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The Prevalence of Complexity in Flammable Ecosystems and the Application of Complex Systems Theory to the Simulation of Fire Spread

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Résumé

Les forêts sont une ressource naturelle importante sur le plan écologique, culturel et économique, et sont confrontées à des défis croissants en raison des changements climatiques. Ces défis sont difficiles à prédire en raison de la nature complexe des interactions entre le climat et la végétation, dont une le feu. Compte tenu de l'importance des écosystèmes forestiers, des dangers potentiels des feux de forêt et de la complexité de leurs interactions, il est primordial d'acquérir une compréhension de ces systèmes à travers le prisme de la science des systèmes complexes. La science des systèmes complexes et ses techniques de modélisation associées peuvent fournir des informations sur de tels systèmes que les techniques de modélisation traditionnelles ne peuvent pas. Là où les techniques statistiques et basées sur équations cherchent à contourner la dynamique non-linéaire, auto-organisée et émergente des systèmes complexes, les approches de modélisation telles que les automates cellulaires et les modèles à base d'agents (MBA) embrassent cette complexité en cherchant à reproduire les interactions clés de ces systèmes. Bien qu'il existe de nombreux modèles de comportement du feu qui tiennent compte de la complexité, les MBA offrent un terrain d'entente entre les modèles de simulation empiriques et physiques qui peut fournir de nouvelles informations sur le comportement et la simulation du feu. Cette étude vise à améliorer notre compréhension du feu dans le contexte de la science des systèmes complexes en développant un tel MBA de propagation du feu. Le modèle utilise des données de type de carburant, de terrain et de météo pour créer l'environnement des agents. Le modèle est évalué à l'aide d'une étude de cas d'un incendie naturel qui s'est produit en 2001 dans le sud-ouest de l'Alberta, au Canada. Les résultats de cette étude confirment la valeur de la prise en compte de la complexité lors de la simulation d'incendies de forêt et démontrent l'utilité de la modélisation à base d'agents pour une telle tâche.

Mots-clés : modèle à base d'agents (MBA/ABM) ; perturbations forestières ; écologie du paysage ; comportement du feu ; simulation d'incendie de forêt ; systèmes complexes

Abstract

Forests are an ecologically, culturally, and economically important natural resource that face growing challenges due to climate change. These challenges are difficult to predict due to the complex nature of the interactions between climate and vegetation. Furthermore, fire is intrinsically linked to both climate and vegetation and is, itself, complex. Given the importance of forest ecosystems, the potential dangers of forest fires, and the complexity of their interactions, it is paramount to gain an understanding of these systems through the lens of complex systems science. Complex systems science and its attendant modeling techniques can provide insights on such systems that traditional modelling techniques cannot. Where statistical and equation-based techniques seek to work around the non-linear, self-organized, and emergent dynamics of complex systems, modelling approaches such as Cellular Automata and Agent-Based Models (ABM) embrace this complexity by seeking to reproduce the key interactions of these systems. While there exist numerous models of fire behaviour that account for complexity, ABM offers a middle ground between empirical and physical simulation models that may provide new insights into fire behaviour and simulation. This study seeks to add to our understanding of fire within the context of complex systems science by developing such an ABM of fire spread. The model uses fuel-type, terrain, and weather data to create the agent environment. The model is evaluated with a case study of a natural fire that occurred in 2001 in southwestern Alberta, Canada. Results of this study support the value of considering complexity when simulating forest fires and demonstrate the utility of ABM for such a task.

Keywords: agent-based model (ABM); forest disturbances; landscape ecology; fire behaviour; wildfire simulation; complex systems science

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Lexicon and Abbreviations

ABM	Agent-Based Model / Agent-Based Modelling
ABWiSE	Agent-Based Wildfire Simulation Environment
CA	Cellular Automata
CFD	Computational Fluid Dynamics
CFFDRS	Canadian Forest Fire Danger Rating System
DGVM	Dynamic Global Vegetation Model
EP	Energy Packet
FBP	Fire Behaviour Prediction system
FFMC	Fine Fuel Moisture Code
FoM	Figure of Merit
FWI	Fire Weather Index
ISI	Initial Spread Index
LFSM	Landscape Fire Succession Model
MARS	Multiple Adaptive Regression Splines
MBA	Modèlisation à Base d'Agents
MBP	Mountain Pine Beetle
MDT	Mountain Daylight Time
pyroCb	Pyrocumulonimbus
RoS	Rate of Spread
SA	Sensitivity Analysis
UA	Uncertainty Analysis
VOC	Volatile Organic Compounds
VOMAS	Virtual Overlay Multi-Agent System
WRF	Weather Research and Forecasting
WUI	Wildland-Urban Interface

To my parents, Janusz and Fabienne,

who taught me curiosity and perseverance.

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Chapter 1 - Introduction and context

1. Introduction

Invoked by Waldo Tobler in 1970, the first law of geography states that "Everything is related, but near things are more related than far things." While this statement pertains more to the spatial nature of interconnectedness, it nevertheless tells us that geography is the study of connected things. Whatever part of the world under study, it does not exist in a void, and is part of a system of interacting elements that connect through processes across and between scales. By looking at these elements and their interactions, we can better understand how and why higher-level characteristics emerge. Complex systems theory provides the means to study these connections and interactions and the resulting characteristics.

In brief, a complex system is one consisting of multiple parts interacting in ways that produce emergent behaviour. This emergence is the result of non-linear dynamics that are not easily predictable by classical mathematical means, and therefore simulation is the primary method for studying complex systems (Batty & Torrens, 2005). Section 2 of this chapter goes into more detail about complex systems and some modelling techniques, and Section 5 describes the general process of complex systems modelling. Among the available simulation techniques, Agent Based Modelling (ABM) is a versatile tool whose basis is the interaction between heterogeneous elements called agents (so-called because they have agency within the simulated world, in acting upon and reacting to the world and other agents) (Sengupta & Sieber, 2007).

Going back to the idea that most of the world consists of interconnected systems, a prime and vital example are forest ecosystems (Filotas et al., 2014; Parrott, 2010). Forests are intrinsically linked to the global climate system, where changes in one feed back into the other, via temperature, precipitation, carbon cycling, respiration, etc. Affecting and affected by both climate and vegetation, fire is another vector of feedback between climate and vegetation (Harris, Remenyi, Williamson, Bindoff, & Bowman, 2016; Messier et al., 2015). The patterns of fire activity that form over time are a result of interactions with climate and vegetation, including the evolution of fire-adapted species (both fire-encouraging and firesuppressing) (Parks, Holsinger, Miller, & Nelson, 2015). At a smaller scale, each individual fire is a complex system in and of itself, dependent on vegetation and weather conditions to start and grow, but feeding back into the atmosphere over its evolution. While individual fires act on a miniscule scale compared to the global climate, complexity and emergence at that scale can inform emergence at the larger scale. Fire, as a necessary component of many ecosystems around the world, is also destructive and dangerous to human lives and property (Bowman et al., 2009; Hammer, Stewart, & Radeloff, 2009). Given also the increasing devastation of forest fires in recent history, linked to climate change, it is more relevant than ever to study them (Chuvieco et al., 2016).

1.1 Research questions

Given that fires are complex, it makes sense to think of them from a complex systems viewpoint. Doing so opens up a toolset of modelling approaches and techniques that can potentially offer new insights into fire behaviour or how to simulate fire behaviour. Agent-Based Modelling, mentioned earlier, offers an intriguing way to simulate fire spread; like an agent, fire is a spatial phenomenon that reacts to local stimuli (fuel, wind, terrain) and acts upon its environment (consuming fuel and affecting wind). This leads us to two broad research questions:

- Can a complex systems approach provide new insights into fire behaviour?
- Can it be simulated with an agent-based modelling approach?

1.2 Research objectives

Answering these questions requires the development and evaluation of an ABM of fire spread. This ABM must incorporate at least the core elements of the system that make fire complex and its evaluation must identify its level of validity enough to make conclusions about the use of ABM for modeling fire spread. This leads us to three research objectives:

- To develop an ABM of forest fire behaviour based on a complex systems approach
- To demonstrate the importance of considering complexity within this model
- To evaluate the model with the best available data

The goal of this research is exploratory, not explanatory. It does not seek to improve our understanding of the processes of fire behaviour at this stage, but rather to see what a new modelling approach can offer. Furthermore, given the difficulties, if not impossibility, of full model validation, the third objective refers instead to evaluation. This objective involves validation efforts, but accepts that the model may not reach a state of validity suitable for reliable predictions of scenarios for which the model is not calibrated. Its validity revolves around the demonstration of ABM applied to forest fires, rather than the exact formulation's ability to predict new fire behaviour.

The rest of this chapter begins with a deeper explanation of complex systems theory, followed by an overview of forests and fire in light of complexity. This aims to demonstrate that it is appropriate to consider both of these as complex systems. Perhaps the best way to study a complex system is not only to model it, but to simulate it (Batty & Torrens, 2005; A. Heppenstall et al., 2021; Puettmann, 2013). Therefore, this chapter follows up with a review of fire models at different scales and levels of complexity, and it ends with a description of a general modelling approach for complex systems. Addressing the research objectives above, the second chapter presents a scientific article that describes and evaluates a model based on a complex system modelling approach, with a literature review that contextualizes it among the most relevant fire behaviour models. Finally, a third chapter presents the general conclusions brought by this research.

2. Complex systems

Complex systems are difficult if not impossible to explain by classical equation or statistic-based means because of certain key properties (Niazi & Hussain, 2013; Parunak, Savit, & Riolo, 1998). Complex systems are dynamic: they change over time and constantly evolve, whether or not the changes are apparent. They are composed of many elements: these can be heterogeneous and they interact with each other. These interactions often involve feedback loops: elements that are not in direct interaction may affect each other through a chain of interactions, possibly between or across scales. These interactions between elements can give rise to self-organisation in the form of hierarchies, groupings, or stable pathways (Puettmann, 2013; Weimer, Miller, & Hill, 2016). The key characteristic of a complex system, and the main reason they are non-linear, is emergence. Through those interactions of myriad elements, patterns form and behaviours appear that are not necessarily predictable based solely on the initial inputs to the system. Because of these properties, the best way to understand, explore, or predict the behaviour of a complex system is to simulate it (Batty & Torrens, 2005; Messina et al., 2008). At the very least, simulation allows interactions over time, something unavailable to classical means.

There are two broad approaches to simulating a complex system, Cellular Automata (CA) and Agent-Based Modeling (ABM). Cellular Automata are a mathematical representation of a complex system wherein a lattice of cells is subject to a set of rules that determine their state and state information is passed between neighboring cells (Gaudreau, Perez, & Drapeau, 2016; Wolfram, 1984). Perhaps the most famous example of a CA is John Conway's Game of Life (Connelly, Berlekamp, Conway, & Guy, 1986), first introduced in 1970. Since then CA models have been used to simulate systems ranging between forests and fires (Hogeweg, 1988; Karafyllidis & Thanailakis, 1997; Yassemi, Dragićević, & Schmidt, 2008), land use and cover change (Kocabas & Dragicevic, 2007) to problems relating to diffusion limited aggregation (Witten & Sander, 1983) and more. However, one of the limits of CA in simulating some systems is the fixed and regular location of the automata. Some complex systems, like ecosystems with roaming prey and predators, need some kind of freedom of movement. Others, instead, may be better represented as networks, where the connectivity between automata is more relevant. In this sense, ABM is the conceptual successor to CA, where agents are computational automata situated in some environment that they can perceive, influence, and react to (Langlois, 2010). The term "agent" reflects the "agency" of the automaton in that it can act upon its environment and with other agents (Grimm et al., 2005).

Because of this agency and the possibility of mobility and interactions among agents and between agents and their environments, ABM is an excellent fit for complex spatial systems (Heppenstall et al., 2021; Langlois, 2010; Torrens, 2010). The focus of both CA and ABM is on complexity from simplicity, i.e., that complex behaviours should emerge from the simplest possible rules. However, the agency and heterogeneity of agents allow for more convoluted, and complex, rules and interactions. This facilitates ABM to address new areas of complexity such as predator-prey relationships (Grimm et al., 2005), environmental planning and policy

(Ager et al., 2018; Pérez & Dragićević, 2010; Spies et al., 2014), evacuation (Helbing & Johansson, 2012) and social networks (Macal & North, 2014), as well as simulate systems that CA could, but with new layers of complexity, such as land use and cover change (Ngo & See, 2012) or forest succession (Keane et al., 2004).

Throughout this thesis, we will discuss a range of models pertaining to forests and fires, each using different approaches and with differing levels of complexity. An objective classification of models is beyond the scope of this work, but we strive to align those presented here on the axis of complexity. The least complex are linear and lack feedback mechanisms, while the most complex feature numerous interacting systems at high granularity. Before getting to the models themselves, we must understand the system in question. Therefore, the next section provides a broad background on forest fires and illustrates how forests and fires both are, and are part of, complex systems. This leads us to the value of simulation modelling and a brief review thereof as applied to fire behaviour.

3. Forests, fires, and complexity

3.1 Forests

Forests cover almost 38% of Canada's land area, consisting of almost 350 million ha, 77% of which is found in the Boreal zone (Natural Resources Canada, 2020). Their cultural, ecological, and economic value makes them an important research topic. Forests are a complex system, exhibiting heterogeneity, hierarchy, self-organization, and non-linearity. Heterogeneity in forests is not limited to biodiversity, but includes variety in time and space, such as age differences among trees that contribute to the biodiversity of understory species as well as disturbance dynamics like gap formation. Even forest stands with little diversity in species can have great intraspecific genetic diversity that can contribute to the emergent resilience of the ecosystem (Filotas et al., 2014). Diversity also exists across larger spatial scales due to soil properties, hydrology, and topography contributing different resources to the ecosystem.

It is the interactions among these heterogeneous components that form the basis for complexity and lead to hierarchy, self-organization, and non-linearity. These interactions can happen across and between spatiotemporal scales. Cross-scale interactions are the basis for the hierarchies present in a complex system (Cash et al., 2006). Trophic levels within a food web serves as a familiar example of hierarchies, where primary producers form a base level, above which lie their consumers, which are in turn dominated by predators (Simon, 1998). A food web itself is a complex system that connects in many ways to broader systems. Socio-economic elements also contribute to the hierarchical organization of forests, where interactions between (human) stakeholders in those systems influences forest development in the form of management, harvesting, and preservation (which themselves may encompass a variety of spatiotemporal scales) (Messier et al., 2015; Parrott & Meyer, 2012; Spies et al., 2014). Hierarchies are also present along a temporal axis, where species longevity, for example, determines the time window over which processes are relevant or planning horizons in forest management (Filotas et al., 2014). In the spatial dimension, hierarchies exist in the scale of influence of individual organisms and plant communities. For a brief example, the Mountain pine beetle (*Dendroctonus ponderosae* Hopkins), is a small wood-boring insect whose collective behaviour can result in large swathes of dead trees (Pérez & Dragićević, 2011; Safranyik & Carroll, 2006). Disturbances also contribute to spatial hierarchies, where small disturbances (e.g., gaps from felled trees, small fires) produce spots where new interactions are available and directly influenced by nearby vegetation (Turner & Simard, 2002). Large disturbances, however, can have vastly different effects. For example, in a large clear-cut, the perimeter is subject to influence by untouched vegetation, but the inner area can suffer soil degradation or follow a successional path unusual for that area of forest (Johnstone et al., 2016; Lesieur, Gauthier, & Bergeron, 2002). Given the variety of effects possible from disturbances of differing sizes, there is a growing trend to mimic natural patterns, such as fires, when actively managing a forest (Drever, Peterson, Messier, Bergeron, & Flannigan, 2006; Hunter, 1993; Messier et al., 2015).

Scale is an important consideration for complexity because small-scale interactions can cause patterns, behaviours, or characteristics to emerge at broader scales. These broad-scale behaviours often act as regulating mechanisms that maintain the lower-level interactions resulting in those patterns and behaviours, leading to an apparent self-organization (Riley & Thompson, 2016; Sneyd, Theraula, Bonabeau, Deneubourg, & Franks, 2001). These mechanisms can in turn act in aggregate to form even higher-level patterns (spatially or temporally). It is important to note that not every small interaction propagates an effect up through scales, and that it is usually the aggregation of small interactions that becomes a pattern at a larger scale. In forest ecosystems, self-organizing behaviours are the driving force behind forest regeneration, and are essential components of forest health (Drever et al., 2006; Johnstone et al., 2016). Forest health is a somewhat ambiguous term, but it generally refers to the ability of a forest to maintain itself and includes productivity, biodiversity, resistance and resilience (Brandt, Flannigan, Maynard, & Thompson, 2013). Competition is a simple form of self-organization that influences the larger-scale pattern of stand composition. For example, Boreal ericaceous shrubs, such as sheep laurel (*Kalmia angustifolia*), exert control on black spruce (*Picea mariana)* growth by reducing nutrient availability, to which black spruce is more sensitive than Kalmia, and by producing allelochemichals which affect the mycorrhizae community and inhibit black spruce seedling growth directly (Yamasaki, Fyles, Egger, & Titus, 1998). Thus, when given the chance (e.g. after a clear-cut or the formation of a gap in the canopy), Kalmia will outcompete black spruce regrowth and maintain its access to sunlight (Reicis et al., 2020).

That particular kind of self-organization is reliant on disturbances. Disturbances are usually exogenous in origin, but forest ecosystems, in turn, influence those disturbances. Some plant species have functional traits that encourage those disturbances by which they regenerate their community. In wetter forests, certain tree species have shallow roots that make them prone to windfall, which encourages gap formation and seedling recruitment of a younger generation of that species (Filotas et al., 2014). In Canada, fire is the main agent of stand renewal across the Boreal forest, and has shaped the landscape for thousands of years (Brandt et al., 2013).

3.2 Fires

3.2.1 Interactions with forests

Wildfires consume an average of about 2 million ha of forest land in Canada annually, although this can vary between years by an order of magnitude and it is difficult to extract a trend due to the complexities of the system (Stocks et al., 2002). Recent years have seen total burned areas well above average (Canadian Forest Service, 2018; McCarten, 2021). Large fires (>200ha) compose 3% of total fires, but account for 97% of area burned, and due in part to the remoteness of Canada's forests, lightning is the main source of ignition for large fires, though human ignitions account for a larger number of fires in general (Stocks et al., 2002).

Given the ubiquity of fires in Canada, and as part of the self-organisation of disturbances, some plant species have evolved to thrive in fire-prone landscapes. Aspen (*Populus tremuloides* Michx), for example, can quickly reclaim burned forest patches by sprouting from stumps and roots (Smith, O'Loughlin, Buck, & St. Clair, 2011). Some trees have even evolved to engage in feedback loops that necessitate and perpetuate fire. In the Boreal forest, jack pine (*Pinus banksiana* Lamb) and lodgepole pine (*Pinus contorta* Douglas ex Loudon) have serotinous cones that only release their seeds under the high temperatures of a stand-replacing fire, and serotiny correlates to dead branch retention, which acts as a fire-ladder that encourages intense crown fires (Bond & Keeley, 2005). The evolutionary benefit of the serotiny-fire feedback loop is since fires clear vegetation from the surface, and to some extent below ground, new seedlings face very little competition from other species. The frequency, pattern, and severity of fires over thousands of years has shaped the Boreal forest into a mosaic of species and stands whose species composition is closely tied to the time since the last fire (Gauthier, Bernier, Kuuluvainen, Shvidenko, & Schepaschenko, 2015).

The evolutionary link between vegetation and fire goes beyond fire-prone landscapes that require and encourage fires, but is also a key factor in the equilibrium between grassland and forest cover in places like Australia and the Great Plains of North America (Bond & Keeley, 2005; Scheffer & Carpenter, 2003). Furthermore, some studies argue that all vegetation is fire-adapted to some extent, as, for example, the temperate forests of the Eastern United States have evolved thick, fire-retardant barks and dense canopies that discourage understory growth (Bond & Keeley, 2005; Pausas & Keeley, 2009).

Another aspect of self-organisation found in the relationship between forests and fires is the accumulation or removal of forest-floor litter (Hurteau, Liang, Westerling, & Wiedinmyer, 2019). Coniferous trees as found in the Boreal forest or the Western US tend to produce a lot of litter that decomposes slowly compared to deciduous forests in the East (Weber & Flannigan, 1997). If dry enough, this bed of litter provides ample fuel for fast-spreading fires.

However, fires are self-limiting, in that they simply cannot burn the same place twice in short succession, as the fuel is gone (barring rare exceptions of low-severity fires followed by high-intensity fires driven by weather) (Parks et al., 2015). This self-organising property of the fire cycle can have devastating consequences if disrupted (Pyne, 2001); the most notorious example is the effect of a policy of total fire suppression by the US Forest Service in the early 20^{th} century. By so disrupting the fire cycle, those efforts resulted in the unnatural accumulation of dead organic litter, which in turn led to larger and stronger forest fires, leading to rising costs of fire suppression (Taylor & Skinner, 2003).

3.2.2 Danger

Not only have extreme fires become more common in the last few years, but the danger to human life and property has increased due to the expansion of communities into forested ecosystems (Hope, McKenney, Pedlar, Stocks, & Gauthier, 2016; Kirchmeier-Young, Zwiers, Gillett, & Cannon, 2017; Lannom et al., 2014). That space where human infrastructure and property encroaches on forests and other vegetative fuels is termed the Wildland-Urban Interface (WUI) (Stewart, Radeloff, Hammer, & Hawbaker, 2007). This term generally relates to interactions between human development and fire, especially the cost of fires. The exact definition of the WUI and the methods to define it vary broadly between studies, but the term generally considers non-industrial infrastructure (homes, towns). However, industrial value is at risk from fire, from not only the destruction of the structures themselves, but also the disruptions to productivity from said destruction, evacuations, or loss of connecting infrastructure (e.g. roads or rails). A recent effort to map the WUI in Canada that includes industrial assets and infrastructure places the total WUI in Canada at 18.1 % of the country's total land area (Johnston & Flannigan, 2018). Because of the varied methods used to define the WUI, it is difficult to quantify how it has changed over time, but the general consensus is that it is growing due to urban sprawl into outlying suburbs, increased demand for recreation properties, and population growth in isolated areas (Hammer et al., 2009).

The encroachment of human structures into fire-prone areas often results in costly losses. Many factors comprise the cost of wildfires, including suppression efforts, destruction of property, natural resource loss, lost revenue, ecosystem degradation, and long-term health impacts (Richardson, Champ, & Loomis, 2012; Cordy Tymstra, Stocks, Cai, & Flannigan, 2020). The average annual fire suppression cost in Canada, from 1970 – 2009, was $537 million (Hope et al., 2016), and some of the most destructive fires, based on insurance claims, cost hundreds of millions, with the largest Canadian wildfire of recent history, the Horse River Fire of 2016 in northern Alberta, costing $3.84 billion (Cordy Tymstra et al., 2020). Or a total of $9 billion according to Natural Resources Canada (2020).

3.2.3 Fire as a complex system

Fire itself is essentially a complex system of interactions between fuel, oxygen, and heat. Combustion occurs when a fuel particle reaches a temperature high enough to sustain rapid, exothermic oxidation (Byram, 1959). Burning material will heat fuel around it until it reaches its temperature of ignition, thus consuming more oxygen and releasing more heat, closing the feedback loop commonly referred to as the fire triangle. However, forest fuels are complicated structures consisting of a variety of combustible materials, which undergo a number of chemical reactions together known as combustion. There are three phases of woody fuel combustion: 1) preheating, in which the temperature rises, moisture evaporates, and some compounds decompose and become volatile, 2) gaseous oxidation of these volatiles, and 3) solid oxidation on the surface of the remaining charcoal (Byram, 1959; Korobeinichev et al., 2013). The energy from combustion transfers to unburned fuel by radiation and convection (Anderson, 1969). For vegetation, moisture content is the most important factor in determining its risk and rate of combustion, which is why precipitation, humidity, and temperature are important factors in determining fire danger and behaviour (Byram, 1959). Moisture content of fuel affects combustion in numerous ways. It absorbs heat as it warms up, and as it evaporates, it smothers flammable gasses and particles released to the air as woody fuels heat up. A higher moisture content is associated with a lower fire temperature and slower rate of spread. Wind plays an important role in directing energy transfer, and local gradients create a “backdraft” that angles the flames of a fire front and blows hot air over unburned fuels ahead of a fire. This preheats and dries the fuel, and the more energy released by a fire, the more pronounced this preheating effect (Byram, 1959; F.-J. Chatelon, Balbi, Rossi, & Marcelli, 2013). As these interactions move between scales, such as from the very local environment of a single burning fuel element to the air moving in to feed that fire, more and more complexity is at play and new behaviours emerge.

Going up in scale from a single fuel element to a burning patch of forest, the release of energy is enough to start affecting local convection. Updrafts caused by the heat of a fire generate horizontal movement as the surrounding air moves into the pressure gradient. Due to this movement, the ambient wind field is not the only driving force of fire behaviour, and the fire-generated wind can even become the dominant driver (Potter, 2002; Yedinak, Strand, Hiers, & Varner, 2018). Although with less complexity, vegetation structure and arrangement can also affect wind flow, usually by damping ambient flow as it drags along grasses, branches, and leaves (Pimont, Dupuy, Linn, & Dupont, 2011). What vegetation remains after the fire passes can also have an effect.

Though difficult to predict, spotting is a common result of fire-atmosphere interactions, whereby wind carries aloft a piece of lightweight, burning material (called a firebrand) and transports it some distance from the fire front (Martin & Hillen, 2016). This can sometimes set ablaze a new section of forest unconnected to the original fire. Before, and as, these two burning areas meet (if they do), their interactions with the atmosphere can affect larger patterns of movement that propagate effects between them (Viegas, Raposo, Davim, & Rossa, 2012).

The complex feedbacks between fire and the atmosphere can result in surprising phenomena, such as the highly localised generalized blaze flash, also known as a "flashover". This phenomenon is the sudden and dramatic change in fire behaviour, where a large area of forest seems to burst suddenly into flames. The exact mechanisms behind this behaviour are unknown, but two broad theories attempt to explain it (Chatelon, Sauvagnargues, Dusserre, & Balbi, 2014). The first postulates that as plants heat up and release volatile organic compounds (VOCs), under some circumstances these VOCs can accumulate until they reach a concentration suitable to sustain an explosion. The second theory posits that the convective flow of air providing oxygen to a fire can manifest as a sudden onrush of air which increases rate of spread, and therefore oxygen consumption, and thus convective airflow (F. Chatelon et al., 2014).

Extremely large fires have correspondingly extreme effects on the atmosphere. A sufficiently large and hot fire can shape the weather around it, either forming or augmenting thunderclouds above it, called pyrocumulonimbus (pyroCb). These pyroCb can send smoke and pollutants into the stratosphere, once thought only possible by volcanoes (Fromm et al., 2010). PyroCb can produce lightning that can potentially ignite new fires. The Horse River Fire of 2016 was the only observed case of a pyroCb starting new fires through lightning (Kochtabajda, Brimelow, Flannigan, Morrow, & Greenhough, 2017).

Fires vary not only in size and rare, emergent phenomena, but also in type, severity, and intensity. Fire type qualifies which part or parts of an ecosystem through which fire propagates: these are ground, surface, and crown fires (Van Wagner, 1976). Ground fires burn in the top layer of soil, usually in a smoldering manner with little flaming. Surface fires consume low vegetation, like grasses, herbs, and shrubs, staying beneath the forest canopy. Finally, crown fires travel up to the tops of trees and between them, consuming the forest canopy. Fires can potentially exhibit any one or any combination of those three broad types; in some cases, even a crown fire may persist without understory burning (Van Wagner, 1976). Intensity, not to be confused with severity, is strictly the energy output of a fire. Specifically, it is the rate of energy release per unit time per unit length of fire front (Byram, 1959). The definition of severity is still subject to debate, but it is generally a measure of fire impact. Keeley (2009) argues that severity should strictly be a measure of the loss or change of organic matter (relating to vegetation killed and depth of burn), and subsequent ecological response (such as time of regrowth and successional path) should be separate. In contrast to the immediacy of severity, the ecological response to a forest fire depends on surviving seedbanks, recolonization, and soil quality, and observing the effects takes years or decades, and thus while it is a result of severity, it should not be a measure of severity (Keeley, 2009). Fire type and severity are related, in that low-severity fires tend to be surface fires, and high-severity fires are often stand-replacing crown fires, where all vegetation is burned away (though not necessarily killed, as with some of the fire-adapted vegetation discussed earlier).

Moving up in the temporal and spatial scales from an individual fire, the characteristics of fires inform the fire regime: a measure of the spatiotemporal patterns and impacts of fire at an ecosystem or landscape scale (Morgan, Hardy, Swetnam, Rollins, & Long, 2001). The elements of a fire regime are typically the frequency, severity, pattern, and seasonality of fires in a given region over a given time period. Fire frequency is the primary descriptor of a fire regime, and there are multiple ways to measure it: fire return interval, probability of occurrence, or rotation period. Fire frequency can be the number of fire events in a specified area over a specified time period (mean frequency), or it can be the length of time over which the entirety of a specified area will have burned (fire return interval), or it can be the number of times a sub-unit of an area has burned (e.g. one pixel) (Morgan et al., 2001). From the perspective of a fire regime, severity of individual fires informs the kinds of fires typical to the region of study over the time period of interest. For example, is a region prone to frequent, low-severity fires, or infrequent, high-severity fires? Fire regime characteristics depend on the nature of fire data (points, areas, individual trees or stands) and the spatial and temporal extents under study. The fire regime of a forested valley may differ greatly from that of its encompassing mountain range, and a century of fire activity may bear no resemblance to the last decade of fire activity in a region. Further complicating the measure of fire regimes, detailed historical fire records go back a century at most, and are not necessarily complete, especially for remote areas. Paleogeographic reconstructions of fire activity extend our knowledge of fire history, but such data are severely spatially limited (Power, Marlon, Bartlein, & Harrison, 2010; Wolf et al., 2013). Defining a baseline fire regime is critical to understanding the drivers of fire regimes, especially in the face of a changing climate. Unfortunately, an extensive history of human activity puts in question the very idea of a "natural" fire regime. Isolating the effects of climate on fire regimes from that of humans is a difficult task, but an increasingly important research question (Bowman et al., 2011).

Fire regimes are a description of the stable interactions between ecosystems and climate, but those interactions that give rise to the patterns used to define a fire regime are complex. As established, vegetation affects fire behaviour in terms of fuel availability and flammability, and fire affects vegetation in terms of matter consumed, as well as affecting species diversity and even adaptations. Fuel availability and flammability are the result of fires, climate/weather, human activity, and evolution. The spatio-temporal patterns of ignition depend on weather and vegetation, and once again human activity. Because they consume fuel, fires limit the spread of subsequent fires in the same area, though the effect decays over time as the forest regrows (Parks et al., 2015). Extreme weather conditions can diminish the damping effect of past fires on current fires. This feedback loop is part of the complex nature of fire regimes, and the resulting autocorrelation is an added challenge to the measurement of fire regimes (Morgan et al., 2001).

3.3 Fire and climate change

As climate changes, so will patterns of ignition and the flammability and availability of fuel. The most direct effect on flammability will be changes to drought and precipitation patterns, temperature anomalies, and longer fire seasons. More subtle, but equally important, will be the changes in vegetation productivity and species composition in an area. Given the importance of environmental variables on forest fires and the inexorable advance of climate change (IPCC, 2021), much effort has been put toward studying how fire activity might change under the effects of climate change (Flannigan & Van Wagner, 1991; Hessl, 2011). Most studies have shown that changes in wildfire behaviour will vary spatially but will affect higher latitudes more strongly than elsewhere (Flannigan, Krawchuk, De Groot, Wotton, & Gowman, 2009). Generally, predictions indicate that fire frequency will increase throughout Canada, mainly in Western and Central Canada, and to a smaller degree in Eastern Canada (Flannigan, 1998; Wang et al., 2017). However, trends in global fire activity are difficult to identify (Doerr & Santín, 2016), due in part to the interregional variability of climate change and the inherently complex nature of fire regimes (Parisien et al., 2012; Williams & Abatzoglou, 2016).

Climate affects fire directly through fire season length, drought and precipitation patterns, and natural ignition patterns. Climate also has indirect effects on fire through vegetation, such as changes to net primary productivity and to ecological niches of species with different relationships with fire, affecting fuel availability and flammability (Parisien et al., 2012). That is leaving aside direct human impacts on ignitions and land use change. Fire, in turn, affects the climate directly though emissions of greenhouse gases, release of atmospheric aerosols, and changes to albedo (Bowman et al., 2009). Post-fire vegetation growth can counteract some these effects over time (as a carbon sink), but until then, other effects such as soil degradation and perturbed successional pathways may influence aspects of the climate-fire-vegetation system. Fire impacts the way climate affects vegetation, as it can accelerate vegetation composition changes that fit new climatic conditions (Stevens, Safford, Harrison, & Latimer, 2015; Stralberg et al., 2018; Terrier, Girardin, Périé, Legendre, & Bergeron, 2013).

This long-term feedback loop could lead to the replacement of fire-encouraging Boreal ecosystems by less flammable deciduous ecosystems (Terrier et al., 2013).

4. Fire modelling

4.1 Global and regional

Complex interactions between climate, fire, and vegetation render predictions of future fire activity challenging. Despite these difficulties, traditional statistical approaches that relate fire probability to environmental factors such as climate, weather, and vegetation, provide meaningful estimates of future fire activity (Krawchuk & Moritz, 2014; Moritz et al., 2012). However, the often coarse scale of the means and norms of the independent variables limits the utility of feedback mechanisms and only provides information on *mean* fire activity over a coarse time scale. Statistical approaches typically assume independent variables such as climate and vegetation will change exogenously, and at coarse timescales that make interactions moot (Harris et al., 2016), but recent studies have developed new statistical approaches that elucidate the importance of interactions. Parisien et al. (2014) demonstrate the impact of temporal resolution on a statistical model of fire by comparing an annual model with an averaged model covering the period 1980 – 2012. They show that, while both model predictions were similar, the divergence of the annual model highlighted the presence of a feedback loop between biomass consumption and fire activity. Their two regression models measured annual area burned, and the annual model updated its climate and vegetation variables annually. Specifically, the annual model updated vegetation maps based on historical fire data to account for the change in vegetation on an annual basis. By accounting for this effect, the model shows that past fire activity can limit future fire activity, and the discrepancy between the two models supports the idea that feedback mechanisms are important considerations when predicting fire activity. This remains a statistical approach *using a data assimilation technique*, and while it can observe the effect of a feedback mechanism, it does not replicate it. For it to predict future fire activity, their annual model would have to incorporate a mechanism that simulates the loss of vegetation due to fire activity, instead of using vegetation loss as an independent variable.

Further highlighting the importance of temporal resolution for models of fire activity in a large landscape (Canada), Wang et al. (2014) developed an empirical model relating daily weather variables to daily fire spread potential for different areas in Canada known to have different fire regime characteristics (Boulanger, Gauthier, & Burton, 2014). They used a linear link function to estimate how potential spread relates to realized fire spread. Wang et al. (2017) used this approach to estimate future realized spread days for those different areas based on various climate scenarios. By accounting for short-term variability in weather, in particular anomalies such as droughts, that greatly influence fire behaviour, this method provides a better estimate of fire activity and variability than those that use monthly or annual averages of weather. However, as shown in their discussion, this study assumes not only that the relationship between potential spread days and realized spread days will remain the same under climate change, but that the factors making up the relationship will remain unchanged. These factors, --vegetation distribution and flammability, ignition patterns, suppression patterns--, all participate in the feedback loops that make fire regimes so complex in the first place.

Some statistical models can tackle non-linear dynamics. Multivariate adaptive regression splines (MARS) is a type of statistical model that can account for interactions between variables and non-linear relationships, making it a suitable technique for tackling the fire-vegetation-climate system. Terrier et al. (2013) use MARS to explore the potential effect of changes in forest composition on boreal wildfires in Eastern Canada. Their study demonstrates the effect of changes in forest composition by building a model of fire occurrence based on fire weather and tree composition variables, then comparing future scenarios with either no tree species dispersal, or unlimited tree species dispersal based on ecological niche. The model predicts that while fire occurrence will increase in the first scenario, the northward migration of deciduous species can produce a net reduction in fire occurrence in the 2071-2100 period. Unfortunately, while the MARS algorithm can model interactions between variables, it does not model feedback loops. So, while the above study explores one aspect of a complex system, it leaves aside many interacting components, such as ignition sources, weather anomalies at sub-annual resolutions, fire-induced fuel limitations, and the actual dispersal and competition mechanisms that regulate tree species migration.

In contrast to statistical models, dynamic models can incorporate not only the changes of such determining factors, but also the interactions that influence those changes, thus accounting explicitly for feedback loops and opening the floodgates of complexity. Following the thematic trend of the previous examples, and building on the work of Wang et al., (2017, 2014), Stralberg et al., (2018) used a novel hybrid empirical and simulation-based modelling approach to address the issue of vegetation species distribution response to climate change and fire activity. They model vegetation as an empirical function of terrain, geology, and climate, and use the Burn-P3 fire probability-mapping model (Parisien et al., 2005) to explicitly simulate fire activity. The study compares 18 scenarios (all combinations of 1) static, climate-driven, or fire-mediated fuel scenarios, 2) constrained or unconstrained fire regimes, and 3) three climate models). In their fire-mediated scenarios, different feedback loops emerge based on the fire regime. In the constrained fire regime scenario, early increases in fire frequency produce an increase in deciduous forests that results in long-term reduction in area burned. In the unconstrained scenario, increases to fire frequency and duration outweigh decreases in flammability and result in a rapid shift to highly flammable, but low biomass grass ecosystems. Even accounting for only one major interaction process, this study highlights the importance of feedback loops in the climate-fire-vegetation system and showcases the utility of dynamic models to that end. Including a dynamic vegetation model that accounts for dispersion, recruitment, succession, and competition dynamics would undoubtedly reveal more feedback loops and potentially produce different results. After all, a fire regime itself is a result of complex interactions and is inherently dynamic.

This brings us to two classes of fire-climate-vegetation models called Landscape Fire Succession Models (LFSMs) and Dynamic Global Vegetation Models (DGVMs). Dynamic Global Vegetation Models, as the name suggests, are global-scale models that explore long-term changes in vegetation due to climate change. Landscape Fire Succession Models are vegetation models that explicitly account for disturbance regimes and can range from local to global scales, though they do not necessarily incorporate climate (Keane et al., 2004). In this sense, global LFSMs that incorporate climate are a type of DGVMs, and fire-enabled

DGVMs are a global LFSM. Hierarchically speaking, the category of DGVM encompasses LFSMs. Both these types of models incorporate interacting processes for vegetation change, fire occurrence, fire behaviour, and climate change, and some even include elements of biogeochemical cycling. The complexity of each component varies greatly between models, making it difficult to compare models and to identify what level of complexity can satisfactorily model the fire-vegetation-climate system (Keane et al., 2004; Rabin et al., 2017). As a matter of course, fire-enabled DGVMs and LFSMs tend to become more complex over time. Early forms of DGVMs only implicitly represented fire effects through generic treatments on plant mortality (Hantson et al., 2016). LFSMs are themselves a specific, fire-centric extension of earlier models of forest dynamics. One source of the increasing complexity of these types of models is the growth in computing power available to researchers (Shifley et al., 2017). However, researchers must still balance complexity with feasibility, and so DGVMs and LFSMs make use of a variety of fire modelling components. The fire components range from statistical relationships between vegetation, climate, and fire activity, down to weather- and vegetation-driven simulations of fire behaviour. Even using statistical methods to recreate fire activity, these types of models are more complex than the statistical models described previously, because these statistical, linear methods serve as input factors for feedback loops between the other large-scale components (e.g. vegetation and climate). Yet for those DGVMs and LFSMs that use process-based fire models, none, so far, use detailed physical simulations of fire, nor any that incorporate atmospheric feedback during a fire. This may be because, generally, such fire-climate-vegetation models operate scales much coarser than the intended application of the more complex fire behaviour models currently available, or because of the high (computational and development) costs of increased complexity.

4.2 Individual fire behaviour

This thesis has already discussed DVGMs and large-scale models of fire behaviour at the regime-scale and up, but such simulations rely on models of individual fire behaviour, of which there are a plethora. These fire behaviour models range from purely linear models to full-physics simulations of combustion and fluid dynamics in space and time. The article in Chapter 2 of this thesis provides a literature review of those models most relevant to the new one described in said article, so this section will discuss some of the history of fire modelling and the state of the art today.

In his three-paper series, Sullivan (2009a, 2009b, 2009c) provides a thorough review of fire behaviour models of all types. With a cumulative 538 citations between them (according to Web of Science, accessed May 20, 2021), these papers are an authoritative and excellent resource for those looking for an in-depth review of the field of fire behaviour modelling and the standouts within. Here, I will present an overview of some of the key models and systems developed for fire research in the US and Canada. Both countries have a long history of wildland fire research, and the key simulation models in use today have roots in the mathematical models developed years ago. In the US, mathematical models of fire spread developed by Rothermel (Rothermel, 1972) eventually formed the basis of the Behave, and subsequent BehavePlus (Andrews, 2007) mathematical modelling software applications, and in parallel, the spatially explicit FARSITE model (Finney, 2004). Fire research in Canada followed a similar path starting with the mathematical models of Van Wagner (1974), used to develop the Fire Weather Index and later the Fire Behaviour Prediction system (Lawson, Stocks, Alexander, & Van Wagner, 1985), which together form the core of the Canadian Forest Fire Danger Rating System (Stocks et al., 1989). This system, in turn, is the mathematical foundation for the spatially explicit Prometheus fire spread model (Tymstra, Bryce, Wotton, Taylor, & Armitage, 2010). Research does not stay behind borders, of course, and work from scientists in either country contributed to the development of both the US and Canadian systems. Complex systems science has also lent a hand to early fire behaviour models, with cellular automata models based largely on stochastic processes (Almeida & Macau, 2011; Karafyllidis & Thanailakis, 1997).

4.3 Early mathematical models

The original mathematical model of Rothermel (1972) calculates spread rate and intensity for surface fires. It uses inputs describing the physical and chemical makeup of fuel and environmental conditions to calculate steady state spread rate and intensity. Steady state behaviour refers to a fire line free of influence from other parts of a fire, i.e., when the head fire is sufficiently far from the back and flank fire lines to move at a constant rate under uniform wind and fuel conditions. The inputs of the model, for fuel characteristics, are loading, depth, particle surface-area-to-volume ratio, particle heat content, particle moisture and mineral content, moisture content for extinction, and fuel element size distribution and arrangement. The other inputs are average wind speed and slope. Because most of the fuel variables are costly and time-consuming to obtain in the field, predetermined parameters for certain vegetation types (in which the parameters are not expected to vary) are tabulated as fuel models. These fuel models represent typical field conditions and contain the inputs necessary to run the fire spread model.

Similar to the Rothermel (1972) model, the Fire Weather Index (FWI) (Van Wagner, 1974) uses the moisture content of three (size) classes of forest fuel to determine intermediary indices of rate of spread and available fuel, and a final index, the eponymous FWI, that represents the intensity (as energy output per unit length of fire front) of a single fire in a standard fuel type. The inputs for this model, however, are simply daily readings of temperature, relative humidity, wind speed, and rain. The purpose of the model is to track fuel moisture content and availability as it changes through time to calculate an index of fire danger. The three fuel classes are represented by indices called moisture codes that track changes in moisture from rain and drying.

Supplementing the FWI, the Fire Behaviour Prediction (FBP) system combines fuel type and topography with the base elements of the FWI to calculate fire behaviour (Forestry Canada Fire Danger Group, 1992). The system also uses geographic location, season, and time-since-ignition to provide information on fire type (surface or crown) and size. The primary outputs are rate of spread, fuel consumption, head fire intensity, and fire description (type and crown fraction burned). The secondary outputs of the system are spread distances, rates of spread, and intensities for head, flank, and back fires, plus area burned and fire perimeter, based on a simple elliptical model of fire spread. (This elliptical model will be discussed further below). Like Rothermel's model, the FBP makes use of fuel models. The 16 fuel types of the FBP are based on forest floor cover and organic layer, surface and ladder fuels, and stand structure and composition. They represent the majority of vegetation types covering Canada, including a mixed-wood fuel type to account for forests with differing proportions of coniferous and deciduous tree species. The fuel types provide parameters for equations relating FWI components to fire behaviour such as fuel consumption (differentiating between fuel elements) and rate of spread. The effect of slope on fire spread is converted to a wind speed equivalent value and combined with the actual wind speed and direction to provide a net effective wind speed for use in calculating fire spread, direction, and size (Forestry Canada Fire Danger Group, 1992; Wotton, Alexander, & Taylor, 2009).

4.4 Spatial spread simulators

The next logical step from these models describing fire behaviour is to make them spatially explicit. That is exactly what the FARSITE (Finney, 2004) and Prometheus (Tymstra et al., 2010) models do, using the American and Canadian mathematical fire models, respectively. Both models use a vector-based approach to simulating the fire perimeter. This approach uses an ellipse as a template shape of fire spread (widely accepted as the best geometric model of a fire shape in uniform conditions (Finney, 2004; Van Wagner, 1969)), and propagates the perimeter in a manner based on Huygen's wavelet principle. An ellipse extends from an ignition point (one of the foci) based on local conditions of fuel, topography, and weather, and at the next time step is discretized into a number of points along its perimeter (vertices), which form the focus of new ellipses which extend in the same manner. The perimeter at each time step is the combination of these new ellipses, from which new ellipses form and so on. Aside from variations in implementation into code, the only differences between FARSITE and Prometheus are the underlying mathematical fuel and spread models (Fujioka, Gill, Viegas, & Wotton, 2008).

Prometheus and FARSITE are mainstays of the fire management and research communities. Not only are they the official operational fire models for the forest services of both Canada and the US, respectively, but they are finding use in Australia and parts of Europe, as well (Fujioka et al., 2008; Opperman, Gould, Finney, & Tymstra, 2006). Because the models were designed to accommodate expert knowledge in the field, they are readily adaptable to new environments with appropriately adjusted fuel models (Opperman et al., 2006). Proper validation of these new fuel models is the limiting factor in using these models in new environments.

Both papers describing FARSITE (Finney, 2004) and Prometheus (Tymstra et al., 2010), respectively, discuss the limitations of the classic alternative to fire modelling, cellular automata (CA). Like the above models, CA models represent the world in a rasterized format (i.e. a continuous lattice of cells or a grid). The simulation world is made up of layers of rasters, each representing a variable. Thus, each cell can contain information about terrain, vegetation, and weather (Clarke & Olsen, 1994; Gaudreau et al., 2016). While vector models simulate fire spread as an expanding polygon, CA models do so on a cell-by-cell basis. There is a large variety of ways to accomplish this, for example as a function of the probability of fire spreading from one cell to another, or by calculating the expected time of arrival to a neighboring cell. The concept of cell neighborhoods is critical to any CA model, and of particular importance to CA models of fire behaviour. The classic neighborhood types for CA are the four cell Von Neuman neighborhood (the four cells sharing a side with the center cell) and the eight cell Moore neighborhood (the four diagonal cells sharing a corner with the center cell in addition to the other four). Of course, any size and shape of neighborhood is possible. The problem with older CA models of fire spread, and the criticism summarized in Finney (2004) and Tymstra et al. (2010) is that they produce distorted fire shapes due to the regularity of the grid and neighborhood. Recent models have largely overcome this limitation by applying specialised rules to fire spread rates in different directions. In their paper, Ghisu, Arca, Pellizzaro, & Duce, (2015) accounted for shape distortions caused by an eight-cell neighborhood with a set of five correction factors applied to Rothermel's model of fire spread. The correction factors adjust the relationship between advection velocity and spread angle to minimize distortion in fire shape. They used a numerical optimizer to find the best values for these correction factors. The resulting CA model produced almost identical fire perimeters as FARSITE for one simulated grass fire on realistic topography. The work of Yassemi, Dragićević, & Schmidt (2008) presents an integrated GIS-based CA model using rules affecting fire spread within a cell. The model considers the proportion of a cell burning (the ratio of burning area to cell area), and uses the FBP system to determine spread rate within a cell. Wind direction affects that rate of spread based on which neighbor fire is spreading into, and special rules account for cells with multiple burned neighbours. Their model compares well against three Prometheus simulations of observed fire scenarios.

4.5 Coupled fire-atmosphere models

All the fire spread models above have one thing in common: they are simple. That is, they do not simulate fire-atmosphere feedbacks, which are, in fact, the reason fires take on an elliptical shape in the first place (Clark, Coen, & Latham, 2004; Coen, 2018). They are nonetheless effective and well-established research and management tools, and offer certain advantages over complex models. They are fast, empirically proven, and have limited data requirements. On the other hand, increases to computational power have lowered the barrier for more complex simulation models, and advances in computational fluid dynamics (CFD) have led to the creation of coupled fire-atmosphere models since the 1990s (J. Coen, 2018).

Computational fluid dynamics is already a complicated research subject, trying to solve the Navier-Stokes equations. This system of equations has analytical solutions for only a few idealized problems, and the rest rely on computational simulation to solve. One consequence of this is that CFD models typically have solutions for only a specific spatiotemporal range. Coupled fire-atmosphere models therefore only solve for atmospheric motion at a scale determined by the choice of CFD model. According to (Coen, 2018), there are two general scales relevant to fire behaviour modelling: the microscale and the mesoscale. The microscale (~ <1 m – 100 m) simulates turbulent eddies and the atmospheric boundary layer, and can include combustion processes but not weather processes. The mesoscale (~ 100 m – 20 km) spans between the boundary layer effects of the microscale to the far-reaching weather patterns at the synoptic scale. It includes vertical motions in clouds and weather systems and terrain-influenced winds. The complex and chaotic nature of fluid dynamics means prediction errors grow during forecasts, and more so at finer scales. Mesoscale predictions are useful for several days, but errors in microscale models grow exponentially with time (Coen, 2018). This is part of the reason CFD models treat these scales separately, as many issues arise when trying to combine them (Moeng & Weil, 2010).

Typically, coupled fire-atmosphere models operating at the microscale of fluid dynamics also simulate combustion processes like pyrolysis of wood, oxidation, and evaporation of water and pitch, as well as gas transport. The HIGRAD-FIRETEC model (Linn & Harlow, 1998; Linn & Cunningham, 2005), hereafter referred to as FIRETEC, is one of the most advanced such coupled fire-atmosphere models. The fire component of FIRETEC uses bulk volumetric representations of vegetation at meter scales that represents fine-fuel elements (twigs and leaves). The atmospheric component uses a Large Eddy Simulation (LES) approach to simulate large turbulent fluctuations as well as modelling sub-grid fluctuations. This 3D model is capable of simulating some of the complex emergent behaviours of fire, such as the elliptical shape of a fire in uniform conditions, the forward tilt of flames at the fire front, as well as “fingering”; where the fire front exhibits small lobes that jut out from the mean representation of the fire line (Linn & Cunningham, 2005). FIRETEC also serves to examine the effects of vegetation structure on turbulent airflow in and around tree canopies (Pimont et al., 2011). However, the model is limited by the huge computational requirements of resolving the complex set of equations in three dimensions. As a result, it seems FIRETEC has largely been used to simulate small fires in simple environments (a few hundred to a thousand m^2 to and uniform grasslands or forests (Bakhshaii & Johnson, 2019; Dupuy et al., 2011; Linn & Cunningham, 2005). Section 1.2 of the paper in Chapter 2 describes the computational requirements of FIRETEC in more detail.

At the mesoscale, the focus of modelling is more on fire-atmosphere feedbacks than combustion dynamics. To this end, the WRF-Fire model uses semi-empirical relationships to parametrize the physical processes of fire, while atmospheric simulation occurs at a coarser scale (Coen et al., 2013). WRF-Fire is a physics module in the Weather Research and Forecasting model (WRF) (Skamarock et al., 2005), which itself is a mesoscale Numerical Weather Prediction model. By using nesting grids, WRF can simulate atmospheric dynamics across many scales, accounting for a range of phenomena such as atmospheric fronts, cloud convective updraft, and bulk characteristics of the daytime turbulent atmospheric boundary layer. Coupled with a semi-empirical fire model that represents two-dimensional surface fire spread and the release of heat, WRF-Fire can simulate fire-atmosphere feedbacks as they propagate from the fire itself to the whole surrounding region. Similar to FIRETEC, the complex feedbacks between fire and atmosphere strongly shapes wind near the fire, and so reproduces the expected elliptical fire shape through emergence alone. In particular, the coupling creates strong winds pushing the fire at the head, produces fire whirls along the flanks that keep the fire from extending laterally too rapidly, and draws wind in at the rear

(Coen et al., 2013). WRF-Fire has slightly lower computational requirements than FIRETEC, but still requires supercomputing resources to achieve faster-than-real-time simulation.

The purpose of such coupled fire-atmosphere models is more than simulating fire growth. These models serve to explore and explain observed fire phenomena that are difficult to measure and poorly understood. In particular, they aim to further our understanding of rare events that arise from the complexities of the fire-atmosphere system such as fire vortexes, generalized blaze flashes, or even extreme, weather-altering effects like the formation of pyroCb (Coen et al., 2013). Experimentation *in-silico* with these models also helps test physical assumptions about fire behaviour (Bakhshaii & Johnson, 2019; Dupuy et al., 2011), as well as test forest management techniques (Marshall et al., 2020). While the science of coupled fire-atmosphere modelling is steadily advancing toward this goal, certain problems remain on two fronts: scale-based distortions in CFD models and computational cost (Coen, 2018; Linn et al., 2020; Linn & Cunningham, 2005). As mentioned earlier, CFD models struggle to combine microscale simulation with meso- and synoptic-scale modelling, and as a result, the choice of scale used in a coupled fire-atmosphere model imposes limitations. Fine-scale models lack the ability to model weather and terrain-influenced airflow (and the chaotic nature of turbulence at that scale and lower makes it technically unpredictable (Lorenz, 1969; Moeng & Weil, 2010)), while mesoscale models can dampen fire behaviour as sharp gradients near the fire are smoothed in the transition between grid scales (Coen, 2018).

There are ways to introduce complexity into fire spread models without huge computational costs. If the goal is not to replicate the full physical environment of a fire to have a tool for exploring poorly understood fire behaviour, but rather to reproduce fire shape by way of feedback dynamics, it is possible to limit atmospheric simulation requirements. With the goal of producing a fast-running fire spread model that incorporates fire-influenced winds as the driver of fire shape, one study demonstrates the use of "pyrogenic potential" to model airflow around a fire (Hilton, Sullivan, Swedosh, Sharples, & Thomas, 2018). This two-dimensional potential flow formulation assumes air flows horizontally close to the ground until it reaches the flame, at which point it immediately turns upwards into the fire plume. The pyrogenic potential produces a wind correction factor around a flaming region, which can be added to the ambient wind field. Hilton et al. (2018) couple the pyrogenic potential model to a fire spread model that uses the level-set method, and demonstrate that the coupled model effectively reproduces fire shape compared to small, low-wind (1-2 m^2) experimental fires. The model is computationally efficient, resolution independent, and takes on the order of seconds to run. One significant limitation to the model, as pointed out by the authors, is the assumption that the plume is not significantly affected by wind. The experiments against which the model was tested involve low wind speeds and the effect on the plume would indeed be minimal in these cases. The authors propose an improvement to the model that would move the location of the local head flux maximum (which determines the pyrogenic potential) to be in line with a displaced plume.

As these three very different coupled fire-atmosphere models show, the level of complexity of a simulation is a choice based on the research goals of the modellers. The complexity of simulation models, for a given system, exists on a continuum. Since a model is intrinsically a simplified representation of a real system, the modeller makes choices on what parts of the system to include in the model (Aumann, 2007; Grimm et al., 2005). There can be a wide range of models of the same system, which may even produce the same results (a concept known as equifinality (Batty & Torrens, 2005; Beven, 1996)). Therefore, the choices of what to include determines the level of complexity of the model. The ellipse-based models of fire spread described above involve no complex feedback loops, instead considering the direct relationship between fuel, topography, and weather on fire spread behaviour. At the other end of the spectrum of complexity, full-physics models include complex atmospheric dynamics as well as complex heat transfer processes within fuel elements and between those and the atmosphere. Slightly less complex than that, coupled CFD-fire spread models add fire effects to the already complex and multi-scale models of atmospheric interactions, which in turn affect the fire behaviour and so on. The choice of how much complexity to include depends on the goals of the modeller. Is the goal to predict fire behaviour in a timely and useful manner for immediate fire-fighting operations? Is it to explore our understanding of the physical processes of fire behaviour at a fine scale too difficult and expensive to test in live fires? Or is the goal to include just enough complexity to capture the essential emergent properties of fire behaviour while minimizing computational load, in order to account for the uncertainties of input data and turbulent airflow while providing insights on potential fire behaviour?

Depending on the goal, the modelling approach will differ. The next section returns to complex systems science in general, where model design frameworks can apply to a variety of environmental, social, or physical systems. It describes the process of model design in relation to research goals, data availability, and calibration and validation requirements.

5. Modelling of a complex system

There are certain key steps in developing a simulation model of a complex system. First, the design itself, which determines how to represent the different parts of the system in a way that can answer the research question(s). Second, verification, which entails ensuring that the implementation (in code) is in accordance with the original design and relevant literature. Third, calibration, which determines model parameters based on measurements of model performance. Fourth, validation, which involves testing the model to determine if, and to what extent, it accurately simulates the system in question in relation to the research goals (Rykiel, 1996). Fifth, sensitivity and uncertainty analyses, which explore the functioning of the model. This last item is not necessarily the last thing to do in developing a model; sensitivity and uncertainty analyses (SA and UA, respectively) are useful processes during design and calibration, as well, since they can help separate influential parameters from unimportant ones, potentially simplifying the calibration process or influencing changes to the design over the course of model development.

5.1 Design

The design of a model stems from the research goals. These goals are reflected not only in the architecture of the model, but also in designing the experimental framework to evaluate the model such as the calibration and validation methods (Aumann, 2007). The research goals determine what elements of a system to include, the spatial and temporal scales, and at what level of complexity (Law, 2011). Once these decisions are made, the design must be implemented as a simulation model. The choice of technique is also related to the research goal, as there are many tools out there offering different advantages and disadvantages (Rixon, Moglia, & Burn, 2005). Considerations include the familiarity of the modeller with the tool, the ease of implementing certain processes, the availability of code libraries relevant to the model, etc. (Castle & Crooks, 2006).

5.2 Verification

Verification is conceptually simple. It involves ensuring the simulation model (the code, algorithms, and equations involved) accurately reflect the model design. Despite it seeming obvious, verification is important because translating a formal model description into code is not necessarily simple, or easy. While model description papers aim to provide sufficient information for other researchers to replicate the model, implementing a complex system model is subject to idiosyncrasies in modeller decisions and software (Crooks, Castle, & Batty, 2008; Dalle, 2012; Wilenski & Rand, 2007). In other words, a given model, as presented in a scientific article, may be implemented in a number of different ways. This is particularly the case if the model description is purely conceptual, but even full mathematical descriptions are subject to idiosyncrasies in event scheduling or even floating-point errors (Dalle, 2012). Tangential to model design and development itself, reproducibility is a challenge in computer simulation modelling in general, and especially for complex systems modelling (Dalle, 2012; Grimm et al., 2020; Wilenski & Rand, 2007).

5.3 Calibration

Once the model is up and running, it must be calibrated to produce the intended results. These intended results are usually that the model can reasonably match observed behaviour of the real system. Exactly what behaviours and what constitutes a reasonable match derives from the research goals and model design (Janssen & Heuberger, 1995). The observed behaviour of the system used for comparison should be detailed enough to represent some the complexity of the system. Aggregated data is not always suitable for this and the best data for comparing with models of complex systems is fine grained enough to show the evolution of the system (Batty & Torrens, 2005; Crooks et al., 2008). This data then serves to quantify agreement between the model and the real system. That measure of agreement depends on the type of data available and the nature of the problem.

Calibration identifies a point or region in the parameter space of the model that satisfies the modeller's criteria of agreement. It is possible that there is a single point in the parameter space that produces a global maximum of the agreement measurement, but it is more likely that this maximum is unidentifiable due to various errors, uncertainties, and variability in the model and data. In this case, calibration identifies a parameter set, or a region in the parameter space, that fits within an acceptable range of agreement. It is also possible to calibrate a model for multiple agreement measures simultaneously, identifying an area in the parameter space that maximizes a vector of measures (Janssen & Heuberger, 1995; Trucano, Swiler, Igusa, Oberkampf, & Pilch, 2006). The idea of multiple measures for calibration corresponds well with the concept of pattern-oriented modelling (Grimm et al., 2005). In this approach, patterns are the object of measurement, and models are judged by their ability to replicate patterns (spatial, temporal, behavioural, etc.) observed in the real complex system. The paper stresses that comparing to multiple patterns at multiple scales improves model design, calibration, and robustness.

5.4 Validation

Validation serves to evaluate the model and support the idea that model results are due to more than just chance (Rykiel, 1996). It confirms the model and, in general, the more instances of validation, the more confident we can be in the model (Crooks et al., 2008; Heath, Hill, & Ciarallo, 2009). Validation is an extension of the calibration process, using the same or new agreement measures to evaluate the model instead of adjusting the model. Validation using the same agreement measures as calibration requires independent data not used during calibration. New agreement measures, such as patterns or behaviours, can be used for validation using the same data as for calibration, as long these measures were not part of model development (Augusiak, Brink, & Grimm, 2014). Such validation is useful in the context of limited data, but researchers must be cautious of these results as they are not necessarily fully independent of the calibration. Validation with independent data is always the better choice. Usually, validation is based on some overall measure of model performance, but it is equally possible to validate parts of the model, such as processes, mechanisms, and sub-models, provided sufficient data and testing procedures (Cooley & Solano, 2011; Ngo & See, 2012). As before, this can serve to increase confidence in the model. However, this confidence must come with the caveat that almost all models of complex systems cannot be fully validated, for quite a variety of reasons (Heath et al., 2009). For one, models are built with a number of explicit and implicit assumptions, and only some of these are testable (Batty & Torrens, 2005). This caveat is an important aspect in any modelling endeavor, and it is the modeller's responsibility to clearly lay out the assumptions included in the model (Boschetti, Grigg, & Enting, 2011). But beyond this, and given that some assumptions are untestable and therefore impossible to validate directly, confidence in the model should be quantified and variance attributed.

5.5 Uncertainty and Sensitivity Analyses

Uncertainty analysis assesses the uncertainty in model output due to uncertainties in input factors (which includes data, parameters, initial states, and sometimes model equations themselves) (Crosetto, Tarantola, & Saltelli, 2000; Pianosi et al., 2016; Riley & Thompson, 2016). The purpose of UA is to determine the overall variance of the model's output, or the distribution of its potential range of outputs. This information, by itself, is a useful addition to model validation, as it refines the limits of model validity (Messina et al., 2008; Wallentin & Car, 2013). Sensitivity analysis builds on UA to apportion the output variance to the input factors. Nevertheless, UA and SA are separate processes, where the first is a measure of overall uncertainty, while the latter apportions uncertainty to input factors and measures their influence as well (Crosetto et al., 2000; Saltelli & Annoni, 2010). In this way, SA is very useful in an iterative model design/development approach (Trucano et al., 2006). Input factors can be ranked by their level of influence, thus identifying the most important, and the least important (Ligmann-Zielinska, Kramer, Spence Cheruvelil, & Soranno, 2014). These negligible factors can even be removed from the model, assuming there are no vital interactions between them and other factors. Sensitivity analysis can also identify interactions between input parameters and discern regions of input variability space that have important consequences of model output.

5.6 Example of modelling a complex system

A model of Mountain pine beetle (MBP) (*Dendroctonus ponderosae* Hopkins) (Pérez & Dragićević, 2011; Safranyik & Carroll, 2006), infestation in British Columbia serves as an example of the above model development steps. The MBP is an invasive species that is currently devastating the pine forest ecosystems in British Columbia, Canada. Although interbeetle interactions are non-social, their behaviour as a whole is the result of individual decision-making, while the swarm behaviour itself affects individual agents. This characteristic makes the MPB and its infestation of the pine ecosystems of British Columbia a perfect candidate for modelling as a complex system (Perez & Dragicevic, 2010).

The system is modelled using an agent-based approach, where both beetles and trees are agents with rules determining their phenology and spatiotemporal interactions. The main pathway for insect infestation of trees is a pheromone production and response system. In the model, female beetles randomly find a healthy tree susceptible to attack, and then produce a pheromone to attract other beetles and begin their attack. Another pheromone response regulates the number of attacking beetles to prevent over-crowding. Comparing the spatial behaviour of beetle agents between the model and an alternative, random behaviour model verified that the model operated as intended

Using data of tree mortality patterns in 2001 and 2006, the model was calibrated by running 5 1-year simulations, to adjust two major parameters that resulted in the patterns most similar to 2006 tree mortality. Sensitivity analysis helped identify the importance and the optimal setting of one of those parameters, the neighborhood size of beetle agent pheromone search (Pérez & Dragićević, 2011; Pérez, Dragićević, & White, 2013). The model was then validated with a full 5-year simulation to determine the accordance between model infestation patterns and 2006 infestation patterns.

Based on the importance of neighborhood size identified by SA, later work on MPB modelling using machine learning techniques integrated neighborhood effects as variables in model calibration, which allowed spatiotemporal complexities to be simulated (Harati, Perez, & Molowny-Horas, 2020)

A model like the one presented above allows researchers and forest managers to predict possible outcomes of policies and treatments to mitigate the damage caused by the MPB. It can also uncover key aspects of modelling assumptions that can inspire new avenues of research. Complex systems science, then, provides the means and guidelines to simulate, investigate, and analyse these kinds of systems.

6. Forest fire modelling via complex systems science

As this chapter has explained, forest fires are a complex system, and complex systems science offers many tools with which to study them. One such tool, Agent Based Modelling, has thus far seen little use in simulating forest fires. That is why the research objectives of this thesis focus on exploring the possibilities of using ABM to simulate forest fires. Chapter 2 presents a paper that responds to the objectives laid out in Section 1.2 of this Chapter.

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Chapter 2 – Scientific Article

Presentation of the article

Katan, J. and Perez, L.: ABWiSE v1.0: toward an agent-based approach to simulating wildfire spread, Nat. Hazards Earth Syst. Sci., 21, 3141–3160, https://doi.org/10.5194/nhess-21-3141-2021, 2021.

Agent-based modelling is an uncommon approach in fire spread modelling and simulation, and the following article aims to explore the advantages it can bring, namely the incorporation of complex feedback mechanisms at low computational cost; hitherto a significant challenge among fire spread models. The article presents the Agent-Based Wildfire Simulation Environment (ABWiSE) model, developed to respond to the research questions posed by this thesis. Developed from a complex systems viewpoint, ABWiSE represents fire as a set of mobile agents which, in aggregate, replicate fire spread. The model design seeks to reproduce realistic fire behaviour based on the interactions of these agents with each other, terrain, vegetation, and a simplified atmospheric feedback mechanism. The article contextualizes the place of ABWiSE within the fire modelling literature, describes the model, the calibration procedures and evaluation methods, and presents and discusses the results of this evaluation.

The article has been published in Natural Hazards and Earth System Sciences, and the peer review comments and our responses to them are available from the Peer review tab at the top of the page displaying the article.

Co-author agreement

This article was co-written by Jeffrey Katan, first author, and Liliana Perez, second author. Jeffrey Katan conceived, developed and evaluated the ABWiSE model, carried out the simulations and analyses of the model, produced the figures, and wrote the manuscript with the support of Liliana Perez. Liliana Perez helped design the study, supervised the project and helped write the manuscript. Both authors discussed the results and contributed to the final paper.

As co-author, I authorize Jeffrey Katan to present the article ABWiSE v1.0: Toward an Agent-Based Approach to Simulating Wildfire Spread in his Master's thesis.

Liliana Perez

Co-author

ABWiSE v1.0: Toward an Agent-Based Approach to Simulating Wildfire Spread

Abstract:

Wildfires are a complex phenomenon emerging from interactions between air, heat, and vegetation, and while they are an important component of many ecosystems' dynamics, they pose great danger to those ecosystems, as well as human life and property. Wildfire simulation models are an important research tool that help further our understanding of fire behaviour and can allow experimentation without recourse to live fires. Current fire simulation models fit into two general categories: empirical models and physical models. We present a new modelling approach that uses agent-based modelling to combine the complexity possible with physical models with the ease of computation of empirical models. Our model represents the fire front as a set of moving agents that respond to, and interact with, vegetation, wind, and terrain. We calibrate the model using two simulated fires and one real fire and validate the model against another real fire and the interim behaviour of the real calibration fire. Our model successfully replicates these fires, with a figure of merit on par with simulations by the Prometheus simulation model. Our model is a stepping-stone in using agent-based modelling for fire behaviour simulation, as we demonstrate the ability of agent-based modelling to replicate fire behaviour through emergence alone.

Keywords: agent-based model (ABM), forest disturbances, landscape ecology, fire behaviour, wildfire simulation

1. Background

Fire is an integral part of ecosystems the world over but also poses a serious danger to human life and property (Bowman et al., 2011; Moritz et al., 2010; Brenkert-Smith et al., 2013; Butry et al., 2001; Carroll et al., 2006; Chuvieco et al., 2014; Kochi et al., 2010; Richardson et al., 2012). In recent years, anthropogenic climate change has exacerbated this danger chiefly by lengthening growing seasons and increasing the risk of drought (Flannigan et al., 2016; Lozano et al., 2017), leading to more frequent and more extreme fires in many parts of the world (Chuvieco et al., 2016; Kirchmeier-Young et al., 2019, 2017). The use of controlled burning has, for a very long time (Gott, 2005; Roos et al., 2021), helped to mitigate the risks of extreme fires and to maintain forest health (Boer et al., 2009; Camp and Krawchuk, 2017; Fernandes and Botelho, 2003). Given the exacerbation of conditions ripe for extreme fires, it is paramount to predict how a fire might spread if it starts, especially for prescribed burns. Fire behaviour models are an important research tool that help further our understanding of fire behaviour and can allow experimentation without recourse to live fires (Hoffman et al., 2018). More specifically, modelling at the scale of individual fires is important for both the study of fire regimes (Keane et al., 2013; Parisien et al., 2019) and the operational management of active fires (Finney, 1999; Lawson et al., 1985; Tymstra et al., 2010; Van Wagner, 1974).

Bearing in mind that a complex system is one in which numerous elements interact in ways that give rise to emergent behaviour, often non-linear in nature, usually featuring feedback loops (Batty and Torrens, 2005; Langlois, 2010), at its base, fire is a complex system of interactions between fuel, oxygen, and heat (Byram, 1959). The dynamics and emerging behaviour are the result of self-organization, and the complex system will exhibit some form of hierarchy (Langlois, 2010), e.g. heat released from combustion warms neighbouring material to the point of combustion and creates convective currents in the air, moving oxygen through the system, which in turn keeps feeding the fire (Anderson, 1969; Byram, 1959). In a forest fire, the heat flux of all the burning material contributes to convection in the air mass surrounding a fire, sometimes enough to alter the flow of air that drives it (Clements et al., 2019; Filippi et al., 2009). This fire leaves a portion of land bereft of vegetation until it is recolonized, and this patch of land responds differently to new ignitions thereafter (Parks et al., 2015). Many fires over many years may affect the climate, which affects the vegetation, affecting the fires as a result, forming a feedback loop (Bowman et al., 2014; Stevens et al., 2015; Stralberg et al., 2018). Nevertheless, the challenge of any fire model is to balance complex behaviour with speed of computation, at a relevant scale.

Our goal is to demonstrate the potential of agent-based modelling (ABM) for the simulation of forest fire spread. Using ABM and a complex systems approach, we build a model that uses simple rules to reproduce fire behaviour as an emergent property of interactions between numerous agents representing fire. Agent-based modelling is a useful tool for modelling complex systems and is broadly much more computationally efficient at reproducing these systems than classical approaches based on solving numerous partial differential equations (Parunak et al., 1998; Sun and Cheng, 2005). As presented in the literature review below, ABM has appeared very little in fire behaviour research, and with this study, we aim to illustrate the potential of this approach to the field of forest fire disturbances and address some of its limitations.

1.1 Fire behaviour models

Bearing in mind that wildfires are a global phenomenon that pose significant and growing threats to human lives, property, wildlife habitat, regional economies, and global climate change, a variety of tools to tackle and envisage fire propagation have been developed. Some of these tools have the purpose of monitoring (Chu and Guo, 2013; Chuvieco et al., 2019; Giglio et al., 2016, 2003), others to forecast the likelihood of wildfire events (Cheng and Wang, 2008; Taylor et al., 2013; Forkel et al., 2019), and lastly some to model and simulate fire behaviour (Sullivan, 2009a, b, c). The literature concerning this latter category is of particular interest to the goal of this study.

There are many fire behaviour models described in the literature, ranging from empirical relations between environmental factors and fire behaviour to physics-based models that simulate the heat transfer of combustion between fuels and between fuel and atmosphere (Sullivan, 2009a). Among the most important advantages of empirical simulation models is their speed of computation; by simplifying the interactions between environmental factors and the fire front, they only have a small set of equations to solve at each time step

(Sullivan, 2009b). The primary design goal for empirical models is operational use by firefighters, who need rapid results and have the expert knowledge to overcome model limitations (Finney, 2004; Stocks et al., 1989). On the other hand, physical simulation models are better able to represent fire–atmosphere interactions and replicate the complexity and emergent behaviour of real fires (Coen, 2018). For example, while semi-empirical models such as FARSITE (Finney, 2004) or Prometheus (Tymstra et al., 2010) assume that fire shape is elliptical, physics-based models do not make this assumption, and fire shape matches observations through emergence (Filippi et al., 2009; Linn and Harlow, 1998). The drawback of physics-based models is their computation time; since they typically simulate interactions at a very small scale and have huge computational requirements, such models struggle to perform faster-than-real-time (FTRT) simulations (Sullivan, 2009a).

Modellers are attempting to bridge this gap between complexity of model behaviour and execution speed in various ways. One is by coupling a computational fluid dynamics model (CFD) with empirical fire behaviour models (Coen et al., 2013; Filippi et al., 2013), though it is argued that the generally coarse scale of the fire behaviour component limits their use (Linn et al., 2020). Yet despite simplifying the fire spread component of a coupled fire–CFD model, FTRT simulation can be difficult to achieve. Using the WRF-Fire (Weather Research and Forecasting – Fire) model (Coen et al., 2013) to simulate a real fire event in Bulgaria, Jordanov et al. (2012) reported simulation speeds based on number of processing cores and noted that FTRT simulation required a minimum of 120 cores. The CFD was the more demanding component of those simulations. It is possible to simulate fire–atmosphere interactions without using a complicated CFD but instead using a model that considers only relevant airflow. Hilton et al. (2018) created a model of pyrogenic potential to simulate two-dimensional airflow at the fire line, and their results match well with real-world experimental fires. While physics-based models provide the most realistic representations of fire behaviour, simplified physical or empirical models are also able to reproduce reasonably realistic fire behaviour by retaining relevant fire–atmosphere interactions. Other models take advantage of principles from complex systems modelling, in which complex phenomena are simplified by spreading calculations to individual, interacting computational units known as automata or agents in order to capture the essential interactions of a system (Sullivan, 2009c).

1.2 Complex systems modelling

In complex systems modelling, there are two broad computational approaches to modelling environmental systems: cellular automata (CA) and agent-based model(ing) (ABM). CA are a mathematical representation of a complex system wherein a lattice of cells is subject to a set of rules that determine their state and state information is passed between neighbouring cells (Gaudreau et al., 2016; Yassemi et al., 2008). Agent-based modelling uses autonomous, interacting agents following a rule set, like in CA. The key differences are that in an ABM, agents are mobile and can be heterogeneous; agents can interact with each other and their environment while moving through it, and different agents can follow different rule sets (Perez and Dragicevic, 2012; Pérez and Dragićević, 2011).

There are numerous CA models of forest fire behaviour. Earlier CA fire models had difficulty simulating correct fire shapes generally due to grid and neighbourhood shape biases (Tymstra et al., 2010). More recently, CA models on par with popular semi-empirical models have been developed; for example, the model by Ghisu et al. (2015) compares well with FARSITE, and that by Yassemi et al. (2008) does so with Prometheus. Due to their simplicity, CA models find use in dynamic fire–vegetation models, which simulate fire–climate–vegetation interactions over long time spans and at coarse spatial scales (Cary et al., 2006; Gaudreau et al., 2016). However, few, if any, CA models we have reviewed account for fire–atmosphere interactions to inform fire behaviour.

Agent-based modelling often simulates systems where mobile individuals are important, such as predator–prey systems (Grimm et al., 2005), flocks of birds or fish (Oloo and Wallentin, 2017), or insect infestations in forests (Pérez and Dragićević, 2011). Agent-based modelling lends itself well to simulating socio-ecological systems, such as forest management (Ager et al., 2018; Pérez and Dragićević, 2010; Spies et al., 2014) in which human decision-making must be modelled. While these examples have so far shown the utility of ABM for simulating decision-making entities, ABM does well with physical systems such as particles or smoke. A recent paper (Smith and Dragicevic, 2018) presents a physics-based ABM of forest fire smoke propagation, including two types of agents, one for fires and one for smoke particles. A single fire agent represents a single fire and produces the smoke agents. The fire agents can be either stationary or move according to a very simplified model of fire spread (2 % of surface wind speed), but fire shape and area are not represented. Because the only aspect of fire behaviour present in the model is smoke production, we do not consider this an ABM of fire behaviour.

The one paper we have found that explicitly claims to be an ABM of fire behaviour is the work by Niazi et al. (2010). It uses a virtual overlay multi-agent system (VOMAS) for validation and verification of their fire spread model, in which the VOMAS serves as a simulacrum of measurement points in the simulated forest.

Our literature search has uncovered only two fire behaviour models that match our description of ABM, yet the authors refer to them as CA. The first is the Rabbit Rules model of Achtemeier (2003) that bases itself on some of the principles of complex systems theory as described by Wolfram (2002). The first paper describing the Rabbit Rules model (Achtemeier, 2003) does explain that it is not a CA model and that "each element, a rabbit, is an autonomous agent … not constrained by the definition of the underlying grid (raster) domain"; nevertheless, the term ABM does not appear. Later papers that use or mention the Rabbit Rules model refer to it as a CA model, masking the fact that it uses a completely different modelling approach (Achtemeier et al., 2012; Achtemeier, 2013; Linn et al., 2020). The Rabbit Rules model recasts the physical and mathematical problems of fire behaviour as a set of rules of "rabbit behaviour" due to the analogical resemblance between fire and rabbit behaviours. Rabbits eat, jump, and reproduce just as fire consumes fuel, passes from fuel element to fuel element or spots, and reproduces as it ignites unburned material. In addition to rules for eating (fuel consumption), jumping (spotting), and reproduction (new ignitions), secondary rules modify these to include the effects of terrain, weather, fuel, and fire–atmosphere feedbacks. The Rabbit Rules model produces a ring shape under windless conditions, and a bowed front in high wind, without any predetermined geography such as in ellipse-based models. Just like an ABM, Rabbits move across the landscape, interact with each other and their environment, and produce reasonable perimeter shapes due to emergence alone.

Achtemeier (2013) presents a field validation of the Rabbit Rules model with the FireFlux experimental grassland fire, conducted in tall-grass prairies near the Gulf Coast of Texas, USA (Clements et al., 2007). The field validation demonstrates a reasonable match between simulated and observed airflow 2 m above the surface at two observation towers used in the FireFlux experiment. That study also notes that the Rabbit Rules model can simulate non-linear processes unachievable by empirical models and much more quickly than full-physics models; while FIRETEC can take about 90 s for each second of simulation on a 64-processor supercomputer, Rabbit Rules took only 0.67 s for each second of simulation on a desktop PC for this experiment. The simulation speed information for FIRETEC comes from a review by Sullivan (2009a). We have not found more recent information on simulation speed for FIRETEC, although the website for HIGRAD/FIRETEC states that "FIRETEC takes the huge computational resources at the Los Alamos National Laboratory to run, so it is currently a research tool only" (https://www.frames.gov/firetec/home, last access: 20 April 2021).

The initial exploration of ABM applied to fire behaviour by Achtemeier (2003, 2013) provided the base for a new model, QUIC-Fire (Linn et al., 2020). QUIC-Fire is a fuel–fire–atmosphere simulation model that combines the rapid wind solver QUIC-Urb (Singh et al., 2008) with their new physics-based fire spread model Fire-CA. This fire spread model builds on the conceptual framework of the Rabbit Rules model, in which instead of "rabbits", energy packets (EPs) represent units of energy that can evaporate moisture, burn fuel, or transfer their energy to the atmosphere. While Fire-CA is described as a cellular automata model, the EPs act like agents that move across the grid-based computational landscape; therefore we include it with the Rabbit Rules model as the only other example of fire behaviour simulation using ABM. Linn et al. (2020) demonstrate the model in two case studies, comparing the simulation results of FIRETEC and QUIC-Fire. The first case study was a simulated grass fire, and the second was a simulated prescribed fire in a forest landscape, replicating conditions typical of a prescribed burn at Eglin Air Force Base, in Florida, USA. Even though the paper does not report simulation speed, it does state QUIC-Fire is capable of FTRT simulation and required ∼1/2000 of the computational cost of FIRETEC for the simulations reported.

As stated earlier, the aim of this study is to demonstrate the potential of ABM for the simulation of forest fire spread. To do so we build an agent-based simulation model of fire behaviour using an empirical approach. This allows us to demonstrate how interactions between agents can produce common patterns found in fires by following simple rules. The model proposed here does not aim to replace or upgrade any fire spread model but rather to showcase the advantages and potential of using an alternative modelling approach. With this in mind, we design it for the simulation of large individual fire events in Canada, as large fires (>200 ha) account for ~3 % of fires in Canada and are responsible for ~97 % of total area burned (Stocks et al., 2002). Fires of this scale are particularly relevant for the study of fire regimes and fire–climate–vegetation interactions, as present in dynamic global vegetation models. These types of models typically use very simple fire spread models (Keane et al., 2004) and could benefit from a computationally efficient fire spread model that accounts for complex interactions during a fire event. An ABM of fire spread could potentially fill this niche.

The proposed and implemented Agent-Based Wildfire Simulation Environment (ABWiSE) model represents the fire front as a set of moving agents whose behaviour is determined by rules accounting for vegetation, terrain, and wind, as well as the interactions among the agents and with their environment (such as fire–wind feedback). We implement the ABWiSE model on two base case scenarios and two parts of one real fire (cases 1 through 4, respectively). The first two cases are simulated fires, and the latter two are from a fire in Alberta, Canada. The cases are detailed in Sect. 3.1 and listed in Table 1. We calibrate the model with cases 1, 2, and 3 and validate the model against case 4, as well as progression data for case 3. While we perform some preliminary uncertainty and sensitivity analyses to calibrate the model and evaluate some assumptions, a thorough uncertainty and sensitivity analysis will be the subject of future work.

2 ABWiSE fire spread simulator

2.1 General overview

ABWiSE translates the concept of a moving fire front as a set of mobile fire agents that, viewed in aggregate, form a line of varying thickness. Ultimately, the goal of such a fire simulation model is to provide predictions of the behaviour of hypothetical fires. Presently, this paper uses ABWiSE to explore how ABM, using simple interactions between agents and a simple atmospheric feedback model, can simulate emerging fire spread patterns. Specifically, we aim to identify the strengths and weaknesses of ABM applied to this purpose and how it differs from other modelling approaches.

We use pattern-oriented modelling as a strategy to both design and evaluate our model (Grimm et al., 2005). The patterns in question are fire line rate of spread (RoS; temporal), fire shape (spatial), and fire–wind interactions (emergence). As mentioned earlier, the ellipse is widely accepted as the generic fire shape (Anderson et al., 1982; Van Wagner, 1969), and it serves as the starting pattern. In uniform fuel and wind conditions, how can we get agents to burn an elliptical area through emergence and not an explicit rule? The guiding assumptions that lead to the model's current form are that fire is slower at the edges of a fire line than the center (Finney, 2004; Van Wagner, 1969), that the relationship between wind speed and rate of spread changes with the angle between the direction of spread and wind direction, and that fire dries the fuel ahead of it, making it more flammable (Byram, 1959). Fire line rate of spread and fire–wind interactions are what create fire shape as it evolves over time (Clark et al., 1996), so we use fire shape to evaluate our model under different conditions and at different times. The specific evaluation scenarios are described in Sect. 3.

2.2 Entities, state variables, and scales

The model entities are fire agents and grid cells. The fire agents have two main properties, heading and rate of spread (RoS), plus their location (floating-point coordinates). The heading is the direction, in degrees, an agent faces. The RoS is the portion of a cell an agent travels every time step (called a tick). The units of the RoS depend on the spatial and temporal scales of the model.

The spatial and temporal resolutions of the model are linearly proportional; e.g. at a 200 m cell size, each time step (or tick) represents 1 min, and at a 400 m resolution, each tick is 2 min. The spatial and temporal extents of the model depend entirely on the scenario to simulate. The model is implemented in the NetLogo multi-agent programmable modelling environment (Wilenski, 1999). The code and data are freely available under an open source license on GitHub (https://doi.org/10.5281/zenodo.4976112, Katan, 2021).

We base the flammability and fuel of cells on the Canadian Forest Fire Danger Rating System (CFFDRS) (Van Wagner, 1974; Wotton, 2009). We chose it due to the availability of fuel type data in Canada and the system's use around the world (Opperman et al., 2006). The system includes 16 classes of vegetation for which there are empirically derived equations relating fuel moisture and weather to fire behaviour. The CFFDRS is currently composed of two subsystems: the Fire Weather Index (FWI), which provides a general rating of fire spread potential based on fuel moisture, temperature, and wind speed, and the Fire Behaviour Prediction (FBP) system, which combines the FWI with fuel type characteristics to provide more detailed fire behaviour information. This system has been in use for decades but does not account for any form of feedback mechanism. Because ABWiSE uses feedback loops to replicate fire behaviour, using the FWI would require reworking its equations without wind, as it is an important variable within its subsystems. Doing so is beyond the scope of this research at this time. Instead, we chose to map the average characteristics of fuel types of the CFFDRS, as described in Forestry Canada Fire Danger Group (1992), to flammability and fuel values (Sect. A1). This keeps wind as a separate input and variable that forms part of a feedback loop.

2.3 Procedures

Figure 1 provides a schematic overview of the procedures. A model run begins with an ignition, creating four fire agents at that point, each facing one cardinal direction. Since flammability is the first driver of fire spread, fire agents have an initial RoS value set to the flammability of the cell they start in. At each time step, fire–wind interactions provide a local effective wind speed and direction for cells within a certain distance of fire agents (Feedback procedure, Sect. A2.1). Next, fire agents update their RoS and heading based on wind, flammability, terrain, and the local density of fire agents and then move by that RoS in that direction (Spread procedure, Sect. A2.2). After moving, agents preheat the cell within the distance of their RoS by a small amount, raising its flammability (Preheating procedure, Sect. A2.3). Next, agents have a chance to be extinguished (or die) based on the fuel value at their location and their RoS (Death procedure, Sect. A2.4). Those that do not die then propagate if they have travelled more than a certain distance from their point of origin and if there are fewer than a set number of other fires already in their current cell (Sect. A2.5). Lastly, fire agents reduce the amount of fuel in a cell based on their RoS (Sect. A2.6). The simulation ends if there are no more fire agents or after a predetermined number of iterations. Detailed descriptions of the procedures, including the equations involved, are included in the Appendix (Sect. A2). However, we will explain here some of the reasoning behind key procedures, namely Feedback and Spread. The Feedback procedure combines the input wind values at a cell with the effect of fire agents nearby and smooths the resulting vector based on the wind in nearby cells. This is a simple proxy for fire–wind interactions that was inspired by the pyrogenic potential of Hilton et al. (2018). The Spread procedure attempts to match the relationship between RoS and wind speed and direction to observations, as well as producing a reasonable fire shape. In short, low wind speeds have a small effect on the fire agents but have a stronger effect on fire agents whose heading is close to the wind direction. The relationship between RoS and wind speed follows a logistic curve based on the same assumption as Forestry Canada Fire Danger Group (1992) that there exists a maximum RoS based on fuel type, though the relationship is not identical. The various feedbacks change the final RoS from that particular logistic equation, so it would be moot to use the exact same relationship between wind speed and RoS as the FBP system.

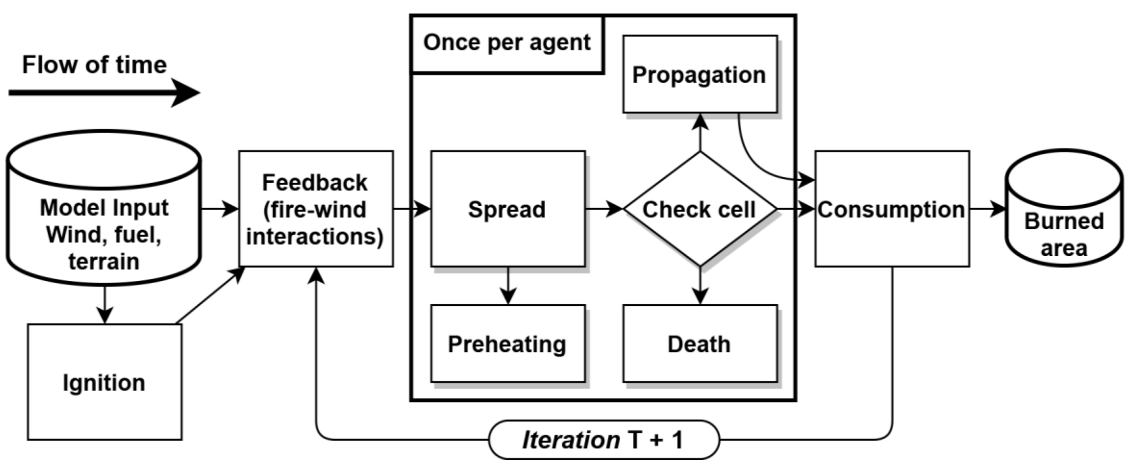

Figure 1. – Schematic description of model procedures.

The "Check cell" diamond represents the check for the **Death** procedure, followed by the check for **Propagation**, after which **Consumption** occurs. Fire agent RoS and heading are updated in the **Spread** procedure, which are used by the **Feedback** procedure at the start of the next iteration. Because agents update asynchronously within a procedure, **Preheating** by one agent can affect the next agent to perform the **Spread** procedure.

The last important detail about model processes is stochasticity. There are two sources of stochasticity in the model: the first is the chance of agents dying out, and the second is the turn order of the agents at each time step. While the operations listed above happen in the order presented, the order of agents or cells performing them is random. This asynchronous updating of agents is a default of the NetLogo programming language and serves to avoid artifacts of execution order. Due to the stochasticity, we base the model evaluation on ensemble maps representing the sum of 100 simulations with the exact same inputs and parameters.

3 Calibration and validation

To calibrate ABWiSE, we compare its output with expected behaviour and adjust the parameters until it performs adequately. Overfitting is a serious problem with this approach, and we try to minimize it by fitting our model to three different scenarios. However, detailed fire behaviour data and corresponding weather data are difficult to come by, especially for large and remote wildfires. Fortunately, the free-to-use Prometheus model (Tymstra et al., 2010) offers a sample dataset of a real fire for download: the Dogrib fire of 2001 in the foothills of the Rocky Mountains in Alberta, Canada (McLoughlin, 2019). We use one part of this fire for calibration, leaving another part for validation. Because we did not find other datasets using the Canadian FBP fuel type as model input, the two other scenarios for calibration are base cases as simulated by Prometheus.

3.1 Scenarios

The four scenarios are listed in Table 1 for ease of reference. The first base case scenario (Fig. 2a) is a 2 h long fire on a flat plane of the C-2 fuel type, Boreal Spruce, with no wind and a temperature of 25 °C. The second base case (Fig. 2b) is the same but with 20 km/h wind speed, coming from the east. Though ABWiSE does not use temperature as an input, Prometheus uses it to calculate the FWI and track changes in fuel moisture over time.

Figure 2. – Base cases 1 and 2

The Dogrib fire started on 25 September 2001 in the Rocky Mountains of southwest Alberta, Canada. The fire was detected at 17:00 MDT (all times are in mountain daylight time) on 29 September and reached a size of 675 ha at 16:30 the next day. Fire suppression started at 06:00 on 1 October. It burned at various rates under some suppression efforts until it grew to 852 ha by 15 October. On the 16th, a wind event pushed the fire through a gap in the surrounding mountains and caused the fire to jump the Red Deer River. After this, it spread 19 km in 6.7 h in a northeast direction. The final fire size was 10 216 ha, 90 % of which was a result of the 16 October fire run (McLoughlin, 2019). The vegetation consumed by the fire consisted mostly of lodgepole pine (*Pinus contorta*), followed by subalpine fir (*Abies lasiocarpa*), and Engelmann spruce (*Picea engelmannii*). Respectively, the FBP fuel types C-3, C-1, and C-2 represent these.

Table 1. Scenarios used for model calibration and evaluation.

Scenarios	Description
Case 1	C-2 (Boreal Spruce) fuel type, no wind
Case 2	C-2 (Boreal Spruce) fuel type, 20 km east
Case 3	Dogrib fire, 16 October portion
Case 4	Dogrib fire, 29 September portion

The example scenario provided with Prometheus provides data for both the initial unsuppressed burn between 17:00 on 29 September and 18:30 on 30 September and the 16 October fire run, shown in Fig. 3. These represent cases 4 and 3, respectively. Case 4 serves as an independent dataset for validation, and the final perimeter of case 3 serves for calibration, while the progression perimeters (solid polygons in Fig. 3, as provided with example data) are used for interim validation. The nearby Yaha Tinda automated weather station provided the necessary weather data for the simulation. According to the case study, this single weather station could not account for the complex topography of the mountainous area. The Dogrib case study includes a manually created weather patch for the Prometheus simulation in order to replicate the wind funnelling effect of the Red Deer River valley observed in the actual fire event. This funnelling is what drove the fire through a gap in the mountains and across the river. The report states that use of this weather patch provided more realistic simulation results in the case study than either uniform winds or dynamically modelled weather grids accounting for topographical influence on wind flow (McLoughlin, 2019). We use the exact same weather information for the ABWiSE simulations.

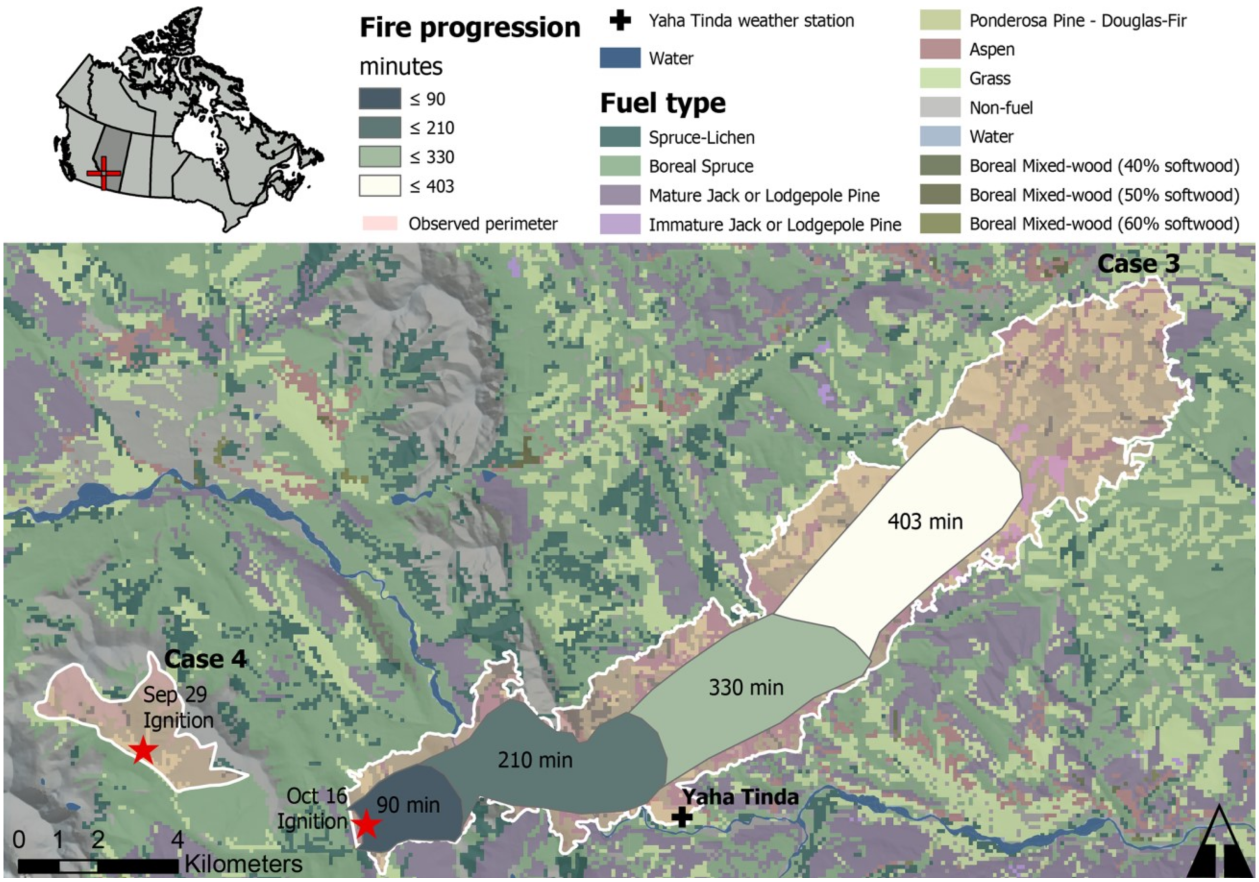

Figure 3. – Study area

Two parts of the Dogrib fire. The ignition points are those provided with the sample data, as used in our simulations as well as the Prometheus simulations. Background is a combination of hill shading, elevation, and fuel-type. The solid polygons show fire progression representing the time by which at least that much area has burned.

3.2 Model evaluation

Evaluation is critical for any simulation model, especially one that relies on empirical relations between variables instead of physical rules. Quantitative spatial methods to measure fire behaviour model performance broadly fall into two categories: final perimeter methods and time-based methods. Final perimeter methods, as the name suggests, measure the similarity between the final simulation perimeter and a final observed perimeter. Such methods are dependent on the error of the observation time and related assumptions about simulation duration, and they provide no information about model performance at intermediate times (Filippi et al., 2014).

In order to measure model performance throughout calibration, we use a final perimeter measure: the figure of merit (FoM) (Eq. 1), equivalent to the Jaccard similarity coefficient (Pontius et al., 2018). Values of the FoM range from 0 to 1, with 1 being a perfect match. In the case of fire perimeters, hits are those cells burned by the simulation that were also burned in the observation, misses are those unburned by the simulation but burned in observation, and false alarms are those burned by the simulation that were not burned in observation. Though there are some criticisms about the FoM and its use in measuring land-use change models (Harati et al., 2021; Varga et al., 2019), it still provides useful information and is easy to interpret when used to compare burned areas (Filippi et al., 2014). In particular, criticisms surrounding the FoM are based on full map comparisons, but in this study, the comparison is between burned perimeters only. Correct rejections far from the area of interest are never considered. Furthermore, simplicity of calculation is an important factor when measuring millions of simulations, as is necessary in calibrating this model.

$$FoM = \frac{hits}{hits+misses+false\ alarms} \tag{1}$$

3.3 Calibration

Calibration begins with manual exploration of the parameter space to eliminate parametrizations that produce very inaccurate results (based on both visual assessment and FoM). Large deviations from these manually identified initial settings produce very poor results (e.g. FoM less than 0.2). The next stage explores promising regions of parameter space at finer resolution, which consists of varying parameters around those manually identified initial settings by steps of about 5 % of their total range, up to three steps above and below the initial setting. We uses up to three steps because varying all 12 parameters by six steps would require just over 2 billion simulations. In addition, the need to repeat simulations for each combination to account for stochasticity acts as a multiplier to that number. We keep our parametrization runs to about 100 000 combinations at a time, with three repetitions, choosing to apply a broader sweep to those parameters deemed to have the most impact and a smaller sweep to the other parameters. The parametrization runs generate a table with each row containing the parameter values and the final FoM of that simulation. After such a run, we use a classification and regression tree (CART) (Brieman et al., 1984; Loh, 2011) based on the table to identify new "search" areas for parametrization. That is, the CART identifies important parameters and determines the values above or below which the FoM was better. However, the non-random nature of how we set the parameters and explore parameter space means the CART models are never as robust as if we had used random samples of the parameter space. We repeat the parametrization–CART process twice to arrive at a parametrization that adequately simulates all three scenarios without over-fitting the model to the few scenarios available to us.

After calibration, we use Monte Carlo methods (Kroese et al., 2014; Metropolis and Ulam, 1949) to account for the stochasticity of the model, producing ensemble maps of 100 simulations of each scenario. One ensemble map is the sum of the output maps of all 100 simulations. Cell values in these maps range between 0 and 100, representing how many times it burned in the ensemble or, in other words, burn probability. Note that this is the probability of that cell burning in the ensemble of simulations, not a prediction of burn probability in reality. We calculate a more robust FoM based on the statistics of these probability maps.

3.4 Validation

Typical model validation compares model output for scenarios not used in model calibration (Hoffman et al., 2018). The only independent scenario available is case 4, the 29–30 September portion of the Dogrib fire that was not subject to suppression efforts. This fire was about 14 km away from the automated weather station that supplied the data for the Dogrib case study and was nestled in a mountain valley. The available weather data are almost certainly less accurate than those for the 16 October run, which had improvements from experts and field observations. Therefore, while independent for the sake of model validation, the quality of the data limits the robustness of this validation. We supplement this validation with a time-based method to validate interim fire behaviour. Because the measure for calibration was only the final perimeter, the measure of intermediate fire behaviour is to some extent independent and can validate interim behaviour (Filippi et al., 2014). Although this cannot validate the whole model, it helps to elucidate the validity of its mechanisms. In addition to burn probability maps, the ensemble simulations provide maps of mean arrival time, which we use with the Dogrib fire progression data for case 3 in a time-based measure of performance to validate interim behaviour. Progression data for case 3 consist of reconstructions of the Dogrib fire perimeter at four instances between the start and end of the fire. Progression data for case 4 are too sparse for this method. Details for this evaluation are in Sect. 4.3.

4 Results

4.1 Ensemble maps

The ensemble maps in Fig. 4 provide a visual overview of model performance. Cases 1 (Fig. 4a and b) and 2 (Fig. 4c and d) both show an excellent agreement between simulated and expected shapes, with case 2 having slightly more variation in its final perimeter. Since there is wind driving the fire in case 2, there is more room for emergence through the fire–wind interactions, and thus we would expect more variability in the ensemble simulation. This variability is even more present in case 3 (Fig. 4e), in which not only is the time of burn longer, but the input wind itself is more dynamic. The ensemble simulations of case 3 demonstrate a wide range of potential outcomes. The majority of simulations do burn within a similar area as the real Dogrib fire, though some also cross the mountains further north and burn a large swath of land parallel to the real fire. Simulation of case 4 often burns far less than the observed fire. The simulation also never burns for the full duration of the observation data, with a mean burn time of 421 min out of 1550 min and a maximum of 1492 min before burning out completely. Table 2 summarizes the FoM of the simulations in an ensemble, i.e. the summary statistics of the score of each individual simulation. To test whether the fire–wind feedback has a meaningful influence on fire behaviour in ABWiSE, we also perform these simulations with the $w1$ parameter (see Sect. A2.1) set to 1, which effectively reduces the effect of fire–wind feedback to 0. The table also includes the FoM for simulations by Prometheus for comparison.

Considering that ABWiSE is designed with coarse scales in mind, we perform the same simulation measurements as before but at a resolution of 500 m per cell instead of 200 m.

The scores, in Table 2, are generally lower due in part to the smaller total number of cells involved in the calculations. As for fire–wind feedback, almost every scenario scores lower without the feedback effect than with it. Only case 1 at a 200 m resolution and case 3 at a 500 m resolution score better without it. Most notably, the maximum scores are all lower. As seen in Fig. 5, simulated fire shape under windy conditions tend to be fan-shaped, rather than elliptical, with case 2 showing the most evident difference between simulations with and without fire–wind feedback.

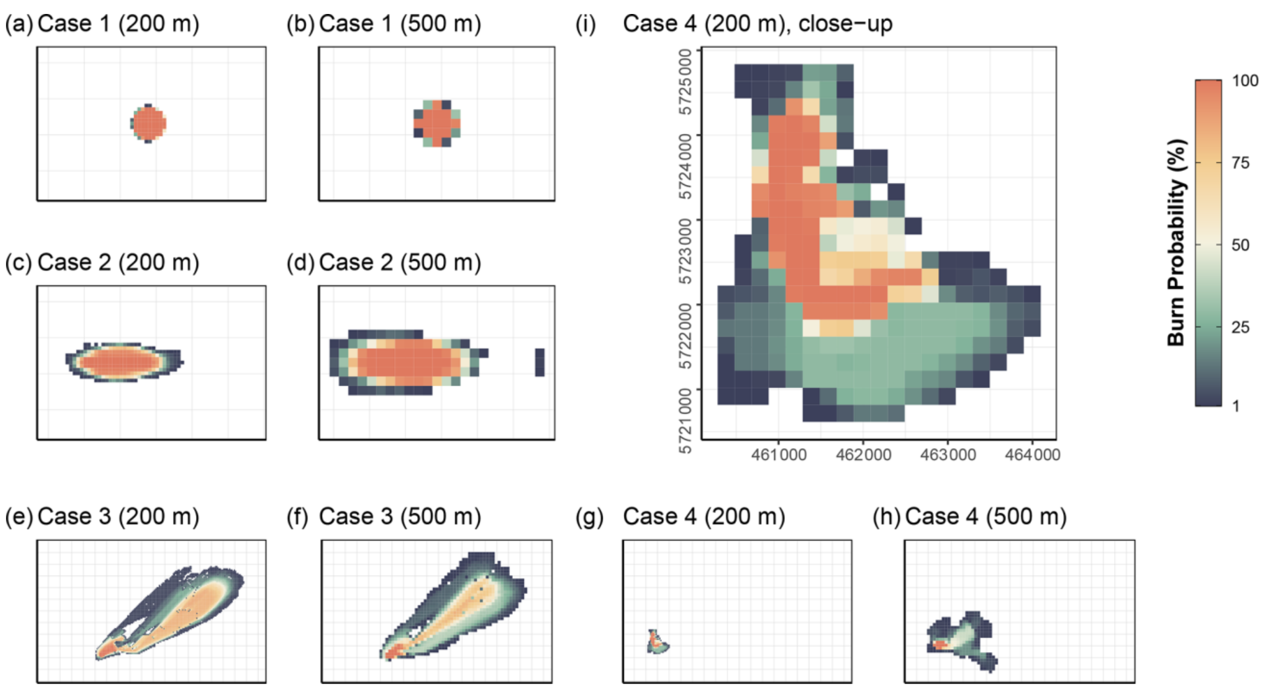

Figure 4. – Ensemble maps for all 4 scenarios at 2 resolutions (200 m and 500 m).

Graticule spacing for every map is 2000 m except (i), for which it is 500 m. This is to help compare the size of each scenario. Panels (e) to (h) have the same spatial extent in order to show the relative size and locations of cases 3 and 4.

Table 2. Figure of Merit (FoM) descriptive statistics based on each run in an ensemble simulation; "(no fb)" specifies scenarios run with the fire-wind feedback disabled.

	200 m resolution			500 m resolution			Prometheus
Case	**Mean FoM**	**Max FoM**	**SD**	**Mean FoM**	**Max FoM**	**SD**	**FoM**
1	0.8322	0.8800	0.0185	0.5416	0.6300	0.0286	1
2	0.8080	0.9300	0.0873	0.5598	0.6900	0.0524	1
3	0.4783	0.6800	0.1830	0.4279	0.7200	0.1839	0.5647
4	0.2817	0.4100	0.0608	0.2139	0.4600	0.0803	0.2108
1 (no fb)	0.8362	0.8769	0.0141	0.4939	0.5882	0.0204	NA
2 (no fb)	0.4558	0.5507	0.0431	0.3716	0.5000	0.0274	NA
3 (no fb)	0.4116	0.4550	0.0214	0.4449	0.5507	0.0731	NA
4 (no fb)	0.1377	0.1806	0.0277	0.1423	0.3673	0.0647	NA

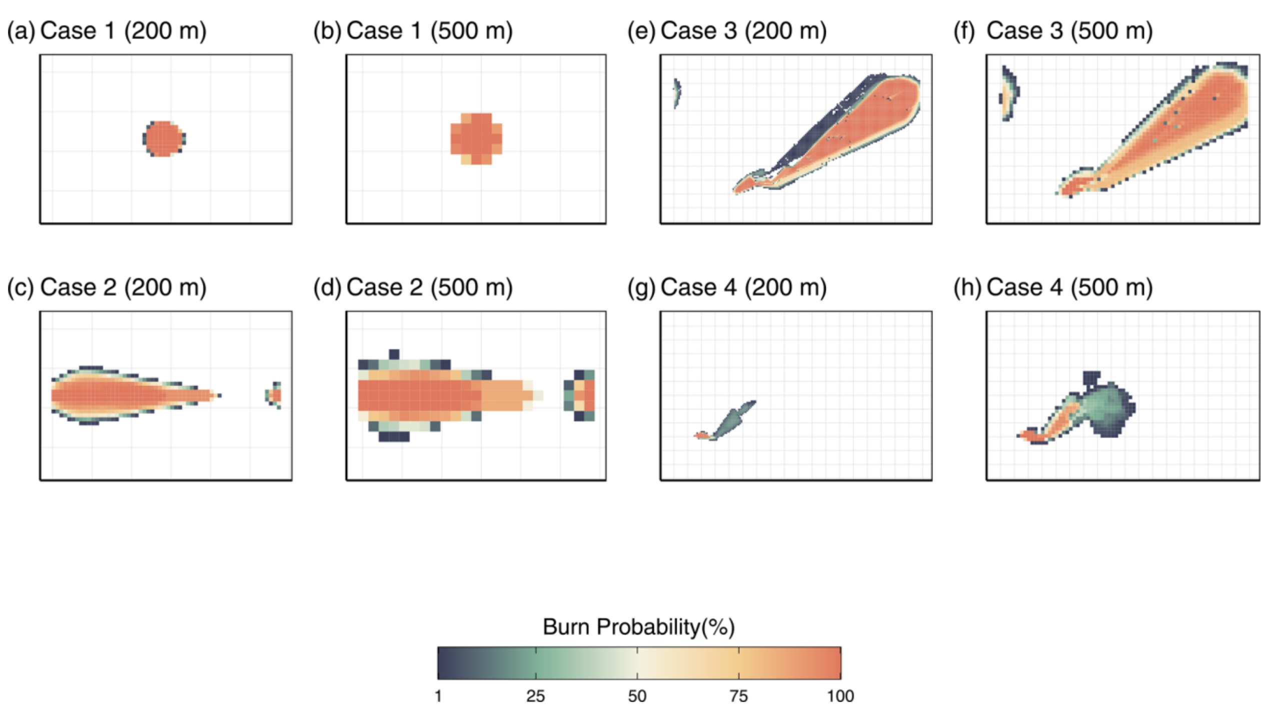

Figure 5. – Ensemble maps for all four scenarios at two resolutions (200 and 500 m) for simulations with no fire-wind feedback.

Note that the simulation space topology is toroidal, meaning that fire agents that reach the edge of the world disappear and reappear at the opposite edge. Under normal circumstances this condition should not be reached, but the lack of fire-wind feedback resulted in exceptionally fast-moving fire fronts that passed the edge of the world before the end of the simulation. The results of this can be seen in panels (c), (d), (e), and (f).

4.2 Figure of Merit maps

There are two ways of calculating and showing the FoM of these ensemble maps. The first, in Fig. 6, shows an ensemble of the FoM components as calculated for each individual simulation. This visualization of the different FoM components provides insight into just how, and where, the model agrees or disagrees with observations. For case 1 (Fig. 6a, b, c), the simulation burns the entirety of the observed burn almost all the time, misses a few cells in a scant 2 % of simulations, and over-burns only a small ring outside the observation perimeter. With a mean FoM of 0.83, the simulation of case 1 is in good agreement with observations and, notably, creates a circular perimeter through emergence alone. Case 2 has a mean FoM of 0.81, also indicating good agreement. Figure 6e and f show that there is a fair amount of under- and over-burning in the ensemble, which contribute to the error. Once again, the simulation perimeter closely resembles the expected ellipse through emergence alone. Case 3 has a mean FoM of 0.48, much lower than the first two cases. Figure 6g shows that the majority of simulations in the ensemble do burn in a similar shape and area as the observation, but the ensemble frequently under-burns the top edge of the Dogrib fire. Figure 6h shows the corollary and demonstrates that the model very rarely burns the full width of the Dogrib fire, particularly in the bottom portion of the fire. Over-burning is the smaller source of error for case 3, with mostly low probabilities, and Fig. 6j highlights the particularly low probability of the northern parallel burn mentioned earlier. Case 4 has a mean FoM of 0.28 and never burns the full extent of the observed fire, as visible in Fig. 6k and l. On the other hand, the simulations very rarely over-burn except a small portion to the north of the fire, which is the top of a ridge.

Figure 6. – Individual FoM components from each simulation, stacked as ensemble maps.

Cell value represents how many times a cell was part of a given component in the ensemble, in other words, the percent occurrence in that category. In this case count and percent are equivalent, given an ensemble consists of 100 simulations.

The second way to calculate FoM from ensemble simulations uses a statistically derived subset of the full ensemble map to calculate FoM. The subset consists of those cells with a burn probability above a certain threshold value, and this subset is compared to the observation data. We calculated the FoM for four threshold values: the mean, 1 standard deviation, 2 standard deviations, and the second quartile. This provides the FoM of the most probable outcome of the model. Figure 7 shows the resultant FoM maps and scores for cases 3 (Fig. 7a to d) and 4 (Fig. 7e to f) for the four different thresholds. These results show that while the mean FoM for cases 3 and 4 are relatively low, the most probable outcomes of the model (as defined by the statistical subsets) score higher.

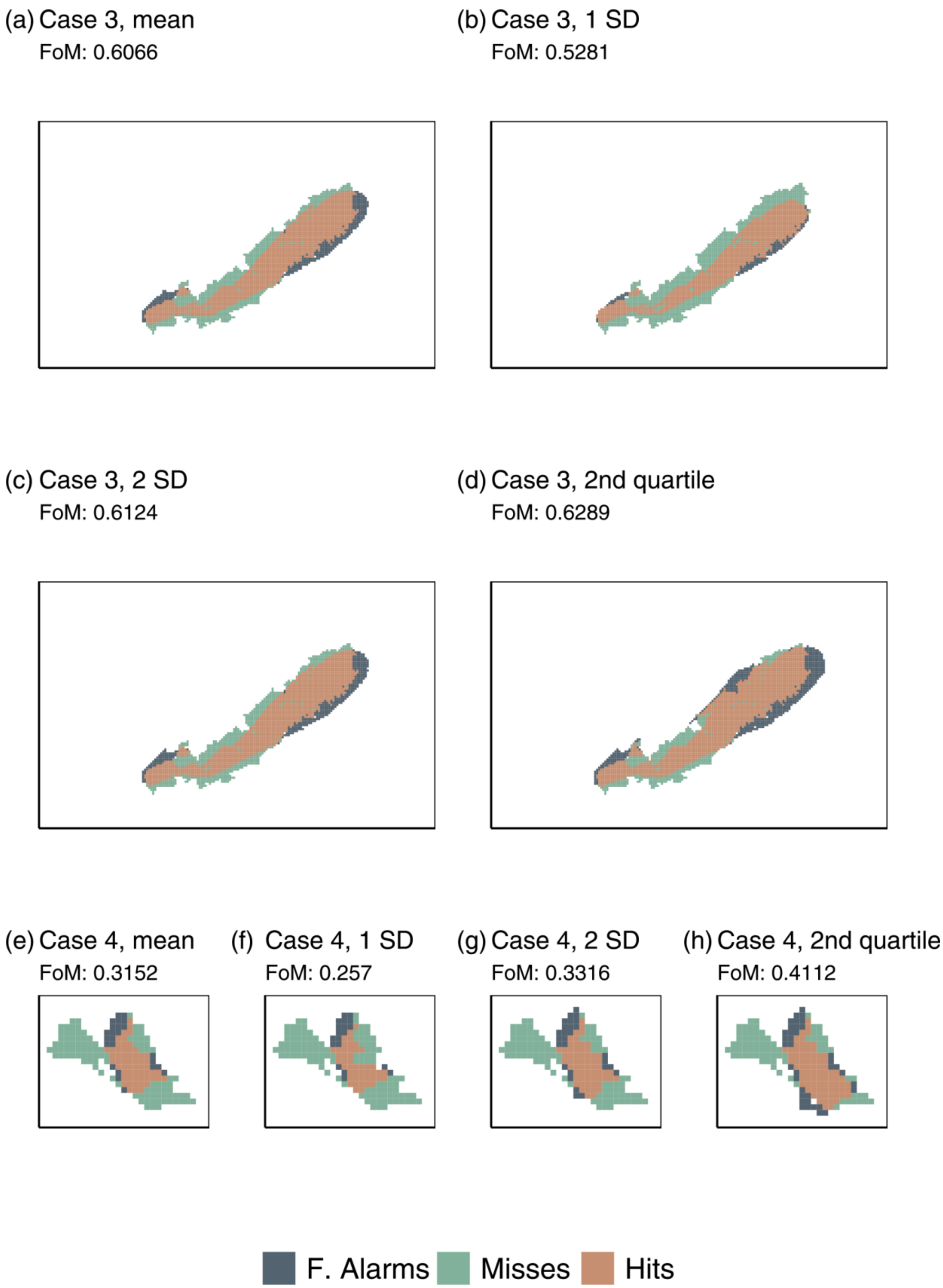

Figure 7. – Components of Figure of Merit.

Each column shows the FoM components and score for cells in the ensemble with a burn probability value above a threshold burn probability. First column is cells in the ensemble with a value above the mean, second column is those above 1 standard deviation below the maximum (100), third is above 2 standard deviations from the max, and fourth is above the 2nd quartile. Note that the real fire shape is the combination of Hits and Misses, while the simulated fire shape is the combination of Hits and False Alarms.

4.3 Time-based evaluation

A time-based measure of model performance allows us to evaluate interim fire behaviour and thus validate to some extent the processes that make up the simulation. In particular, it reduces the impact on FoM of impossibly burned cells, as mentioned above. Figure 8 shows how our simulation corresponds to the coarse reconstructions of the Dogrib fire (which are included with the sample data). Simulation progression uses the mean arrival time of a cell to determine those burned within a time period, and we use the mean probability subset (shown in Fig. 7a for comparison). In the first time period (Fig. 8a), both reconstructed and simulated fires grow similarly, though offset, but their fronts advance to a similar point. In the second period (Fig. 8b), the simulation fire continues to over-burn to the north and lags behind the furthest eastward extent of the reconstructed perimeter. By the third period (Fig. 8c) the simulation fire rushes ahead of the reconstruction, though the width of the fires stays similar. At the end of the fire the simulation has burned further and wider than the reconstruction. These tests show a degree of agreement between the progression of the simulated fire and that described in the case study (McLoughlin, 2019) in that the fire grows slowly in the first two periods, and then spreads very quickly in the last two.

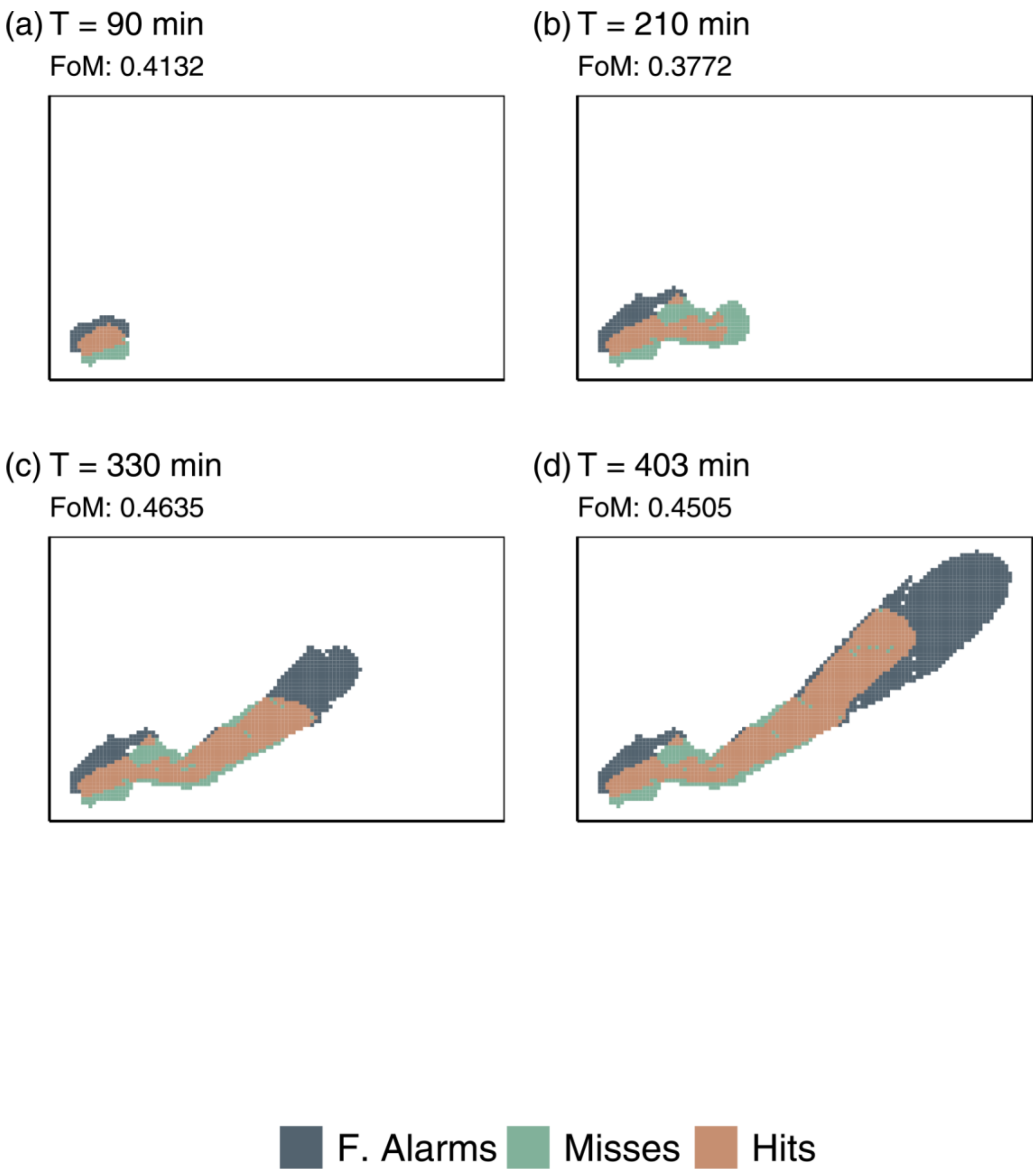

Figure 8. – Components of FoM for case 3, at four times past ignition.

Table 3. Figure of merit values for ensemble simulations for different fuel types.

Scenario	Figure of merit		Hits		Misses		False alarms	
Fuel type and wind speed	Mean	SD	Mean	SD	Mean	SD	Mean	SD
C-1 00 km	0.16	0.01	3	0	0	0	16.37	0.86
C-1 20 km	0.27	0.02	33.69	2.04	89.31	2.04	1.57	1.32
C-2 00 km	0.83	0.02	56.96	0.2	0.04	0.2	11.35	1.28

C-2 20 km	0.82	0.06	146.11	9.23	15.89	9.23	15.86	8.52
C-3 00 km	0.11	0	9	0	0	0	72.46	1.91
C-3 20 km	0.54	0.04	105.29	4.02	1.71	4.02	89.4	16.89
C-4 00 km	0.79	0.02	64	0	0	0	17.45	1.97
C-4 20 km	0.79	0.06	168.77	9.4	18.23	9.4	28.49	13.81
C-5 00 km	0.1	0.01	2	0	0	0	17.39	1.01
C-5 20 km	0.61	0.03	23.73	0.51	3.27	0.51	11.94	2.46
C-6 00 km	0.46	0.02	9	0	0	0	10.43	0.87
C-6 20 km	0.22	0.01	34.42	1.79	118.58	1.79	0.87	1.31
D-1 00 km	1	0	1	0	0	0	0	0
D-1 20 km	0.17	0.01	1	0	0	0	5	0.4
M-1 00 km	0.84	0.04	19.3	0.83	3.7	0.83	0	0
M-1 20 km	0.62	0.03	34.93	1.98	21.07	1.98	0.77	1.05
O-1 00 km	0.8	0.03	21	0	0	0	5.18	0.95
O-1 20 km	0.84	0.05	36.32	1.17	1.68	1.17	5.17	2.84
Case 3 random	0.04	0.02	104.58	65.19	2318.42	65.19	0.25	1.35

5 Discussion

Overall, the results of our simulations show good agreement between ABWiSE simulations and observations. The model performs very well in simulating the two base cases, while its performance decreases when simulating the real fire of cases 3 and 4. Ensemble simulation produces an improved score but also introduces certain problems related to the process-based nature of the phenomenon for case 3 (Fig. 7b), in which using the second quartile as a threshold includes cells in the subset that could only have been burned if the fire had burned further north earlier in the simulation. The core concept of using ABM to simulate fire spread has proven successful. The agent-based framework lends itself well to the complex nature of forest fires. Integrating complexity at the level of a disaggregated fire line means fire behaviour emerges from the bottom up, as in physical models, but with far less computational load. While the fire–wind feedback mechanism has a role in adequately simulating fire behaviour, it is clearly not the sole factor at play, both as a source of error and a vital part of successful simulation. Despite the simplicity of the fire–wind feedback sub-model, the results presented in Table 2 and Fig. 5 do indicate that ABWiSE produces more realistic simulations with it than without it. Even though the results of the validation are promising, there is still room for improvement. Two avenues for improvement are, of course, more data and an enhanced model. Exploring the limitations of both the data and the model helps us by highlighting the successes and failures of this approach and guides future work.

5.1 Error and data limitations

Differentiating between input error and model error requires high-quality data to minimize input error, leaving the model as the only potential source of error. Data availability and quality limit the validation of the model, in particular the weather observation data for case 4. Simulation of case 4 by Prometheus has an FoM of 0.21 (compared to the Dogrib perimeter at a 200 m resolution) because it over-burns a large area southwards, which indicates that case 4 is difficult and complex to simulate and reinforces the notion that input data for it are inaccurate and a large source of error. However, we can consider our test cases 1 and 2 to have perfect input data since the comparison was another model's output based on the same data. Any inaccuracy in cases 1 and 2 is due to model error. The data for case 3 are the best real-world data available to us and are of sufficient quality for the Prometheus model to have an FoM of 0.568. On the other hand, there are obvious problems with the reconstructed fire perimeters used for the time-based validation of case 3: the reconstructed fire progression does not reach the full extent of the observed final perimeter, nor is it as wide, indicating some discrepancy between reconstruction and reality. Limits to input data do not mean model errors are the same between ABWiSE and Prometheus. Attributing sources of error and uncertainty in model output is the goal of sensitivity and uncertainty analyses (SA and UA, respectively).

The preliminary sensitivity analysis pertaining to fuel types demonstrates that fuel is an important subject of error in the model. The true source of error is presently indistinguishable between the model procedures using the fuel type variables and the fuel type variables themselves. The Spread, Death, Preheating, and Consumption procedures all use or affect these variables. Furthermore, this analysis shows only the discrepancy between ABWiSE and Prometheus, not real fire behaviour. However, the fact that randomized fuel resulted in an extremely low FoM for case 3 means that fuel is an important input factor, and its parametrization is at least somewhat correct. Described further in Sect. 5.3, SA and UA are the next step for the model presented in this paper.

The general problems of data limitations can be addressed by new field experiments and observation techniques (Chuvieco et al., 2019). In particular, the proliferation of publicly available satellite data is a great resource for forest fire observations, though limits to return time and resolution affect the quality and applicability of these observations (Andela et al., 2019). Canada's future WildFireSat mission (https://www.asc-csa.gc.ca/eng/satellites/wildfiresat/default.asp, last access: 9 June 2021) will address this issue and provide daily infrared observations of wildfires at a 200–500 m resolution; an ideal scale for the niche ABWiSE aims to fill.

5.2 Model Limitations

ABWiSE makes many assumptions about fire behaviour in the form of the equations that define fire agent RoS and heading and their relation to environmental variables. Another assumption is the simple fire–wind feedback sub-model. There was no intention for the equations based on these assumptions to be a new way to explain fire behaviour. Rather, they were kept relatively simple in order to explore the potential of ABM as a way to simulate fire behaviour in a bottom-up, complex systems approach. The design of these equations makes use of numerous parameters so that the relations between agents and input variables could be honed in on through calibration across many scenarios. Although the equations are purely empirical in nature, not adhering to the physics of fire (thus imposing an ultimate limit on the model's accuracy and validity), the modelling approach and the calibration framework mean that the model could be continuously improved with more data up to that limit. However, the corollary to this – that the model performs well in spite of a purely empirical formulation – supports our objective of demonstrating the potential of ABM for fire spread simulation.

5.3 Future Work

Future work on ABWiSE may focus on sensitivity and uncertainty analyses. Together, SA and UA quantify the overall uncertainty of a model and partition the output variation among the input factors. These input factors include not only parameters but data and even the model's equations and algorithms. By this process, we could clearly identify the limits of the model and attribute the uncertainty to specific sources. From this point, a renewed calibration effort could proceed on the sources (input factors) most influential to the model output. However, this would require more input data to analyze the model over a larger spread of scenarios, as well as potentially billions of simulations to properly explore the parameter space. As demonstrated with the brief sensitivity analysis presented above, examining one factor at a time is not necessarily enough to identify precise sources of error. However, if we performed similar analyses pertaining to wind and terrain, we might discern which of the major environmental inputs upon which to focus our efforts first.

Given that ABWiSE is currently a proof-of-concept model, and we consider that it has proven the concept of using ABM to simulate fire spread, a simpler way forward may be to replace many of its algorithms and equations with adaptations of empirical models: specifically, implementing the FWI and FBP system equations in a way that accommodates the ABM approach and fire–wind interactions. This wind feedback, in turn, may be generated by coupling with a CFD or most likely implementing the pyrogenic potential model of Hilton et al. (2018). ABWiSE, in its current state, would then serve as the benchmark for improvements.

One of the benefits of the ABM approach, and the NetLogo environment in general, is that it is relatively easy to add functionalities to the model, such as fire suppression. For example, firefighting efforts are an important factor in the behaviour of fires subjected to it, and suppressed fires tend to be significant for their proximity to the wildland–urban interface (Johnston and Flannigan, 2018). In its current form, ABWiSE could simulate the effect of firefighting by simply reducing the flammability and/or available fuel in those cells being suppressed. The matter of simulating intelligent firefighter behaviour is a completely different challenge, however.

5.4 Computation

All simulations in this study used a desktop PC with a 12-core, 64 bit processor. On average, simulation speed is 10 time steps per second, though speed goes down as the number of agents grows very large (>500, occasionally surpassed in case 3). The most intense scenario, case 3, runs in under 80 s, on average, which compares favourably to Prometheus' 93 s on the same computer. ABWiSE's simulation time goes down for ensemble simulations, as NetLogo can take advantage of multi-threading for simultaneous runs. The Monte Carlo simulations of all four cases at two different resolutions (800 runs, producing the ensemble maps) took approximately 40 min. Simulation speed varied greatly during calibration, with some parameter sets resulting in very slow speeds, and so calibration took the longest time, with each parameter sweep taking about 30 h to complete.

6 Conclusions

Through a complex systems approach focusing on key interactions and conceiving of fire as a set of mobile agents, this study demonstrates the potential of agent-based modelling for use in simulating forest fire behaviour. We present ABWiSE, an empirically calibrated ABM of fire behaviour, which succeeds at the key goal of replicating fire shape through emergence from basic rules. We evaluate the model with a suite of perimeter comparison techniques, including a time-based method, which identify specific strengths and weaknesses in simulation results. ABWiSE is still in the early stages of development and requires more data for both calibration and validation, which will help refine its output and determine its range of applicability. It is no replacement for existing models of fire behaviour but rather a step in exploring a new avenue of modelling. While other ABMs of fire spread such as the Rabbit Rules model or QUIC-Fire demonstrate the potential of ABM at small scales, ABWiSE applies another formulation to large forest fires, highlighting how ABM can track the core elements of complexity of fire across scales. By using the interactions of individual agents to simulate fire behaviour, complex patterns and behaviours emerge without specifically coding them in. We believe the use of ABM in fire modelling merits further research as it leverages efficient bottom-up simulation of complex systems for coupled fire–wind interactions.

Code and data availability

The ABWiSE code, along with the data used for the simulations presented in this paper, is freely available on GitHub (https://doi.org/10.5281/zenodo.4976112, Katan, 2021).

Author contributions

JK conceived, developed, and evaluated the ABWiSE model, carried out the simulations and analyses of the model, produced the figures, and wrote the manuscript with the support of LP.

LP helped design the study, supervised the project, and helped write the paper. Both authors discussed the results and contributed to the final paper.

Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

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Review statement

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Appendix A

A1. Fuel type characteristics

Table A1 presents a detailed description of the variables mapped and used in our model. The Dogrib fire case study does not include all 16 fuel types of the FBP system, thus we only present those present. The mapping of fuel types to fuel and flammability values for our model uses the curves presented in (Forestry Canada Fire Danger Group, 1992). The flammability value is based on the steepness and maximum value of the Rate of Spread vs Initial Spread Index curves in section 7.2 of the aforementioned report. Fuel values are based on assumptions of fuel type characteristics. This is a gross simplification of fuel type characteristics, but the use of a simple index for each value means a sub-model could later serve to generate more accurate values.

Table A1. – Fuel type and variable values

Fuel type		Model value	
Code	Name	Fuel	Flammability
C-1	Spruce-Lichen	0.5	0.5
C-2	Boreal Spruce	0.5	0.85
C-3	Mature Jack or Lodgepole Pine	0.5	0.9
C-4	Immature Jack or Lodgepole Pine	0.5	0.85
C-7	Ponderosa Pine-Douglas Fir	0.5	0.2
D-1/D-2	Aspen	0.5	0.1
O-1a/O-1b	Grass	0.4	0.6
M-1/M-2	Boreal mixed-wood	0.5	0.6
-	Non-fuel	0	0
-	Water	0	0

A2. Procedures

A2.1 Fire-wind interactions

The local wind vector $\vec{L}$ is the weighted average of the global (or ambient) wind $\vec{G}$, the effect of fire on wind $\vec{F}$, and the current local wind $\overrightarrow{L_0}$, written as:

$$\vec{L} = w_1\vec{G} + (1 - w_1)(w_2\overrightarrow{L_0} + (1 - w_2)\vec{F}) \quad \text{(A1)}$$

where $\overrightarrow{L_0}$ is the local wind based on values of the previous time step, and w_1 and w_2 are weighting parameters. Only cells within a certain distance of fire agents (6 cells if the resolution is 200m) calculate a local wind vector, and only a subset of these (cells within 4 cells of fire), calculate the effect of fire on wind and apply a smoothing function to their wind vectors. The smoothed local wind vector for the subset is the Inverse Distance Weighted (IDW) interpolation (eq. 2) of $\vec{L}$ of the larger set. The general formula for IDW is

$$IDW(x) = \frac{\sum_{i=1}^{n} \frac{x_i}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \qquad \text{(A2)}$$

Where d is the distance between x and x_i, and p is a constant value affecting the influence of distance. These calculations mean that at the exterior edge of this active wind zone, global wind is the most influential factor on local wind, and fire has the strongest effect in cells with fire agents present.

The fire influence, $\vec{F}$ in equation 1, is the sum of a local gradient of fire RoS, ∇_{RoS}, and a smoothed fire vector, *IDW(RoS)*. The gradient ∇_{RoS} is a vector pointing to the greatest change in the sum of the RoS of fire agents in the eight neighboring cells (aka the Moore neighborhood), with the exception that if there are no fires in one of the neighboring cells, the value for that cell is substituted with that of the center cell. The value of $\vec{F}$ is then,

$$\vec{F} = k\nabla_{RoS} + IDW(RoS) \qquad \text{(A3)}$$

With the constant, k, scaling the effect of ∇_{RoS}. Because fire agents spawn and die suddenly at each time step, we used *IDW(RoS)* of fires in that Moore neighborhood to improve continuity between time steps. This is a very simple proxy for actual fire-wind interactions and it was inspired by the pyrogenic potential of Hilton et al. (2018).

A2.2 Fire spread

Fire agent RoS is the result of flammability, wind, and slope at its present location. Many corrective factors were necessary to match the relationship between RoS and wind speed and direction to observations, as well as producing a reasonable fire shape. In short, low wind speeds have a small effect on the fire agents, but have a stronger effect on fire agents whose heading is close to the wind direction. The relationship between RoS and wind speed follows a logistic curve based on the same assumption as (Forestry Canada Fire Danger Group, 1992) that there exists a maximum RoS based on fuel type. Equation 4 shows how fire agent RoS, wind, and slope vectors are combined to determine the new RoS by which a fire agent will move this time step, and carry on to the next.

$$RoS = RoS_b f_{mod} d_{mod} + \vec{L}(1.05 - f_{mod}) w_{mod} + \vec{S} s_{mod} \qquad \text{(A4)}$$

where

$$RoS_b = \left[f_1 RoS_0 + (1 - f_1)\,(flam^{1.3} + flam + w_3 \|\vec{L}\| |collinear| + s_1 \|\vec{S}\| coslope \right] m_1 w_{mod} \qquad \text{(A5)}$$

where *flam* is the flammability of a cell; f_1, w_3, s_1, and m_1 are user-defined parameters; *collinear* and *coslope* are the cosines of the difference between the fire agent's heading and the wind direction and terrain aspect, respectively. Using the absolute value of *collinear* means that fires moving directly into the wind still increase their RoS instead of slowing to a stop. This reflects an assumption that the oxygen supplied by the wind in this case is sufficient to increase the strength of the fire, allowing fire to move against the wind in low-wind conditions. The term w_{mod} represents the logistic equation with parameters *a*, *b*, and *k*:

$$w_{mod} = \frac{a + \frac{flam}{30}}{\left[1 + be^{-k\|L\|}\right]^{\frac{1}{flam + 2.6 + RoS}}} \qquad \text{(A6)}$$

In Eq. 4, f_{mod} is an additional correction component with some constants fixed at values that appeared to provide acceptable model behaviour, and one parameter, f_2, is left open to more thorough parametrization.

$$f_{mod} = f_2(1.2 - \frac{w_{mod}}{1.3}) \qquad \text{(A7)}$$

Finally, d_{mod} is another correction factor based on the density of fire agents, representing an assumption that closely clumped fire agents stay hotter, longer, and fire agents out on their own lose heat more quickly and don't move as fast. Density, *d*, is expressed as the number of fire agents within a radius of 1 of the agent calculating it, and the near-density, *nd*, is the mean density of those same agents in a radius of 1, such that the density modifier is:

$$d_{mod} = 1 + \left(\frac{d+1}{d_{max}} - \frac{nd+1}{d}\right) \times d1 \qquad \text{(A8)}$$

Where d_{max} is the maximum density of all fire agents at that time step. It is scaled by parameter $d1$.

A2.3 Preheating

Agents heat the cell ahead of them at a distance of their RoS by raising its flammability. RoS may be less than 1, thus the "cell ahead" may be the cell the agent is already in. The modelling software determines cell location by the center of the cell, so a cell that is one RoS away may have a different distance from the agent. For example, if the edge of a cell is one RoS away, its distance to the agent is one RoS + 0.5. Therefore, the distance between the cell and the agent, d in equation 9, is not the same as the RoS. Only cells with a flammability below 1 (the maximum) are heated by the amount defined by:

$$flam = flam_0 \frac{0.005 \times RoS}{(1+d)^2} \qquad \text{(A9)}$$

A2.4 Death

Just after moving, fire agents have a chance to die out if the fuel value at their location is below a certain threshold modulated by their own RoS (eq. 10). This means that slower fires have a higher chance to die out at higher fuel values than faster fires. If the fuel of their current cells is lower than that threshold, agents die if they generate a random floating-point number between 0 and RoS^{-1} that is less than 1. This means that slower fires, while triggering this condition sooner than fast fires, have a smaller chance of actually dying out. This counterbalancing aims to simulate a kind of smouldering behaviour.

$$fuel\ threshold = 0.2(1.1 - RoS) \qquad \text{(A10)}$$

$$P_{die} = ran\left(\frac{1}{RoS}\right) \qquad \text{(A11)}$$

A2.5 Propagation

If, after moving, fires find themselves beyond $\sqrt{4 \times RoS}$ cell lengths from their start location, and if there are fewer than 3 other fire agents already in that cell, they spawn three new fire agents then die. The limit of 3 prevents an excessive number of agents from suddenly appearing in one cell and very rapidly consuming all the fuel. Slower fire agents spawn and die more frequently than faster fires. The new fire agents each inherit their "parent's" RoS and heading and deviate from that heading by -45, 0, and +45 degrees, respectively. These new fire agents consume fuel on this tick, but only start moving on the next tick.

A2.6 Consumption

Finally, the fires present at this time step of the simulation consume fuel. They reduce the fuel value of the cell they are in by $RoS \times fuel \times B^{-1}$ where B is another parameter. Including the *fuel* variable in the rate of consumption means that cells with high fuel levels lose fuel quickly, but as fuel reduces, it burns away more slowly.

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Chapter 3 – General conclusion

1. Addendums

Between submitting this thesis to the jury and receiving their report, the article in Chapter 2 was published with minor revisions. These revisions were not part of the original thesis submission, and the article now in Chapter 2 is the final published version. The published version of the article addresses some of the jury's comments, but not all. In order to maintain the form of the published article, additional analyses are presented here to respond to the jury's comments more completely.

In order to clarify the calibration process somewhat, Fig. 9 shows one of the CART results that helped determine the model parameters. The FoM is the dependent variable, and all the parameters are the dependent variables. The CART shows which parameter/value pairs had the most impact on the dataset (the higher up the node, the more important). Based on this tree it is possible to narrow the search range of parameter settings to obtain a better FoM score. For example, the CART in Fig. 9 indicates that FoM improves with parameters *f1* <= 0.25, *b* >= 25, *w1* < 0.35, *k* < 35, and *d1* < 3, and also if *w2* >= 0.65, and *burnscaler* < 18. Note that *burnscaler* was renamed to *B* in the article, and note that the right branch in the tree indicates that the condition of the fork is false. With these results, a new parameter sweep can be performed where each parameter is varied close to those settings, to explore the "nearby" parameter space. The final parameter set used for the simulations in Chapter 2 is the default for the downloadable version of the model, but it is also presented in Table 4.

Table 4. Model parameters

Parameter	Procedure	Value
f1	Spread	0.2
f2	Spread	0.81
d1	Spread	2.5
s1	Spread	0.019
w3	Spread	4.2
m1	Spread	0.2

a	*wmod*	0.57
b	*wmod*	180
k	*wmod*	16
B	Consumption	17
w1	Fire-wind interactions	0.44
w2	Fire-wind interactions	0.24

The revised paper contains more evaluation efforts than the previous version. It compares ABWiSE's performance with that of Prometheus, where applicable. It also tests whether the fire-wind feedback has meaningful influence on model performance, and evaluates the fuel type parameterization. To provide one more measure of model performance, the kappa statistic for the statistical subsets of ensemble outputs for cases 3 and 4 are presented in Table 5. The kappa statistic, a.k.a. Cohen's kappa coefficient (Cohen, 1960) is a measure of interrater reliability, i.e., it measures to which extent raters (or classifiers) agree, while accounting for the possibility of chance agreement. The kappa statistic has gained widespread use in fields where map comparison is necessary (Filippi, Mallet, & Nader, 2014), but it has certain limitations and there are arguments for discontinuing its use (Pontius & Millones, 2011). Nevertheless, it is a familiar measure for map comparison, and so provides a way to compare the performance of different simulation models.

Table 5. Kappa statistics. Colour serves to better visualize differences; green is high, red is low.

		Evaluation domain proportion		
		0	0.5	1
Case 3	mean	-0.1888532	0.28753686	0.41143052
	Q2	-0.26045408	0.23947592	0.37289707
	1 SD	-0.10489359	0.33947792	0.45254875
	2 SD	-0.19339313	0.28460851	0.40909771
	Prometheus	-0.13442408	0.32164281	0.43848052
Case 4	mean	-0.32014719	0.19544103	0.33703891
	Q2	-0.34274931	0.17745469	0.32220596
	1 SD	-0.3197366	0.19576011	0.33730099
	2 SD	-0.33178079	0.18629008	0.32950716
	Prometheus	-0.41319331	-0.20357896	-0.08701451

One of the issues with the kappa statistic is that evaluates agreement over an entire area of interest (evaluation domain), and there is no formal way to determine the extent of the evaluation domain (Filippi et al., 2014). The evaluation domain can have a large impact on the final score. This issue is particularly relevant to fires, as one of the components of the kappa statistic is correct rejections. For a fire, anywhere that is unburned in either the observed fire or the simulated fire is a correct rejection. Therefore, the larger the evaluation domain relative to the burned area, the better the score. To demonstrate this, I used three different evaluation domains to calculate the kappa statistics of ABWiSE's simulations. The evaluation domain proportion, as shown in Table 5, is the proportion of the observed fire area added to the calculation of kappa as correct rejections. Consider it as a buffer around the observed perimeter to be used as an evaluation domain. At a proportion of 0, the evaluation domain is exclusively those cells burned by either the observed fire or the simulated fire, or in other words, only the area in which change occurred. I calculated the kappa statistic this way for each statistical subset of ABWiSE's results, as well as with the results of Prometheus' simulations of the same scenarios.

First, results show that the evaluation domain proportions has a major impact on the kappa statistic for all comparisons. At a domain proportion of 1, ABWiSE has fair agreement with the observed fire of Case 4 (the validation fire), while Prometheus has a negative score. For the other domain proportions, ABWiSE scores better than Prometheus for Case 4, and scores similarly for Case 3. This new evaluation supports the claims made in Chapter 2, and also highlights one of the caveats of using the kappa statistic to compare observed and simulated fire areas.

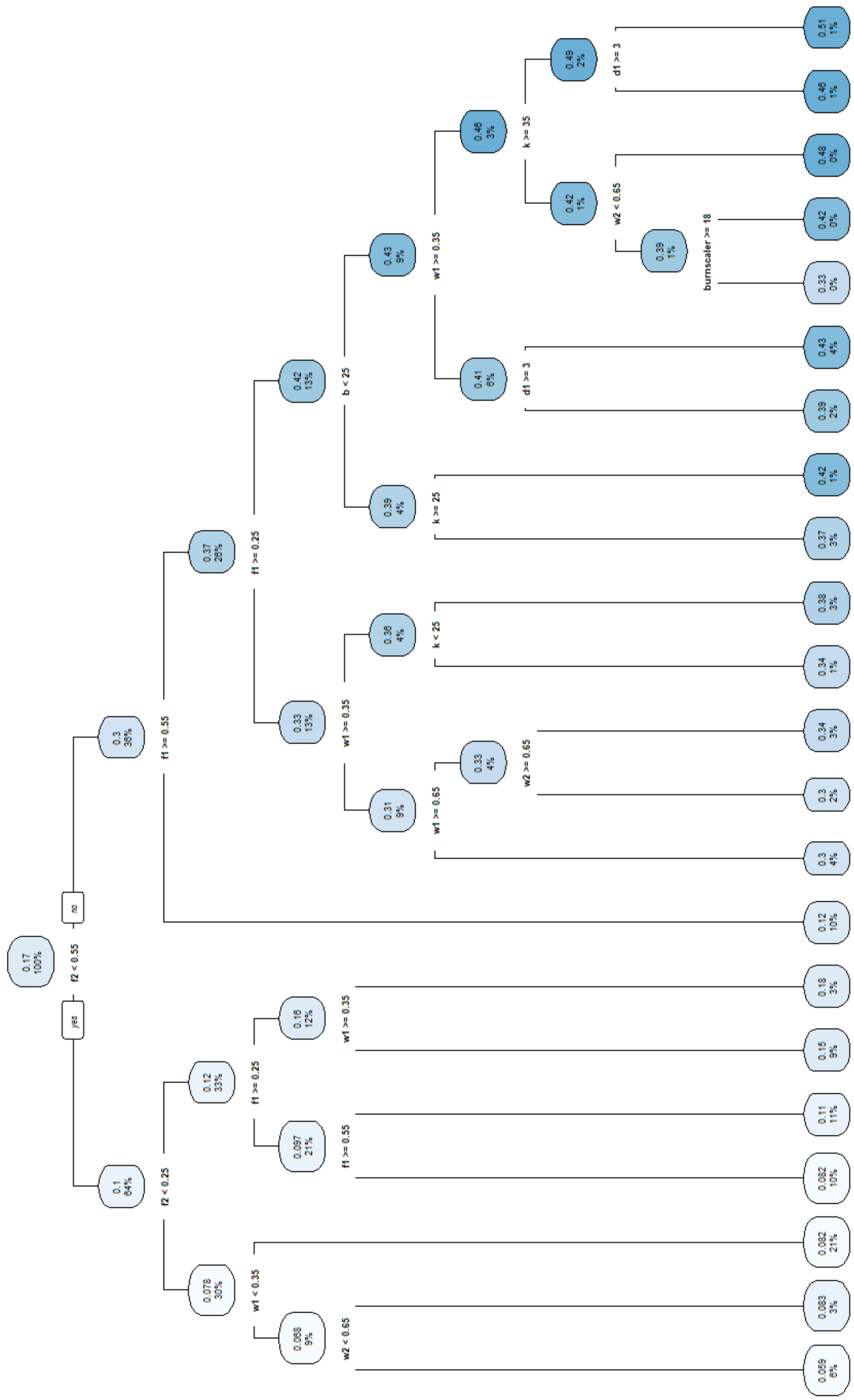

Figure 9. – Example of CART output from calibration procedure.

Nodes indicate first the predicted FoM score and then the percent of observations present in each. Blue shade is based on predicted score. Below each node is the parameter and its value above or below which the score differs meaningfully within the parameterization dataset.

2. Discussion

Chapter 1 introduces complexity and its prevalence in forest ecosystems. It shows that forest fires are important for ecological reasons, but that they are also very, and increasingly, dangerous. In particular, it shows that forests, fires, and the links between the two are all complex, and that this complexity extends to become part of the global fire-climate-vegetation system. As said at the very beginning, geography is about understanding a system by looking at the pieces, and always remembering that they are connected. That is the purpose of this thesis: to look at one part of one part of one part of the whole Earth System. To follow the links from one conceptual level down, until there is one tractable system to model. To see that system, the forest fire, and understand its links up, down, and across scales, all the while trimming them away, to arrive at a model.

Developing that simulation is the crux of this research, the start and the end. The core concept is very simple: what if we simulate fire as numerous agents that travel continuously across a landscape? The assumptions and simplifications of the model are straightforward: 1) fire agents have a direction and a rate of spread, as if you were looking at a point along a fire line, 2) they respond like fire by moving according to wind, vegetation, and slope, and 3) they interact with each other and affect the wind in their vicinity. These elements make up a minimum complexity that can make use of and demonstrate the strengths of ABM (directly responding to the first research objective).

As demonstrated implicitly in Chapter 2, ABWiSE differs from other known ABMs of fire spread namely in its approach of representing complexity and its intended scale of use. While for the other two ABMs, complex behaviour is a consequence of the physical mechanisms included in the design, ABWiSE's design focuses on how to simply represent the interactions that result in observed fire behaviour. Complex behaviour is the objective, rather than a consequence. Admittedly, this is a small conceptual difference, and the effective difference is in the empirical vs physical basis of the equations governing agent behaviour and the links between mechanisms. The second difference of ABWiSE is that it is made to simulate large fires (and evaluated with a large fire), whereas the other two ABMs seem to focus on small-scale fires (e.g. in grasslands or prescribed burns).

An early goal of this research project, that was later abandoned, was to then incorporate this ABM in a Landscape Fire Succession Model (LFSM) in order to incorporate more granular complexity than is typically found in these models. The challenge of developing just one simulation model quickly became apparent, but some traces of that ulterior objective still guided its design. This original goal resulted chiefly in striving for a low computational cost of simulation, being suitable for a coarse resolution, and being able to simulate large fires. Other requirements for a successful LFSM, such as measures of burn severity, biomass loss, and CO_2 release, would have required much longer model development, from design through validation. Initially considering the requirements of a LFSM also helped delimit the level of complexity the ABM should have. Because it had to operate at a coarse scale, considering individual trees was not an option. At the time, weather in the LFSM would have been stochastic but based around seasonal and projected norms, so the atmospheric feedback mechanism did not need to propagate effects back up to the meso-scale. Given enough resources, every feedback link could be considered, but by adding complexity one strand at a time, we effectively perform a conceptual sensitivity analysis. Not a thorough or quantifiable one, but nonetheless, by adding complexity piecemeal to a model of the fire-climate-vegetation system, we may see whether that complexity is relevant to the whole system. Some complex behaviours propagate effects upwards through scale to form emergent behaviours, but others may dampen and dissipate. In the end, the ABM developed for this research simulates just fire spread, and the context of its complexity within a LFSM remains unexplored. But at a lower scale, the context of atmospheric complexity within a fire spread simulator *is* explored.

This context of complexity within the ABWiSE model responds to the second research objective. It is the feedback loops, both among agents and between them and their environment, which allow realistic fire behaviour to emerge. As stated in the article's conclusion, ABM is a viable way to capture the complexity of fire behaviour at low computational cost in order to produce meaningful simulations.

In response to the third research objective, ABWiSE is evaluated against data of a real fire using geospatial and ensemble simulation methods. The evaluation shows that the model output is in good agreement with fires for which it has been calibrated, and somewhat less so for a fire it was not calibrated for. However, its performance is quite similar to that of Prometheus, and is in fact slightly better for the validation fire. Nevertheless, the disagreements with observed fire data are useful in identifying model limitations and future avenues of improvement. By quantifying the model's performance, the evaluation demonstrates the functionality of ABWiSE and supports the viability of ABM for fire behaviour simulation.

As discussed in the article, data limitations proved to be a challenge for better model calibration and validation. Other challenges presented themselves in model design and development. The core idea of incorporating complexity without excessive computation meant an empirical approach was more desirable than trying to precisely replicate physical processes. However, the way ABWiSE uses feedback loops to replicate fire behaviour made it difficult to integrate existing empirical models (which lack complexity). In particular, ABWiSE's variables for fuel availability and flammability are similar to the Buildup Index and the Fine Fuel Moisture Code components of the Fire Weather Index, respectively; however, for the latter pair, the FFMC takes wind speed as an input, as it forms a component of the Initial Spread Index (another component of the FWI), while flammability in ABWiSE does not. Thus, using the FWI to supply fuel availability and flammability values for ABWiSE would have required a reworking of the FWI without wind. It is certainly possible to do so, but that fell outside the scope of this research project.

Despite these challenges, using ABM to model fire behaviour has advantages other than its suitability for modelling and simulating complex geospatial phenomena. Since ABM is an increasingly popular modelling approach in diverse fields of study, there exist well-developed platforms and tools to build and evaluate ABMs. As noted in the article (Chapter 2), ABWiSE was developed in NetLogo, whose simple semantics and Agent-Based Modelling focus were suitable for rapid prototyping and testing. On the other hand, the numerous requirements of ABWiSE revealed certain difficulties in NetLogo and its code extensions, particularly in working with geospatial datasets. In addition, while NetLogo comes with a tool for automated model experimentation, it was not well suited to the exploration of parameter space on the scale required for calibrating ABWiSE.

Nonetheless, NetLogo's strengths outweigh its limitations. In particular, its popularity and its suitability for rapid prototyping may encourage engagement by the scientific community with either ABWiSE or new ABMs of fire behaviour. Since ABWiSE is open source and freely available for download, other researchers can, first of all, easily replicate the simulations presented in the article above, and second, they can copy or modify it as they wish, and in so doing add their expertise to the budding realm of Agent-Based Modelling of fire behaviour.

3. Conclusion

The article in Chapter 2 presents the ABWiSE simulation model. Where Chapter 1 is broad and tries to be holistic, the article is narrow and focused, describing only those links between systems and scales that are necessary to contextualize it among other models. The article applies the ideas and methods of complex systems theory to the simulation of forest fires. It presents an agent-based simulation model based on this application and evaluates it as well as possible with the available data. This research contributes to the modelling community by reinforcing the versatility of ABM. Agent-based modelling is still a nascent field of research, more so applied to forest fires, and ABWiSE serves as a new data point in charting what ABM can and cannot do. This research adds to the list of what they can do, and provides insights on how. The article shows a way to break a system down into interacting elements and retain only the most relevant complexities. Some of these elements then serve as the Agents of the model, where the system's behaviours emerge from their governing rules. As the article explains, there are very few ABMs of fire spread, including ABWiSE, and all are fundamentally different. What they have in common is the ability to bridge the gap between complexity and simplicity imposed by computational limits. A new ABM of fire spread benefits the fire science community by exploring a new avenue of simulation that can offer insights into fire behaviour, and by providing a new framework in which to model the complex interactions of fire, vegetation, and atmosphere. Specifically, ABWiSE successfully simulates a real fire through simple rules of interaction between agents, highlighting the importance of considering complexity and demonstrating the value of ABM for fire simulation.

References

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