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An Uncertainty Analysis of Wildfire Modeling

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ABSTRACT

Before fire models can be understood, evaluated, and effectively applied to support decision making, model-based uncertainties must be analyzed. In this chapter, we identify and classify sources of uncertainty using an established analytical framework, and summarize results graphically in an uncertainty matrix. Our analysis facilitates characterization of the underlying nature of each source of uncertainty (inherent system variability versus limited knowledge), the location where it manifests within the modeling process (inputs, parameters, model structure, etc.), and its magnitude or level (on a continuum from complete determinism to total ignorance). We adapt this framework to the wildfire context by identifying different planning horizons facing fire managers (near-, mid-, and long-term) as well as modeling domains that correspond to major factors influencing fire activity (fire behavior, ignitions, landscape, weather, and management). Our results offer a high-level synthesis that ideally can provide a sound informational basis for evaluating current modeling efforts and that can guide more in-depth analyses in the future. Key findings include: (1) uncertainties compound and magnify as the planning horizon lengthens; and (2) while many uncertainties are due to variability, gaps in basic fire-spread theory present a major source of knowledge uncertainty.

13.1. INTRODUCTION

13.1.1. Wildfire Modeling and Uncertainty Analysis

Land and fire managers rely on wildfire modeling techniques to better understand potential wildfire activity and evaluate alternative risk management strategies. A wide range of wildfire models exists with varying inputs, structures, outputs, and intended uses [*Sullivan*, 2009a, 2009b, 2009c; *Papadopolous and Pavlidou*, 2011; *Thompson and Calkin*, 2011]. The ability of these models to support efficient and effective risk management is determined to a large degree by how well model-based uncertainties are understood and communicated [*Marcot et al.*, 2012].

Analyzing model-based uncertainties is a process of identifying, classifying, and evaluating sources of uncertainty and their influence on model outputs [*Thompson and Warmink*, Chapter 2, this volume]. Identification and classification, our principal foci here, are systematic and iterative steps that articulate and characterize essential attributes of uncertainties. These steps are a prerequisite for subsequent evaluation of salient sources of uncertainty, which can range from qualitative expert review to computationally demanding quantitative techniques [*Refsgaard et al.*, 2007; *Jimenez et al.*, 2008; *Duff et al.*, 2013]. Uncertainty analysis provides important information for modelers and analysts, aiding selection of appropriate data and modeling techniques, and guiding model calibration and validation efforts. It is crucial that

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managers understand model-based uncertainties as well, to establish confidence in results, and to determine the value of investing in additional data collection, research, or more extensive modeling efforts. Adoption of a systematic, rigorous, and consistent process for analyzing uncertainties facilitates the communication of important features of uncertainties faced within modeling and decision contexts.

In this chapter, we focus on uncertainties related to the intersection of wildfire modeling and wildfire management. Our primary objectives are (1) to illustrate application of uncertainty analysis to wildfire modeling, and (2) to introduce a conceptual framework that researchers and managers can apply to guide future modeling and decision support efforts. Ideally, increased adoption of uncertainty analysis principles will lead to targeted and efficient investments in gathering additional information, improved communication between modelers and managers, and more informed decision-making processes [*Walker et al.*, 2003; *Warmink et al.*, 2010].

To begin, we briefly review conceptual models of wildfire activity to help set the stage for our uncertainty analysis framework. Next, we introduce uncertainty analysis techniques in more detail, focusing on the identification and classification of sources of uncertainty, and describe how we tailored our analysis to the wildfire modeling context. We present results that identify where uncertainties manifest in modeling processes, and how uncertainties vary as planning horizons change. Last, we discuss implications of our findings and offer concluding thoughts.

13.1.2. Conceptual Models of Wildfire Activity

The dynamics of wildfire activity and management result from a coupling of human and natural systems with complex feedback loops that operate across a broad spectrum of spatial and temporal scales [*Liu et al.*, 2007; *Spies et al.*, 2014]. (Note that "wildland fire" is a broader term referring to both wildfires and prescribed (i.e., intentionally ignited) fires; although much of this chapter is likely applicable to the prescribed fire context, our focus is on wildfires (i.e., unplanned ignitions)). The management of a single wildfire incident evolves over the course of hours to weeks, with fire sizes ranging from less than a hectare to over a million hectares. Fire growth is dictated by varying weather patterns, landscape conditions, and human responses. Across larger landscapes and longer time horizons, uncertainty about the timing and location of ignitions, along with the weather conditions driving fire behavior, leads to reliance on risk-based characterization of wildfire variables to help support management decisions. At even larger spatiotemporal scales, long-term strategic planning necessarily considers broader drivers of the human-natural system, including changes in wildfire policy, land use and vegetation dynamics, and climate change. These uncertainties pose great challenges to land and fire managers, who are increasingly being asked to account for the effects of climate changes and human-natural system dynamics in their land management plans (for example, US Forest Service direction at http://www.fs.fed.us/emc/nepa/climate_change/includes/cc_land_mgmt_plan _rev_012010.pdf).

To provide background, we review a simple conceptual model of the major factors that influence the number, extent, and intensity of wildfires in the natural environment, in the absence of human management (Fig. 13.1). The frequency and location of ignitions (both human-caused and lightning-caused) determines the number of wildfires. Depending upon the location, ignition frequency can be driven predominately by human activity, climatic and weather patterns that cause lightning, or some combination of the two. Recent weather conditions influence both fuel moisture (via recent precipitation, relative humidity, and temperature) and rate of spread (via wind and fuel moisture). Because weather influences fuel moisture and rate of spread, it is a primary driver of fire intensity as well as fire extent. Landscape conditions

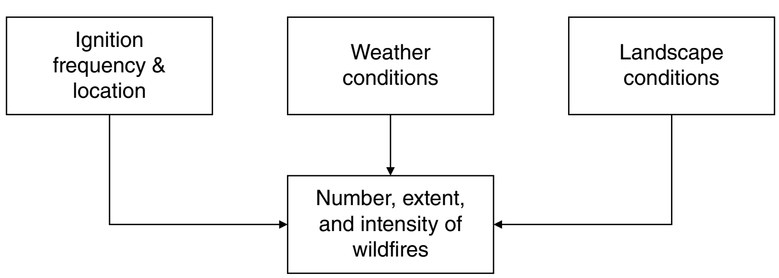

Figure 13.1 A simplified model of factors driving the number, extent, and intensity of wildland fires in the natural environment. (Note that, for example, weather is a source of ignitions, and that ignitions are affected by the landscape as well, since an ignition must land on a receptive fuel in order to be viable. For the sake of simplicity, however, these relationships are not shown.)

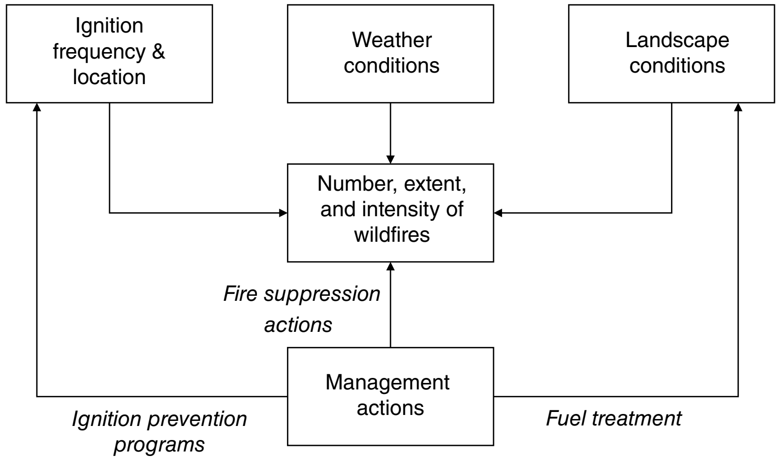

Figure 13.2 A simplified model of factors driving the number, extent, and intensity of wildland fires and how management actions interact with wildfire in a coupled human-natural system.

relate to topography and the composition, structure, and continuity of fuels (flammable vegetation), which influence the intensity of wildfires in concert with weather.

Next, we expand upon this model to illustrate the effects of management actions (Fig. 13.2). Wildfire incident response entails the strategic and tactical deployment of firefighting resources that generally aim to restrict fire growth in order to minimize loss of highly valued resources while balancing safety and cost concerns. Wildfire management options extend beyond incident response to the midterm planning horizon, and include implementing prevention programs to reduce human-caused ignitions and manipulating vegetation and fuel characteristics to reduce extreme fire behavior [*Agee and Skinner*, 2005; *Prestemon et al.*, 2013]. Fuel treatment programs include a range of approaches to remove flammable vegetation via mechanical means as well as through burning from either prescribed fire or managed natural fire.

Last, we incorporate a longer temporal horizon (Fig. 13.3). Policies establishing the emphasis and direction of management actions have and may again change in response to wildfire activity and associated consequences. Landscape conditions are influenced through time by a combination of succession, land use changes resulting from management actions or human development, and natural disturbances like wildfire. Climate can influence all three primary drivers of wildfire activity (for example, changed storm activity leading to changed ignition patterns [*Romps et al.*, 2014]; changed weather patterns; changes in vegetation and fuel composition across the landscape) and these can have a feedback effect on climate (for instance, where increased evapotranspiration due to climate change prevents a burned forest from regenerating, resulting in a net carbon flux). Management actions outside of the wildfire context, such as climate change mitigation activities, are omitted from the figure, but could play a role.

13.2. METHODS

13.2.1. Identifying and Classifying Uncertainties

We consider three primary dimensions of uncertainty in our analysis of wildfire modeling: (1) the underlying cause or *nature* of the uncertainty; (2) where in the modeling or decision process the uncertainty manifests itself, that is, the *location* of the uncertainty; and (3) where along the continuum of total determinism to total ignorance the uncertainty resides, that is, the *level* of the uncertainty [*Walker et al.*, 2003; *Kwakkel et al.*, 2010]. We rely mainly on the work of *Ascough II et al.* [2008], *Warmink et al.* [2010], and *Skinner et al.* [2014] for our characterization of the three dimensions of uncertainty, which we tailor to the wildfire modeling context for our analytical purposes (see Section 13.2.2). Figure 13.4 summarizes the three dimensions, each of which is described in more detail below.

For the nature of uncertainty, we consider two main categories: (1) *knowledge* (also known as epistemic), which refers to limitations of understanding and is considered reducible (in the sense that additional research can increase knowledge and reduce uncertainty); and (2) *variability* (aleatory), which refers to the inherent variation in natural and human systems and is considered irreducible. We consider five main locations of uncertainty: (1) *context*, meaning the assumptions and choices outside of the model boundaries that underlie the modeling process; (2) *inputs*, referring to data for a specific model run; (3) *model structure*, meaning the relationships between

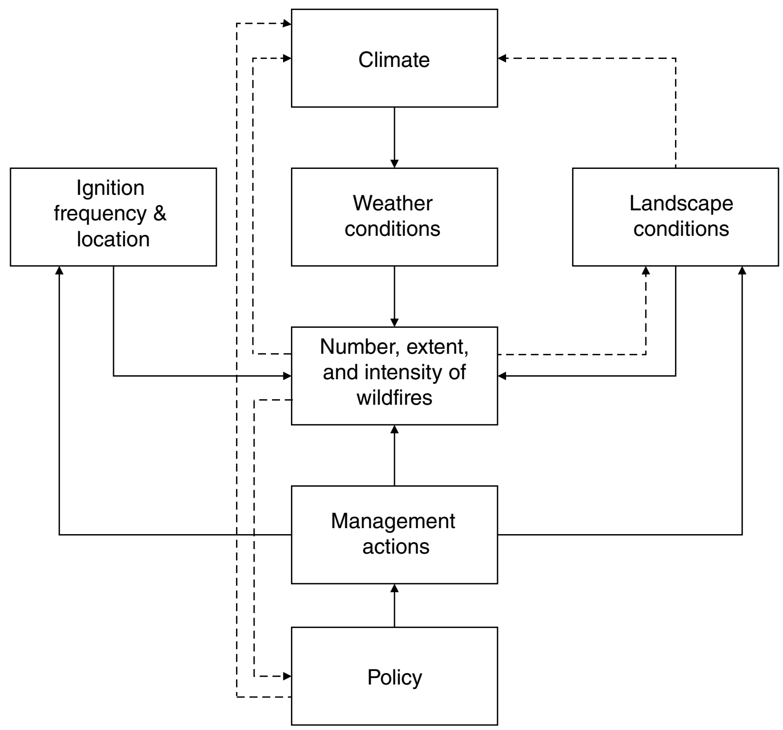

Figure 13.3 A simplified model of factors driving the number, extent, and intensity of wildland fires and how management actions interact with wildfire in a coupled human-natural system, including temporal dynamics. Feedback loops are presented with dashed arrows.

variables and the underlying system; (4) *model technical*, referring to the technical and numerical aspects related to algorithmic and software implementation; and (5) *parameters*, which refers to values invariant within a chosen model context. The third dimension of uncertainty, the level, reflects a spectrum from total determinism (which as it is fully known isn't required in an uncertainty analysis) to total ignorance (which as it is completely unknown cannot be included in an uncertainty analysis) (Fig. 13.4). Between these two endpoints, we consider three levels of uncertainty, in order of increasing uncertainty: (1) *statistical*, in which uncertainties can be quantified probabilistically or quantitatively; (2) *scenario*, in which outcomes or possibilities can be identified but not their likelihood; and (3) *recognized ignorance*, in which factors are known to be a source of uncertainty, but different possibilities or their likelihoods cannot be identified.

13.2.2. Wildfire-Specific Considerations

To organize our uncertainty analysis, we identify three planning horizons facing fire managers: (1) near-term incident response (days to weeks), (2) midterm planning (1–10 yr), and (3) long-term planning (10–50 yr). Note that the relevant spatial scale of interest expands as the temporal horizon increases. Uncertainties for each planning horizon are summarized in Table 13.1. We further organize our analysis according to primary modeling domains, that is, key functions, processes, or actions that drive wildfire activity (see Figs. 13.1–13.3). Specifically, we identify five modeling domains: (1) fire behavior, (2) ignitions, (3) weather, (4) landscape conditions, and (5) management activities. Using this organizational framework (planning horizon and modeling domain), we then identify and classify sources of uncertainty according to the three dimensions listed above (nature, location, and level). We present results in an uncertainty matrix, which is a graphical or tabular summarization of uncertainty analysis findings [*Walker et al.*, 2003; *Warmink et al.*, 2010; *Thompson and Warmink*, Chapter 2, this volume].

To populate our uncertainty matrix, we leverage our own experience applying fire models to support hazard and risk assessment with peer-reviewed literature relating to fire modeling, decision support, and uncertainty analysis. We focus principally on simulation models that implement fire spread in a geospatial context to explicitly model fire growth across a landscape, and that often provide probabilistic outputs for risk-based applications [e.g., *Atkinson et al.*, 2010; *Thompson et al.*, 2011; *Calkin et al.*, 2011; *Salis et al.*, 2013; *Scott et al.*, 2012a; *Scott et al.*, 2012b; *Ager et al.*, 2013; *Han and Braun*, 2013; *Thompson et al.*, 2015; *Thompson et al.*, Chapter 4, this

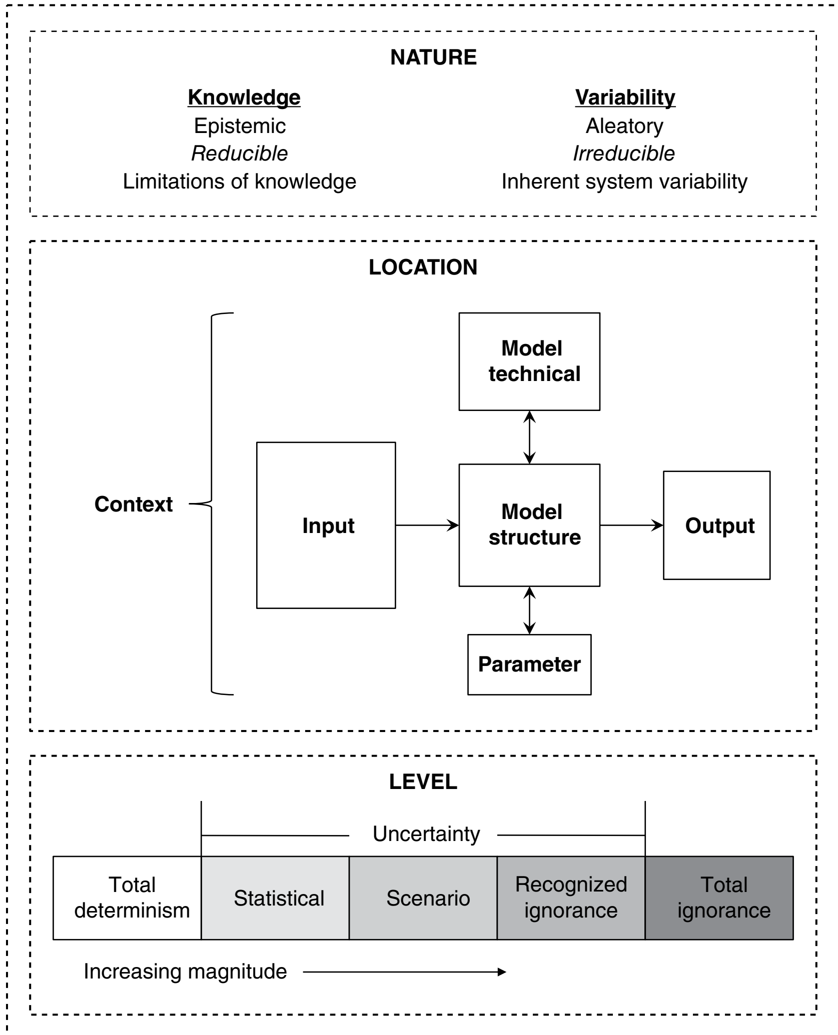

Figure 13.4 Representation of the three dimensions of uncertainty (nature, location, level).

Table 13.1 Factors Influencing Fire Extent and Intensity Across Planning Horizons, in Terms of Uncertain Information

Planning horizon	Ignitions	Weather	Landscape	Management
Wildfire incident response	Observed	Forecasts and historical patterns	Static landscape	Suppression tactics provided by incident commander
Midterm (1–10 yr)	Historical patterns	Historical patterns	Static landscape	Historical patterns of suppression effectiveness; policy scenarios for suppression and fuel management provided by land manager
Long-term (10–50 yr)	Scenarios for changes in patterns due to climate change and land use change	Climate scenarios	Scenarios for biome migration, land use change, management, and disturbance (including no-analog fuel conditions)	Scenarios for policy change in suppression, fuel management, and land use

Note: Fire behavior was not included in this table since it presents a source of uncertainty that is constant across all three planning horizons (the reader is referred to Section 13.3.1 for more information).

volume]. We further limit our focus to operational fire-spread models that have been applied to support analysis and planning efforts, most of which are empirical or quasi-empirical (i.e., a statistical approach based on a physical model; *Sullivan* [2009c]). We draw primarily from our experience with operational fire-modeling systems used in federal wildfire management in the United States [*Finney*, 2004; 2006; *Finney et al.*, 2011a; *Finney et al.*, 2011b], although we expect our analytical framework and findings to be broadly applicable.

In creating the uncertainty matrix, we balance breadth and depth, attempting to address all major influencing factors while recognizing that it is possible to drill down into any given modeling domain or source of uncertainty more comprehensively. Many fire models consist of a collection of equations and submodels; for example, a spatial fire model might employ a one-dimensional surface fire spread equation, a transition to crown fire equation, a one-dimensional crown fire propagation equation, a spatial implementation of fire spread in two dimensions across a heterogeneous landscape, a statistical weather generation algorithm, and a fire suppression module [e.g., *Finney et al.*, 2011b]. Examining the uncertainties in each of the equations and submodels exhaustively would have produced a rather cumbersome and likely unintelligible analysis, so instead we evaluate uncertainties from the perspective of the geospatial fire models themselves (each of which is a collection of submodels and equations). In some cases, separate modeling systems produce inputs for the fire models, for example, in the case of fuel treatment optimization models that provide alternative representations of landscape conditions [e.g., *Ager et al.*, 2013], or in the case of wind models that provide spatially varying wind fields [e.g., *Forthofer et al.*, 2009]. Similarly, we do not examine the uncertainties in these separate modeling systems, but because they can produce landscape or wind data to be used as inputs in the fire models, we consider uncertainty within these models to be a source of input uncertainty from the standpoint of fire modeling. Our results can be interpreted, therefore, as a high-level synthesis that can provide a sound informational basis for evaluating current modeling efforts, and that can guide more in-depth analyses in the future.

13.3. RESULTS

A list of salient uncertainties in fire modeling is presented in the uncertainty matrix, broken down according to planning horizon and primary modeling domain (Table 13.2). Uncertainty in predicting fire behavior is common across planning horizons, with similar factors influencing incident, midterm, and long-term planning. These uncertainties are identified, briefly described, and classified in Section 13.3.1. Sources of uncertainty in the other four domains vary across planning horizons. We discuss how considerations and questions vary, from the perspective of the modeler, across the incident (Section 13.3.2), midterm (Section 13.3.3), and long-term (Section 13.3.4) planning horizons. Building from the uncertainty matrix, we align the primary modeling domain with the five possible locations of uncertainty in the modeling process, following *Warmink et al.* [2010] (Figs. 13.5–13.7).

13.3.1. Uncertainties Common Across Planning Horizons: Fire Behavior

Uncertainty in fire-behavior modeling entails both theoretical [e.g., *Finney et al.*, 2012] and applied [e.g., *Jimenez et al.*, 2008] concerns. Notably, the mechanisms producing fire spread are not yet known despite modeling used extensively for the past few decades [e.g., *Rothermel*, 1972]. Recent work demonstrates that radiation is insufficient to cause ignition in fine fuels, with direct flame contact produced by buoyancy-driven instabilities being a more likely mechanism for fire spread [*Cohen and Finney*, 2014; *Finney et al.*, 2015]. Within the buoyancy dynamics, there is a certain amount of stochasticity in intermittent flame contacts, which would introduce variability uncertainty into particle ignition. It may be a number of years before new physically-based models are ready for operational implementation in the incident, midterm, and long-term planning horizons. We classify the current state of the science regarding fire physics as a source of recognized ignorance and model context uncertainty, since at this time researchers are not sure which physical processes are operating and need to be included in models.

We deem fire behavior to have a location of "model context," since the current lack of physical understanding affects the assumptions and choices underlying the construction of the model (Table 13.2). Once improved physical models are available, they will undoubtedly have sources of input, structure, technical and parameter uncertainty, but at this stage, such uncertainties cannot be listed. Because that is the case, every other source of uncertainty identified in this chapter could be considered to fall into the realm of recognized ignorance and model context uncertainty. Rather than discussing fire modeling in that sense, which would seem to have limited utility, the remainder of the uncertainty analysis regards uncertainties in fire occurrence and behavior as they are currently implemented in fire models and thus used to support decision making.

As they are currently constructed, we classify rate-of-spread and intensity equations as a source of model structure uncertainty, rooted in the mathematical relations between variables. There is a degree of uncertainty

Table 13.2 An Uncertainty Matrix Identifying and Classifying Uncertainties in Fire Modeling

Management and planning context	Uncertainty source		Nature		Location					Level		
			Knowledge	Variability	Context	Input	Model structure	Model technical	Parameter	Statistical	Scenario	Recognized ignorance
Across Contexts												
	Fire Behavior (Physical Basis)											
		Convective and radiative transfer mechanisms	x		x							x
		Rate-of-spread and intensity equations	x		x							x
	Fire Behavior (As Currently Implemented)											
		Rate-of-spread and intensity equations	x				x				x	
		Empirical model coefficients	x						x	x		
		Fire behavior fuel model parameters	x						x	x		
		Fire spread algorithms (2D)	x					x		x		
Wildfire Incident Response												
	Weather											
		Wind speed and direction forecasts		x		x				x		
		Temperature and relative humidity forecasts		x		x				x		
	Landscape											
		Vegetation type and configuration	x			x					x	
		Surface and canopy fuel models	x			x					x	
		Discretized landscape representation	x					x			x	
		Fuel moisture	x			x					x	
	Management											
		Tactics		x	x						x	

(*Continued*)

Table 13.2 (Continued)

Management and planning context	Uncertainty source		Nature		Location					Level		
			Knowledge	Variability	Context	Input	Model structure	Model technical	Parameter	Statistical	Scenario	Recognized ignorance
		Productive capacity and effectiveness of firefighting resources	x				x				x	
Midterm (1–10 yr)												
	Ignitions (natural and human)											
		Timing		x		x				x		
		Location		x		x				x		
		Frequency/number		x		x				x		
	Weather											
		Wind speed and direction distributions		x		x				x		
		Temperature and relative humidity distributions		x		x				x		
	Landscape											
		Changes in vegetation type and configuration										
		Local, due to disturbance, management, and land use change		x		x					x	
		Systematic, due to succession and regeneration		x		x					x	
		Changes in surface and canopy fuel models										
		Local, due to disturbance, management, and land use change		x		x					x	

		Systematic, due to succession and regeneration		x	x			x	
	Management								
		Response capacity and initial attack success	x		x			x	
		Ignition prevention effectiveness	x		x		x		
		Hazardous fuel reduction effectiveness	x		x			x	
Long-term (10–50 yr)									
	Fire behavior (physical basis)								
		Changes in relationship between fuel characteristics and fire spread	x			x			x
		Changes in relationship between fuel characteristics and ignition probability	x		x				x
	Ignitions								
		Changes in lightning patterns		x	x				x
		Changes in development patterns (human-caused ignitions)		x	x			x	
	Weather								
		Changes in precipitation regimes		x	x			x	
		Changes in wind patterns		x	x			x	
		Changes in temperature and relative humidity distributions		x	x			x	
		Changes in season length		x	x			x	
	Landscape								
		Biome migration		x	x			x	

(*Continued*)

Table 13.2 (Continued)

Management and planning context	Uncertainty source		Nature		Location					Level		
			Knowledge	Variability	Context	Input	Model structure	Model technical	Parameter	Statistical	Scenario	Recognized ignorance
		No-analog vegetation conditions		x		x						x
		Changes in vegetation type, cover, and height (systematic, due to changes in climate)		x		x					x	
		Changes in surface and canopy fuel models (systematic, due to changes in climate)		x		x					x	
		Changes in land use		x		x					x	
	Management											
		Wildfire policy		x		x					x	

Note: Across the incident, midterm, and long-term planning horizons, sources of uncertainty are listed in the uncertainty matrix according to the fire behavior, ignition, weather, landscape, and management domains. Sources of uncertainty from the incident planning horizon are also present at the midterm planning horizon, and sources of uncertainty from the midterm are also present at the long-term planning horizon, so only additional sources of uncertainty are listed as the temporal scope increases.

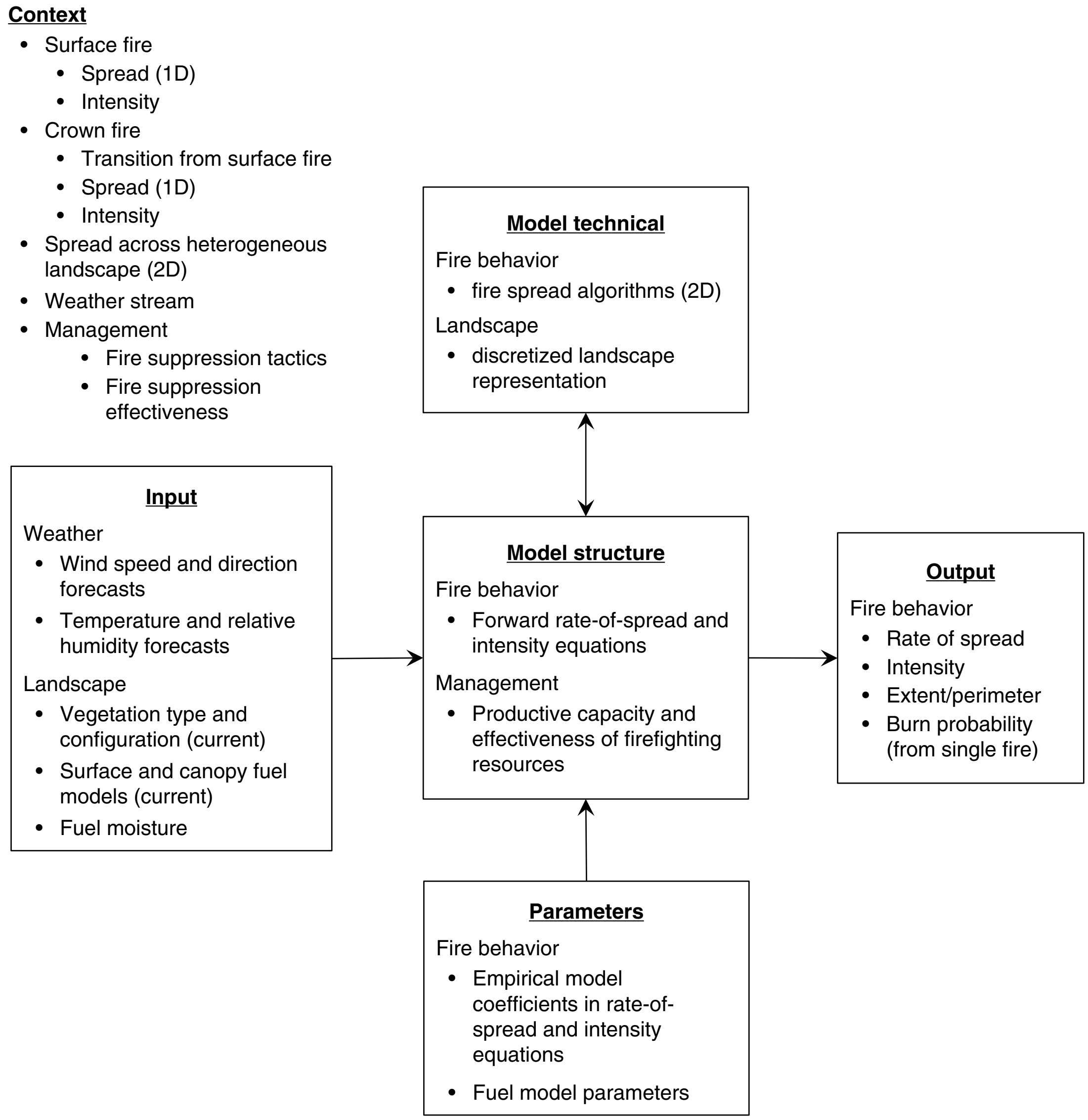

Figure 13.5 Location of uncertainties in wildfire model architecture at the near-term (incident) planning horizon [format after *Warmink et al.*, 2010].

in the factors chosen to be included in the rate of spread models, resulting in model structure uncertainty [*Wilson*, 1990]. Current fire spread models used commonly in the United States [e.g., *Rothermel*, 1972] are based on empirically derived coefficients and provide reasonable estimates of fire spread regardless of the mechanism. The values of the coefficients themselves are a source of parametric uncertainty, and are highly dependent on the source data with which the statistical relationships were built [*Liu et al.*, 2015; *Sullivan*, 2009b]. This uncertainty can be particularly relevant for prediction outside the scope of the initial experiments. Due to factors not included in surface and crown fire spread models (including subpixel variability in fuels, empirical tuning of coefficients that "ought" to be physically related to fire spread, and fire spotting), however, the results are widely considered to be accurate within a factor of two or three [*Albini*, 1976; *Wilson*, 1990]. This source of uncertainty is sometimes handled by modelers testing different rate-of-spread parameters based on expert judgment, producing a set of scenarios.

Two separate classes of models exist for predicting surface fire and crown fire. The *Rothermel* [1972] rate of spread model accounts for the spread of surface fire only, across litter, grass, and shrubs. Fire behavior fuel models developed to integrate with the *Rothermel* [1972] spread model have a standardized set of parameters defining fuel characteristics such as loading, bulk density, and

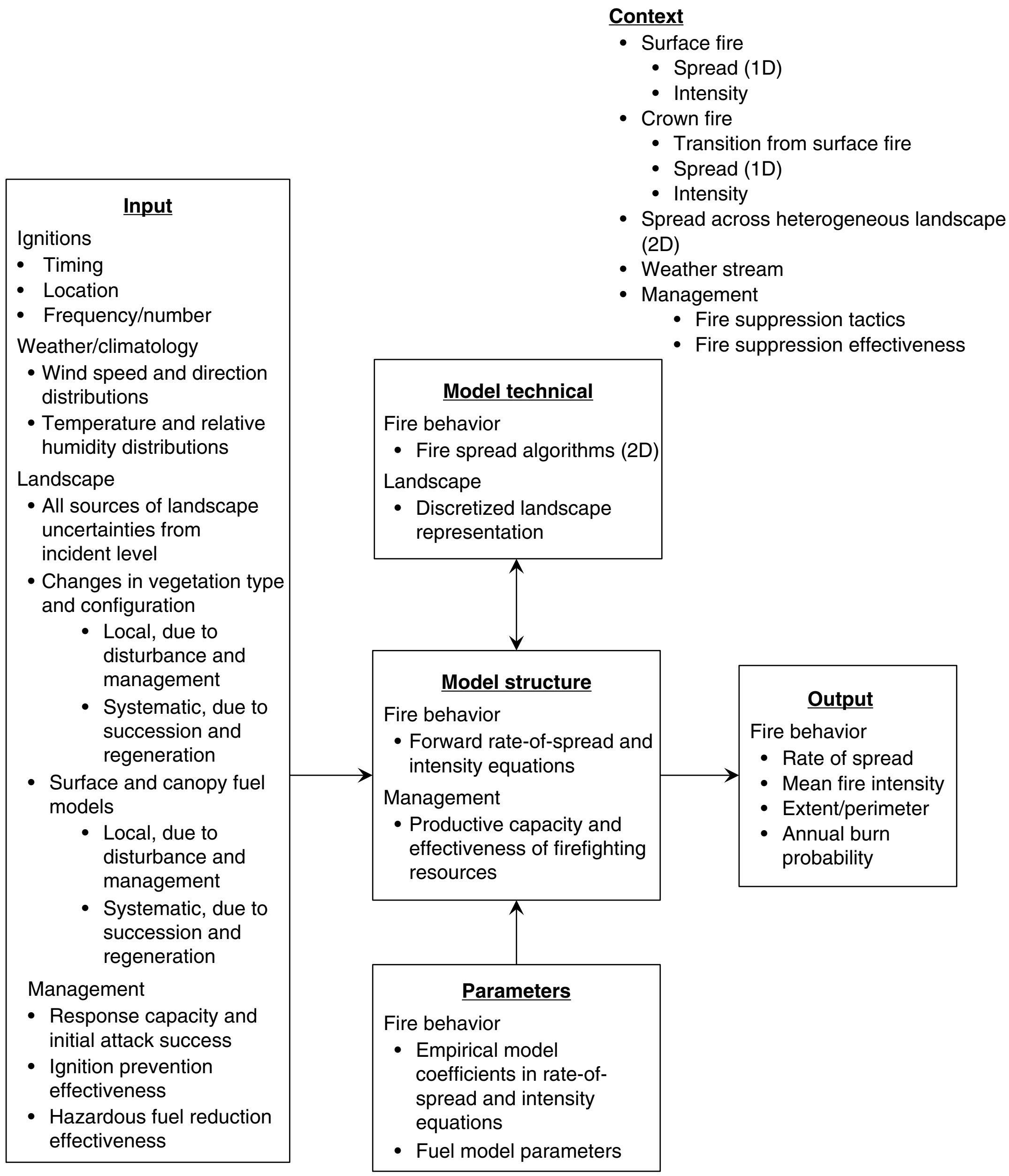

Figure 13.6 Location of uncertainties in wildfire model architecture in the midterm (1–10 yr) planning horizon [format after *Warmink et al.*, 2010]. While the sources of model technical, structural, and context uncertainties remain the same compared to the incident context (Fig. 13.5), additional uncertainties in model inputs are in play and different model outputs are available.

particle size [*Scott and Burgan*, 2005], and the degree to which these values reflect actual physical conditions represents a source of parametric uncertainty in fire behavior modeling. Several models are commonly used to simulate the transition of fire from surface to crown fire and the subsequent spread of crown fire [*Rothermel*, 1991; *Van Wagner*, 1977; *Finney*, 2004; *Scott and Reinhardt*, 2001]. These models have been criticized for underrepresenting or overrepresenting the initiation and spread of crown fire [e.g., *Alexander and Cruz*, 2013]; however, comparison of empirical measurements of the active crown fire rate of spread with modeled estimates suggests that the error rates are low enough that in practical terms the models can be utilized to support decision making during fires [*Cruz et al.*, 2005].

As noted above, fire-spread models make a number of simplifying assumptions, for example, that fuels are homogeneous, which we classify as a source of model

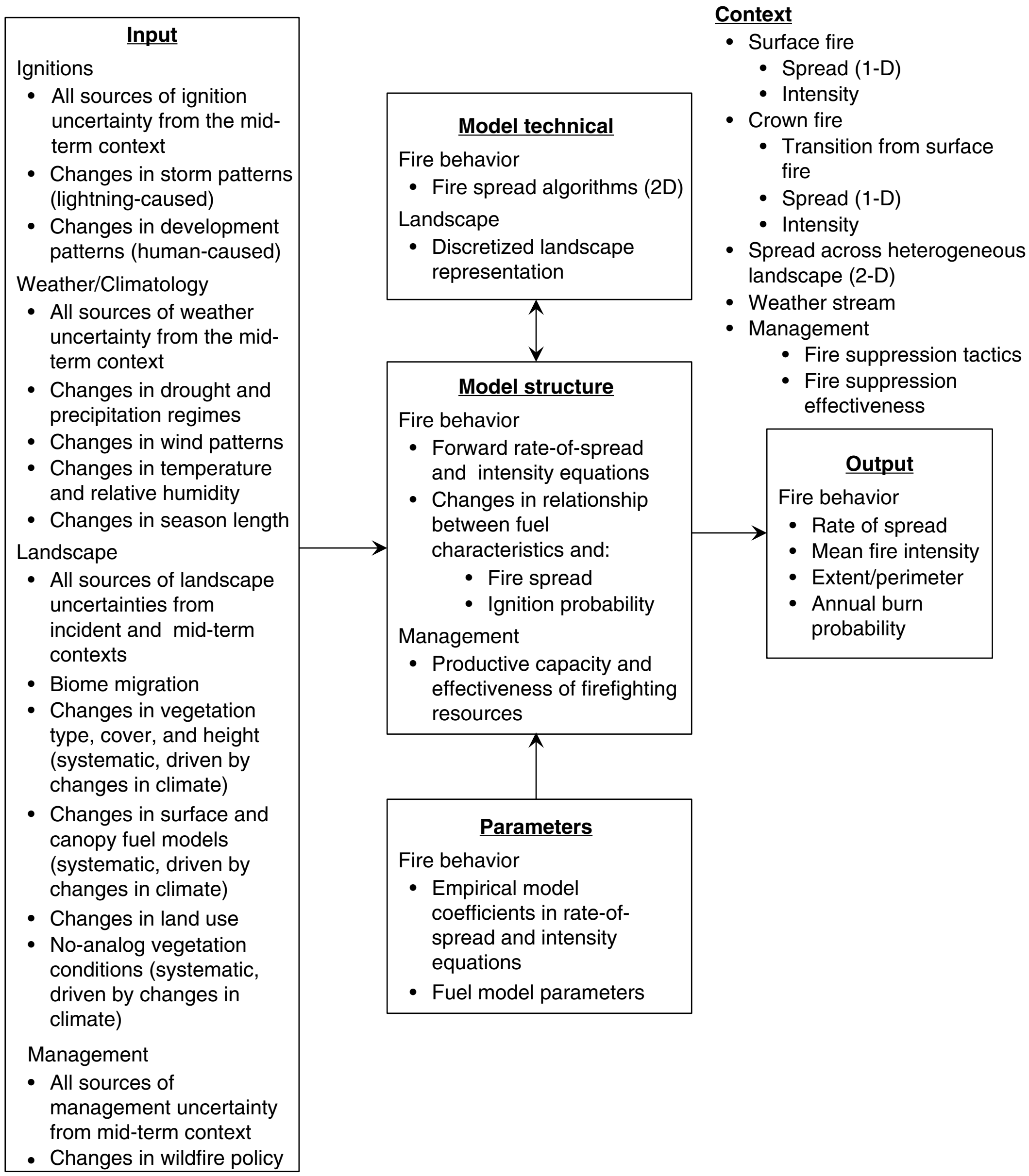

Figure 13.7 Location of uncertainties in wildfire model architecture in the long-term (10–50 yr) context [format after *Warmink et al.*, 2010]. Additional sources of input uncertainty have come into play in four of the five domains (ignitions, weather, landscape, and management). Uncertainties in long-term planning inputs are of greater magnitude, including shifts in vegetation type and composition, changes in wildfire policy, and possible no-analog fuel conditions.

structure uncertainty. In addition, fire-spread algorithms may then be implemented spatially in a model, where the paths of fastest spread across heterogeneous landscape can be quite complex [i.e., *Finney*, 2002], a source of model technical uncertainty. Field measurements of fire-spread rate and historical fire sizes serve as a check on model outputs in the face of these uncertainties regarding fire behavior and spread [e.g., *Cruz and Alexander*, 2013; *Finney et al.*, 2011b]. Model inputs are often adjusted by analysts in order to calibrate model outputs such as fire size to better match historical data.

13.3.2. Near-Term Modeling and Uncertainty: The Wildfire Incident (1–30 Days)

In the context of a given wildfire incident, one of the domains of uncertainty can be eliminated: the timing and location of the ignition is more or less known (subject to measurement error). Weather presents a form of variability uncertainty, however, in the incident planning horizon (typically a week or less), fire behavior analysts often utilize forecasts of temperature, precipitation, relative humidity, and wind. Where weather forecasts are not available or reliable, statistical predictions can be made based on historical weather records [*Finney et al.*, 2011a]. Multiple statistical weather predictions can be combined by some models to produce an ensemble simulation that outputs spatially resolved estimates of the probability of burning [e.g., *Finney et al.*, 2011a].

The landscape is rendered for use in common fire models based upon measurements and expert judgment, subject to knowledge uncertainty (since landscape configuration theoretically can be known). A static landscape reflecting current topographic and vegetation conditions is commonly used as a basic input for modeling [*Ryan and Opperman*, 2013; *Scott et al.*, 2013], with the landscape itself being a stylized model of reality. By this, we mean that the landscape must be discretized into homogenous spatial units for the model, rendering the landscape layers into a map of polygons or grids of a certain resolution (a source of model technical uncertainty). In addition, vegetation conditions are typically discretized; for example, surface fuel conditions are often represented using a discrete set of fire-behavior fuel models [*Scott and Burga*, 2005]. The degree to which assignment of these fire-behavior fuel models reflects on-the-ground fuel conditions is a source of uncertainty. Fuel moisture conditions, which are important in rate of spread calculations, vary across the landscape based on aspect and elevation. Some fire models use fuel moisture conditioning to geospatially estimate this variability [*Nelson*, 2000] based on recent weather conditions, while others assign constant fuel moisture values for the entire landscape. In either case, fuel moisture values are discretized to a pixel or assumed to be homogenous for the landscape as a whole. Uncertainties in fuel moisture and landscape vegetation values (e.g., crown bulk density and crown base height) can be quantified statistically at small scales (i.e., forest plot). However, at the landscape level, probabilities of various vegetation configurations relevant to fire models are not currently known, so we assigned a scenario level of uncertainty to the landscape representation at landscape scales. In the future, remote sensing techniques may make statistical quantification of uncertainties in some landscape variables possible at larger scales.

When fire suppression is practiced for multiple decades, the effects are thought to create positive feedbacks with negative consequences in certain ecosystems (in other words, fire suppression may lead to a buildup of vegetation that makes future fires more severe, more difficult to control, and larger), a phenomenon sometimes termed "the wildfire paradox" [*Arno and Brown*, 1991; *Calkin et al.*, 2014; *Calkin et al.*, 2015]. However, how suppression activities affect the growth and evolution of individual incidents is poorly understood. This uncertainty is particularly salient for the management of fires that escape initial containment efforts, especially under extreme weather conditions leading to intense fire behavior inherently resistant to control. While the modeling of initial containment typically assumes a single function for suppression resources, to build fire line, and compares the rate of fire line production to the rate of fire spread [*Fried and Fried*, 1996], large fire containment efforts are far more dynamic and complex [*Thompson*, 2013], with a very limited empirical basis to characterize effectiveness or efficiency [*Finney et al.*, 2009; *Holmes and Calkin*, 2013; *Thompson et al.*, 2013b; *Calkin et al.*, 2014b]. It is important to note that although large escaped fires typically account for only a small fraction of total ignitions, they also account for the majority of area burned and suppression expenditures [*Calkin et al.*, 2005; *Short*, 2013]. Productive capacity and effectiveness of firefighting resources theoretically could be known (knowledge uncertainty) and form a source of model structure uncertainty, but tactics are subject to human variability and the factors that need to be included in models are not clear (model context uncertainty).

Under some circumstances, fire behavior analysts may work with incident personnel to incorporate potential barriers to future fire spread such as known or expected fire line, burnouts, or natural barriers into model runs. However, existing operational models don't have the capacity to directly model fire line construction activities based on the amount and type of firefighting resources present [*Calkin et al.*, 2011]. Further, these models are unable to account for the broader suite of suppression tactics such as aerial retardant delivery. Reliance on expert judgment and intuition is therefore common.

The location of each uncertainty in incident-level wildfire modeling is shown in Figure 13.5. Within the incident planning horizon, sources of uncertainty are mostly located in model inputs, with the remainder being more or less equally divided between model technical, model structure, parameters, and model context. However, this doesn't mean that the input uncertainties necessarily outweigh the other locations of uncertainty in magnitude, as the respective levels of each source of uncertainty also come into play (Table 13.2).

13.3.3. The Midterm Planning Horizon: Modeling and Uncertainty in the 1–10 Year Time Frame

As the temporal dimension of fire modeling expands from the incident to the midterm (next 1–10 years), sources of uncertainty are compounded in four of the five domains (ignitions, weather, landscape, and management; Table 13.2, Fig. 13.6). In this time frame, the location and number of ignitions cannot be known, as it will be based on natural variability in weather (for example, storm tracks, temperature, and precipitation patterns) as well as variability in human behavior resulting in human-caused ignitions. Historical ignition patterns often form the basis for statistical estimates of future ignition likelihood in the modeling environment [*Andrews et al.*, 2003; *Syphard et al.*, 2008], although the accuracy of these estimates can be degraded by incomplete or inadequate fire history records [*Short*, 2013].

Weather inputs for models in the midterm planning horizon are often based on historical distributions of wind speed and direction, temperature, relative humidity, and precipitation [*Finney et al.*, 2011b]. An array of weather station records and more recently interpolated gridded weather products [e.g., *Abatzoglou*, 2011] are available to analysts. Relative to the incident planning horizon where the sequence of weather is known for the previous days (and can be used as a starting point for modeled weather) and forecasts are generally available, these midterm estimates entail a greater degree of uncertainty, being based on statistical distributions and time-series analysis of historical weather. Broader climatic factors such as interannual and decadal oscillations, including the El Niño Southern Oscillation, Atlantic Multidecadal Oscillation, and Pacific Decadal Oscillation, also exert an influence on drought and weather patterns at this temporal scale. The effects of such oscillations vary spatially, and neither their onset nor influence on fire behavior via weather can be modeled reliably at this point in time, adding to uncertainty in weather variability in the midterm planning horizon.

The uncertainties regarding the accuracy of the depicted landscape at the incident level are still present, and will increase over time as disturbances, plant growth, and succession affect the landscape. In addition, landscape changes are likely to occur due to management, including fuel reduction and timber harvest. Both the rate and location of these changes are uncertain due to factors such as market volatility and litigation. Land-use changes, including expansion of the wildland-urban interface, are also likely during this time frame. In contrast to the landscape at the incident planning horizon, which theoretically can be known, the landscape during the midterm planning horizon is subject to variability uncertainty. This uncertainty could be addressed in the modeling realm by using different landscape scenarios as inputs to fire models.

Similarly, sources of uncertainty in management present at the incident planning horizon still exist, and are augmented by additional factors. Historical patterns of suppression effectiveness often form the basis for model structure in this planning horizon [*Finney et al.*, 2009]. The effectiveness of fire suppression during both initial and extended attack is not currently well understood, but can be modeled statistically. The effectiveness of other management actions such as fire prevention and fuel management can be inferred empirically or through simulation modeling (sources of knowledge uncertainty, with statistical and scenario level, respectively) [*Ager et al.*, 2010; *Prestemon et al.*, 2013; *Thompson et al.*, 2013a]. Additional sources of uncertainty affect fire management at this scale. Burn probability models often simulate only "large" fires, since small fires contribute little to landscape-scale burn probability [e.g., *Finney et al.*, 2011b]. The number of "large" fires is affected by initial attack success and response capacity across potentially simultaneous wildfires, as well as the effectiveness of prevention programs, forming a source of input uncertainty. Rate of spread and intensity may be affected by fuel treatment programs via their effect on fuel model assignment, producing additional input uncertainty. At this planning horizon, most management factors can be considered a source of input uncertainty, but can be modeled using a statistical or scenario approach.

In summary, additional sources of input uncertainty appear when moving from the incident to midterm planning horizon, while the sources of uncertainty in the model technical, model structure, parameter, and model context locations are common across the two planning horizons (Fig. 13.6). Additional model outputs (including mean fire intensity and annual burn probability) are typically available as well.

13.3.4. The Long-Term Planning Horizon: Modeling and Uncertainty During the 10–50 Yr Time Frame

At the long-term planning horizon, many of the uncertainties present in the incident and midterm planning horizons increase in magnitude, and several new sources of uncertainty appear, with the result of moving the level of uncertainty toward recognized ignorance in some cases. Because shifts in vegetation composition and climate may produce nonequilibrium and no-analog conditions, unprecedented changes in fire behavior are possible. For example, changes in the relationship between fuel characteristics (such as fuel moisture) and ignition probability may occur, since these probabilities vary across different ecosystems. In addition, changes in the relationship between fuel conditions (such as fuel moisture) and fire spread may occur, as different pairings between vegetation and climate manifest. These possible changes fall into the realm of recognized ignorance, and present a major challenge for fire modeling in this time frame.

Within the ignitions domain, the number, frequency, and timing of ignitions are likely to change as storm tracks are altered due to climate change [*Romps et al.*, 2014]. However, the mechanisms are driven by natural variability and are not well understood, resulting in a level of recognized ignorance. In addition, human development may change the number and location of ignitions, for example, by increasing the presence of humans in previously remote areas and by making some previously burnable areas nonburnable through irrigated agriculture or paving. The patterns are unpredictable, resulting in a scenario level of uncertainty in model inputs for human ignitions.

As the climate changes, so will the short-term weather that drives large wildfires. Among these predicted changes are alterations in drought and rainfall regimes; changes in wind patterns, temperature, and relative humidity; lightning activity; and fire season length [*Kirtman et al.*, 2013; *Westerling et al.*, 2006]. These projected changes vary spatially, with some areas predicted to become wetter and others predicted to become drier, for example. Interactions among these changing weather factors and how they affect the availability of fuels to burn are complex [*Loehman et al.*, 2014]. For example, if precipitation and temperature during fire season both increase, are fires likely to become more or less frequent? Further complicating the issue, outputs from General Circulation Models (GCMs) indicate a range of possible future climate predictions based on both different carbon emissions trajectories and differences in model architecture [*Kirtman et al.*, 2013]. Changes in global, national, and local policies may affect carbon emissions trajectories and the resulting degree of climate change. In any case, because changes in climate are expected to alter weather probability distributions, uncertainty in weather inputs increases to scenario level, where emissions pathways and the outputs of GCMs present possible scenarios for model inputs.

In addition, changes in local and national policies could result in systematic land-use change. Changes in land management policy may result in differences in harvest rates, fuel treatment rates, and how disturbances such as wildfires are managed, causing widespread changes in landscape conditions. These changes have a nature of variability, and produce sources of input uncertainty.

At this timescale, landscape conditions will be affected by complex feedbacks driven by climate change. These changes could include biome migration and type conversions (e.g., from forest to grassland) driven by changes in climate [*Loehman et al.*, 2014]. No-analog vegetation conditions may result from changes in climate, meaning that the set of current fuel models may need to be augmented or modified in ways that aren't clear yet, resulting in a source of recognized ignorance. Climate change will likely affect the rate and magnitude of disturbances including wildfire and bark beetle infestations, which may systematically impact the landscape. While alterations in the landscape are likely to be mainly local in scale in the midterm planning horizon, they are likely to be widespread and systematic during the long-term planning horizon. Since stochastic natural variability cannot be predicted, different landscape scenarios might be utilized as model inputs.

Because it is not possible to predict the exact trajectory of climate and because possible no-analog weather conditions may occur, as well as natural and human variability inherent in the system, definitive predictions of changes in fire behavior and occurrence are currently not feasible to predict during this time frame [*Kirtman et al.*, 2013]. However, scenario planning based on the outputs of GCMs can be used as a tool for the long-term planning horizon.

In summary, when moving from the midterm to the long-term planning horizon, more sources of input uncertainty come into play in four of the five domains (ignitions, weather, landscape, and management; Table 13.2; Fig. 13.7). Uncertainties in long-term planning inputs are of greater magnitude, including systematic shifts in vegetation type and composition, changes in wildfire policy, and possible no-analog fuel conditions.

13.4. DISCUSSION

Globally, a wide variety of approaches to fire modeling exist, ranging from rapid simulation to inform incident decision making to computationally intensive fluid dynamic models aimed more at improving physical understanding of fire propagation [*Linn*, 1997; *McGrattan*, 2010]. In this chapter, we largely abstracted from specific modeling approaches to focus on uncertainties surrounding the major drivers of wildfire activity and their role in modeling to support wildfire management. That multiple uncertainties are identified doesn't mean models aren't useful, and in fact models will likely grow in importance moving forward, due to a number of factors including: (1) increasing human development in some parts of the world with commensurate increases in values at risk, and (2) climate change likely to cause widespread changes in fire dynamics as well as fires in some areas that haven't previously experienced them.

Our analysis revealed that that the current state of knowledge about fire physics places modeling efforts in the realm of recognized ignorance, pending improved understanding of fire physics [*Finney et al.*, 2012]. However, multiple existing fire models have empirically tuned coefficients over the past few decades, resulting in model outputs that replicate fire spread and intensity reasonably enough for use across planning horizons. Future research may reduce knowledge gaps as a better understanding of the physical process is gained, and it is possible that in the future, natural variability may be the dominant source of uncertainty due to turbulence and buoyancy dynamics.

Weather variables presented a form of variability uncertainty across all planning contexts. Ignitions are known at the incident planning horizon, but fall into the category of variability uncertainty at the midterm and long-term planning horizons, where they are driven by weather as well as human behavior. Landscape variables are a source of knowledge uncertainty at the incident planning horizon (where they theoretically could be measured and known), but become a source of variability uncertainty at midterm and long-term planning horizons (where they are driven by changes due to natural disturbance, management, succession, and climate change). Many management variables could theoretically be known (for example, success rates from fire prevention programs), while others (such as choice of suppression tactics during an incident) fall into the category of variability uncertainty.

At the near-term incident response horizon, sources of uncertainty are fairly evenly divided in their location across model structure, model technical, and input uncertainty. However, additional sources of input uncertainty come into play at the midterm and long-term planning horizons, so that location of uncertainty is dominated by inputs at the long-term planning horizon.

At the incident and midterm planning horizons, ignitions and weather tended to be possible to quantify with a statistical level of uncertainty, but landscape and management factors tended to have a scenario level of uncertainty across all planning horizons. The proportion of factors with a scenario rather than statistical level increased in the long-term context, reflecting the increasing degree of uncertainty as the scope of the planning horizon expands. On the whole, while some sources of uncertainty could be represented with a statistical level of uncertainty (for example, distributions of temperature and precipitation from weather station records), most factors could only be represented with a scenario level of uncertainty (including landscape vegetation variables), reflecting, for instance, the inability to quantify spatiotemporal landscape patterns, or to place error bounds on measurements of input variables such as vegetation characteristics at the landscape scale. Recognized ignorance is rare in our classification, relating only to conceptual understanding of basic fire physics across all planning horizons, and several uncertainties in the long-term planning horizon, specifically changes in the relationship between fuel characteristics and ignition probability and fire spread, changes in storm patterns, and no-analog vegetation conditions. Admittedly, the level and location dimensions were difficult to ascertain, and are in some sense subjective judgments given our experience and understanding of contemporary model application. Future research may reduce the level of some of these uncertainties from recognized ignorance to scenario, or from scenario to statistical.

One important finding of this uncertainty analysis is that uncertainty increases as the spatial and temporal scale of the fire modeling analysis increases. Figure 13.8

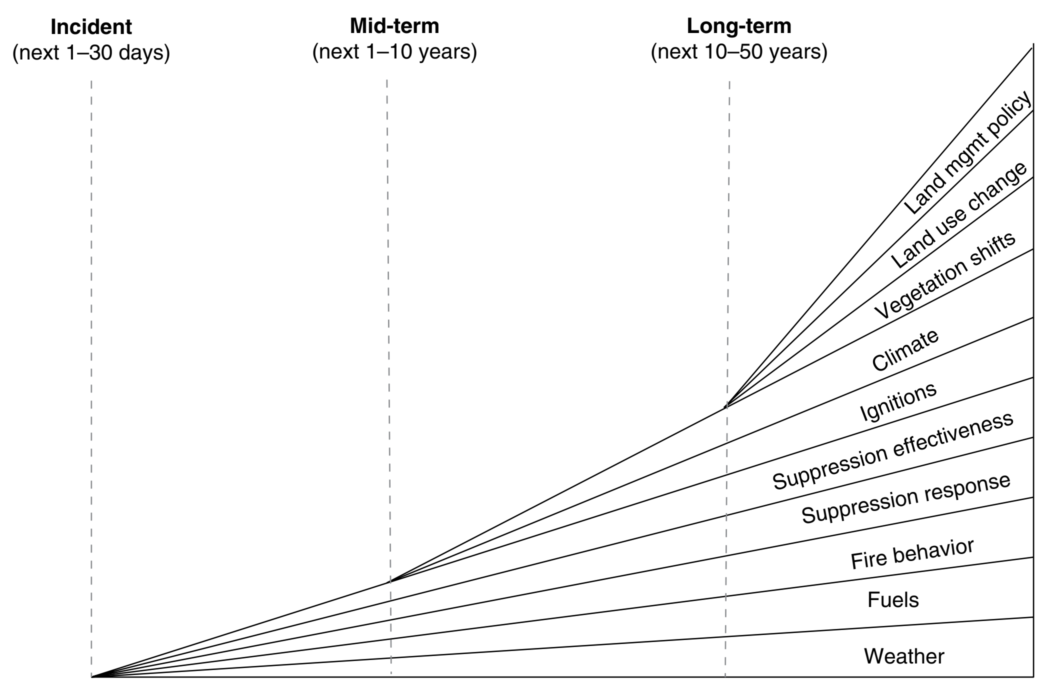

Figure 13.8 Compounding uncertainty across planning levels. As modeling frameworks move from shorter to longer-term planning contexts, additional sources of uncertainty come into play, and existing sources of uncertainty grow in magnitude.

illustrates how uncertainty compounds across the three planning horizons. Many of the sources of uncertainty remain nominally the same across planning contexts, but expand in magnitude as the time frame grows longer. For example, during an incident, weather during the next few days is uncertain but can be modeled using weather forecasts with better accuracy than can be derived from using climatological averages. The uncertainty in weather grows at the landscape assessment level, but can still be modeled using weather records and a statistical approach. Moving to the long-term planning horizon, climate itself is uncertain, producing a higher magnitude of uncertainty in predicting the weather events that produce the ignition and spread of wildland fire. In addition, moving from the incident to midterm to long-term planning context, additional sources of uncertainty come into play, for example, changes in land use. Awareness of how uncertainty increases with spatial and temporal scale can help researchers to encompass uncertainty meaningfully into study designs.

Although uncertainty increased with the time frame of the planning horizon in this analysis, this is not always the case: more uncertainty can be present in the short term than in the long term. For example, this pattern was seen in projections of polar bear populations, based on arctic sea ice extent under various scenarios for atmospheric greenhouse gas concentrations. Due to dynamics of regional warming in these scenarios, far lower certainty existed during the first 2–3 decades of the analysis, but by the end of the 21st century, projections converged on high certainty of low sea ice coverage and commensurately low polar bear populations [*Amstrup et al.*, 2008]. Whether uncertainty increases or decreases with time, the conclusion is that planning across both short- and long-term time frames is important, and enables management decisions in the short term, which can set the stage for ecosystem health and resiliency in the longer term in light of uncertainty.

13.5. CONCLUSIONS

This work systematically identifies and classifies model-based uncertainties faced in wildfire modeling, and represents an expansion of uncertainty analysis as applied to wildfire risk management. We organize presentation of our uncertainty matrix around real-world planning horizons (incident, midterm, and long-term), and primary modeling domains (fire physics, ignitions, weather, landscape, and management), which allows for an enhanced identification of salient uncertainties. Within this framework, we delineate and distinguish commonalities and differences in sources of uncertainty and their respective natures, locations, and levels. An important finding of this study is that while some sources of uncertainty are common across all planning horizons, more sources of uncertainty appear while others grow in magnitude (i.e., change in the level dimension) as the scale of the planning horizon increases. The result is compounding uncertainty and, more important, a need to rethink whether modeling approaches applied in one planning horizon are appropriate for use in other planning horizons.

The presence of all these sources of uncertainty need not deter analysts and need not undermine confidence in model predictions. Explicit recognition and analysis of uncertainties can increase the confidence of managers in model predictions, improve the modeling process, improve study design, and enhance communication across modelers, analysts, decision makers, and stakeholders. The framework developed here can provide a powerful tool for future analyses of wildfire activity, and we hope will help organize critical thinking to ensure the right questions are being asked, the right models are being used for the right reasons, and model outputs are properly understood in the context of model-based uncertainty analysis.

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