Chapter 4
Modeling Wildfire Regimes in Forest Landscapes: Abstracting a Complex Reality

Donald McKenzie and Ajith H. Perera

Contents

D. McKenzie (✉)
Pacific Wildland Fire Science Lab, USDA Forest Service,
400 N. 34th Street, Suite 201, Seattle, WA 98103, USA
e-mail: dmck@uw.edu

A.H. Perera
Ontario Forest Research Institute, Ontario Ministry of Natural Resources and Forestry,
1235 Queen St. E., Sault Ste. Marie, ON P6A 2E5, Canada
e-mail: ajith.perera@ontario.ca

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4.1 Introduction

Fire is a natural disturbance that is nearly ubiquitous in terrestrial ecosystems. The capacity to burn exists virtually wherever vegetation grows. In some forested landscapes, fire is a principal driver of rapid ecosystem change, resetting succession (McKenzie et al. 1996a) and changing wildlife habitat (Cushman et al. 2011), hydrology (Feikema et al. 2013), element cycles (Smithwick 2011), and even landforms (Pierce et al. 2004). In boreal forests, for example, recurring wildfires are the main cause of compositional and spatial patterns (Wein and MacLean 1983), where a fire-induced "shifting spatial mosaic" governs the heterogeneity in ecosystem patterns and processes on the landscape (Goldammer and Furyaev 1996). In forest ecosystems where dominant species are long-lived, mature trees may provide a buffer against extreme weather such as drought or heat waves, but fires and other disturbances such as insect outbreaks eliminate the buffering of the canopy, leaving a hotter and drier microclimate conducive to the establishment of new species. In a warming climate, fire is expected to amplify and accelerate changes in forest composition, spatial pattern, and structure (Littell et al. 2010; Loehman and Keane 2012; Raymond and McKenzie 2012; Cansler and McKenzie 2014). Anticipating these changes will be a key to successful forest management and conservation.

The value that land managers place on wildfires varies widely, as do strategies for their management (Bowman et al. 2011). In some parts of the world (e.g., Mediterranean), wildfires are seen as a natural hazard to human settlements, and attempts are made to reduce or eliminate their occurrence (Rego and Silva 2014). In other regions (e.g., Fennoscandia) wildfires have been virtually eliminated by centuries of aggressive fire suppression, and now are being re-introduced to restore biodiversity patterns and ecosystem processes (Wallenius 2011). Analogously, in North America, emulating natural disturbances such as fire is a growing forest-management paradigm, mostly where spatial and temporal patterns of wildfires are used as templates for silvicultural prescriptions (Perera et al. 2004). All these approaches to management demand spatially reliable and spatio-temporally explicit knowledge of wildfires in forest landscapes.

Fire is a dynamic stochastic process. Observed fires and time series of fire events can be seen as single realizations of that process (Lertzman et al. 1998; McKenzie et al. 2011). Rarely will two fire events be the same, because each event includes unique instances of fire ignition, spread, and extinguishment. The array of geo-environmental factors that control these three steps (in the case of wildfires), and social factors that modify their effects (in the case of man-made and managed fires), make each fire event different. Climate and weather, vegetation (fuel) composition and spatial arrangement, and topography interact to produce *fire regimes* with aggregate properties that reflect these drivers. We define fire regimes broadly, sensu Krebs et al. (2010), as characteristic combinations of antecedent conditions (i.e., climate, fuels, topography), fire attributes, and fire effects. For example, topographic complexity engenders characteristic fire shapes and sizes over time,

Table 4.1 Properties of wildfire regimes versus individual wildfires

	Individual fire	Fire regime
Temporal properties	Fire date(s)	Fire frequency (fire return interval or fire cycle), fire season
Cause	Specific ignition source (e.g., lightning, arson, fireworks, smoldering)	Characteristic ignition (lightning or human)
Process	Fire behavior: fireline intensity, flame length, spread rate, torching, crowning Fire effects: consumption, emissions, plant mortality	Productivity, fuel build-up, succession, leaf phenology, disturbance interactions (e.g., insects, pathogens, windthrow)
Material	Fuel loading, fuel connectivity (horizontal and vertical)	Species composition, biomass
Climate and weather	Wind, humidity, temperature, fuel moisture	Water balance deficit, summer temperature, winter precipitation, drought frequency, El Niño Southern Oscillation
Extent	Fire size, fire perimeter	Annual area burned (mean and variance), fire-size distribution
Spatial pattern	Simple versus complex, fire progression, fire severity classes or spatial variability	Spatial pattern of landscape fuel types (fuel mosaic), patch size distributions (fire area and fire severity)
Management	Initial attack, suppression, backfires, evacuations	Fuel treatments, let burn versus suppression, demographic planning, education

Lists are meant to be representative but not exhaustive

even though individual fire perimeters and areas are generally not well predicted (Kennedy and McKenzie 2010; McKenzie and Kennedy 2012). Similarly, fire and climate interact with vegetation across multiple spatial and temporal scales, producing characteristic fire patterns at broad scales (Higuera et al. 2009; Gedalof 2011). Understanding fire regimes comprehensively, especially broader characteristics such as fire-return intervals, fire-size distributions, spatial probabilities of occurrence, and spatial patterns of severity, is the primary value to the aforementioned management interests (Krebs et al. 2010; Table 4.1).

To understand wildfire regimes in forest landscapes, we seek a level of generality that is different from what is required for the behavior of individual fires and cannot be achieved by simply “summing over” fire events and their effects. For example, fire-scarred trees provide a temporally accurate record of historical fires, but a spatially imperfect one because the extent and perimeters of fire events are known only imprecisely, even when sophisticated interpolations are applied (Falk et al. 2011; Swetnam et al. 2011). Interpolation errors accumulate such that aggregate statistics and general characteristics of the fire history are biased or unacceptably inaccurate.

Unlike historical fire regimes for which we have incomplete records, contemporary wildfires take place within a rich data matrix: fire weather and fuels may be known with greater accuracy. With sufficient input data, at appropriate temporal and spatial resolutions, individual fires can be simulated reasonably well, particularly with "full-physics" models (Linn et al. 2002; Mell et al. 2007), but sensitivity to initial conditions, especially with extreme events that involve convective fire plumes and long-distance spotting, still leads to considerable uncertainty in outcomes (Werth et al. 2011). Furthermore, full-physics models are currently impractical at the scale of forest landscapes, in that their grid spacing is on the order of centimeters. This may always be the case, because not only is their execution at the scales required computationally infeasible, but also they will encounter the so-called "middle-number" problem (McKenzie et al. 2011): a combinatorial explosion of spatial variation in parameters across their domain that cannot be compensated by judicious choices of averages or other summary statistics.

In this chapter, we confront a conceptual issue in modeling whose clarification should enhance the appropriate use of simulation models that focus on wildfire regimes (hereafter "WRSMs," as distinct from finer-scale models that focus on individual fires) in forest landscapes. Many good overviews of landscape fire models are available (e.g., Keane et al. 2004; Cary et al. 2006, 2009; Scheller and Mladenoff 2007) and we eschew more coverage of the same territory. Instead, we examine what (and how) we abstract by WRSMs and how the *level of abstraction* characteristic of a WRSM depends on the resources available to initialize, compute, inform, and evaluate the model (Kennedy and McKenzie 2012). We provide an analogous overview of model complexity, drawing on Keane et al. (2004), and show how models fall along an orthogonal (to abstraction) gradient of complexity. We focus on aspects of WRSMs that deal explicitly with fire, acknowledging that the fire regime is only one component of landscape forest dynamics.

We draw on a decades-long history of addressing issues of complexity and abstraction in ecological models (Levins 1966; Scheffer and Beets 1993; Logan 1994; Cale 1995; Jackson et al. 2000), which provides much useful discussion but understates the independence of the two concepts or does not explicitly contrast them. For example, Levins (1966) emphasizes tradeoffs among *generality*, *realism*, and *precision*, each of which overlaps both complexity and abstraction. Jackson et al. (2000) equate abstraction and complexity, setting the stage for us to propose that these concepts are as likely to be orthogonal as to be parallel. We build on this earlier work with a conceptual model that maps the WRSM "landscape" onto a two-dimensional space of abstraction and complexity. We provide three contrasting examples of working models and their levels of complexity and abstraction, and suggest that relevant information available to the modeler will guide the model's "position" in that space. We conclude with recommendations for making explicit choices about what to include in WRSMs in forests, guided not only by the ideas of complexity, abstraction, and available information, but also by more general considerations.

4.2 Abstracting Reality and Defining Complexity

Science builds models of reality. In contrast to other disciplines such as history or fiction-writing, however, scientific models must be continually confronted with data (Hilborn and Mangel 1997). All models of reality entail a degree of *abstraction*; otherwise they would be mere replicates. In this chapter we adopt the idea that abstractions of reality may be "formed by reducing the information content of a concept or an observable phenomenon, typically to retain only information that is relevant for a particular purpose." (https://en.wikipedia.org/wiki/Abstraction). Consequently, the level of abstraction of a WRSM reflects how much its information content is reduced and generalized to inform the model's objectives (Kennedy and McKenzie 2012). Depending on these objectives, processes modeled at different scales will be subject to more or less abstraction.

Some models have lower bounds on their level of abstraction than do WRSMs. For example, the aim of weather-forecast models would appear to be to mimic reality as closely as possible, because they have no other purpose. In contrast, the purpose of most WRSMs is to ask scientific questions whose answers will be models of reality (accepting that reality can never be known perfectly) rather than explicit predictions of future conditions.

In landscape ecology, the *complexity* of models is more common parlance than their abstraction. For example, a detailed comparison of the complexity of WRSMs, with respect to several metrics, is in Keane et al. (2004). While acknowledging the value of this work, we take a more generic view of complexity as associated with the amount of information required to describe the regularities or patterns in a system (Gell-Mann 1994). As such, complexity is defined quantitatively (Gell-Mann and Lloyd 1996), while being distinguishable from both purely information-theoretic definitions and subjectively chosen metrics. Abstraction and complexity are both properties of models, but the opposite of "abstract" is "concrete," not "simple," whereas both "complex" and "complicated" are opposites of simple. We further propose that complexity and abstraction can be viewed orthogonally, such that models, both existing and possible, live in a two-dimensional space bounded by limits on four edges (Fig. 4.1).

In modeling wildfire regimes, we seek to match the levels of abstraction and complexity with (1) the resources available to initialize, compute, inform, and evaluate the model, and (2) the specific objectives of the model. For example, if we have no fuels data to validate model inputs, does it even make sense to specify fuel loadings, even though fuels are a critical driver of the size and severity of fires. These data are typically lacking for both historical and future fires. Two alternatives are (1) [increase complexity—yes, by introducing more state variables] to estimate fuels allometrically from other variables, sensu Loehman and Keane (2012) and many other studies, or (2) [increase abstraction while reducing complexity] to replicate fuel-dependent dynamics via a more abstract representation of fire (Kennedy and McKenzie 2010).

A useful corollary to level of abstraction in a WRSM is the level of *aggregation*, both in model dynamics and model outcomes. At the most concrete level,

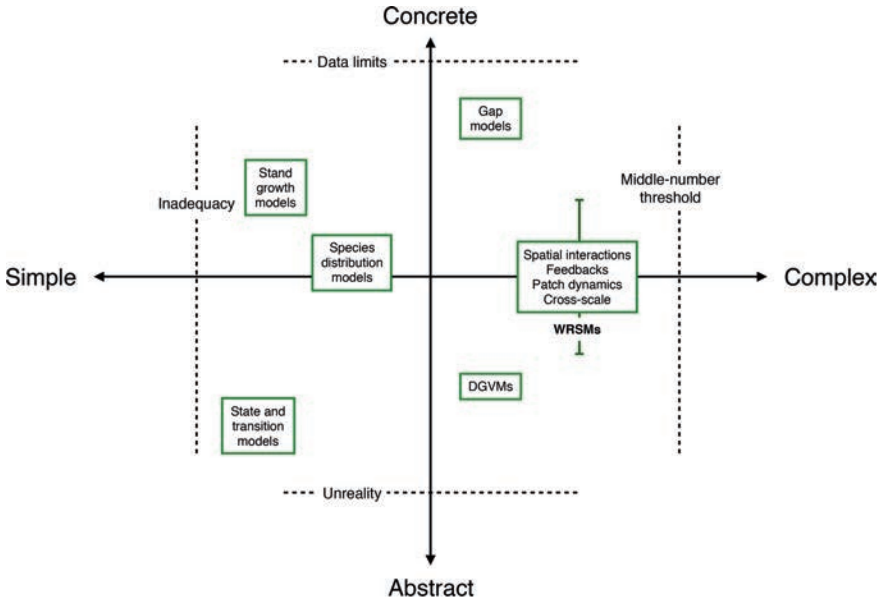


Fig. 4.1 Qualitative positions of different ecological models in the two-dimensional space of complexity and level of abstraction. Wildfire regime simulation models (WRSMs) are generally complex, but a heuristic "error bar" is placed around the associated processes on the abstraction axis, because they often vary more in this dimension than in complexity. In practice, the domain is bounded by the dotted lines, beyond which models would be either infeasible (beyond data limits or the middle-number threshold) or not useful (inadequate or unrealistic). DGVM = Dynamic Global Vegetation Model. See text for further explanation

individual fires are simulated (Keane and Finney 2003). Such models are appropriate when fire perimeters and fire progression need explicit representation. In contrast, if aggregate properties of the fire regime, such as annual area burned or spatial patterns of fire severity, are the key outcomes, explicit simulation of fire behavior and fire spread may introduce unneeded precision, and with it the potential for cumulative errors (McKenzie et al. 1996b, 2014).

Besides informing model objectives, model abstraction, or aggregation, should match available information. Within the realistic complexity bounds defined heuristically in Fig. 4.1, available information corresponds to the optimal position a model can occupy along gradients from abstract to concrete and from simple to complex (Fig. 4.2). Models simulating time-specific outcomes, such as past fire regimes or the future, will be compromised in different ways. For example, a model of Holocene fire may use sediment charcoal data that are spatially resolved to 1 km or finer, but have no better temporal resolution of fire, climate, or vegetation than centuries. A model of future fire regimes may have finely resolved downscaled climate, but essentially no data for evaluation. Note that Fig. 4.2 represents available information for the present as informing a model at a level of detail that exceeds the middle-number threshold. This figure reiterates how either complexity or available information can be a limiting factor for model concreteness.

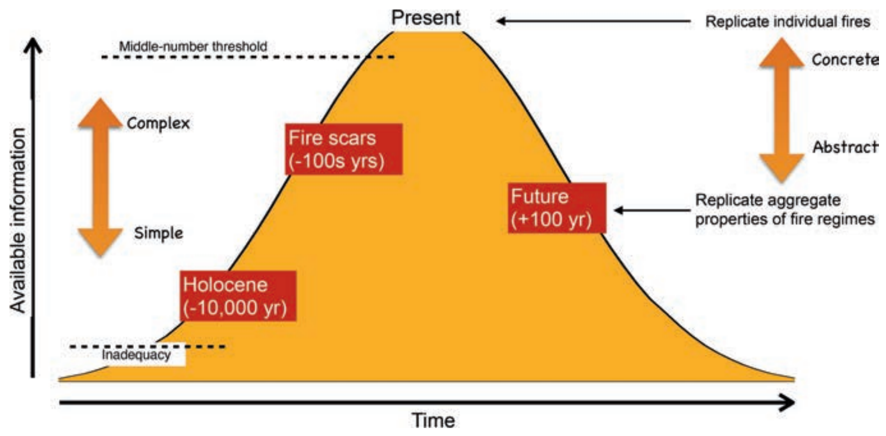


Fig. 4.2 The level of detail in a model is constrained by available information, e.g., input data, calibration data, and robustness of algorithms. Points on the information axis in this figure refer to data, specifically: vegetation, fuels, weather or climate, land use, etc. Available information provides a constraint on both concreteness and complexity, and ideally helps to identify an optimum (see text) on both axes. Landscape fire models are also constrained by the middle-number threshold of complexity (Fig. 4.1), such that whereas they can, for example, simulate individual fires in the present, inferences must be restricted to more aggregate properties, even if information is rich. This is because of the cumulative error associated with representing too many processes explicitly (see text)

An obvious goal for modeling is to find optima along the continua of abstraction and complexity. At least two distinct efforts are required to achieve this. First, model content and structure must be ecologically informed in a way specific to the model objectives (Keane et al. 2015). Whereas it is a truism to claim that ecological models should be ecologically informed, here we mean that processes should be simulated at scales that match the questions being asked. For example, returning to the aggregate properties of fire regimes, suppose we want to estimate patch-size distributions of high-severity fire in a warmer climate, and contrast those with current observations. A model that simulates individual fires, capturing their perimeters and spatial patterns of severity, will accumulate errors (and false precision) by misplaced concreteness (i.e., we seek patch structure, not the shape of any individual fire), no matter how ecologically sophisticated (Kennedy and McKenzie 2010; Swetnam et al. 2011). In contrast, a more abstract and less complex model, still ecologically informed, has fewer calculations and parameters, and one could argue that if each parameter has uncertainty associated with it the reduced cumulative error of this type offsets errors of omission associated with aggregating key processes, particularly if the characteristic scales of these processes are not violated.

Second, all models must be "confronted with data" (Hilborn and Mangel 1997). This confrontation should be "unguarded," so that any discrepancies that are revealed will be informative (see Sect. 4.4.4 below). At an early stage in model development, attention to discrepancies can inform not only model structure and

Table 4.2 Contrasting elements of the three example models, drawing from properties in Table 4.1

	FireBGCv2	WMFire	BFOLDS
Fire time step	Sequential not linked to vegetation	Sequential not linked to vegetation	Hourly linked to weather
Cause	Random ignition based on fire-return interval	Random ignition	Random ignition associated with weather
Process	Mainly mechanistic, partly stochastic	Stochastic	Mainly mechanistic, partly stochastic
Material	Fuel loading, fuel connectivity (horizontal and vertical)	Fuel loading (from RHESSys vegetation)	Forest cover, fuel
Climate and weather	Wind, humidity, temperature, fuel moisture, foliar moisture	Wind, fuel moisture as surrogate	Wind, humidity, temperature, fuel moisture, moisture
Extent	Fire size, fire perimeter, max extent prescribed	Fire size, fire perimeter, max extent emergent	Fire size, fire perimeter
Spatial pattern	Generated by rule-based percolation	Generated by probabilistic fire spread	Generated by mechanistic fire behavior
Management	Implemented in scenarios	Not implemented	Not implemented

algorithms, but also levels of abstraction and complexity that are manageable; only later will the data confrontation be used to tune model parameters (Kennedy and Ford 2011). In our example of patch-size distributions, confronting a model with explicit polygons and dates would fail globally, because to achieve this level of concreteness would exceed the middle-number threshold (Fig. 4.1). Confronting it with aggregate properties of patches is manageable, and therefore informative.

We emphasize that optimal abstraction and complexity are not necessarily to be found at the high ends of what is possible. Indeed they are closely tied to available information, though not strictly parallel or correlated (Fig. 4.2), and coupled to model objectives, as many have observed (Keane et al. 2015). Below we provide three examples of different solutions to the questions “how abstract” and “how complex.” Differences among the models are outlined in Table 4.2.

4.3 Example Modeling Approaches

4.3.1 FireBGCv2: Complex, Concrete

A detailed description of FireBGCv2 is given in Chap. 8. Here we highlight briefly the aspects of the model that are germane to our discussion. The FireBGC models have evolved over 15+ years under the guidance of Robert Keane (Keane et al. 1996, 2011), and simulate fire and succession on Rocky Mountain landscapes.

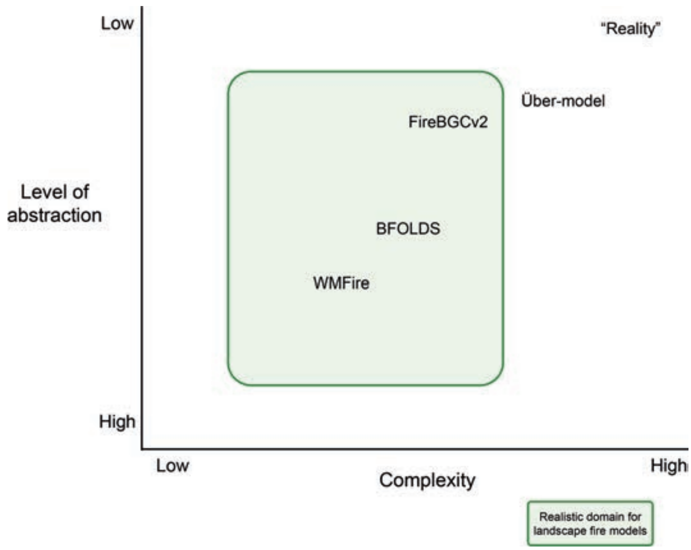


Fig. 4.3 Domain of landscape fire models on two axis (see Fig. 4.1), with positions of models discussed in the text. Reality is more concrete, and more complex, than any existing model or the "über-model" envisioned by Keane et al. (2015). The concreteness of FireBGCv2 approaches the limit of feasibility and desirability, whereas its complexity is still less than what might be desired. See text for further explanation

The model is standalone and includes detailed biogeochemistry (the BGC part) coupled with a gap-like model to represent individual-tree-based succession. The current version operates at five distinct spatial scales, from individual tree to "landscape." Finer scales are used for physiological processes such as photosynthesis, respiration, and decomposition, whereas fire is implemented stochastically at the landscape scale at which its explicit spatial nature can be represented. Finer-scale processes are made as mechanistic as possible, combining theoretical models from the literature with parameters calibrated to specific ecosystem types.

FireBGCv2 operates at the high end of complexity and concreteness for existing landscape fire models (Keane et al. 2004). Indeed it may be at the high end of what is feasible (Keane et al. 2015; Fig. 4.3). As such, it could be said that no key ecological process is left unrepresented, to be a source of unexplained variability. A key strength of the model is that not only are all these processes included, but they are also modeled as mechanistically as possible instead of arising from purely empirical approaches, particularly those that are so much in vogue in the era of "big data." Because of their emphasis on pattern-matching, empirical approaches can be very suspect when extrapolated outside their original domain (Cushman et al. 2007).

A model this complex is subject to several limitations, as acknowledged by Keane et al. (2011). With literally hundreds of parameters, model behavior can be unstable and highly nonlinear. Fire-return interval, which may interact with individual species dynamics to produce unrealistic outcomes (Keane et al. 2011), is a key source of model sensitivity. The developers recommend frequent and thorough comparisons of model output with observations (good advice when building any model). A difficulty with this for a complex model is that comparisons can lack transparency because of the high-dimensional space (many simultaneous comparisons), or lack validity simply because of the dearth of historical data for comparison. A further limitation is the cumulative uncertainty from multiple approximations in complex processes. For example, the developers found that coarse-graining of spatial processes from 30 to 100 m, when simulating large landscapes, preserved most of the important details in the outcome. This likely illustrates a "balance" of errors between loss of resolution and the multiplicative errors associated with detailed process-based modeling replicated at many sites over many years.

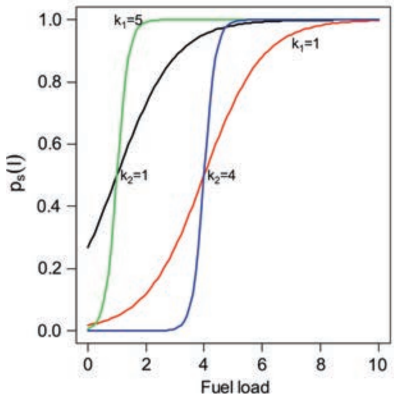
4.3.2 WMFire: Less Complex, Abstract

WMFire arose from a need to incorporate fire into a process-based ecohydrological model, RHESSys (Regional HydroEcological Simulation System; Tague and Band 2004), which simulates the effects of climate change on forested watersheds of the western United States. WMFire's design and structure were motivated by the successful reconstruction of the spatial properties of historical fire regimes by inverse modeling that combined probabilistic fire spread and Monte Carlo methods to fit fire-spread parameters to historical fire-scar records (Kennedy and McKenzie 2010; McKenzie and Kennedy 2012). WMFire receives an input watershed-scale database from RHESSys and a weather stream, spreads fire stochastically following a product of probabilities, each associated with a weather, fuel, or topographic variable (Fig. 4.4), and passes the record of burned cells back to RHESSys. Fire severity and fire effects are then computed within RHESSys by coupling an index of fire weather with a western United States-wide database of fire effects (Ghimire et al. 2012).

Simulation of both fire itself and vegetation dynamics and succession are substantially less complex, and more abstract (especially fire) in the WMFire-RHESSys combination than in FireBGCv2, except that RHESSys has hydrological routing, absent in FireBGCv2. In comparison, the WMFire approach has advantages and disadvantages. Its key advantage (over most landscape fire models, including many that are less complex than FireBGCv2) is that its relative simplicity permits a formal optimization procedure to fit parameters in such a way that output can be compared to observations robustly. Multi-criteria optimization (Kennedy and Ford 2011) quantifies (and therefore can minimize) the multivariate distance between model output and a comparison data set. This optimization is possible only if a model is simple enough that evaluation does not become a middle-number problem (see text above and Fig. 4.1), and is not feasible for a complex mechanistic model.

Two key limitations are associated with a model as simple as WMFire (this propagates to the WMFire-RHESSys combination). First, some potentially

$$p_{spread(j,z)} = p_s(load_z) * p_s(moisture_z) * p_s(wind_{j,z}) * p_s(slope_{j,z})$$



Parameter	Interpretation
k_1 load	Steepness of p_s(load)
k_2 load	Value of load at which p_s(load) crosses p_c
k_1 moisture	Steepness of p_s(moisture)
k_2 moisture	Value of moisture at which p_s(moisture) crosses p_c
k_1 wind	p_s(wind) perpendicular to wind direction at maximum wind speed
k_2 wind	p_s(wind) against wind direction (backing fire)
k_1 slope	p_s(slope) at zero slope
k_2 slope	Steepness of p_s(slope) (increasing with + slope, decreasing otherwise)

Fig. 4.4 Pixel-to-pixel fire spread (here from cell *j* to cell *z*) forms the core of WMFire. Fire spread depends nonlinearly on fuel abundance (*load*), fire weather (moisture and wind), and topography (*slope*). The shape of the response of the fire-spread probability (p_{spread}) depends on two parameters (*k*) associated with each variable. Monte Carlo analysis on multiple fires in modeled watersheds is used to fit the parameters such that fire regimes emerge from combinations of the biophysical variables. See text for further explanation

important questions cannot be answered because the relevant processes are not simulated. For example, exact times and places of individual fire events, with simulated fire behavior that replicates these events as accurately as possible, will not be represented by simulating fire spread stochastically, because this method focuses on aggregate properties of fire regimes. Similarly, individual species responses to climate change cannot be projected, because tree species composition is ignored in RHESSys.

A second more subtle limitation is associated with the problem of attribution. With a simple model that produces aggregate properties of systems, a many-to-one relationship exists between drivers and outcomes. We suggest below (Sect. 4.4.4) that transparency of outcomes is an important property of a simulation model. A model that is too simple or too abstract may have *reduced* transparency in that the sensitivity to initial conditions (i.e., previous time steps or inputs) is muted by a model algorithm to the point that many starting points may produce the same outcome. Differences in dynamics represented in a complex model, important for future projections, may collapse when abstracted or aggregated.

4.3.3 BFOLDS: Intermediate Complexity and Abstraction

BFOLDS (Perera et al. 2008) was designed to explore Ontario's boreal forest fire regime. By mechanistic and spatial simulation of fire, this model overcomes the limitations of reliance on fire-history information (Li et al. 1997), temporal-only projections (Boychuk and Perera 1997), and includes spatio-temporal changes in vegetation cover explicitly (Yemshanov and Perera 2002). It is a hybrid model that simulates individual fires mechanistically and forest cover transitions empirically. Each fire event is modeled as a result of spatially explicit placement of ignitions on a forest landscape, with its realization determined by spatially explicit fire-weather patterns and fuel conditions at that point. If ignited, the fire spreads on a raster grid based on the rates of fire spread computed from input of fire weather, fuel patterns, and topography. Extinguishment is also mechanistic—based on fuel patterns and fire weather. Parameter choices use the principles of the Canadian Fire Behavior Prediction system (Forestry Canada Fire Danger Group 1992). The forest cover changes are temporally discrete, governed by a time-dependent Markov chain model populated with probabilities of state transitions (Yemshanov and Perera 2002) with spatially explicit interactions with geo-environment (Weaver and Perera 2004). Vegetation cover generates the fuel-pattern grids for fire-event simulations.

In the model multiple fire events are simulated daily during a fire season guided by fire weather, fuel, and topography information for a given area. As such, no presumptions are made of the number of fires, sizes of fires, or their locations during the simulations; the ensuing fire regime is an emergent property of the model function (logic, assumptions, and data). By replicated simulations, BFOLDS constructs probability distributions of aggregate properties of fire regimes: fire-size distribution, fire-return interval, fire severity, as well as spatial biases in these properties. Therefore, BFOLDS is typically applied to explore, discover, and understand regional-scale fire regimes (>10 million ha, >100 years) and inform forest policy development and analysis (Rempel et al. 2007; Perera and Cui 2010).

Although fires are simulated far less intensively than in a physical model, and the types of input data required are fewer, BFOLDS is still data- and information-hungry. This is mostly true for weather data (wind, precipitation, temperature). The resolution and extent of data demand (1 ha) and periods (hourly over a fire season) exceed what is typically collected. Therefore, the model relies on interpolation and extrapolation to produce continuous surfaces and temporal series. This is an abstraction of input data that may not be evident to model users, and may lead to false expectations of model precision. Another source of false precision is in fixing model parameters. Simulation steps of some physical processes, for example, fire extinguishment and smoldering, require an understanding of fine-scale dynamics that exceeds the present state of knowledge. This leads to model assumptions, though explicit, that contribute to false precision. Most such limitations should be overcome in time as data resolutions, extents, and scientific knowledge improve. In the short term, clear communication of model limitations and the degree of abstraction is essential to avoid misinterpretation of accuracy and precision.

4.4 Some Criteria for Developing and Applying WRSMs

We have framed fire-regime models in terms of gradients of abstraction and complexity, and given three examples that occupy distinct positions along those gradients. We now turn to more general criteria for building models that we believe should apply at most levels of abstraction and complexity. We draw heavily on the discussion in McKenzie et al. (2014), while noting that those authors were addressing regional-scale models of climate change, whereas we focus on forest landscapes, with their own characteristic key processes, such as contagious disturbance. For each criterion, we suggest how consideration of the polarities simple–complex and concrete–abstract is germane. Our hope is that the modeling criteria that follow are robust across spatial and temporal domains, and across a wide range of objectives in ecological modeling.

4.4.1 Be Clear with Scale and Goal

As computing power and empirical knowledge of fire science improves, wildfire regime modelers will find it difficult to resist the temptation to simulate every detail of fire process possible. This is a futile pursuit since the accuracy of input data at regional scales, where fire regimes are modeled, will never match those accuracies expected by modelers. Instead, they must pursue improving robustness of models at the correct scale. It also behooves the modelers to stress the goals of simulations: is it the past (backcasting), future (forecasting), or what could be (what-if potential) that they seek? Model applications commonly overlook that the first two are subsets of the last (Fig. 4.5; Perera and Cui 2010). A model must be **complex** enough to capture fire process (but no more complex), but **abstract** enough to be robust, i.e., not tied to particulars that will not be stationary in new regimes.

4.4.2 Wildfire Regimes Should Be Emergent Rather than Prescribed

A potential critique of all simulation models is that by their very nature they reproduce the expectations of modelers. Clearly this is an inferior situation to reproducing reality, at whatever level of abstraction is optimal in the context. With fire regimes, aggregate properties are often specified in simulation models, with individual fire events remaining stochastic (see Sect. 4.3). For example, a mean fire-return interval (FRI) may be associated with each of the different vegetation types but individual fires depend on suitable weather and fuel condition and abundance (Lenihan et al. 2008). If conditions repeatedly do not favor a fire, fire extent when it does occur can be adjusted to match the prespecified FRI, particularly

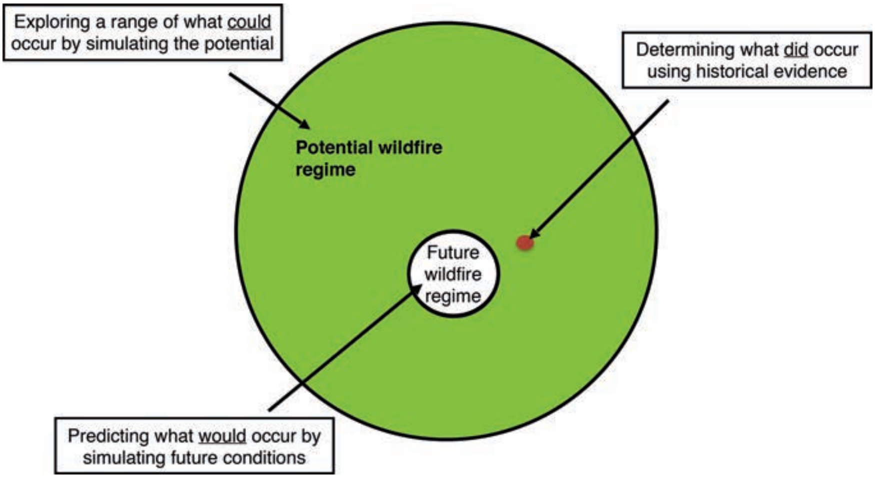


Fig. 4.5 A Venn diagram of the conceptual domains of wildfire modeling goals. Forecasting and backcasting are nested subsets of the potential wildfire regimes—what could happen. The broad goal of wildfire regime modeling, given that future conditions are uncertain, must be simulating what-if scenarios, i.e., to expand the smaller domain by improving robustness of models, but narrowing the larger domain (*green circle*) to what is plausible given all uncertainties associated with the future drivers of fire (adapted from Perera and Cui 2010)

in the case where fire frequency is area-based, e.g., via a natural fire rotation or fire cycle. A limitation of this approach, even (or especially) if it calibrates well to observations, is that in a non-stationary climate, FRIs can change more rapidly than vegetation types, making this model with a prescribed FRI less robust for future projections. Such a model is too **simple** and too **concrete**.

Alternatively, one can build a model that also generates fire events from first principles, such as thresholds of fire weather and fuel moisture, but lets the aggregate fire-regime properties emerge from the cumulative effects of individual events (Perera and Cui 2010). In this paradigm, future or potential fire regimes are less constrained to predetermined values, and projections should be more robust to a changing climate, but evaluating the model with current observations will be more challenging because of the lack of simple metrics such as FRIs for comparison (see also Sect. 4.4.4). We note that this particular criterion does not apply universally to all modeling objectives. For example, if we seek to understand vegetation response to wildfire scenarios we have identified explicitly, they are best specified in advance.

4.4.3 Distributions Are Better than Points

The Climate Model Intercomparison Project (CMIP5; Taylor et al. 2012) evinces the value of ensemble simulations rather than individual model runs. Stochastic variation within the same model can produce very different and sometimes contradictory outcomes (Deser et al. 2012). Whereas running multiple models in the same project may be infeasible to forest landscape modelers, sensitivity to a reasonable amount of stochastic variation in the model of choice can reveal weaknesses or uncertainties in both model structure and inferences about results. Because fire itself is a realization of a stochastic process, multiple instances are needed to capture fire-regime properties, from annual area burned to fire-size distributions or proportions of area in different severity classes. As Perera and Cui (2010) showed, each of these properties has characteristic variability, in current and potential conditions. Here the **complexity** associated with ensembles is irreducible, but necessary. In such ensembles, complexity may be traded for **abstraction**, e.g., the **concreteness** of a model such as FireBGCv2 may make an ensemble approach prohibitive.

A caveat to the call for looking at ensemble projections is associated with understanding extreme events (McKenzie et al. 2014). The "regression to the mean" that occurs when focusing on distributions and ranges of variation should be balanced by a vigilance toward outliers that may inform the answers to research questions. For example, what is the future likelihood of what is now a 95th-percentile event (Stavros et al. 2014)?

4.4.4 Methods Must Be Transparent

Different replications from one model may give qualitatively different results. It is important to understand why the results differed. Did you get the right answer for the wrong reasons (Dennis et al. 2010)? Sensitivity analysis provides quantitative transparency, along with an understanding of model variation, but just as important are semantic and logical transparency. Can you explain, for example, why the one realization that is an outlier gave you the outcome it did? For landscape fire models, a particularly useful time for model transparency is when extreme events (see Sect. 4.4.2) occur in some realizations but not others. Did these fires emerge realistically from their precursors, or are they artifacts of some coincidence in parameter space that is opaque to evaluation? This need for transparency, for developers and for users, limits how **complex** and how **abstract** a model can be.

4.4.5 Aim for Progressive Improvements

This criterion is general and is difficult to associate directly with complexity and abstraction, except that it is clearly linked to model transparency (Sect. 4.4.4). Observations, and "validation," are important for simulation modeling, but bringing them in too soon and tuning the model to fit them will be counter-productive: it may camouflage basic errors in model content or not account for feedbacks that are present in observations (Ford 2000). Being "wildly wrong" at some stage may be the most informative thing that could happen. Maximizing the concurrence of a model with observations by uncritically adding predictor variables and statistical interactions (in an empirical model), or finding the most parsimonious calibration to match "reality" (in a simulation model) makes a model less robust to predictions outside its domain (Cushman et al. 2007).

On the other hand, it is possible to start out with faulty assumptions that ensure the inevitability, rather than the chance, of being wrong. For example, as discussed in Sect. 4.4.2, a potential pitfall is assuming that the natural fire regimes for particular vegetation types are stationary. Such a model is very likely wrong from the outset, and correspondence with the real future will be coincidental.

4.4.6 Implications for Model Development and Use

As all models are abstractions of reality, how much detail can be subsumed into thoughtful parameter choices, aggregated in some other way to produce emergent properties of the system faithfully, or even simply ignored? The expression "as simple as possible, but no simpler" is attributed to Einstein, and can be a useful heuristic along both our axes: complexity and abstraction (Fig. 4.1). Ecological science, and with it ecological modeling, is of course filled with contingencies and "unsimple truths" (Mitchell 2009). This limits our ability to generalize about optimal levels of abstraction or complexity, as does the universal need for models to be designed and run with research objectives in mind.

Given this contingent optimality, and the other criteria we have proposed above (Sect. 4.4), we suggest three further considerations for abstraction and complexity. First, there will always be tradeoffs between model complexity and the feasible amount of replication. There may be cases in which a refined algorithm should be sacrificed for a parallel but cruder one that admits to an ensemble approach wherein multiple realizations "solve" the original algorithm without introducing false precision. A higher level of abstraction (in which a totally different algorithm is used) may also give a more realistic outcome, even if less precise.

Second, what are the limits on information available for evaluating increased complexity? For example, our best measurements of landscape fire are for the contemporary period. For the historical period (roughly pre-1900) we have no fuels data, no fire-start dates, and usually only a rough idea of fire perimeters. Historical fire spread must be reconstructed indirectly, and with necessarily simpler models (Kennedy and McKenzie 2010). For the future, no measurements are available other than the range of possibilities starting at the present, which we can only simulate. The many complexities in those simulations, though manageable for the present for which we have observations, constitute false precision when applied to the future, especially for fire (Kennedy and McKenzie 2012).

Third, decide which uncertainties you can live with for your objectives. At what level of abstraction do you need outcomes? For example, if you need fire sizes and shapes to predict landscape connectivity and distance to seed source in the interior of high-severity patches, you will need different precision (and will need to accept different levels of uncertainty, proportionally) than if you are projecting the likelihood of extreme fires in future decades.

4.5 Conclusion

We have offered a conceptual framework for WRSMs in the hope of providing modelers with a different view, and different filters, for developing and using these tools for simulating forest landscapes. In doing so, we step back from the many valid day-to-day concerns of modelers to a level of abstraction that may be useful particularly when modelers encounter obstacles that are ill-defined or embedded in layers of processes that are hard to separate. We believe that re-assessing the levels of abstraction and complexity in a model, and how they depend on available information, can be a useful reflective pause at any stage in the modeling process.

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