*	*820.17*	*1.3%*
93		*Non-burnable*	*NB3*	*21591*	*21591*	*1943.19*	*3.0%*
98		*Non-burnable*	*NB8*	*13747*	*13747*	*1237.23*	*1.9%*
99		*Non-burnable*	*NB9*	*3343*	*3343*	*300.87*	*0.5%*
101		Grass	GR1	2383	2383	214.47	0.3%
102		Grass	GR2	77022	77022	6931.98	10.6%
103		Grass	GR3	2052	2052	184.68	0.3%
121		Grass-Shrub	GS1	14748	14748	1327.32	2.0%
122		Grass-Shrub	GS2	80237	80237	7221.33	11.1%
123		Grass-Shrub	GS3	2	2	0.18	0.0%
141		Shrub	SH1	789	789	71.01	0.1%
142		Shrub	SH2	120867	120867	10878.03	16.7%
143		Shrub	SH3	435	435	39.15	0.1%
145		Shrub	SH5	66	66	5.94	0.0%
146		Shrub	SH6	4	4	0.36	0.0%
147		Shrub	SH7	24	24	2.16	0.0%
161		Timber-Understory	TU1	6223	6223	560.07	0.9%
162		Timber-Understory	TU2	203173	203173	18285.57	28.1%
165		Timber-Understory	TU5	37788	37788	3400.92	5.2%
181		Timber-Litter	TL1	3104	3104	279.36	0.4%
182		Timber-Litter	TL2	887	887	79.83	0.1%
183		Timber-Litter	TL3	16289	16289	1466.01	2.2%
184		Timber-Litter	TL4	161	161	14.49	0.0%
185		Timber-Litter	TL5	959	959	86.31	0.1%
186		Timber-Litter	TL6	8604	8604	774.36	1.2%
188		Timber-Litter	TL8	100483	100483	9043.47	13.9%
189		Timber-Litter	TL9	3	3	0.27	0.0%
			Total:	724097	724097	65168.73	100.0%

Table 2: **Fuel type frequency and surface area within the study area.**
Table based on FBFM40 fuel type classification and data for the study area.

Simulation period

To determine the optimal simulation duration, wildfire simulations with Flammap 6.2 and the resulting MTT have been compared with the observed fire perimeter of the River Road East fire. The simulation period started with one day (24hours) and was increased by one day until a large over-simulation was observed. All other input data, such as the fuel model, landscape maps, ignition points and fire behaviour model have been kept constant.

The daily simulated area, which shows the highest level of intersection plus the minimum under- and over-prediction errors in the observed burned area, was used as the simulation period. The determined simulation period has been used as a constant parameter for all simulations with different levels of aggregation.

3.5 Fuel type aggregation

Aggregating fuel type classes is a way to determine the impact of each class on the producer accuracy of the model. Aggregating classes based on their size and fire behaviour characteristics is an input data simplification method. This simplification method or, down sampling is used to adjust data resolution and to reduce the computational load. The size of a certain class is quantified as the percentage of the total simulated area.

The influence of the aggregation steps is being determined by comparing the simulated fire perimeters based on aggregated input data and the reference data (non-aggregated data).

Aggregation steps.

The data processing of the fuel types starts with reducing the number of classes to consider only those present in the study area (*table 3).*

After removing the non-present fuel types the fuel types classified as **non-burnable** where grouped. These fuel types where urban (NB1), agricultural (NB3), open water (NB8) and bare ground (NB9). All fuel types considered non-burnable were reclassified in the NB3 fuel type which represented the largest area of all non-burnable in the study area.

To determine the influence of aggregation based on different fuel type characteristics on the model simulation outcomes different rulesets have been used. The characteristics and their influence on fire behaviour can be found in APPENDIX A. The FBFM40 gives different levels for the *Fuel Load,* the *Rate of Spread* and the *Flame Length.*

Therefore, the aggregation process took place four times. The first series of aggregations takes place on the available fuel types within the study area <u>without taking any fire behaviour characteristics into account</u> (table 3). For the following aggregations series, there was a rule set which states that aggregations only occur for fuel classes with the same fire behaviour characteristics

In total 28 wildfire simulations have been conducted with the Flammap software (version 6.2) based on the FBFM40 fuel model. Categorization took place based on **fire behaviour characteristics.** These are: Fuel Loads, Rate of Spread Flame Lengths or without taking any specific characteristics into account (No Characteristics). When no specific characteristic was taken into account, no aggregation outside the original fuel group of the fuel type take place. These fuel groups are, as described in the FBFM40 classification: *non-burnable, grass, grass-shrub, shrub, timer*-understory and *timber-litter*.

<u>Smaller fuel types were always aggregated into a bigger fuel type based on their frequency percentage. So, an individual fuel class, which has a relatively small frequency at the start of the aggregation process, will not be able to have substantial growth due to a big fuel type class being added to the smaller fuel type.</u>

Rule Description, without taking fire behaviour characteristics into account.

For the aggregation process without taking the fire behaviour characteristics into account, the following rules have been applied:

The first aggregation was done by grouping all individual fuel types which have <u>a frequency below 0.85%</u> in the study area, as these represent tiny and fragmented fuel types that shown no notable impact on the fire behaviour modelling.

These minor fuel types were aggregated to their nearest significant neighbour <u>within</u> their *Fuel Groups.* This first aggregation step provides a balance between maintaining data accuracy and reducing noise.

The following aggregations were based on the <u>lowest</u> *Frequency Percentage* and to be kept within the respectable Fuel Groups.

The aggregation process was completed upon achieving one overall fuel type for each individual *Fuel Group.* Each step taken in this process can be found in *table 3*.

NOT TAKING ANY FIRE BEHAVIOUR CHARACTERISTICS INTO ACCOUNT.

AGGREGATION STEP:					ONE			TWO			THREE			FOUR			FIVE			SIX		
FUEL TYPE COMBINATION		REFERENCE DATA			GR2+1+3//GS2+3//SH2+1+3+5+6+ TL3+1+2+4//TL6+5//TL8+9			TU2+TU1			TL8+ TL6			GS2+ GS1			TL8+TL3			TU2+TU5		
Fuel Group	Fuel Code	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*
Grass	GR1	2383	0,329%	2383	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Grass	GR2	77022	10,637%	77022	**81457**	**11,249%**	**77022**	81457	11,249%	77022	81457	11,249%	77022	81457	11,249%	77022	81457	11,249%	77022	81457	11,249%	77022
Grass	GR3	2052	0,283%	2052	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS1	14748	2,037%	14748	14748	2,037%	14748	14748	2,037%	14748	14748	2,037%	14748	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS2	80237	11,081%	80237	**80241**	**11,081%**	**80237**	80241	11,081%	80237	80241	11,081%	80237	**94989**	**13,118%**	**80237**	94989	13,118%	80237	94989	13,118%	80237
Grass-Shrub	GS3	4	0,001%	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Shrub	SH1	789	0,109%	789	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Shrub	SH2	120867	16,692%	120867	**122185**	**16,874%**	**120867**	122185	16,874%	120867	122185	16,874%	120867	122185	16,874%	120867	122185	16,874%	120867	122185	16,874%	120867
Shrub	SH3	435	0,060%	435	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Shrub	SH5	66	0,009%	66	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Shrub	SH6	4	0,001%	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Shrub	SH7	24	0,003%	24	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Understory	TU1	6223	0,859%	6223	6223	0,859%	6223	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Understory	TU2	203173	28,059%	203173	203173	28,059%	203173	**209396**	**28,918%**	**203173**	209396	28,918%	203173	209396	28,918%	203173	209396	28,918%	203173	**247184**	**34,137%**	**203173**
Timber-Understory	TU5	37788	5,219%	37788	37788	5,219%	37788	37788	5,219%	37788	37788	5,219%	37788	37788	5,219%	37788	37788	5,219%	37788	-	-	-
Timber-Litter	TL1	3104	0,429%	3104	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Litter	TL2	887	0,122%	887	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Litter	TL3	16289	2,250%	16289	**20441**	**2,823%**	**16289**	20441	2,823%	16289	20441	2,823%	16289	20441	2,823%	16289	-	-	-	-	-	-
Timber-Litter	TL4	161	0,022%	161	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Litter	TL5	959	0,132%	959	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Litter	TL6	8604	1,188%	8604	**9563**	**1,321%**	**8604**	9563	1,321%	8604	-	-	-	-	-	-	-	-	-	-	-	-
Timber-Litter	TL8	100483	13,877%	100483	**100487**	**13,878%**	**100483**	100487	13,878%	100483	**110050**	**15,198%**	**100483**	110050	15,198%	100483	**130491**	**18,021%**	**100483**	130491	18,021%	100483
Timber-Litter	TL9	4	0,001%	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Total:	724100	100,0%	724100	724100	100,0%	713228	724100	100,0%	707005	724100	100,0%	698401	724100	100,0%	683653	724100	100,0%	667364	724100	100,0%	629576
*Bold written numbers indicate growing class.					Rules: 1 Every class below 0,85%, 2 If possible: within Fuel Gr.			Rules: 1 Lowest Freq. % 2 If possible: within Fuel Gr.			Rules: 1 Lowest Freq. % 2 If possible: within Fuel Gr.			Rules: 1 Lowest Freq. % 2 If possible: within Fuel Gr.			Rules: 1 Lowest Freq. % 2 If possible: within Fuel Gr.			Rules: 1 Lowest Freq. % 2 If possible: within Fuel Gr.		

Table 3: **Aggregation process without taking fire behaviour characteristics into account.**

After six aggregation steps, all classes within the five fuel groups have been combined and further aggregation is not possible. The fire behaviour characteristics of the remaining fuel types can be found below (table 4).

Fuel Group	Fuel Code	Frequency %	Fuel Load	Rate of Spread	Flame length
Non-burnable	NB1,3,8,9	6.6%	NB	NB	NB
Grass	GR2	11.3%	L	No effect	No effect
Grass-Shrub	GS2	13.1%	M	H	M
Shrub	SH2	16.9%	M	L	L
Timber-Understory	TU2	34.1%	M	M	L
Timber-Litter	TL8	18.0%	M	M	L

Table 4: **Remaining fuel types without considering specific fire behaviour characteristics.**

Rule Description, including fire behaviour characteristics.

For the aggregation process including the fire behaviour characteristics, aggregations only occur for fuel classes with the same fire behaviour characteristics. These levels are defined by Scott and Anderson (2005) by using the following scale: very low, low, moderate, high, very high and no effect.

Therefore, the ruleset applied to aggregation processes is the following:
The first aggregation was by grouping all individual fuel types which have a frequency below 0.85% in the study area, as these represent tiny and fragmented fuel types that show no notable impact on the fire behaviour modelling.
This first aggregation step provides a balance between maintaining data accuracy and reducing noise. These minor fuel types were aggregated to their nearest significant neighbour with an equal *fire behaviour characteristic.*

There was no aggregation without similarity in fire behaviour influence level. For example, fuel type classes with a low fuel load were not aggregated with fuel types with a moderate fuel load. Aggregated to their nearest significant neighbour preferably within their fire behaviour characteristic.

The following aggregations were based on the lowest *Frequency Percentage* and are to be kept within the fire behaviour level of the specified characteristic.
In the case of several aggregation options within the same level in fire behaviour influence, similarity within the other two fire behaviour characteristics is being considered.
When there is still a 1:1 in similarity in characteristics, the metrics used to define Packing Ratio and the Fine Fuel load from the FBFM40 (Scott & Burgan, 2005) was used. These metrics are used at the 5th aggregation step for the Rate of Spread aggregation process (APPENDIX B).

The aggregation process was completed upon achieving an overall fuel type for each available *fire behaviour characteristic level.* An overview of the aggregation process in which the *fuel loads* are used as the leading fire behaviour characteristic can be found in table 5. In APPENDIX B and C, the aggregation process tables for the *Rate of Spread* and for the *Flame Lengths* are presented.

FUEL LOAD

NO FUEL TYPE AGGREGATION WILL TAKE PLACE WITHOUT SIMILARITY IN FUEL LOAD.

AGGREGATION STEP:			REFERENCE DATA			ONE			TWO		
FUEL TYPE COMBINATION						GR2+1+3+SH1 //GS2+3 // SH2+ GS1+SH6//TU1+TL1+2//TL3+TL TL5 + SH5 // TU5+SH7+TL9			TL8+TL6		
Fuel Group	Fuel Code	FUEL LOAD	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	NB	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*
Grass	GR1	Low	2383	0,329%	2383	-	-	-	-	-	-
Grass	GR2	Low	77022	10,637%	77022	**82246**	**11,358%**	**77022**	82246	11,358%	77022
Grass	GR3	Low	2052	0,283%	2052	-	-	-	-	-	-
Grass-Shrub	GS1	Low	14748	2,037%	14748	**14752**	**2,037%**	**14748**	14752	2,037%	14748
Grass-Shrub	GS2	Moderate	80237	11,081%	80237	**80241**	**11,082%**	**80237**	80241	11,082%	80237
Grass-Shrub	GS3	Moderate	4	0,001%	4	-	-	-	-	-	-
Shrub	SH1	Low	789	0,109%	789	-	-	-	-	-	-
Shrub	SH2	Moderate	120867	16,692%	120867	**121302**	**16,752%**	**120867**	121302	16,752%	120867
Shrub	SH3	Moderate	435	0,060%	435	-	-	-	-	-	-
Shrub	SH5	High	66	0,009%	66	-	-	-	-	-	-
Shrub	SH6	Low	4	0,001%	4	-	-	-	-	-	-
Shrub	SH7	Very High	24	0,003%	24	-	-	-	-	-	-
Timber-Understory	TU1	Low	6223	0,859%	6223	**10214**	**1,411%**	**6223**	10214	1,411%	6223
Timber-Understory	TU2	Moderate	203173	28,059%	203173	203173	28,059%	203173	203173	28,059%	203173
Timber-Understory	TU5	Very High	37788	5,219%	37788	**37816**	**5,222%**	**37788**	37816	5,222%	37788
Timber-Litter	TL1	Low	3104	0,429%	3104	-	-	-	-	-	-
Timber-Litter	TL2	Low	887	0,122%	887	-	-	-	-	-	-
Timber-Litter	TL3	Moderate	16289	2,250%	16289	**16450**	**2,272%**	**16289**	16450	2,272%	16289
Timber-Litter	TL4	Moderate	161	0,022%	161	-	-	-	-	-	-
Timber-Litter	TL5	High	959	0,132%	959	**1025**	**0,142%**	**959**	1025	0,142%	959
Timber-Litter	TL6	Moderate	8604	1,188%	8604	8604	1,188%	8604	-	-	-
Timber-Litter	TL8	Moderate	100483	13,877%	100483	100483	13,877%	100483	**109087**	**15,065%**	**100483**
Timber-Litter	TL9	Very High	4	0,001%	4	-	-	-	-	-	-
	Total:		724100	100,0%	724100	724100	100,0%	714187	724100	100,0%	705583

AGGREGATION STEP:	THREE			FOUR			FIVE		
FUEL TYPE COMBINATION	GS1+TU1			TL8+TL3			GR2+GS1		
Fuel Code	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
NB1+3+8+9	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*
GR1	-	-	-	-	-	-	-	-	-
GR2	82246	11,358%	77022	82246	11,358%	77022	**107212**	**14,806%**	**77022**
GR3	-	-	-	-	-	-	-	-	-
GS1	**24966**	**3,448%**	**14748**	24966	3,448%	14748	-	-	-
GS2	80241	11,082%	80237	80241	11,082%	80237	80241	11,082%	80237
GS3	-	-	-	-	-	-	-	-	-
SH1	-	-	-	-	-	-	-	-	-
SH2	121302	16,752%	120867	121302	16,752%	120867	121302	16,752%	120867
SH3	-	-	-	-	-	-	-	-	-
SH5	-	-	-	-	-	-	-	-	-
SH6	-	-	-	-	-	-	-	-	-
SH7	-	-	-	-	-	-	-	-	-
TU1	-	-	-	-	-	-	-	-	-
TU2	203173	28,059%	203173	203173	28,059%	203173	203173	28,059%	203173
TU5	37816	5,222%	37788	37816	5,222%	37788	37816	5,222%	37788
TL1	-	-	-	-	-	-	-	-	-
TL2	-	-	-	-	-	-	-	-	-
TL3	16450	2,272%	16289	-	-	-	-	-	-
TL4	-	-	-	-	-	-	-	-	-
TL5	1025	0,142%	959	1025	0,142%	959	1025	0,142%	959
TL6	-	-	-	-	-	-	-	-	-
TL8	109087	15,065%	100483	**125537**	**17,337%**	**100483**	125537	17,337%	100483
TL9	-	-	-	-	-	-	-	-	-
Total:	724100	100,0%	699360	724100	100,0%	683071	724100	100,0%	668323

AGGREGATION STEP:	SIX			SEVEN			EIGHT		
FUEL TYPE COMBINATION	SH2+GS2			TU2+TL8			TU2+SH2		
Fuel Code	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
NB1+3+8+9	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*	*47794*	*6,600%*	*47794*
GR1	-	-	-	-	-	-	-	-	-
GR2	107212	14,806%	77022	107212	14,806%	77022	107212	14,806%	77022
GR3	-	-	-	-	-	-	-	-	-
GS1	-	-	-	-	-	-	-	-	-
GS2	-	-	-	-	-	-	-	-	-
GS3	-	-	-	-	-	-	-	-	-
SH1	-	-	-	-	-	-	-	-	-
SH2	**201543**	**27,834%**	**120867**	201543	27,834%	120867	-	-	-
SH3	-	-	-	-	-	-	-	-	-
SH5	-	-	-	-	-	-	-	-	-
SH6	-	-	-	-	-	-	-	-	-
SH7	-	-	-	-	-	-	-	-	-
TU1	-	-	-	-	-	-	-	-	-
TU2	203173	28,059%	203173	**328710**	**45,396%**	**203173**	**530253**	**73,229%**	**203173**
TU5	37816	5,222%	37788	37816	5,222%	37788	37816	5,222%	37788
TL1	-	-	-	-	-	-	-	-	-
TL2	-	-	-	-	-	-	-	-	-
TL3	-	-	-	-	-	-	-	-	-
TL4	-	-	-	-	-	-	-	-	-
TL5	1025	0,142%	959	1025	0,142%	959	1025	0,142%	959
TL6	-	-	-	-	-	-	-	-	-
TL8	125537	17,337%	100483	-	-	-	-	-	-
TL9	-	-	-	-	-	-	-	-	-
Total:	724100	100,0%	588086	724100	100,0%	487603	724100	100,0%	366736

Low	High
Moderate	Very High

*Bold written numbers indicate growing class.

Step ONE – Rules:
1 Every class below 0,85%,
2 No aggregation outside FUEL LOAD similarity
3 If possible: within Fuel Gr.

Steps TWO, THREE, FOUR, FIVE, SIX – Rules:
1 Lowest Freq. %
2 No aggregation outside FUEL LOAD similarity
3 If possible: within Fuel Gr.

Step SEVEN – Rules:
1 Lowest Freq. %
2 No aggregation outside FUEL LOAD similarity
3 If possible: within Fuel Gr.

Fuel Code	CHARACTERISTICS
SH2	M,L,L
TU2	M,M,L
TL8	M,M,L

4 Therefore: TU2+TL8

Step EIGHT – Rules:
1 Last avaialbe combination

Table 5: **Aggregation Process focused on fuel load similarity.**

3.6 Validation

The Sørensen Similarity Index, SSI, (figure 7) is focused on measuring the similarity between two datasets (Equation 1). This statistical approach often used in ecology to compare the presence of certain species over a period.

The intersection of the two areas is divided by the total area and the outcome value is between 0 and 1. Often, this index is used as a hit-or-miss analysing method to determine the level of agreement between the simulated and observed data. It produces a value representing the similarity. The value of 1 represents a perfect similarity between the two datasets, and the value 0 means there is no similarity (Perry, 1999).

$$\boldsymbol{S} = \frac{\boldsymbol{2(S^{o}(t)\ \cap\ S(t))}}{\boldsymbol{(S^{o}(t)) +\ (S(t))}}$$

Equation 1: **The Sørensen similarity index** (Filippi et al., 2013).

The S stands for the Sørensen Similarity Index.

$\underline{S^{o}(t)}$ is Reference simulation and $\underline{S(t)}$ is the Simulation with aggregated fuel type classification.

For this research, the similarity translates to the intersection between simulations based on aggregated fuel type classifications, relative to simulations based on unaggregated fuel type classifications (reference simulation). In figure 7 this approach is visualized, where the intersection is being made by an overlay between $\boldsymbol{S^{o}(t)\ \cap\ S(t)}$.

Over-simulation is defined as areas that are simulated to burn in a run with an aggregated fuel type classification, that was not simulated to burn in the original fuel type classification. Under-simulated refers to the surface size of the burned area which has not been simulated after fuel type aggregation but has its boundaries within the burned area of the simulation run with the complete FBFM40 fuel type classification (Figure 7).

$$\boldsymbol{S(t)} - \frac{\boldsymbol{2(S^{o}(t)\ \cap\ S(t))}}{\boldsymbol{(S^{o}(t))+\ (S(t))}}$$

Equation 2: **Under-simulation calculation method.**

$$\boldsymbol{S^{o}(t)} - \frac{\boldsymbol{2(S^{o}(t)\ \cap\ S(t))}}{\boldsymbol{(S^{o}(t))+\ (S(t))}}$$

Equation 3: **Over-simulation calculation method.**

Results for calculating the under and or over-simulation does not always show a consistent decrease. Because the dividing factor includes the reference simulated area, as well as the simulated outcome after fuel type aggregation. The size of the simulations based on an aggregated fuel type classification, changes during the aggregation process. This causes the relative proportion of the under and or over-simulated areas to fluctuate instead of monotonous increase or decrease.

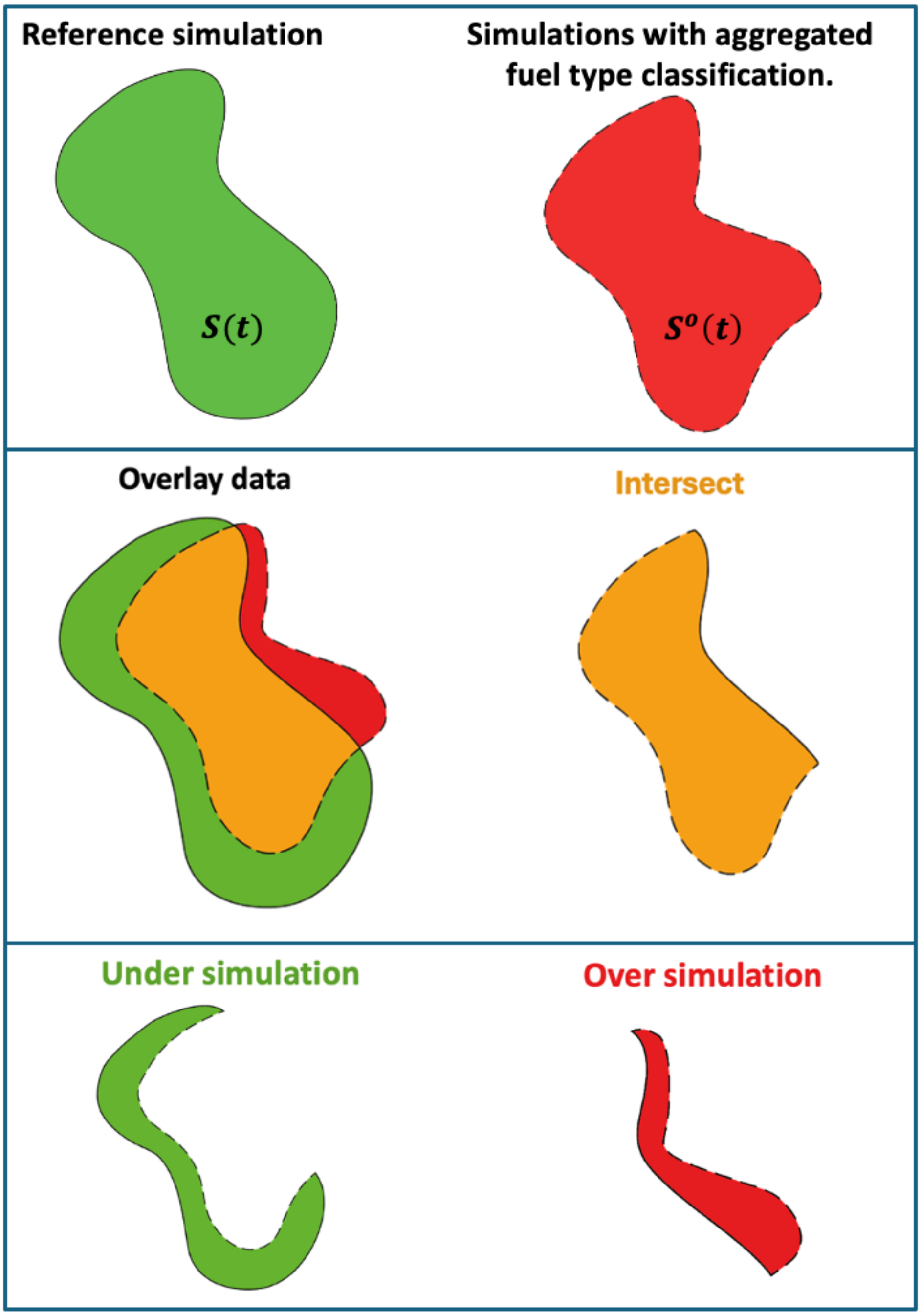


Figure 7: **Reference- vs. aggregated fuel type simulations, intersection and calculation of under-over-simulation based off the Sørensen Similarity Index.**

The Sørensen Similarity Index has been used as a percentage to present the similarity values in a more interpretable format. It is referred to as the *SSI %* in the tables presented in the results chapter.

Understanding errors and accuracy trends

Instead of relying on a fixed threshold to define an error significance, observing trends was the chosen approach. Trends in the accuracy levels provide understanding in a larger context of the moment in which accuracy begins to deteriorate. This approach avoids set threshold values that may not be usable for all scenarios, cases or situations.

Therefore, analysing the trend lines opened up the possibility to evaluate both the reliability and the consistency of the fire behaviour characteristics, individually or combined. A clear increase or decrease in the accuracy trends suggests potential over- or under-processing of data. By looking at the trends for individual fire behaviour characteristics, irregularities within these trends will have less impact on determining an appropriate threshold for the accuracy.

This method identified when a negative trend in accuracy occurred, this information was used in deciding the optimal level of data aggregation. The most important point of interest within the trendlines was the moment when accuracy errors started to show a steep change.

Clear identification of these trend shifts is important. The steep trend shifts represent the moment in which under- and or over-simulation starts to occur. The over-simulation can be seen as an overgeneralizing of individual fuel types.

To reduce the influence of outside factors on the validation process, only the producer accuracy levels of the model have been used. The accuracy levels are being calculated relative to the total area predicted by the model (reference data). As the model used is solely simulating fire spread without taking any mitigation efforts into account, the observed burned perimeter has not been used as a dataset to validate the aggregation process.

Entropy

By aggregating fuel types based on different criteria, the heterogeneity of the available fuel type classes changes. To assess the change in heterogeneity within the available fuel type classes, entropy can be used as an index of heterogeneity.

Entropy is a concept that measures the degree of variety within the input data. In the context of fire behaviour simulations, entropy quantifies the variability between fuel types between different aggregation steps. A high entropy value indicates larger variability in size for each individual fuel type within the classification, whereas a low entropy value indicates a more even distribution (Carter, 2014).

In wildfire simulations, entropy can serve as an indication on how the total composition of fuel types becomes more homogeneous after each aggregation step. By calculating the entropy levels for each aggregation step, insight is created in how much reliability is lost as fuel type diversity decreases (Parsons et al., 2017).

When entropy drops substantially at a certain aggregation step, it indicates over-generalization, leading to larger increases in under- and or over-simulation. On the other hand, stable entropy values suggest that little variability is lost during the aggregation step (Rashmi & Ghose, 2020).

Processing Time

Throughout the entire aggregation process, the time it takes to complete each individual simulation has been recorded. Collecting this data gave insight into the influence the aggregation process had on the time it takes to complete a simulation. All simulations have been obtained on the same machine and without running any other program or usage other than Flammap.

4. Results

4.1 Simulation period

With an increasing duration of the simulation, the over-simulation increases and the under-simulation decreases (table 6). These trends are observed in comparison to the reference simulation, which serves as the reference data to calculate the over- and under-simulation. A sharp increase in over-simulation was observed when the simulation period became >6 days. Whereas the under-simulation trend shows a relatively constant decrease. When simulating for a period of 6 days the highest producer accuracy levels where recorded (table 6 and figure 8).

Simulation outcomes without aggregation

In the following table the sizes of the wildfire simulations are presented as well as the under- and over-simulations levels in percentages.

Sim. period	**Sim. area**	**Observed burn**	**Intersection *Sim. vs. Obs.***		**UNDER-SIMULATION**		**OVER-SIMULATION**	
Days	Hectares	Hectares	Hectares	SSI %	Hectares	SSI %	Hectares	SSI %
1	473	-	412	87.24%	6,501	94.04%	60	0.87%
2	1,094	-	1,000	91.36%	5,914	85.54%	95	1.37%
3	1,872	-	1,705	91.10%	5,208	75.33%	167	2.41%
5	3,806	-	3,130	82.24%	3,783	54.72%	676	9.78%
6	4,762	6,913	3,655	76.76%	3,259	47.13%	1,107	16.01%
7	34,254	6,913	4,907	14.33%	2,007	29.02%	29,347	424.49%

Table 6: **Simulation data overview EAST- AND WEST- SIDE.**

The table shows the area sizes of the simulations for a simulation period from 1 to 7 days.
The observed burn perimeter remained relatively stable after day 6, due to active suppression efforts. Making it a reference for evaluating under- and over-simulation across all time steps. Since the simulation period had to be pre-set within Flammap, the closest match to the observed burned perimeter had to be determined. Therefore, the intersection of the simulated area, relative to the observed burned area, has been calculated for evaluation of simulation outcome and to determine the optimal simulation period (time step). The observed burned perimeter (actual perimeter) has only been used in the process to determine the reference perimeter which has been in assessing the outcomes of the aggregation process.

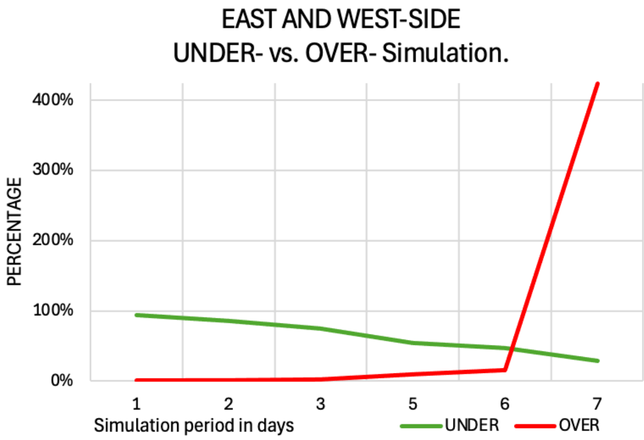


Figure 8: **UNDER- VS. Over-simulation.**

Graph table 6.

Fire spread is showing mainly east- and westward around the river over the duration of the simulations (Figure 9), and a large change in burnt area can be observed from day 6 to 7.

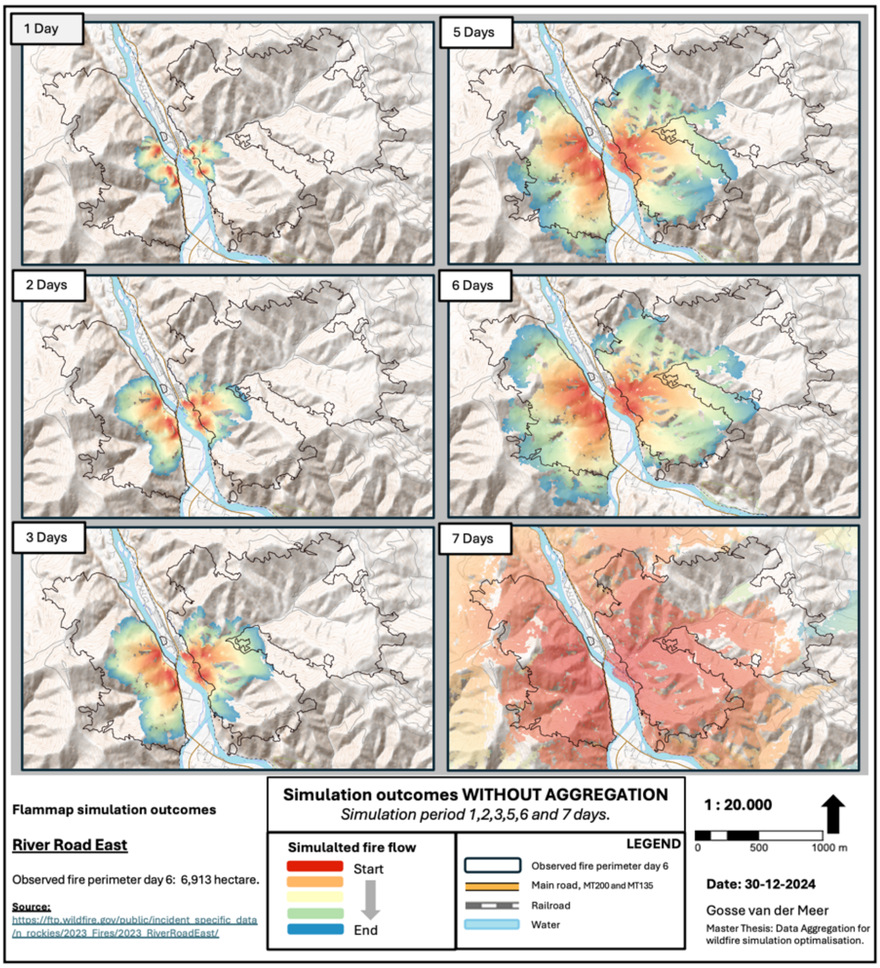


Figure 9: **Simulation outcomes WITHOUT AGGREGATION.**

No data aggregation steps have taken place. Simulation outcomes have been generated to determine the optimal simulation period in days.

On the east side a large part of the actual fire is not simulated, leading to under-simulation. The fire spread in the west-side was showing a spread following the contour lines of the observed fire area. This was not the case on the east side. The outputs for a simulation for day 5 and day 6 confirmed the lack of fire spread in the east side but a relatively accurate spread in on the west-side. Even when substantial over-simulation was being observed for a 7-day simulation period, relatively large areas on the east side show no signs of fire spread (figure 10). An explanation for the underperformance of the model can be related to the fuel type classification located close to the burned-non-burned boundary on day 6. Only the ignition points for the west-side fire perimeter have been accurately determined and published in the fire reports. On the east side spread is being observed into areas that have already been simulated to be burning for the first six days before stopping. This would suggest that variations in fuel type classification, rather than ignition location uncertainty, are the cause for the local underperformance of the model.

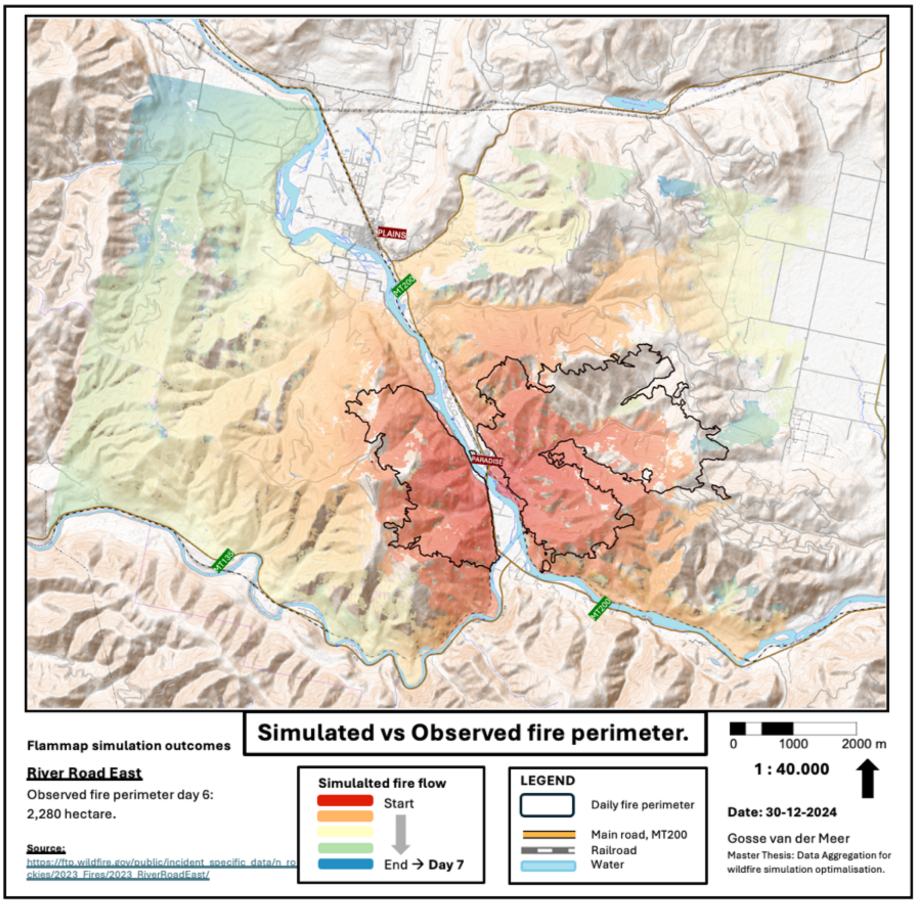


Figure 10: **Day-7 simulated- vs Observed fire perimeter.**

An over-simulation 424.49% was being observed for a simulation period of >7 days. The simulated burned area was reaching the outside borders of the landscape file. Whereas Flammap cannot simulate fire spread over water or roads this can be seen in figure 4 as well. For example, on the South side of the simulation area, the area is parallel to the river which runs through the study area. There was no simulated fire spread on the opposite side of the river.

When focusing only on the west-side, higher overall accuracies were found, mainly because the large under-simulation for the eastern side was left out. Therefore, the simulation outcomes achieved higher producer accuracy levels for the west-side only than for the east- and west-side together.
The results for the west-side only are being presented in table 7 and figure 11 where day 6 shows a 23.85% under-simulation. In table 6 the under-simulation for the east- and west-side shows a 47.13% under-simulation for a 6-day simulation period.

Table of simulation size WEST-SIDE ONLY								
Sim. Period	Simulated area	Burn perimeter	Intersection		UNDER SIMULATION		OVER SIMULATION	
Days	Hectares	Hectares	Hectares	SSI %	Hectares	SSI %	Hectares	SSI %
1	259.65	-	258.59	99.59%	2,021.34	88.66%	1.06	0.41%
2	609.48	-	608.94	99.91%	1,671.00	73.29%	0.54	0.09%
3	942.21	-	939.78	99.74%	1,340.16	58.78%	2.43	0.26%
5	1,700.10	-	1,437.31	84.54%	842.63	36.96%	262.79	15.46 %
6	2,244.60	2,279.94	1,736.19	77.35%	543.75	23.85%	508.41	22.65 %
7	21,181.77	2,279.94	2,031.21	9.59%	248.73	10.91%	19,150.56	90.41 %

Table 7: **Simulation data overview WEST-SIDE only.**

The entire east-side simulated fire area has been removed from the simulation outcomes, using only the west-side ignition points to simulate the outcomes. The east-side observed fire area has also been removed from the total observed burned area.

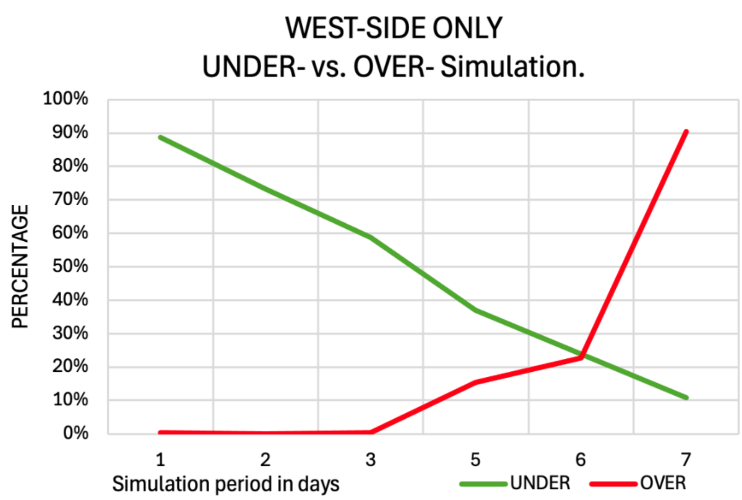


Figure 11: **WEST-SDIE ONLY UNDER- VS. Over-simulation.**

Graph table 2.

Looking at 6-day simulation periods for the west-side only (figure 12) a substantial increase in model accuracy was observed. The over-simulation was similar with 22.65% (versus 23.24 for east and west). However, the under-simulation decreased to 23.85% (versus 47.15% for east and west).

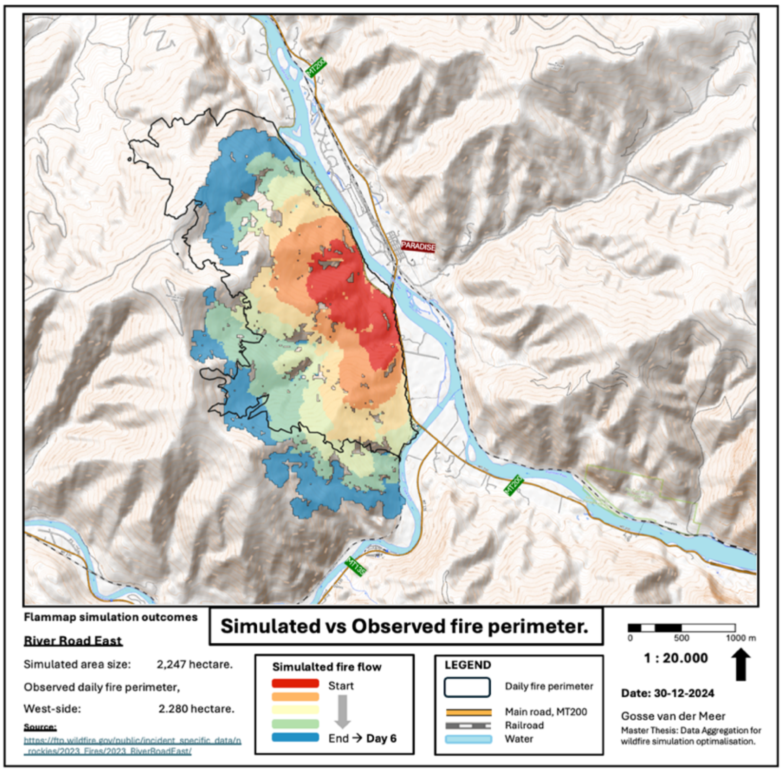


Figure 12: **6-day simulation period for WEST-SIDE ONLY.**

The under- and over-simulation was calculated based on:
- the simulated area after each aggregation step,
- the base simulated area (starting situation before aggregation) and
- intersected area.

The under-simulation represents the reference data subtracted by the intersected area. And the over-simulation represents the simulated area subtracted by the intersected area.
The area size of the reference data before aggregation is **1,682 hectares.** This area as shown in figure 12 is the area used for geoprocessing the intersection values with QGIS. This data was used as a constant to calculate the under- and over-simulation for each aggregation step.
Based on these observations, only the west-side of the area was included in the analysis of fuel type aggregation this with a 6-day simulation period.

Results of the fuel type aggregation process are presented in table 9.

4.2 Simulation results based on aggregated fuel type classifications

In table 8 the results of each simulation run based on their corresponding aggregation step as proposed in the methods chapter are presented.

Fire behaviour characteristics			Simulated	Intersection		Under-simulation		Over-simulation	
Agg. step	Classes	Run time							
FUEL LOADS		Seconds	Hectares	Hectares	SSI %	Hectares	SSI %	Hectares	SSI %
1	12	52.4	1,685	1,681	99.79%	1.0	**0.06%**	3.5	**0.21%**
2	11	52.3	1,690	1,680	99.45%	2.0	**0.12%**	9.4	**0.55%**
3	10	52.8	1,687	1,676	99.36%	6.8	**0.40%**	10.8	**0.64%**
4	9	52.9	1,763	1,676	95.07%	6.8	**0.40%**	86.9	**4.93%**
5	8	52.9	1,765	1,676	94.97%	6.8	**0.40%**	88.8	**5.03%**
6	7	52.7	1,763	1,676	95.02%	6.8	**0.40%**	87.8	**4.98%**
7	6	54.8	2,333	1,676	71.83%	6.9	**0.41%**	657.2	**28.17%**
8	5	100.2	3,102	1,679	54.13%	3.2	**0.19%**	1423.0	**45.87%**
RATE OF SPREAD									
1	12	53.0	1,683	1,682	99.90%	0.9	**0.05%**	1.6	**0.10%**
2	11	52.5	1,680	1,680	100.00%	2.3	**0.13%**	0.0	**0.00%**
3	10	53.8	1,674	1,674	99.98%	8.6	**0.51%**	0.4	**0.02%**
4	9	52.2	1,694	1,674	98.85%	8.4	**0.50%**	19.5	**1.15%**
5	8	52.8	1,769	1,675	94.71%	7.1	**0.42%**	93.5	**5.29%**
6	7	54.5	2,281	1,675	73.43%	7.2	**0.43%**	606.2	**26.57%**
FLAME LENGTH									
1	13	52.5	1,680	1,680	99.99%	2.3	**0.13%**	0.1	**0.01%**
2	12	52.3	1,689	1,682	99.57%	0.9	**0.05%**	7.3	**0.43%**
3	11	52.9	1,677	1,670	99.57%	12.3	**0.73%**	7.2	**0.43%**
4	10	51.9	1,675	1,670	99.67%	12.6	**0.75%**	5.6	**0.33%**
5	9	52.4	1,766	1,671	94.63%	11.3	**0.67%**	94.9	**5.37%**
6	8	50.9	1,609	1,546	96.10%	136.4	**8.11%**	62.7	**3.90%**
7	7	55.3	2,024	1,598	78.94%	85.0	**5.05%**	426.2	**21.06%**
8	6	60.1	2,703	1,657	61.30%	25.3	**1.50%**	1046.2	**38.70%**
NO CHARACTHERISTICS									
1	11	42.6	1,681	1,681	99.99%	1.9	**0.11%**	0.2	**0.01%**
2	10	48.8	1,690	1,682	99.52%	0.6	**0.04%**	8.1	**0.48%**
3	9	50.4	1,703	1,682	98.77%	0.6	**0.04%**	21.0	**1.23%**
4	8	56.5	1,697	1,682	99.14%	0.6	**0.04%**	14.7	**0.86%**
5	7	53.7	1,777	1,682	94.64%	0.6	**0.04%**	95.3	**5.36%**
6	6	55.7	1,862	1,682	90.35%	0.6	**0.04%**	179.7	**9.65%**

Table 8: **Results table aggregation process.**

Presented are the simulation results for each aggregation step, categorized by fire behaviour characteristics, showing the number of unique fuel type classes and their effects on the simulation outcomes.

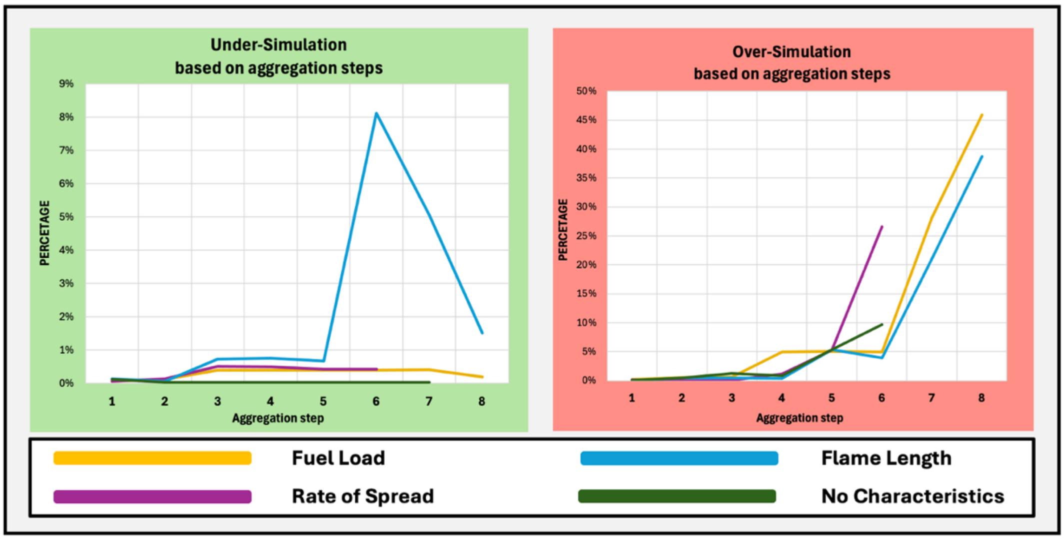


Figure 13: **Under- and Over-simulation based on the amount of unique fuel type classes.** *Showing Under- and over- simulation of the of the simulated area versus the reference data.*

Under-simulation observations

The flame length characteristic has shown the highest under-simulation, showing 8.11% after the 6th aggregation step *(GS2+TU5)*. During the first 5 aggregation steps, under-simulating was remaining stable in the range of 0.13%–0.75%. This suggests that after a certain threshold, the model is increasing to underestimate the fire behaviour, which could affect fire risk assessments. Looking at the Fuel Loads, Rate of Spread, and No Characteristics the under-simulation remained < 1%. This is indicating these fire behaviour characteristics are less affected by the aggregation process and can be aggregated without major accuracy loss.

In wildfire management practices this indicates that aggregation based on flame lengths should be handled with care. Underestimating flame length can lead to misjudgement in the fire suppression needs, decreasing the effectiveness of resource allocation. The stability shown by the other characteristics suggested that aggregation is possible without substantially impacting the simulation accuracy.

Over-simulation observations

The trend showed that over-simulation increased. This increases the negative trend in accuracy as the number of aggregation steps rises as well. Specifically, when taking individual fire behaviour characteristics into account.

An increase in over-simulation was observed from the 6th aggregation onwards, this was shown for all fire behaviour characteristics. In aggregation steps 7 and 8 the fuel loads and flame lengths were showing the highest increase in over-simulation, both aggregated the same fuel types*:* step 7: TU2+TL8 and step 8: TU2+SH2. The rate of spread showed the highest increase after the 5th step *(TU2+TU5)*, increasing from 5.29% at step 5 to 26.57% at step 6 *(TU5+TL8)*. When no specific characteristics were considered the most gradual rate of over-simulation was being observed.

For all characteristics, the over-simulation remained stable for the first 4 steps of the aggregation process showing < 1% of over-simulation, at the 5th aggregation percentages ranged from 5.03% - 5.37% as shown in table 8 and figure 13.

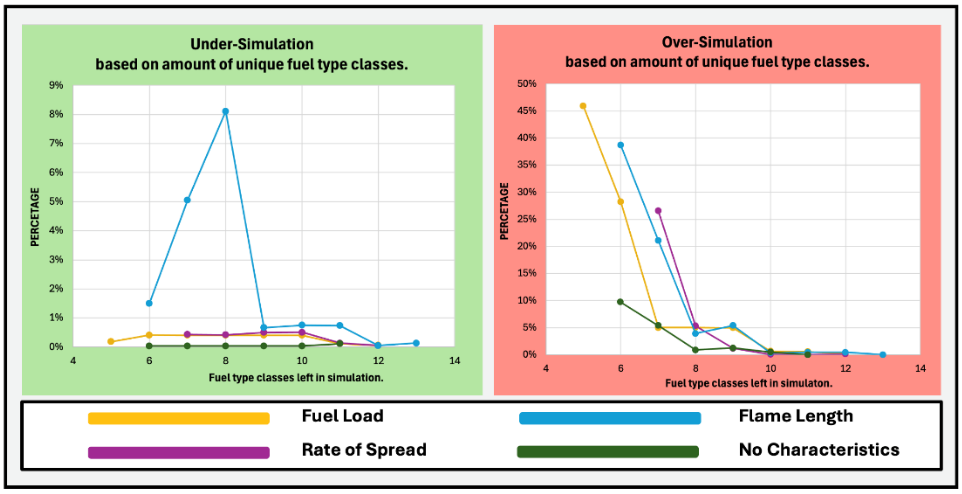


Figure 14: **Under- and Over-simulation based on the amount of unique fuel type classes.**
These graphs represent the simulation behaviour for each of the three fire behaviour categories or without taking any specific category into account. Exact values have been presented in table 8.

Figure 14 shows an inverse relationship between the number of unique fuel types within the study area and the simulation outcomes. Decreasing the number of unique fuel types and therefore, simplifying the fuel classification, was showing a decrease in accuracy. An over-simulation of more 5% in comparison to the simulation outcome without data aggregation was observed when the number of unique classes became < 8.

The under-simulation showed stable results, except for the flame lengths when the unique fuel classes reached < 8. The over-simulation showed a clear surge from the moment the number of unique fuel types, within the simulation, became <8.

A minor decrease in over-simulation, when the number of unique fuel types turned from 8 to 7, for the fuel load *(GR2+GS1)* and flame lengths *(TU2+TL8)* was observed. However, these two fire behaviour characteristics were also showing a substantial increase in over-simulation as soon as the number of unique fuel types decreased to < 7.

4.3 Key observations

When decreasing the number of fuel type classes, the under-simulation stayed relatively stable, while the over-simulation showed a loss in accuracy. Looking at the results in table 8 and figures 13 and 14 the key observations for the individual fire behaviour characteristics are the following:

Fuel Loads

12 unique fuel types showed a 0.21% over-simulation, where 8 unique fuel types show an over-simulation of 5.03%. The highest over-simulation, out of all results, 45.87% was recorded when <5 unique fuel type classes where left. Simplifying the classification was decreasing accurate representation of the fuels based on their fuel loads, resulting in over-predictions in the fuel availability.

Rate of Spread

Starting with 12 unique classes an over-simulation of 0.1% is recorded, a decline to 0.02% in over-simulation at 10 unique classes. Sharp over-simulation was observed when the unique fuel type classes became < 7. Therefore, the fire spread rates were over-predicting with less unique fuel types and a higher level of similarity for the rate of spread within the study area.

Flame Length

A drastic increase in over-simulation was observed when the unique fuel type classes became <8. With 5 unique classes left an over-simulation of 38.70% was recorded, which is the second highest level over-simulation observed. The over-simulations stayed relatively stable while reducing the number of unique classes from 13 to 10. However, a spike in under-simulation was recorded when the amount of unique fuel type classes reached 8. The remaining simulation outcomes for the aggregation steps focussing on the flame length show similar trends as for the fuel load and rate of spread fire behaviour characteristics.

No characteristics

Overall, the best results found for under and over-simulations are being simulated without taking specific fire behaviour characteristics into account. Despite the over-simulation increasing with the number of unique fuel types decreasing, the under-simulations remained stable throughout the aggregation process. An over-simulation of 9.65% was observed while having 6 unique fuel types.

The lowest percentages for under- and over-simulation versus the number of unique fuel types have been observed during this aggregation process. An increase from 0.01% up to 9.65% of over-simulation was observed during the aggregation process when the unique fuel types decreased from 11 to 6 classes.

Fire behaviour characteristic	Agg. Step	Individual fuel types	Under Sim.	Over Sim.
Fuel Load	6	7	0.40%	4.98%
Rate of Spread	5	8	0.42%	5.29%
Flame Length	5	9	0.67%	5.37%
No Characteristics	5	7	0.04%	5.36%

Table 9: **Optimal aggregation levels for each fire behaviour characteristics.**

For each individual fire behaviour characteristic, the optimal level of aggregation has been determinate based on trend line analysis as introduced in the method section.

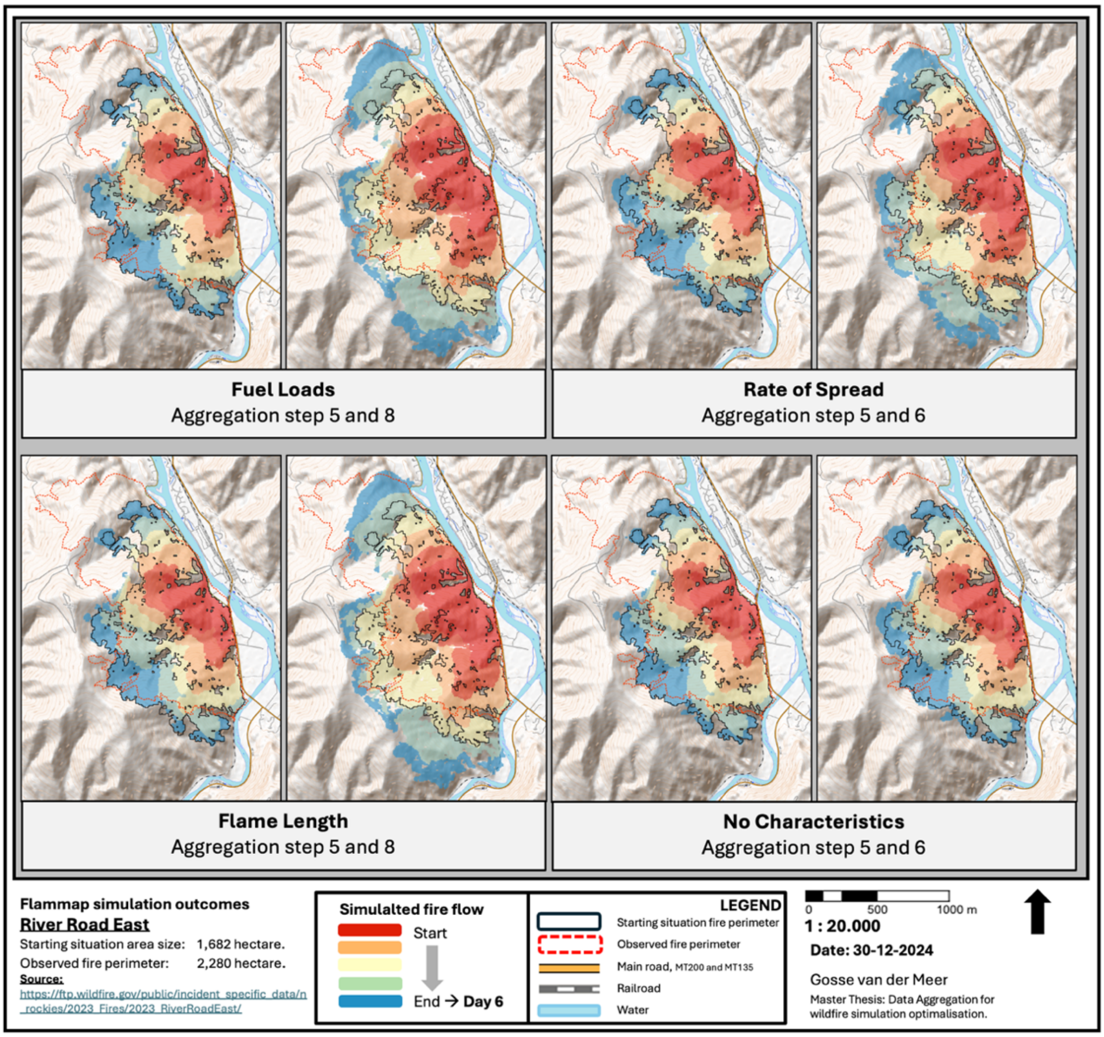


Figure 15: **Simulation outcomes based on fire behaviour characteristics.**

These maps show the simulation outcomes as presented in table 8. For each characteristic the outcomes of the 5th aggregation step and the last aggregation step is being presented.

In figure 15 the fire spread is shown for each of the fire behaviour characteristics. At the 5th aggregation step number of unique fuel types for the fuel loads *(GR2+GS1)* and rate of spread *(TU2+TU5)* were 8. Whereas for the flame lengths there were 9 unique fuel types left, when taking no specific characteristic into account there were 7 unique fuel type classes left in the simulation. During each of the last aggregation steps the fuel loads *(last step: (TU2+SH2)* have 5 individual fuel type classes left, and the rate of spread *(last step: (TU5+TL8)* had 7 left. The Flame Lengths *(last step: (TU2+SH2)* and No Characteristics *(last step: (TU2+TU5)* both finished the aggregation process with 6 unique fuel type classes left.

For the three individual fire behaviour characteristics, the last aggregation step shows in over-simulation taking place in a similar area within the study area.
This could be identified as the north- and the south-sides of the simulation areas. For the No Characteristics category, the over-simulation was determined to be on the west-side as well as on the north-side of the simulation outcomes.

4.4 Flame length irregularity

Figure 16 shows the observed peak in under-simulation after the 6th aggregation step *(GS2+TU5)*. Highlighted is the area in which the under-simulation mainly was observed. During this aggregation step 8 unique fuel type classes were left within the classification. An under-simulation of 8.11% was determined while the over-simulation showed 3.90%.
At the 6th step the Grass-Shrub fuel types were aggregated with the Timber-Understory which both were classified with moderate flame length in the FBFM40 Fuel type classification (see appendix A).

During the 7th aggregation *(TU2+TL8)* the Timber-Understory fuel type, which have been classified to have a low flame length, have been aggregated with the Timber-Litter (also low flame length). Under-simulation decreased 5.05%, whereas the over-simulation was observed as 21.06%. Eventually finalizing the aggregation process after 8 steps with a 1.50% under-simulation and a 38.70% over-simulation.

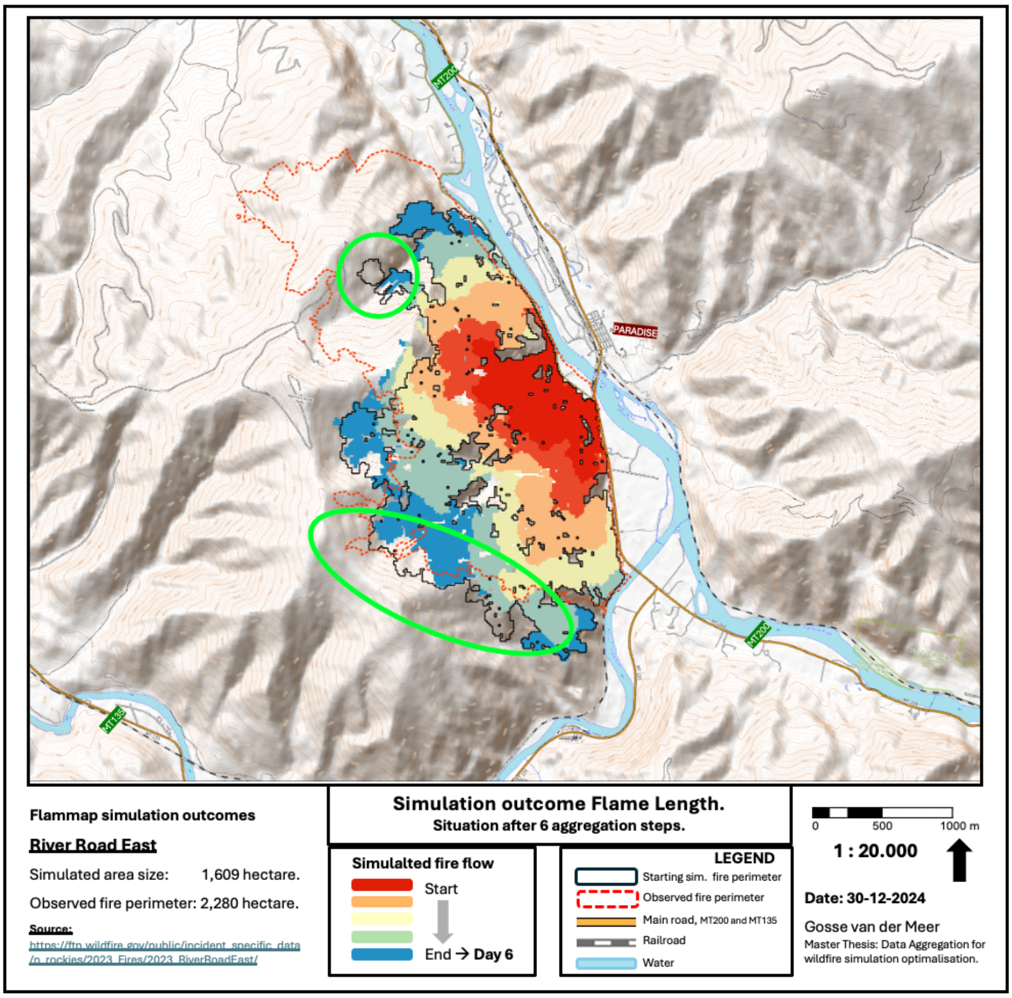


Figure 16: **Simulation outcome Flame Length after 6 aggregation steps.**
With a simulated area size of 1,609 hectare versus the 1,682 hectares for the simulated size without any aggregation steps (figure 6). An under-simulation of 8.11% and an over-simulation of 3.90% was determined.

4.5 Entropy results

The entropy levels show the variation between fuel type class sizes during the aggregation process. Entropy values closer to 1 indicate a more diverse classification, while lower values (closer to 0) are suggesting an increase in generalization.

Enthropy				
Agg. steps	Fuel Loads	Rate of Spread	Flame Lenght	No Charact.
1	0.89	0.88	0.88	0.88
2	0.87	0.87	0.87	0.87
3	0.86	0.84	0.85	0.85
4	0.83	0.81	0.82	0.82
5	0.79	0.75	0.79	0.79
6	0.71	0.61	0.74	0.72
7	0.58		0.61	
8	0.37		0.44	

Table 10: **Entropy levels across aggregation steps.**

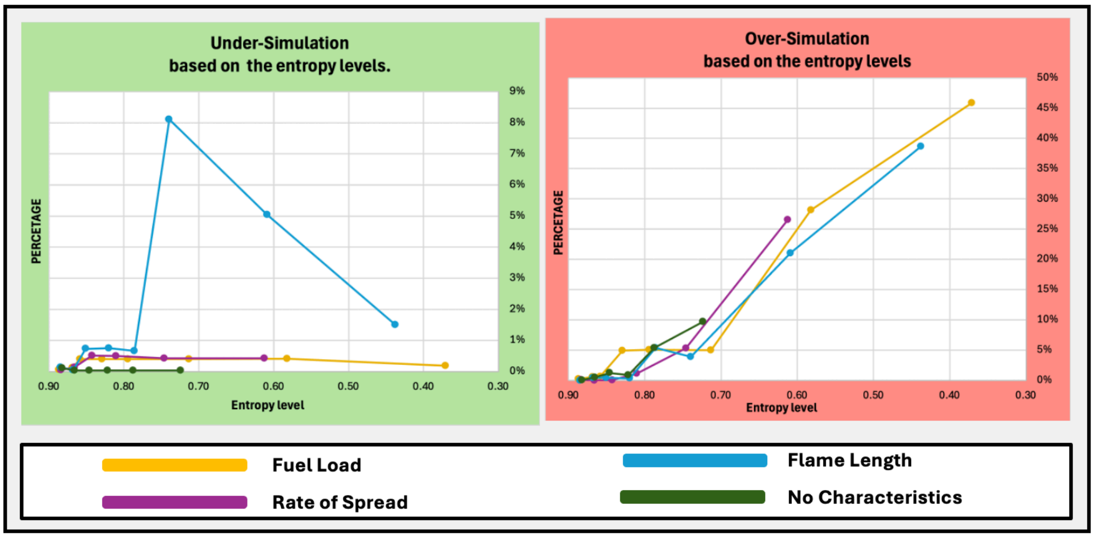


Figure 17: **Entropy levels across aggregation steps**

For each of the individual simulations during the data aggregation process, the entropy levels have been calculated based on the fuel type classification as a result of each aggregation step.

The results show that most aggregation strategies yield similar entropy values across different fire behaviour characteristics. However, the rate of spread shows a systematic lower entropy at much earlier aggregation steps compared to fuel loads, flame lengths, and no characteristics. This suggests that the rate of spread is more sensitive to fuel type aggregation.

All fire behaviour characteristics present similar entropy levels during the first 6 steps of the aggregation process. The fuel loads decrease the most, from 0.89 to 0.37 which is a loss of 0.52 in entropy during the 8 aggregation steps. Indicating that the fuel loads are more sensitive to over aggregation. Looking at the rate of spread it shows the lowest level of entropy at the 5th and 6th aggregation steps, comparing this with the over-simulation (table 8) this could indicate that the rate of spread is less sensible to simplifying the fuel type classes.

The entropy levels confirm that simplifying the fuel type classifications is leading to a loss of detail, which could affect the wildfire simulation outcome.

The entropy trends are in line with the results of the under- and over-simulation, confirming that over aggregation leads to a loss in accuracy which decreases the effectiveness of the wildfire simulation results.

4.6 Processing time results

Processing time: time to run a complete fire spread simulation of the study area.

Fire behaviour characteristics			
FUEL LOADS	Run time	**FLAME LENGTH**	Run time
Agg. step	Seconds	Agg. step	Seconds
1	52.4	1	52.5
2	52.3	2	52.3
3	52.8	3	52.9
4	52.9	4	51.9
5	52.9	5	52.4
6	52.7	6	50.9
7	54.8	7	55.3
8	100.2	8	60.1
RATE OF SPREAD	Run time	**CHARACTHERISTICS**	
Agg. step	Seconds	Agg. step	Seconds
1	53.0	1	42.6
2	52.5	2	48.8
3	53.8	3	50.4
4	52.2	4	56.5
5	52.8	5	53.7
6	54.5	6	55.7

Table: 11.

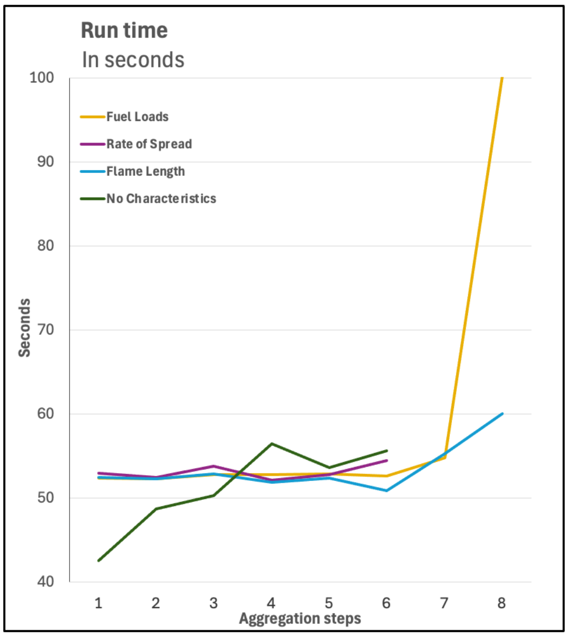


Figure: 18.

Table 11 and Figure 18: **Processing times Flammap simulations.**
For each of the individual runs during the data aggregation process the run times in comparison with the aggregation step.

The results observed for the processing time were in line with the expectations. The aggregation process based on fuel loads shows the largest area size for over-simulation this trend was also visible in the processing times. The difference between the fastest and the slowest simulations is 47.9 seconds.

As the size of the simulated areas was increasing the run time was also increasing for all fire behaviour characteristics. Other than the fuel loads, all other characteristics presented a difference of <10 seconds throughout the aggregation process.

Flammap is processing fire spread at the pixel level, by calculating how the fire spreads for each pixel individually. The fire spread stops when no further spread is possible, based on the fuel type assigned to a pixel. In other words, if a pixel has no "burning" neighbours, or no spread through spotting is possible the fire and the simulation will stop.

The processing time, is following a similar trend as the trends for the simulated area sizes.

5. Discussion

During this research the impact of fuel type aggregation on wildfire simulation accuracy has been studied. The results show that as the number of unique fuel type classes decreases, the over-simulation of the model rapidly increases. This rapid increase in over-simulation appears when the number of unique fuel types left gets lower than eight classes. Trendline analysis showed a great loss in accuracy from the moment the rapid increase in over-simulation appeared.
Different aggregation strategies, based on individual fire behaviour characteristics (fuel load, rate of spread, flame length, and no specific characteristic) have been applied to determine which individual characteristic influences simulation accuracy the most.
Understanding the impact of data aggregation can help improve computational efficiency and practical usability while maintaining acceptable accuracy levels for wildfire simulation outputs.

5.1 Reducing the wickedness

Wildfire management can be seen as a wicked problem due to the interconnectivity of the ecological, social, economic, and political dimensions. This study aims to reduce this complexity by proposing a method where fuel type aggregation can optimize simulation efficiency while maintaining reliable fire behaviour predictions.
For the ecological dimension, a method to simulate fire spread more effectively is provided without oversimplifying critical ecological variations.
Based on the social and economical dimension, an improvement in simulation usability supports increased use for fire risk assessments. Which helps to reduce wildfire-related losses in lives and assets, as well as potentially lowering wildfire response costs due to earlier and more effective suppression efforts.
For the political dimension this study can be used as a standardized method with an adaptable aggregation approach to use more data-driven policies. Helping to achieve a balance between fire suppression efforts, ecological restoration goals, and land management practices. By introducing a structured method that can be adjusted to different fire-prone regions, this study increases the practical usability of wildfire simulations. Aiming to reduce the wickedness by offering more informed and responsive wildfire management strategies.

5.2 Effect of aggregation on simulation accuracy

This phenomenon was visible in the trendlines for all specific fire behaviour characteristics, as well as when an aggregation method was used without taking specific characteristics into account. As the amount of unique fuel type classes decreased, the input data (fuel map) becomes more homogeneous. This leads to a loss of local variation in fuel types. As the behaviour of a wildfire is very depending on fuel type variation, location and characteristics. Oversimplification of input data causes an over-simulation of fire spread.
For example, when looking specifically at the fire behaviour characteristic for the fuel loads. When the aggregation process decreased the number of unique fuel types from 12 to 5, the over-simulation spiked from 0.21% to 45.87%. This extreme over-simulation shows that fuel load aggregation significantly impacts the fire spread predictions, and therefore the simulation outcomes. This is a likely output as the model is no longer able to identify the high-fuel-load and the low-fuel-load areas, as they have been aggregated in one class. As a result, simulated fires spread shows a large over-simulation. Similar outcomes have been presented by (Parsons et al., 2017). This reduces the predictive reliability of the model and decreases its practical usability and these findings.

A similar pattern (as for the fuel loads) was shown in the trendlines for the aggregation outcomes based on the rate of spread. Also, here the accuracy decreased sharply after the 5th aggregation step. From the

moment the amount of unique fuel types reaches < 6, the over-simulation increased rapidly. This confirmed that the rate of spread is a key factor in simulating wildfires just like Rothermel, (1972) did in his publication "*A mathematical model for predicating fire spread in wildland fuels*". Other than the fuel loads, which primarily effects the intensity of the fire, the rate of spread has a direct influence on the growth of the fire perimeters. Therefore, showing that the rate of spread is crucial for accurate wildfire simulation outcomes.
The under-simulation, on the other hand, remains relatively stable throughout the aggregation process. This is shows that aggregating of fuel types does not lead to a substantial under-simulation of the burned areas. This is as expected, because, as the amount of individual fuel types decreases, the total simulated burned area increases (over-simulation). This is similar to results presented by Taneja et al., (2021), as they found that decreasing the spatial resolution of the fuel types, does not lead to substantial under-simulation. Instead, it leads to an over-simulation as a result of the loss of detailed fuel type information.
However, a sudden rise in under-simulation was observed in the flame length-based aggregation outputs. As a sudden spike in under-simulation occurred after step 6. This exception suggests that specific fire behaviour characteristics, as in this case the flame lengths, can cause unpredictable effects due to spotting when the aggregation creates in a high level of homogeneousness within the input data (fuel map).

5.3 Which fire behaviour characteristic shows the most influence

After testing all individual fire behaviour characteristics, the rate of spread showed the greatest influence on the simulation outcomes. The over-simulation showed a sharp increase in the trendlines between aggregation steps 5 and 6, where the accuracy levels decreased from 5.29% to 26.57%. Here a substantial drop in entropy (0.75 à 0.61) was observed confirming that a rapid loss in fuel type diversity has a negative impact on the producer accuracy of the model. Causing the simulations to lose the ability to realistically predict fire spread.
The rate of spread is a key factor with regard to wildfire simulations because it determines how quickly fire is moving throughout the landscape (Rothermel, 1972). When too many individual fuel types have been aggregated, the model can no longer differentiate between fuel types that either slow down or speed up the fire spread (Cardil et al., 2023) . This results in fire modelling with a constant fire spread rate, causing high over-simulation in the output data. As a result of these over-simulated outputs, fire management decisions, could over-allocate fire suppression resources to actual areas in which substantially less fire activity is taken place. And therefore, decreasing the efficient use of available resources.

Besides the rate of spread, the fuel loads and flame length also influence the accuracy but show less impact. Meaning that oversimplification of their classifications does not directly lead to extreme over-simulation for the burned areas. The sudden spike in under-simulation for flame length after the 6th aggregation step, may suggest that the flame lengths cause simulation inconsistencies. This can be related to the interactions between flame lengths and wind effects. Which may result in spotting taking place (Egorova et al., 2022)

5.4 Identifying the critical threshold for aggregation

A key finding of this study is that 8 unique fuel types serve as a threshold to maintain wildfire simulation accuracy. When the amount of unique fuel types within the input data, was greater than eight, the model showed stable trendlines for the accuracy levels. Only minor increases in over-simulation have been observed throughout the aggregation process for all fire behaviour characteristics. However, from the moment the amount of unique fuel types became <8, a spike in over-simulation was observed. Clearly showing a decrease in the model's reliability and therefore, useability. The simplification of the fuel type classification was also visible in the entropy levels, showing that entropy levels of > 0.8 are crucial to maintaining simulation accuracy.

This threshold was observed in the outcomes of all individual aggregation methods (based on the rate of spread, fuel load, flame length, or no without regards to any specific characteristics). The results show all fire behaviour characteristics are following the same trends. Therefore, suggesting that the aggregation process in this study case should be stopped before the number of unique fuel types becomes <8, no matter the fire behaviour characteristic. In other cases, a different distribution of fuel types can result different behaviour in trendlines and therefore different threshold values. Keeping the entropy levels > 0.8 is preventing oversimplification and the loss of local variations in fuel types which can have a direct impact the simulation outcomes.

Finding these thresholds is important as it provides a practical balance between computational- and data-efficiency with regard to the simulation accuracy. And because wildfire simulations require large computational resources and input data specification (fuel maps), reducing the complexity of input data is often necessary. However, as this study shows, the data aggregation process must be monitored. Because, reducing the amount of unique fuel types too much, and therefore oversimplification of the input data, leads to unreliable predictions. And can be defeating the purpose of increasing efficiency and usability for wildfire simulations to support wildfire management and resource allocation decisions.

These findings are in line with previous research (Parsons et al., 2017) on data aggregation with regards to wildfire fire modelling. But data aggregation often comes at the cost of a decrease in accuracy (Rösch et al., 2024). However, previous studies have not provided a clear numerical threshold for balancing simulation accuracy and efficiency. This study addresses the challenges faced when simplifying a fuel type classification. By introducing an approach to simplify fuel maps this study shows that a classification with > 8 unique fuel types and entropy levels of >0.8 provides reliable wildfire simulation accuracy.

Rather than focusing on these specific threshold values, the novelty of this work can be found in the methodology used to determine an optimal balance (threshold) between classification simplification and simulation accuracy. This approach can be used as a guideline for future wildfire modelling. Allowing researchers and fire management decision-makers to use similar data aggregation methods for different ecosystems and user-cases.

The outcome of this study can be used directly in operational wildfire response. Wildfire simulation models often support the decision-making process, and therefore needing to be both efficient, reliable and have a practical usability.

Overall, the results of this study show the importance of rate of spread as the main fire behaviour characteristic to be affecting the simulation accuracy. The key findings confirm that data aggregation based on fuel types is a suitable approach to improve computational efficiency and practical usability. For the case study of this research, it was essential that the amount of unique fuel types within the input data (fuel map) stays > 8. However, to take general usability into account it is important to state that the number of unique fuel type classes stay above, the defined threshold. This to make sure that the wildfire simulation model remains usable for large-scale simulations while still providing usable predictions for fire management decision-making.

5.5 Comparison with existing research

Recent research (Alipour et al., 2023) showed that aggregating fuel type classes for the input datasets led to a 7.2% accuracy loss when reducing the number of unique fuel type by 50%, for Mediterranean ecosystems in California. This study extends those findings to boreal forest ecosystems. The results are demonstrating that the impact of a data aggregation process depends on the type of ecosystem as well as the fire behaviour characteristics of the individual fuel types which present in the area of interest. Prior studies were mainly focused on increasing spatial resolution to increase the simulation accuracy.

5.6 Practical usability

Simplified fuel models can speed up the total simulation process as less detailed input data is needed. Keeping a minimum of 8 unique fuel types maintains acceptable accuracy levels for the simulation outputs to be used in wildfire management decision-making.

As fire models often struggle with complex data this research shows that a substantial reduction in complexity for the fuel type input data comes with a minor loss of accuracy. Therefore, this shows that fuel type aggregation can be an effective way in reducing the need for complex fuel type input data while maintaining acceptable accuracy.

Wildfire management has to constantly find a balance between real-time fire predictions and resource allocation. These resources always come with certain limitations as financial, technological and the lack of human resources. Enabling an increase of usability of wildfire simulation practices, throughout the decision-process of wildfire management, can increase efficiency during fire events.

Therefore, a recommendation within the decision-making policy of wildfire management should be to not only look at the availability of certain fuel types within an area of interest. But also keep their specific fire behaviour characteristics into account. Additional, when aggregating fuel types to decrease data complexity, the rate of spread should be considered as the primary factor within fire behaviour models.

5.7 Current limitations

This study provides valuable insights into fuel type aggregation methods for wildfire simulations, but several limitations must be considered. During the simulation process Flammap assumes constant environmental conditions as it uses a static fire behaviour model, whereas fire behaviour in the real world is also affected by (locally) changing winds, humidity levels, and temperatures. In addition to this, fire suppression efforts have not been taken into account. These limitations may prevent the direct application of the results to real wildfire events and therefore the user accuracy cannot be determined.

Another limitation can be found within the focus of this research being on a single wildfire (River Road East fire) in a boreal forest ecosystem. While boreal forests are prone to wildfires, the identified threshold of 8 unique fuel types may not be universally applicable to other ecosystems such as Mediterranean ecosystems, tropical forests or boreal forests with a different spatial lay-out. This research also has been relying on the FBFM40 classification and fuel maps with a spatial resolution of 30 meters. This spatial resolution may cause an oversimplification of local fuel type variety causing a decrease in the accuracy. Data with a higher spatial resolution, such as LiDAR-based fuel models, could enhance data aggregation techniques. However, this comes with increased process complexity and a higher computational cost due to some characteristics of LiDAR data.

5.8 Future research

An irregularity in the trendline was observed in the outcomes of the aggregation process specific to the flame length. This sudden spike in under-simulation at the 6th aggregation step shows an irregular fire behaviour that requires further research.

These challenges can be addressed by aiming future research towards using dynamic fire behaviour models. The aggregation process and thresholds should be tested across various ecosystems. Exploring machine learning methods during the aggregation process could be useful in researching irregularities in the outputs during an aggregation process. These improvements would enhance the total accuracy (user and producer), increase the usability of wildfire simulations and generalise a data aggregation method. This while maintaining computational efficiency and reliable simulation usability within the field of wildfire management.

Whereas the current simulations used assume unrestricted fire spread, during a real fire event active management takes place. Suppression efforts such as creating firebreaks, backburning (using controlled fire to remove burnable materials to stop fire spread) and aerial suppression (water bombing) are taking place. Research focusing on the effects of aggregated fuel type maps and the relationship with suppression efforts would improve practical usability (user accuracy) within wildfire management decision-making.

Machine learning provides dynamic aggregation strategies, increasing the fuel classification based on the real-time active fire behaviour.

Finally, testing the effects of dynamic fuel type aggregation during an active fire event (including active suppression efforts) could determine the real-world usability for wildfire management decision-making. Real-time case studies on active fires could validate if and when simplified fuel classifications balance accuracy with computational speed and power. Making wildfire simulations a more reliable, useful and efficient tool for wildfire management with regards to suppression efforts and resource allocation.

Therefore, the proposed future research areas could refine data aggregation methods as well as wildfire modelling, aiming to achieve aggregation methods to improve both efficiency and the total model accuracy (user- and producer accuracy).

6. Conclusion

This research has been devoted to the effects of fuel type aggregation on wildfire simulation accuracy. Finding a balance between computational efficiency (simplification of the input data) and simulation accuracy has been a key factor. The findings show that while aggregation simplifies the data processing, over-simplification leads to a substantial over-simulation. These spikes in over-simulation trends are indicating a great decrease in the model accuracy.

The first research question aims to understand if and or how aggregating fuel types, either by fire behaviour characteristics or only by presence, is affecting the simulation accuracy. The results show that reducing the number of unique fuel types within the fuel map is increasing the over-simulation of the model. With a critical threshold identified of 8 unique fuel types and entropy levels of < 0.8. When the unique fuel types left reach an amount of >8 and entropy levels reach < 0.8, the model loses its ability to identify correct fire spread patterns, resulting in a great loss of accuracy.

The second research question analysed which fire behaviour characteristic has the most influence on the simulation accuracy. The rate of spread showed to be the most critical factor, with over-simulation increasing substantially when < 8 unique fuel types remained. The entropy levels > 0.75 at the moment the unique fuel types became > 8 shown greater variation between the fuel type sizes. Other than for the fuel loads or flame lengths, the rate of spread has a direct impact on the fire expansion, and therefore heavily influencing the accuracy the wildfire simulations.

These findings show valuable insights into wildfire modelling. But maintaining at least 8 fuel types needs to be ensured so that the model accuracy is not completely compromised. In addition to the < 8 unique fuel types, the rate of spread should be prioritized as a fire behaviour characteristic in fuel type classifications. This can improve the reliability and usability of the wildfire simulations. And therefore, efficiently supporting wildfire management practices.

Future research should test the aggregation ruleset and thresholds in other boreal forests and different ecosystems. As well as integrating dynamic weather models and or exploring aggregation techniques based on machine learning to create real time adaptive fuel type classification and wildfire simulations.

Concluding, this research has determined an optimal threshold for fuel type aggregation, while balancing computational efficiency with wildfire simulation accuracy.
By implementing these findings, wildfire management can be more efficient and therefore, increase effective response efforts, suppression strategies and optimization resource
allocation.

6.1 Recommendations

Based on the findings of this study, the following recommendations are being made.
The entropy levels showed that over aggregation beyond the 6th step led to a substantial decline in simulation accuracy, especially when looking at the over-simulation results.

To minimize the effects of oversimplification, it is recommended that aggregation thresholds be kept to > 8 unique fuel type classes and to maintain entropy levels of > 0.8, to ensure sufficient fuel type diversity to have realistic fire spread predictions.
Additionally, integrating dynamic aggregation approaches, in which the fuel type aggregations are based on unique fire behaviour for given environments, could further improve model accuracy.

Further validation using real-world fire datasets is encouraged to confirm the minimum number of unique fuel types and the entropy-based thresholds and their usability across different fire-prone regions or even complete ecosystems. By incorporating entropy as a quality control metric for input data to use in wildfire simulation, the optimal balance between simplification and accuracy can be reached.

Eventually increasing the usability and effectiveness of wildfire simulations to support the decision-making process in fire management and risk assessment.

6.2 Ethical considerations and risks

For this research only freely, available public data has been used to minimize privacy concerns. Processing of this data has taken place by using freely available open-source software such as Flammap and QGIS. By using public data and open-source software the goal is to create transparency, accessibility as well as reproducibility of the results. Open-source tools also create higher levels of inclusivity as well as opening up for future collaborations within this specific research field. Ethical concerns regarding unequal access to the data and software used have been substantially reduced.

However, ethical risks will stay present, especially with regard to potential misinterpretations or misuse of the simulation outcomes. Therefore, wildfire simulation outcomes need to be documented in a transparent way, to limit uncertainties and to avoid decision-making based upon wrong or incomplete assumptions.

Decisions have been made during the aggregation process. Any decision has a risk involved in creating a potentially uneven accuracy level and or wrongly identifying areas of high- or low-risk. Therefore, the simulation outputs are solely used for comparison and validation with the reference data to determine the effects of data aggregation, based on fire behaviour characteristics, for the simulation accuracy levels.

It is important to state that simulation outcomes for potential wildfire scenarios should only be used in consideration with other critical factors involved, such as local knowledge, experience and other forms of information, in any decision-making process. Simulation outcomes should just be a tool to create insight and to be able to make well-balanced decisions.

APPENDICES

APPENDIX A:

Fire behaviour characteristics and their influence on fire behaviour as described by Scott and Burgan for the FBFM40 classification (Scott & Burgan, 2005).

Fuel Group	Fuel Code	Fuel Load	Rate of Spread	Flame length	Description
Non-burnable	NB1,3,8,9	NB	NB	NB	
Grass	GR1	L	L	L	Short, sparse dry climate grass is short, naturally or heavy grazing.
Grass	GR2	L	No effect	No effect	Dry climate grass primarily grass with some small amounts of fine, dead fuel, any shrubs.
Grass	GR3	L	No effect	No effect	Very coarse, humid climate grass continuous, coarse humid climate grass, any shrubs.
Grass-Shrub	GS1	L	M	L	Dry climate grass-shrub shrub about 30cm high, grass load low._
Grass-Shrub	GS2	M	H	M	Dry climate grass-shrub, shrubs are 30-90cm high.
Grass-Shrub	GS3	M	H	M	Humid climate grass-shrub, moderate grass/shrub load, grass/shrub depth is less than 60cm.
Shrub	SH1	L	L	L	Dry climate shrub, woody shrubs and shrub litter, fuel bed depth about 30cm, may be some grass.
Shrub	SH2	M	L	L	Dry climate shrub, woody shrubs and shrub litter, fuel bed depth about 30cm, no grass.
Shrub	SH3	M	L	L	Humid climate shrub, woody shrubs and shrub litter, possible pine overstory, fuel bed depth 60-90cm.
Shrub	SH5	H	VH	VH	Dry climate shrub litter and woody shrubs, heavy load with depth 120-180cm.
Shrub	SH6	L	H	H	Humid climate shrub, woody shrub and shrub litter, dense shrubs, little or no herbaceous fuel, depth about 60cm.
Shrub	SH7	VH	H	VH	Dry climate shrub, woody shrubs and shrub litter, very heavy shrub load, depth 120-180cm.
Timber-Understory	TU1	L	L	L	Dry climate timber grass shrub, low load of grass and/or shrub with litter.
Timber-Understory	TU2	M	M	L	Humid climate timber-shrub, moderate litter load with some shrub.,
Timber-Understory	TU5	VH	M	M	Dry climate timber shrub, heavy forest litter with shrub or small tree understory.
Timber-Litter	TL1	L	L	L	Compact conifer litter, compact forest litter, light to moderate load, 2,5-5cm deep, may represent a recent burn.
Timber-Litter	TL2	L	L	L	Broadleaf litter, broadleaf, hardwood litter.,
Timber-Litter	TL3	M	VL	L	Conifer litter, moderate load conifer litter, light load of coarse fuels.
Timber-Litter	TL4	M	L	L	Small downed logs of fine litter and coarse fuels, small diameter downed logs.
Timber-Litter	TL5	H	L	L	Conifer litter, light slash or dead fuel.
Timber-Litter	TL6	M	M	M	Broadleaf litter.
Timber-Litter	TL8	M	M	L	Long needle litter, long needle pine litter, may have small amounts of herbaceous fuel.
Timber-Litter	TL9	VH	M	M	Broadleaf litter, may be heavy needle drape.

NB= Non Burnable,VL= Very Low, L= Low, M=Moderate, H = High, VH = Very High and No affect is referring to the affect on fire behaviour.

APPENDIX B

Rate of Spread aggregation process.

RATE OF SPREAD

NO FUEL TYPE AGGREGATION WILL TAKE PLACE WITHOUT SIMILARITY IN RATE OF SPREAD

			AGGREGATION STEP:			ONE			TWO			THREE		
			FUEL TYPE COMBINATION REFERENCE DATA			GR2+3//GS2+3+SH6+7// SH2+1+3+GR1//TL8+9 TU1+TL1+2+4+5			TL8+TL6			SH2+TU1		
Fuel Group	**Fuel Code**	**Rate of Spread**	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	NB	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*
Grass	GR1	Low	2383	0.329%	2383	-	-	-	-	-	-	-	-	-
Grass	GR2	No affect	77022	10.637%	77022	**79074**	**10.920%**	**77022**	79074	10.920%	77022	79074	10.920%	77022
Grass	GR3	No affect	2052	0.283%	2052	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS1	Moderate	14748	2.037%	14748	14748	2.037%	14748	14748	2.037%	14748	14748	2.037%	14748
Grass-Shrub	GS2	High	80237	11.081%	80237	**80269**	**11.085%**	**80237**	80269	11.085%	80237	80269	11.085%	80237
Grass-Shrub	GS3	High	4	0.001%	4	-	-	-	-	-	-	-	-	-
Shrub	SH1	Low	789	0.109%	789	-	-	-	-	-	-	-	-	-
Shrub	SH2	Low	120867	16.692%	120867	**124474**	**17.190%**	**120867**	124474	17.190%	120867	**135808**	**18.755%**	**120867**
Shrub	SH3	Low	435	0.060%	435	-	-	-	-	-	-	-	-	-
Shrub	SH5	Very High	66	0.009%	66	66	0.009%	66	66	0.009%	66	66	0.009%	66
Shrub	SH6	High	4	0.001%	4	-	-	-	-	-	-	-	-	-
Shrub	SH7	High	24	0.003%	24	-	-	-	-	-	-	-	-	-
Timber-Understory	TU1	Low	6223	0.859%	6223	**11334**	**1.565%**	**6223**	11334	1.565%	6223	-	-	-
Timber-Understory	TU2	Moderate	203173	28.059%	203173	203173	28.059%	203173	203173	28.059%	203173	203173	28.059%	203173
Timber-Understory	TU5	Moderate	37788	5.219%	37788	37788	5.219%	37788	37788	5.219%	37788	37788	5.219%	37788
Timber-Litter	TL1	Low	3104	0.429%	3104	-	-	-	-	-	-	-	-	-
Timber-Litter	TL2	Low	887	0.122%	887	-	-	-	-	-	-	-	-	-
Timber-Litter	TL3	Very Low	16289	2.250%	16289	16289	2.250%	16289	16289	2.250%	16289	16289	2.250%	16289
Timber-Litter	TL4	Low	161	0.022%	161	-	-	-	-	-	-	-	-	-
Timber-Litter	TL5	Low	959	0.132%	959	-	-	-	-	-	-	-	-	-
Timber-Litter	TL6	Moderate	8604	1.188%	8604	8604	1.188%	8604	-	-	-	-	-	-
Timber-Litter	TL8	Moderate	100483	13.877%	100483	**100487**	**13.878%**	**100483**	**109091**	**15.066%**	**100483**	109091	15.066%	100483
Timber-Litter	TL9	Moderate	4	0.001%	4	-	-	-	-	-	-	-	-	-
Total:			724100	100.0%	724100	724100	100.0%	713294	724100	100.0%	704690	724100	100.0%	698467

			FOUR			FIVE			SIX		
			TU2+GS1			TU2+TU5			TU5+TL8		
Fuel Group	**Fuel Code**	**Rate of Spread**	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	NB	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*
Grass	GR1	Low	-	-	-	-	-	-	-	-	-
Grass	GR2	No affect	79074	10.920%	77022	79074	10.920%	77022	79074	10.920%	77022
Grass	GR3	No affect	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS1	Moderate	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS2	High	80269	11.085%	80237	80269	11.085%	80237	80269	11.085%	80237
Grass-Shrub	GS3	High	-	-	-	-	-	-	-	-	-
Shrub	SH1	Low	-	-	-	-	-	-	-	-	-
Shrub	SH2	Low	135808	18.755%	120867	135808	18.755%	120867	135808	18.755%	120867
Shrub	SH3	Low	-	-	-	-	-	-	-	-	-
Shrub	SH5	Very High	66	0.009%	66	66	0.009%	66	66	0.009%	66
Shrub	SH6	High	-	-	-	-	-	-	-	-	-
Shrub	SH7	High	-	-	-	-	-	-	-	-	-
Timber-Understory	TU1	Low	-	-	-	-	-	-	-	-	-
Timber-Understory	TU2	Moderate	**217921**	**30.096%**	**203173**	**255709**	**35.314%**	**203173**	**364800**	**50.380%**	**203173**
Timber-Understory	TU5	Moderate	37788	5.219%	37788	-	-	-	-	-	-
Timber-Litter	TL1	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL2	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL3	Very Low	16289	2.250%	16289	16289	2.250%	16289	16289	2.250%	16289
Timber-Litter	TL4	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL5	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL6	Moderate	-	-	-	-	-	-	-	-	-
Timber-Litter	TL8	Moderate	109091	15.066%	100483	109091	15.066%	100483	-	-	-
Timber-Litter	TL9	Moderate	-	-	-	-	-	-	-	-	-
Total:			724100	100.0%	683719	724100	100.0%	645931	724100	100.0%	545448

Low	High
Moderate	Very High

*Bold written numbers indicate growing class.

ONE – Rules:
1 Every class below 0,85%,
2 No aggregation outside RATE OF SPREAD similarity
3 If possible: within Fuel Gr.

TWO – Rules:
1 Lowest Freq. %
2 No aggregation outside RATE OF SPREAD similarity
3 If possible: within Fuel Gr.

THREE – Rules:
1 Lowest Freq. %
2 No aggregation outside RATE OF SPREAD similarity
3 If possible: within Fuel Gr.

FOUR – Rules:
1 Lowest Freq. %
2 No aggregation outside RATE OF SPREAD similarity
3 If possible: within Fuel Gr.
4

Fuel Code	CHARACTERISTICS
GS1	L,M,L
TU2	**M,M,L**
TU5	VH,M,M
TL8	**M,M,L**

Therefore: TU2+GS1

FIVE – Rules:
1 Lowest Freq. %
2 No aggregation outside RATE OF SPREAD similarity
3 If possible: within Fuel Gr.
5 Because Packing Ratio and Fine Fuel Load is closest in simimarity.

Fuel Code	FFL	PR
GS1	1.35	0.002
TU2	1.15	0.006
TL8	5.8	0.04

Source: FBFM40 (2005)

SIX – Rules:
1 Lowest Freq. %
2 No aggregation outside RATE OF SPREAD similarity
3 If possible: within Fuel Gr.

APPENDIX C

Flame Length aggregation process.

FLAME LENGTH

NO FUEL TYPE AGGREGATION WILL TAKE PLACE WITHOUT SIMILARITY IN FLAME LENGTH.

AGGREGATION STEP: REFERENCE DATA; ONE (GR2+3//GS1+GR1//GS2+3 SH2+1+3//SH5+SH7 TL3+1+2+4+5//TL6+TL9); TWO (TU2+TU1)

FUEL TYPE COMBINATION			REFERENCE DATA			ONE: GR2+3//GS1+GR1//GS2+3 SH2+1+3//SH5+SH7 TL3+1+2+4+5//TL6+TL9			TWO: TU2+TU1		
Fuel Group	Fuel Code	Flame Length	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	NB	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*
Grass	GR1	Low	2383	0.329%	2383	-	-	-	-	-	-
Grass	GR2	No affect	77022	10.637%	77022	**79074**	**10.920%**	**77022**	79074	10.920%	77022
Grass	GR3	No affect	2052	0.283%	2052	-	-	-	-	-	-
Grass-Shrub	GS1	Low	14748	2.037%	14748	**17131**	**2.366%**	**14748**	17131	2.366%	14748
Grass-Shrub	GS2	Moderate	80237	11.081%	80237	**80241**	**11.082%**	**80237**	80241	11.082%	80237
Grass-Shrub	GS3	Moderate	4	0.001%	4	-	-	-	-	-	-
Shrub	SH1	Low	789	0.109%	789	-	-	-	-	-	-
Shrub	SH2	Low	120867	16.692%	120867	**122091**	**16.861%**	**120867**	122091	16.861%	120867
Shrub	SH3	Low	435	0.060%	435	-	-	-	-	-	-
Shrub	SH5	Very High	66	0.009%	66	**90**	**0.012%**	**66**	90	0.012%	66
Shrub	SH6	High	4	0.001%	4	4	0.001%	4	4	0.001%	4
Shrub	SH7	Very High	24	0.003%	24	-	-	-	-	-	-
Timber-Understory	TU1	Low	6223	0.859%	6223	6223	0.859%	6223	-	-	-
Timber-Understory	TU2	Low	203173	28.059%	203173	203173	28.059%	203173	**209396**	**28.918%**	**203173**
Timber-Understory	TU5	Moderate	37788	5.219%	37788	37788	5.219%	37788	37788	5.219%	37788
Timber-Litter	TL1	Low	3104	0.429%	3104	-	-	-	-	-	-
Timber-Litter	TL2	Low	887	0.122%	887	-	-	-	-	-	-
Timber-Litter	TL3	Low	16289	2.250%	16289	**21400**	**2.955%**	**16289**	21400	2.955%	16289
Timber-Litter	TL4	Low	161	0.022%	161	-	-	-	-	-	-
Timber-Litter	TL5	Low	959	0.132%	959	-	-	-	-	-	-
Timber-Litter	TL6	Moderate	8604	1.188%	8604	**8608**	**1.189%**	**8604**	8608	1.189%	8604
Timber-Litter	TL8	Low	100483	13.877%	100483	100483	13.877%	100483	100483	13.877%	100483
Timber-Litter	TL9	Moderate	4	0.001%	4	-	-	-	-	-	-
	Total:		724100	100.0%	724100	724100	100.0%	713298	724100	100.0%	707075

FUEL TYPE COMBINATION			THREE: GS2+TL6			FOUR: SH2+GS1			FIVE: TL8+TL3		
Fuel Group	Fuel Code	Flame Length	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	NB	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*
Grass	GR1	Low	-	-	-	-	-	-	-	-	-
Grass	GR2	No affect	79074	10.920%	77022	79074	10.920%	77022	**79074**	**10.920%**	**77022**
Grass	GR3	No affect	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS1	Low	17131	2.366%	14748	-	-	-	-	-	-
Grass-Shrub	GS2	Moderate	**88849**	**12.270%**	**80237**	88849	12.270%	80237	88849	12.270%	80237
Grass-Shrub	GS3	Moderate	-	-	-	-	-	-	-	-	-
Shrub	SH1	Low	-	-	-	-	-	-	-	-	-
Shrub	SH2	Low	122091	16.861%	120867	**139222**	**19.227%**	**120867**	139222	19.227%	120867
Shrub	SH3	Low	-	-	-	-	-	-	-	-	-
Shrub	SH5	Very High	90	0.012%	66	90	0.012%	66	90	0.012%	66
Shrub	SH6	High	4	0.001%	4	4	0.001%	4	4	0.001%	4
Shrub	SH7	Very High	-	-	-	-	-	-	-	-	-
Timber-Understory	TU1	Low	-	-	-	-	-	-	-	-	-
Timber-Understory	TU2	Low	209396	28.918%	203173	209396	28.918%	203173	209396	28.918%	203173
Timber-Understory	TU5	Moderate	37788	5.219%	37788	37788	5.219%	37788	37788	5.219%	37788
Timber-Litter	TL1	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL2	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL3	Low	21400	2.955%	16289	21400	2.955%	16289	-	-	-
Timber-Litter	TL4	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL5	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL6	Moderate	-	-	-	-	-	-	-	-	-
Timber-Litter	TL8	Low	100483	13.877%	100483	100483	13.877%	100483	**121883**	**16.832%**	**100483**
Timber-Litter	TL9	Moderate	-	-	-	-	-	-	-	-	-
	Total:		724100	100.0%	698471	724100	100.0%	683723	724100	100.0%	667434

FUEL TYPE COMBINATION			SIX: GS2+TU5			SEVEN: TU2+TL8			EIGHT: TU2+SH2		
Fuel Group	Fuel Code	Flame Length	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.	Frequency	Freq. %	Exact M.
Non-burnable	*NB1+3+8+9*	NB	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*	*47794*	*6.600%*	*47794*
Grass	GR1	Low	-	-	-	-	-	-	-	-	-
Grass	GR2	No affect	79074	10.920%	77022	79074	10.920%	77022	79074	10.920%	77022
Grass	GR3	No affect	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS1	Low	-	-	-	-	-	-	-	-	-
Grass-Shrub	GS2	Moderate	**126637**	**17.489%**	**80237**	126637	17.489%	80237	126637	17.489%	80237
Grass-Shrub	GS3	Moderate	-	-	-	-	-	-	-	-	-
Shrub	SH1	Low	-	-	-	-	-	-	-	-	-
Shrub	SH2	Low	139222	19.227%	120867	139222	19.227%	120867	-	-	-
Shrub	SH3	Low	-	-	-	-	-	-	-	-	-
Shrub	SH5	Very High	90	0.012%	66	90	0.012%	66	90	0.012%	66
Shrub	SH6	High	4	0.001%	4	4	0.001%	4	4	0.001%	4
Shrub	SH7	Very High	-	-	-	-	-	-	-	-	-
Timber-Understory	TU1	Low	-	-	-	-	-	-	-	-	-
Timber-Understory	TU2	Low	209396	28.918%	203173	**331279**	**45.751%**	**203173**	470501	64.978%	203173
Timber-Understory	TU5	Moderate	-	-	-	-	-	-	-	-	-
Timber-Litter	TL1	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL2	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL3	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL4	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL5	Low	-	-	-	-	-	-	-	-	-
Timber-Litter	TL6	Moderate	-	-	-	-	-	-	-	-	-
Timber-Litter	TL8	Low	121883	16.832%	100483	-	-	-	-	-	-
Timber-Litter	TL9	Moderate	-	-	-	-	-	-	-	-	-
	Total:		724100	100.0%	629646	724100	100.0%	529163	724100	100.0%	408296

Low	High
Moderate	Very High

*Bold written numbers indicate growing class.

ONE — Rules:
1 Every class below 0,85%,
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

TWO — Rules:
1 Lowest Freq. %
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

THREE — Rules:
1 Lowest Freq. %
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

Fuel Code	CHARACTERISTICS
GS2	M,H,M
TU5	VH,M,M
TL6	M,M,M

Therefore: GS2+TL6

FOUR — Rules:
1 Lowest Freq. %
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

FIVE — Rules:
1 Lowest Freq. %
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

SIX — Rules:
1 Lowest Freq. %
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

SEVEN — Rules:
1 Lowest Freq. %
2 No aggregation outside FLAME LENGTH similarity
3 If possible: within Fuel Gr.

Fuel Code	CHARACTERISTICS
SH2	M,L,L
TU2	M,M,L
TL8	M,M,L

Therefore: TU2+TL8

EIGHT — Rules:
1 Last avaialbe combination.
2
3

LIST OF REFERENCES

Abreu, S. J. D. (2021). Toward a Holistic Approach: Considerations for Improved Collaboration in Wildfire Management. *Open Journal of Forestry*, *12*(1), Article 1. https://doi.org/10.4236/ojf.2022.121006

Ager, A. A., & Finney, M. A. (2009). Application of wildfire simulation models for risk analysis. *Geophysical Research Abstracts. 11: EGU2009-5489*. https://research.fs.usda.gov/treesearch/42278

Al Abri, I., & Grogan, K. (2021). The Impact of Heterogeneous Management Interests in Reducing Social Losses from Wildfire Externalities. *Forests*, *12*(10), Article 10. https://doi.org/10.3390/f12101326

Albini, F. A. (1976). *Estimating Wildfire Behavior and Effects*. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.

Alipour, M., La Puma, I., Picotte, J., Shamsaei, K., Rowell, E., Watts, A., Kosovic, B., Ebrahimian, H., & Taciroglu, E. (2023). A Multimodal Data Fusion and Deep Learning Framework for Large-Scale Wildfire Surface Fuel Mapping. *Fire*, *6*(2), Article 2. https://doi.org/10.3390/fire6020036

Alley, R. B., Emanuel, K. A., & Zhang, F. (2019). Advances in weather prediction. *Science*, *363*(6425), 342–344. https://doi.org/10.1126/science.aav7274

Anderson, H. E. (1982). *Aids to determining fuel models for estimating fire behavior* (INT-GTR-122; p. INT-GTR-122). U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. https://doi.org/10.2737/INT-GTR-122

Andrews, P. L. (2013). Current status and future needs of the BehavePlus Fire Modeling System. *International Journal of Wildland Fire*, *23*(1), 21–33. https://doi.org/10.1071/WF12167

Andrews, P. L., & Queen, Ll. P. (2001). Fire modeling and information system technology. *International Journal of Wildland Fire*, *10*(4), 343. https://doi.org/10.1071/WF01033

Aparício, B. A., Pereira, J. M. C., Santos, F. C., Bruni, C., & Sá, A. C. L. (2022). Combining wildfire behaviour simulations and network analysis to support wildfire management: A Mediterranean landscape case study. *Ecological Indicators*, *137*, 108726. https://doi.org/10.1016/j.ecolind.2022.108726

Aragoneses, E., García, M., Salis, M., Ribeiro, L. M., & Chuvieco, E. (2022). *Classification and mapping of European fuels using a hierarchical-multipurpose fuel classification system*. https://doi.org/10.5194/essd-2022-184

Arroyo, L. A., Pascual, C., & Manzanera, J. A. (2008a). Fire models and methods to map fuel types: The role of remote sensing. *Forest Ecology and Management*, *256*(6), 1239–1252. https://doi.org/10.1016/j.foreco.2008.06.048

Arroyo, L. A., Pascual, C., & Manzanera, J. A. (2008b). Fire models and methods to map fuel types: The role of remote sensing. *Forest Ecology and Management*, *256*(6), 1239–1252. https://doi.org/10.1016/j.foreco.2008.06.048

Bakhshaii, A., & Johnson, E. A. (2019). A review of a new generation of wildfire–atmosphere modeling. *Canadian Journal of Forest Research*, *49*(6), 565–574. https://doi.org/10.1139/cjfr-2018-0138

Barboni, T., Morandini, F., Rossi, L., Molinier, T., & Santoni, P.-A. (2012). Relationship Between Flame Length and Fireline Intensity Obtained by Calorimetry at Laboratory

Scale. *Combustion Science and Technology*, *184*(2), 186–204. https://doi.org/10.1080/00102202.2011.625373

Barros, A. M. G., Ager, A. A., Day, M. A., Krawchuk, M. A., & Spies, T. A. (2018). Wildfires managed for restoration enhance ecological resilience. *Ecosphere*, *9*(3), e02161. https://doi.org/10.1002/ecs2.2161

Benali, A., Ervilha, A. R., Sá, A. C. L., Fernandes, P. M., Pinto, R. M. S., Trigo, R. M., & Pereira, J. M. C. (2016). Deciphering the impact of uncertainty on the accuracy of large wildfire spread simulations. *Science of The Total Environment*, *569–570*, 73–85. https://doi.org/10.1016/j.scitotenv.2016.06.112

Bian, L., & Butler, R. (n.d.). *Comparing Effects of Aggregation Methods on Statistical and Spatial Properties of Simulated Spatial Data*.

Burgan, R. E., Klaver, R. W., & Klaver, J. M. (1998). Fuel Models and Fire Potential From Satellite and Surface Observations. *International Journal of Wildland Fire*, *8*(3), 159–170. https://doi.org/10.1071/wf9980159

Cardil, A., Monedero, S., Schag, G., de-Miguel, S., Tapia, M., Stoof, C. R., Silva, C. A., Mohan, M., Cardil, A., & Ramirez, J. (2021). Fire behavior modeling for operational decision-making. *Current Opinion in Environmental Science & Health*, *23*, 100291. https://doi.org/10.1016/j.coesh.2021.100291

Cardil, A., Monedero, S., SeLegue, P., Navarrete, M. Á., de-Miguel, S., Purdy, S., Marshall, G., Chavez, T., Allison, K., Quilez, R., Ortega, M., Silva, C. A., & Ramirez, J. (2023). Performance of operational fire spread models in California. *International Journal of Wildland Fire*, *32*(11), 1492–1502. https://doi.org/10.1071/WF22128

Cardil, A., Monedero, S., Silva, C. A., & Ramirez, J. (2019). Adjusting the rate of spread of fire simulations in real-time. *Ecological Modelling*, *395*, 39–44. https://doi.org/10.1016/j.ecolmodel.2019.01.017

Carter, T. (2014). An introduction to information theory and entropy. *2014-09-03*.

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M. P., Vilar, L., Martínez, J., Martín, S., Ibarra, P., de la Riva, J., Baeza, J., Rodríguez, F., Molina, J. R., Herrera, M. A., & Zamora, R. (2010). Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecological Modelling*, *221*(1), 46–58. https://doi.org/10.1016/j.ecolmodel.2008.11.017

Clelland, A. A., Marshall, G. J., Baxter, R., Potter, S., Talucci, A. C., Rady, J. M., Genet, H., Rogers, B. M., & Natali, S. M. (2024). Annual and Seasonal Patterns of Burned Area Products in Arctic-Boreal North America and Russia for 2001–2020. *Remote Sensing*, *16*(17), Article 17. https://doi.org/10.3390/rs16173306

Deluca, T. H., & Boisvenue, C. (2012). Boreal forest soil carbon: Distribution, function and modelling. *Forestry: An International Journal of Forest Research*, *85*(2), 161–184. https://doi.org/10.1093/forestry/cps003

Demarchi, D. A. (2011). *An Introduction to the Ecoregions of British Columbia*.

Egorova, V. N., Trucchia, A., & Pagnini, G. (2022). Fire-spotting generated fires. Part II: The role of flame geometry and slope. *Applied Mathematical Modelling*, *104*, 1–20. https://doi.org/10.1016/j.apm.2021.11.010

Filippi, J.-B., Mallet, V., & Nader, B. (2013). Representation and evaluation of wildfire propagation simulations. *International Journal of Wildland Fire*, *23*(1), 46–57. https://doi.org/10.1071/WF12202

Finney, M. A. (1998). *FARSITE: Fire Area Simulator-model development and evaluation* (RMRS-RP-4; p. RMRS-RP-4). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. https://doi.org/10.2737/RMRS-RP-4

Finney, M. A. (2002). Fire growth using minimum travel time methods. *Canadian Journal of Forest Research*, *32*(8), 1420–1424. https://doi.org/10.1139/x02-068

Finney, M. A. (2006). An Overview of FlamMap Fire Modeling Capabilities. *In: Andrews, Patricia L.; Butler, Bret W., Comps. 2006. Fuels Management-How to Measure Success: Conference Proceedings. 28-30 March 2006; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 213-220*, *041*. https://www.fs.usda.gov/research/treesearch/25948

Finney, M. A. (2023, March 3). *The Rothermel Fire Spread Model: A 50-year milestone in fire research | Missoula Fire Sciences Laboratory*. https://www.firelab.org/news/rothermel-fire-spread-model-50-year-milestone-fire-research

Firelab. (2017, July 20). WindNinja Tutorial 1: The Basics [U.S. Forest Service.]. *WindNinja Tutorial 1: The Basics.* https://firelab.github.io/windninja/pdf/WindNinja_tutorial1.pdf

García-Cimarras, A., Manzanera, J. A., & Valbuena, R. (2021). Analysis of Mediterranean Vegetation Fuel Type Changes Using Multitemporal LiDAR. *Forests*, *12*(3), Article 3. https://doi.org/10.3390/f12030335

Goss, M., Swain, D. L., Abatzoglou, J. T., Sarhadi, A., Kolden, C. A., Williams, A. P., & Diffenbaugh, N. S. (2020). Climate change is increasing the likelihood of extreme autumn wildfire conditions across California. *Environmental Research Letters*, *15*(9), 094016. https://doi.org/10.1088/1748-9326/ab83a7

Hall, S. A., & Burke, I. C. (2006). Considerations for characterizing fuels as inputs for fire behavior models. *Forest Ecology and Management*, *227*(1), 102–114. https://doi.org/10.1016/j.foreco.2006.02.022

Halofsky, J. E., Peterson, D. L., & Harvey, B. J. (2020). Changing wildfire, changing forests: The effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA. *Fire Ecology*, *16*(1), 4. https://doi.org/10.1186/s42408-019-0062-8

Hartter, J., Hamilton, L. C., Ducey, M. J., Boag, A. E., Salerno, J. D., Christoffersen, N. D., Oester, P. T., Palace, M. W., & Stevens, F. R. (2020). Finding common ground: Agreement on increasing wildfire risk crosses political lines. *Environmental Research Letters*, *15*(6), 065002. https://doi.org/10.1088/1748-9326/ab7ace

Hazlett, C., & Mildenberger, M. (2020). Wildfire Exposure Increases Pro-Environment Voting within Democratic but Not Republican Areas. *American Political Science Review*, *114*(4), 1359–1365. https://doi.org/10.1017/S0003055420000441

He, T., Lamont, B. B., & Pausas, J. G. (2019). Fire as a key driver of Earth's biodiversity. *Biological Reviews*, *94*(6), 1983–2010. https://doi.org/10.1111/brv.12544

Herrera, M., Natarajan, S., Coley, D. A., Kershaw, T., Ramallo-González, A. P., Eames, M., Fosas, D., & Wood, M. (2017). A review of current and future weather data for building simulation. *Building Services Engineering Research and Technology*, *38*(5), 602–627. https://doi.org/10.1177/0143624417705937

Illingworth, A. J., Cimini, D., Gaffard, C., Haeffelin, M., Lehmann, V., Löhnert, U., O'Connor, E. J., & Ruffieux, D. (2015). Exploiting Existing Ground-Based Remote Sensing Networks to Improve High-Resolution Weather Forecasts. *Bulletin of the American Meteorological Society*, *96*(12), 2107–2125. https://doi.org/10.1175/BAMS-D-13-00283.1

Johnson, E. A., & Wagner, C. E. V. (1985). The theory and use of two fire history models. *Canadian Journal of Forest Research*, *15*(1), 214–220. https://doi.org/10.1139/x85-039

Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. J. S. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, *6*(1), 7537. https://doi.org/10.1038/ncomms8537

Kalabokidis, K., Athanasis, N., Palaiologou, P., Vasilakos, C., Finney, M., & Ager, A. (2014). Minimum travel time algorithm for fire behavior and burn probability in a parallel computing environment. In D. X. Viegas, *Advances in forest fire research* (pp. 882–891). Imprensa da Universidade de Coimbra. https://doi.org/10.14195/978-989-26-0884-6_95

Kitzberger, T., Brown, P. M., Heyerdahl, E. K., Swetnam, T. W., & Veblen, T. T. (2007). Contingent Pacific–Atlantic Ocean influence on multicentury wildfire synchrony over western North America. *Proceedings of the National Academy of Sciences*, *104*(2), 543–548. https://doi.org/10.1073/pnas.0606078104

Kreider, M. R., Higuera, P. E., Parks, S. A., Rice, W. L., White, N., & Larson, A. J. (2024). Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation. *Nature Communications*, *15*(1), 2412. https://doi.org/10.1038/s41467-024-46702-0

Laamrani, A., Valeria, O., Bergeron, Y., Fenton, N., Cheng, L. Z., & Anyomi, K. (2014). Effects of topography and thickness of organic layer on productivity of black spruce boreal forests of the Canadian Clay Belt region. *Forest Ecology and Management*, *330*, 144–157. https://doi.org/10.1016/j.foreco.2014.07.013

Loehman, R. A., Keane, R. E., & Holsinger, L. M. (2020). Simulation Modeling of Complex Climate, Wildfire, and Vegetation Dynamics to Address Wicked Problems in Land Management. *Frontiers in Forests and Global Change*, *3*. https://doi.org/10.3389/ffgc.2020.00003

Mansoor, S., Farooq, I., Kachroo, M. M., Mahmoud, A. E. D., Fawzy, M., Popescu, S. M., Alyemeni, M. N., Sonne, C., Rinklebe, J., & Ahmad, P. (2022). Elevation in wildfire frequencies with respect to the climate change. *Journal of Environmental Management*, *301*, 113769. https://doi.org/10.1016/j.jenvman.2021.113769

McKenzie, D., & Perera, A. H. (2015). Modeling Wildfire Regimes in Forest Landscapes: Abstracting a Complex Reality. In A. H. Perera, B. R. Sturtevant, & L. J. Buse (Eds.), *Simulation Modeling of Forest Landscape Disturbances* (pp. 73–92). Springer International Publishing. https://doi.org/10.1007/978-3-319-19809-5_4

McNorton, J. R., & Di Giuseppe, F. (2024). A global fuel characteristic model and dataset for wildfire prediction. *Biogeosciences*, *21*(1), 279–300. https://doi.org/10.5194/bg-21-279-2024

Molina, J. R., Lora, A., Prades, C., & Rodríguez y Silva, F. (2019). Roadside vegetation planning and conservation: New approach to prevent and mitigate wildfires based on fire ignition potential. *Forest Ecology and Management*, *444*, 163–173. https://doi.org/10.1016/j.foreco.2019.04.034

Moritz, M. A., Batllori, E., Bradstock, R. A., Gill, A. M., Handmer, J., Hessburg, P. F., Leonard, J., McCaffrey, S., Odion, D. C., Schoennagel, T., & Syphard, A. D. (2014). Learning to coexist with wildfire. *Nature*, *515*(7525), 58–66. https://doi.org/10.1038/nature13946

Parsons, R. A., Linn, R. R., Pimont, F., Hoffman, C., Sauer, J., Winterkamp, J., Sieg, C. H., & Jolly, W. M. (2017). Numerical Investigation of Aggregated Fuel Spatial Pattern Impacts on Fire Behavior. *Land*, *6*(2), Article 2. https://doi.org/10.3390/land6020043

Penman, T. D., McColl-Gausden, S. C., Cirulis, B. A., Kultaev, D., Ababei, D. A., & Bennett, L. T. (2022). Improved accuracy of wildfire simulations using fuel hazard estimates based on environmental data. *Journal of Environmental Management*, *301*, 113789. https://doi.org/10.1016/j.jenvman.2021.113789

Perry. (1999). *A GIS-supported model for the simulation of the spatial structure of wildland fire, Cass Basin, New Zealand—Perry—1999—Journal of Applied Ecology—Wiley Online Library*. https://besjournals.onlinelibrary.wiley.com/doi/10.1046/j.1365-2664.1999.00416.x

Pham, B. T., Jaafari, A., Avand, M., Al-Ansari, N., Dinh Du, T., Yen, H. P. H., Phong, T. V., Nguyen, D. H., Le, H. V., Mafi-Gholami, D., Prakash, I., Thi Thuy, H., & Tuyen, T. T. (2020). Performance Evaluation of Machine Learning Methods for Forest Fire Modeling and Prediction. *Symmetry*, *12*(6), Article 6. https://doi.org/10.3390/sym12061022

Ramírez, J., Monedero, S., & Buckley, D. (2011). New approaches in fire simulations analysis with Wildfire Analyst. *South Africa*.

Rashmi, & Ghose, U. (2020). Hybrid Entropy Method for Large Data Set Reduction Using MLP-ANN and SVM Classifiers. In U. Batra, N. R. Roy, & B. Panda (Eds.), *Data Science and Analytics* (pp. 49–63). Springer. https://doi.org/10.1007/978-981-15-5827-6_5

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a General Theory of Planning. *Policy Sciences*, *4*(2), 155–169.

Robinson, S. (2023). Exploring the relationship between simulation model accuracy and complexity. *Journal of the Operational Research Society*, *74*(9), 1992–2011. https://doi.org/10.1080/01605682.2022.2122740

Rochoux, M. C., Delmotte, B., Cuenot, B., Ricci, S., & Trouvé, A. (2013). Regional-scale simulations of wildland fire spread informed by real-time flame front observations. *Proceedings of the Combustion Institute*, *34*(2), 2641–2647. https://doi.org/10.1016/j.proci.2012.06.090

Rösch, M., Nolde, M., Ullmann, T., & Riedlinger, T. (2024). Data-Driven Wildfire Spread Modeling of European Wildfires Using a Spatiotemporal Graph Neural Network. *Fire*, *7*(6), Article 6. https://doi.org/10.3390/fire7060207

Rothermel, R. C. (1972). *A Mathematical Model for Predicting Fire Spread in Wildland Fuels*. Intermountain Forest & Range Experiment Station, Forest Service, U.S. Department of Agriculture.

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *International Journal of Geosciences*, *08*(04), Article 04. https://doi.org/10.4236/ijg.2017.84033

Schauberger, B., Jägermeyr, J., & Gornott, C. (2020). A systematic review of local to regional yield forecasting approaches and frequently used data resources. *European Journal of Agronomy*, *120*, 126153. https://doi.org/10.1016/j.eja.2020.126153

Schoennagel, T., Balch, J. K., Brenkert-Smith, H., Dennison, P. E., Harvey, B. J., Krawchuk, M. A., Mietkiewicz, N., Morgan, P., Moritz, M. A., Rasker, R., Turner, M. G., & Whitlock, C. (2017). Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences*, *114*(18), 4582–4590. https://doi.org/10.1073/pnas.1617464114

Schwerdtner, P., Law, F., Wang, Q., Gazen, C., Chen, Y.-F., Ihme, M., & Peherstorfer, B. (2024). Uncertainty quantification in coupled wildfire–atmosphere simulations at scale. *PNAS Nexus*, *3*(12), pgae554. https://doi.org/10.1093/pnasnexus/pgae554

Scott, J. H., & Burgan, R. E. (2005). *Standard fire behavior fuel models: A comprehensive set for use with Rothermel's surface fire spread model* (RMRS-GTR-153; p. RMRS-GTR-153). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. https://doi.org/10.2737/RMRS-GTR-153

Šerić, L., Marasović, J., & Stipanicev, D. (2005). *Fire modeling in forest fire management*.

Shang, B. Z., He, H. S., Crow, T. R., & Shifley, S. R. (2004). Fuel load reductions and fire risk in central hardwood forests of the united states: A spatial simulation study. *Ecological Modelling*, *180*(1), 89–102. https://doi.org/10.1016/j.ecolmodel.2004.01.020

Steel, Z. L., Safford, H. D., & Viers, J. H. (2015). The fire frequency-severity relationship and the legacy of fire suppression in California forests. *Ecosphere*, *6*(1), art8. https://doi.org/10.1890/ES14-00224.1

Stefanidou, A., Gitas, I. Z., & Katagis, T. (2022). A national fuel type mapping method improvement using sentinel-2 satellite data. *Geocarto International*, *37*(4), 1022–1042. https://doi.org/10.1080/10106049.2020.1756460

Stein, S. M., Alig, R. J., White, E. M., Comas, S. J., Carr, M., Eley, M., Elverum, K., O'Donnell, M., Theobald, D. M., Cordell, K., Haber, J., & Beauvais, T. W. (2007). *National forests on the edge: Development pressures on America's national forests and grasslands.* (PNW-GTR-728; p. PNW-GTR-728). U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/PNW-GTR-728

Syifa, M., Panahi, M., & Lee, C.-W. (2020). Mapping of Post-Wildfire Burned Area Using a Hybrid Algorithm and Satellite Data: The Case of the Camp Fire Wildfire in California, USA. *Remote Sensing*, *12*(4), Article 4. https://doi.org/10.3390/rs12040623

Taneja, R., Hilton, J., Wallace, L., Reinke, K., & Jones, S. (2021). Effect of fuel spatial resolution on predictive wildfire models. *International Journal of Wildland Fire*, *30*(10), 776–789. https://doi.org/10.1071/WF20192

Thomas, D., Butry, D., Gilbert, S., Webb, D., & Fung, J. (2017). *The Costs and Losses of Wildfires: A Literature Review*. https://doi.org/10.6028/NIST.SP.1215

van Hees, P. (2013). Validation and Verification of Fire Models for Fire Safety Engineering. *Procedia Engineering*, *62*, 154–168. https://doi.org/10.1016/j.proeng.2013.08.052

Vogler, K., Ager, A., Day, M., Jennings, M., & Bailey, J. (2015). Prioritization of Forest Restoration Projects: Tradeoffs between Wildfire Protection, Ecological Restoration and Economic Objectives. *Forests*, *6*(12), 4403–4420. https://doi.org/10.3390/f6124375

Walker, X. J., Baltzer, J. L., Bourgeau-Chavez, L., Day, N. J., Dieleman, C. M., Johnstone, J. F., Kane, E. S., Rogers, B. M., Turetsky, M. R., Veraverbeke, S., & Mack, M. C. (2020). Patterns of Ecosystem Structure and Wildfire Carbon Combustion Across Six Ecoregions of the North American Boreal Forest. *Frontiers in Forests and Global Change*, *3*. https://doi.org/10.3389/ffgc.2020.00087

Wunder, S., Calkin, D. E., Charlton, V., Feder, S., Martínez de Arano, I., Moore, P., Rodríguez y Silva, F., Tacconi, L., & Vega-García, C. (2021). Resilient landscapes to prevent catastrophic forest fires: Socioeconomic insights towards a new paradigm. *Forest Policy and Economics*, *128*, 102458. https://doi.org/10.1016/j.forpol.2021.102458

Young, D. J. N., Koontz, M. J., & Weeks, J. (2022). Optimizing aerial imagery collection and processing parameters for drone-based individual tree mapping in structurally complex conifer forests. *Methods in Ecology and Evolution*, *13*(7), 1447–1463. https://doi.org/10.1111/2041-210X.13860

Zhao, B., Zhuang, Q., Shurpali, N., Köster, K., Berninger, F., & Pumpanen, J. (2021a). North American boreal forests are a large carbon source due to wildfires from 1986 to 2016. *Scientific Reports*, *11*(1), 7723. https://doi.org/10.1038/s41598-021-87343-3

Zhao, B., Zhuang, Q., Shurpali, N., Köster, K., Berninger, F., & Pumpanen, J. (2021b). North American boreal forests are a large carbon source due to wildfires from 1986 to 2016. *Scientific Reports*, *11*, 7723. https://doi.org/10.1038/s41598-021-87343-3

Zimmerman, T. (2011). Fire science application and integration in support of decision making. *In: Proceedings of the 5th International Wildland Fire Conference; 9-13 May 2011; Sun City, South Africa. 10 p.* https://research.fs.usda.gov/treesearch/39278