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Review

Uncertainty and risk in wildland fire management: A review

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ABSTRACT

Wildland fire management is subject to manifold sources of uncertainty. Beyond the unpredictability of wildfire behavior, uncertainty stems from inaccurate/missing data, limited resource value measures to guide prioritization across fires and resources at risk, and an incomplete scientific understanding of ecological response to fire, of fire behavior response to treatments, and of spatiotemporal dynamics involving disturbance regimes and climate change. This work attempts to systematically align sources of uncertainty with the most appropriate decision support methodologies, in order to facilitate cost-effective, risk-based wildfire planning efforts. We review the state of wildfire risk assessment and management, with a specific focus on uncertainties challenging implementation of integrated risk assessments that consider a suite of human and ecological values. Recent advances in wildfire simulation and geospatial mapping of highly valued resources have enabled robust risk-based analyses to inform planning across a variety of scales, although improvements are needed in fire behavior and ignition occurrence models. A key remaining challenge is a better characterization of non-market resources at risk, both in terms of their response to fire and how society values those resources. Our findings echo earlier literature identifying wildfire effects analysis and value uncertainty as the primary challenges to integrated wildfire risk assessment and wildfire management. We stress the importance of identifying and characterizing uncertainties in order to better quantify and manage them. Leveraging the most appropriate decision support tools can facilitate wildfire risk assessment and ideally improve decision-making.

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1. Introduction

Wildfire is a global phenomenon, with attendant global investigation into the impacts of wildfires on human life and property, ecosystems, and other valued resources, and into the factors contributing to wildfire occurrence and spread. Managing wildland fire is subject to manifold sources of uncertainty. Beyond the unpredictability of wildfire behavior, uncertainty stems from inaccurate/missing data, incomplete scientific understanding of ecological response to fire, incomplete scientific understanding of fire behavior response to management treatments (suppression, fuel reduction, etc.), and limited resource value measures to guide prioritization across fires and resources at risk. Strategic management is subject to significant additional uncertainty when attempting to consider the spatiotemporal dynamics of climate change, vegetative succession, species migration, and disturbance regimes.

Recognizing that there are various manifestations of uncertainty, decision scientists have developed myriad tools to address particular aspects of decision-making under uncertainty. Here we review extant approaches to managing uncertainty adopted in the wildfire management literature, and attempt to systematically align sources of uncertainty with the most appropriate decision support methodologies, in order to facilitate efficient, risk-informed wildfire planning efforts. Our work therefore examines wildfire risk assessment largely through the lens of resource economics and decision science.

Uncertainty is essentially a lack of information; complete ignorance represents one end of the spectrum and perfect information (i.e., certainty) the other. Managing uncertainty is of course nothing new to fire managers, who have and continue to make decisions with imperfect information. Where one can express uncertainty quantitatively (e.g., modeled as a probability distribution), one can speak in terms of managing risk. Objective, repeatable measures of risk can better inform management (Roloff et al., 2005). Our challenge is to better understand the nature of uncertainty, identify where it can be integrated into quantitative risk management frameworks, and where it cannot, to identify what additional information is necessary to reduce the scope and magnitude of the uncertainty.

In this paper we view wildfire management through the lens of a widely accepted ecological risk assessment framework (Fairbrother and Turnley, 2005; U.S. Environmental Protection Agency, 1998). Risk

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assessments are decision support tools that integrate information regarding the likelihood and magnitude of resource response to risk factors, in order to synthesize a conclusion about risk that can inform decision-making (Sikder et al., 2006). Risk assessments inform strategic, tactical, and operational decision-making, and are used in decision support models as developed by operations researchers and other management scientists. In the absence of fire risk assessments, decisions and management are likely to be less effective (Bar Massada et al., 2009). The process of evaluating how risk to various resources changes in response to alternative management scenarios (including no action) is crucial to risk-informed decision-making (e.g., Ager et al., 2010a, 2007; O'Laughlin, 2005; Roloff et al., 2005).

Increasingly, wildfire management is being viewed as a form of risk management, with a corresponding increase in analytical rigor and alignment with risk management principles. Developing and using wildfire risk assessment models can aid active and preventative forest management decision-making (González et al., 2006). The literature continues to expand with examples of wildfire risk analyses from around the globe (e.g., Atkinson et al., 2010; Dlamini, 2010; Kaloudis et al., 2010; Li et al., 2009; Zhijun et al., 2009). Planning scales for wildfire management range from incident-specific to regional/national assessment, and applications include fire prevention, fire detection, deployment and initial attack dispatch, large fire management, and strategic planning and fuel management (Martell, 2007). Managing fire risk involves analyzing both exposure and effects (i.e., likelihood and magnitude of potential beneficial/detrimental effects), and then developing appropriate management responses to reduce exposure and/or mitigate adverse effects (Fairbrother and Turnley, 2005; Finney, 2005). Effective management of wildfire risk requires a clear definition of management objectives, and where multiple objectives are present, an understanding of relative management priorities.

The primary aim of this paper is to review the state of wildfire risk assessment and management, with a specific focus on uncertainties challenging implementation of integrated risk assessments that consider a suite of human and ecological values. We begin by describing a typology of uncertainties faced in natural resource and environmental decision-making, briefly review decision support systems developed to address these types of uncertainty, and then map the uncertainties faced in strategic fire planning to appropriate decision tools. This work is motivated in part by past calls for frameworks to guide research and management by identifying uncertainties faced and offering appropriate decision strategies (e.g., Borchers, 2005). Pairing risk assessments with decision analysis tools offers a framework for making management decisions in an uncertain world (Harwood, 2000). With this framework established we then offer a comprehensive and illustrative, although not exhaustive, review of past and ongoing applications of wildfire risk assessment and management.

2. Characterizing and managing uncertainty

Within the forestry, natural resources, and environmental management literature there exist numerous characterizations of uncertainty. Kangas and Kangas (2004) for instance offer the generalized categories of metrical (measurement variability/imprecision), structural (system complexity), temporal (past/future states of nature), and translational (explaining results) uncertainty. Mendoza and Martins (2006) identify randomness, imprecision, and unknown preferences as factors contributing to uncertainty in multi-criteria decision analysis. Leskinen et al. (2006) point to errors in inventory and measurement, projections of future market conditions, projections of forest development over time in response to management intervention, and unknown preferences as sources of uncertainty in forest plans. Regardless of the specific typology ultimately chosen, using a coherent framework informs management by facilitating the identification of potential sources of uncertainty and the quantification of their impact.

For the purposes of this paper we adopt the uncertainty typology of Ascough et al. (2008), which synthesizes various extant characterizations of uncertainty in the environmental decision-making context. According to this typology, four broad categories of uncertainty exist: linguistic uncertainty, variability uncertainty, knowledge uncertainty, and decision uncertainty. Linguistic uncertainty refers to issues of vagueness, ambiguity, the contextual dependency of words, evolving definitions, and difficulty in explaining results. Brugnach et al. (2010) describe ambiguity as a source of uncertainty in which there may exist more than one valid way of understanding the system to be managed, thus leading to alternate problem definitions and solution approaches. In the wildfire context the term "risk" has been used somewhat loosely, engendering confusion (Chuvieco et al., 2010; Schmoldt, 2001). Hardy (2005), for instance, defines risk as the probability of fire occurrence, whereas Finney (2005) adopts an actuarial approach, defining risk as the probabilistic expectation of net resource value change in response to fire. For the purposes of this paper we adopt the latter definition, consistent with our risk assessment framework (e.g., Fairbrother and Turnley, 2005) as well as other approaches in the forest planning literature (e.g., Gadow, 2000).

Variability uncertainty refers to the inherent variability that manifests itself in natural systems. Elsewhere in the literature this uncertainty may have been referred to as external, objective, random, or stochastic. The frequency and spatial pattern of ignition locations, or the weather conditions driving extreme fire behavior are examples of variability uncertainty. Probabilistic approaches are most often used to handle variability uncertainty, such as modeling fire occurrence, spread, and/or intensity (e.g., Ager et al., 2010a; Carmel et al., 2009; Krougly et al., 2009; Bar Massada et al., 2009; Podur et al., 2009; Wei et al., 2008; Amacher et al., 2005). Operations research and management science approaches that incorporate probabilistic elements include stochastic dynamic programming, chance-constrained programming, scenario analysis, and Markov decision models (Weintraub and Romero, 2006).

Knowledge uncertainty refers to the limits of our knowledge, and/or the limits of our scientific understanding. This type of uncertainty is present with respect to how we conceptualize the natural processes occurring around us, how we choose to model those processes (approximations, variable definitions, etc.), the nature and quality of the data we use to inform those models, and propagated uncertainty in model outputs. Jones et al. (2004), for instance, identify a need to generate uncertainty estimates for spatial data layers when mapping fuels, and Bachmann and Allgöwer (2002) describe uncertainty propagation in fire behavior modeling due to uncertainty regarding input variables. More recently, Cruz and Alexander (2010) highlight knowledge gaps and errors common to many fire modeling systems regarding crown fire behavior. Two key sources of knowledge uncertainty are modeling the ecological response of resource values (in terms of provision of ecosystem services, etc.) to fire (Keane et al., 2008), and the efficacy of various suppression activities (Finney et al., 2009). Knowledge uncertainty is considered reducible, in that we can reduce the scope of this uncertainty through additional research and empirical investigation.

In contrast to variability uncertainty, non-probabilistic approaches are in general better suited for managing knowledge uncertainty (Kangas and Kangas, 2004). Managing knowledge uncertainty usually involves some form of expert system, which is based on the premise that in the absence of perfect information the judgment of experts is likely the best proxy. In complex resource management problems, such as wildfire management, a formal recognition of uncertainty paired with expert judgment is often the best approach (Borchers, 2005). Expert knowledge and judgment can be incorporated in a number of ways, including knowledge-based systems, hierarchical multi-attribute models, logic models, fuzzy set theory, and hybrids thereof (e.g., Vadrevu et al., 2009; González et al., 2007; Hessburg et al., 2007; Nadeau and Englefield, 2006; Kaloudis et al., 2005; Hirsch et al., 2004, 1998; Schmoldt, 2001).

Decision uncertainty refers to imperfect information involved in social cost/benefit analysis. It has also been referred to as value uncertainty, or preference uncertainty. To the degree that we don't fully know social preferences/values, our ability to manage for social welfare is limited. This type of uncertainty is usually handled with some form of a value measurement method (Diaz-Balteiro and Romero, 2008; Mendoza and Martins, 2006). Here we see the intersection of resource economics with the decision science literature. Economic non-market valuation approaches include hedonic pricing, travel-cost models, contingent valuation, and choice modeling (Venn and Calkin, 2009). Approaches in the forestry decision support literature to handle decision uncertainty include the Analytic Hierarchy Process, utility theory, outranking models, and social choice theory (Mendoza and Martins, 2006). Addressing decision uncertainty requires us to identify the best vehicle to elicit preferences, and to ask how confident we are in expressions of preference.

Managing decision uncertainty can be quite challenging, due to the presence of multiple stakeholders with varying perspectives, perceptions and objectives, and the fact that preferences may change with time or as more information becomes available. Managing decision uncertainty is further challenged by the realization that individuals do not with certainty know their own preferences, are inconsistent in expressing their preferences, and are limited in their cognitive ability to fully process information associated with multiple, conflicting criteria, in turn limiting their ability to accurately articulate preferences (Ariely, 2009; Brown et al., 2008; Reiskamp et al., 2006; Braga and Starmer, 2005; Holmes and Boyle, 2005; Maguire and Albright, 2005; DeShazo and Fermo, 2002; Samuelson and Zeckhauser, 1988).

Table 1 illustrates a non-exhaustive mapping from sources of uncertainty in the wildland fire context to the generic uncertainty type, along with the most common decision support approaches used. In some circumstances there is a one-to-many mapping between the fire context and uncertainty typology. Modeling fire behavior, for instance, entails variability uncertainty in terms of processes such as ignition frequency/location and wind patterns, as well as knowledge uncertainty in terms of how we represent fuel conditions, the quality of the input data regarding landscape and fuel characteristics, and how we model fire movement across the landscape. Often managers must simultaneously address numerous sources of uncertainty, such as likely fire spread and likely fire response, requiring integrated approaches to managing uncertainty. Decision support systems help reduce the scope of this uncertainty and facilitate risk-informed decision-making. We now turn to approaches to assess and manage wildfire risk.

3. Assessing wildfire risk

Risk assessment entails four primary steps: problem formulation, exposure analysis, effects analysis, and risk characterization (U.S. Environmental Protection Agency, 1998). Assessing wildfire risk requires an understanding of the likelihood of wildfire interacting with valued resources, and the magnitude of potential beneficial and negative effects to resources from fire (Finney, 2005). The sections below describe in more detail the steps of risk assessment in the context of wildland fire.

3.1. Problem formulation

Problem formulation is a crucial first step, as each analysis must be crafted to address specific management objectives (Keane et al., 2010). In some instances management objectives are singular, such as maximizing expected timber revenue under risk of fire loss (e.g., Konoshima et al., 2010). Other ownership classes, such as state or federal government, may manage for ecological as well as economic objectives (Reinhardt et al., 2008). Kennedy et al. (2008), for instance, develop optimal fuel treatment strategies to simultaneously protect habitat of an endangered species, protect late successional forest reserves, and minimize the total area treated. More recent examples assess wildfire risk to a suite of human and ecological values (Calkin et al., 2010; Chuvieco et al., 2010) to inform monitoring and treatment prioritization.

3.2. Exposure analysis

Exposure analysis explores the predicted scale and spatiotemporal relationships of the risk factors (Fairbrother and Turnley, 2005). Researchers have pursued both probabilistic and non-probabilistic approaches to model exposure to wildfire. Probabilistic approaches include simulation (e.g., Finney et al. in press, 2007; Beverly et al., 2009; Carmel et al., 2009; Bar Massada et al., 2009), logistic regression (e.g., Brillinger et al., 2009; Martínez et al., 2009; Prasad et al., 2007; Preisler and Westerling, 2007; González et al., 2006; Preisler et al., 2004), and Poisson processes (e.g., Crowley et al., 2009; Podur et al., 2009; Podur and Martell, 2007; Amacher et al., 2006). In some instances researchers have adopted complementary approaches. Mbow et al. (2004), for instance, employed both the simulation model FARSITE (Finney, 1998) and a semi-empirical algorithm to categorically identify risk levels given spectral parameters, in order to assess the likelihood of intensive fire propagation in Brazilian savanna ecosystems. Probabilistic models built on historical data (e.g., Preisler et al., 2009; Brillinger et al., 2006; Mercer and Prestemon, 2005) differ from simulation models that estimate burn probability given ignition locations and weather streams. Continuing research into simulation models is seeking to

Table 1
Mapping of some uncertanties faced in strategic wildland fire planning to the uncertainty typology of Ascough et al. (2008). Better understanding the nature of the uncertainty at hand allows for improved management of that uncertainty.

Map: Fire → Uncertainty → Methodology		
Wildland fire context	Uncertainty type	Methodology
Fire occurrence	Variability	Probability-based
Fire behavior	Variability; knowledge	Probability-based; Expert system
Accounting for role of climate change	Variability; knowledge	Probability-based; Expert system
Interaction of fire with other disturbance	Variability; knowledge	Probability-based; Expert system
Temporal vegetation & fuel dynamics	Variability; knowledge	Probability-based; Expert system
Ecological response to fire	Knowledge	Expert system
Efficacy of management treatments	Knowledge	Expert system
Valuation of non-market resources	Decision	Value measurement

better understand the influence of environmental factors on burn probability patterns (Parisien et al., 2010).

Non-probabilistic approaches instead use expert judgment incorporated into a variety of approaches (e.g., knowledge bases, fuzzy logic, and neural networks) that Schmoldt (2001) classifies under the umbrella of artificial intelligence. Employing some manifestation of fuzzy set theory is probably most common. For instance, Vadrevu et al. (2009) processed expert judgment using fuzzy-logic membership functions to estimate fire risk for a region of southern India. Hessburg et al. (2007) also adopted a fuzzy logic approach, using the Ecosystem Management Decision Support System (Reynolds et al., 2003) to assess fire danger in the Rocky Mountain region of Utah as a function of composite indices related to fire hazard, fire behavior, and ignition risk. Iliadis (2005) and Iliadis et al. (2002) used fuzzy set theory and fuzzy machine learning techniques to predict fire occurrence in Mediterranean basin countries. Other non-probabilistic examples include use of a Bayesian belief network to analyze factors influencing wildfire occurrence in Swaziland (Dlamini, 2010), and use of neural networks to predict wildfire occurrence in Canada (Vega-Garcia et al., 1996).

Another important distinction across approaches to exposure analysis is whether they account for contagion. Many of the approaches listed above, such as logistic regression, do not consider spread at all. Other approaches, such as the fuzzy logic system of Hessburg et al. (2007), include measures of potential fire behavior in their hierarchical models but do not explicitly model spread. Sullivan (2009a,b,c) identifies three main classes of approaches to modeling wildland surface fire spread: physical and quasi-physical models, empirical and quasi-empirical models, and simulation models and mathematical analogs. Models that are based on purely physical constructs are generally very computationally intensive, precluding use for many applications of decision support (Sullivan, 2009a). Empirical and quasi-empirical models to the contrary are frequently used, most commonly to predict rate of spread given inputs on wind speed and direction and fuel moisture (Sullivan, 2009b). The quasi-empirical model of Rothermel (1972), for instance, is widely used and forms the basis for simulation models such as BEHAVE (Andrews, 1986). In fact most simulation models incorporate a pre-defined spread model, implementing it to simulate the spread of fire across a landscape. Of existing simulation tools, FARSITE (Finney, 1998) and Prometheus (Tymstra et al., 2009) have been found to best simulate historical fires (Sullivan, 2009c). Mathematical analog approaches to modeling spread include cellular automata (Encinas et al., 2007), fuzzy logic and neural networks (Vakalis et al., 2004a,b), and spatial Markov chains (Catchpole et al., 1989).

If available data and computing capacity are sufficient, adopting an approach to exposure analysis that captures both stochasticity and contagion is the preferred option. First, it is a stochastic representation of a fundamentally stochastic process (McKenzie et al., 2006). Second, burn probabilities are expressed in ratio-scale, i.e., a burn probability of 4% is twice a burn probability of 2%; composite indices and other non-probabilistic metrics are not as easily interpreted. Probabilistic models of fire occurrence and spread are also more easily validated against historical observation in that they can be compared to empirical statistics. Understanding how fire is likely to move across the landscape is extremely important for informing suppression and pre-suppression decision-making (e.g., Ntaimo et al., 2008; Ager et al., 2007; Finney, 2007; Lehmkuhl et al., 2007; Podur and Martell, 2007).

Advancements in algorithmic development (e.g., Finney, 2002) paired with ever increasing computational capacity have allowed for major leaps in probabilistic wildfire behavior modeling. Spatially explicit burn probability information is a crucial input to strategic fire and fuels management planning (Miller et al., 2008). Thus for instance researchers and practitioners are able to project near-term fire behavior using real-time weather information (e.g., Andrews et al., 2007) or to project wildfire behavioral changes in response to fuel treatments (e.g., Kim et al., 2009). The design and functionality of simulation-based approaches span a range of intended applications, from modeling a specific fire event given an ignition to projecting wildfire likelihood and intensity at landscape scales for strategic planning. Applications are now able to model thousands of individual fire events (e.g., Finney et al., in press), in contrast to earlier work where fire likelihood was quantified with relatively few predetermined ignition locations (e.g., Schmidt et al., 2008; LaCroix et al., 2006; Roloff et al., 2005). However, just because algorithmic and computational advances now allow for advanced wildfire simulation modeling does not ensure more reliable estimates, nor does it obviate the need for validation (Cruz and Alexander, 2010). Table 2 presents an illustrative set of examples from the literature that demonstrate wildfire exposure analysis on real-world landscapes.

3.3. Effects analysis

Effects analysis occurs in concert with exposure analysis, to explore the magnitude of response when resources are exposed to varying levels of the risk factors (Fairbrother and Turnley, 2005). It is important to note that effects analysis is a prospective exercise requiring some prediction or forecast of resource response. Combining response functions describing the impact of fire on the resource(s) in question with burn probability maps allows for a quantitative, actuarial representation of risk in a spatial context (Finney, 2005). Many approaches consider not only the likelihood of fire interacting with a resource but also the intensity of the fire, as fire intensity can be a major driver of resource response (e.g., Ager et al., 2007). Equation (1) presents the mathematical formulation for calculating risk in terms of net value change (NVC), which is depicted graphically in Fig. 1.

$$E(NVC_j) = \sum_i p(f)_i RF_j(f_i) \tag{1}$$

where: $E(NVC_j)$ expected net value change to resource j, $p(f_i)$ probability of a fire at intensity level i, $RF_j(f_i)$ "response function" for resource j as a function of fire intensity level i.

Effects analysis has presented a major challenge to risk assessments, due to a limited understanding of the type and magnitude of changes wrought by wildfire to ecological and other non-market values (Keane et al., 2010, 2008; Venn and Calkin, 2009; Black and Opperman, 2005; Fairbrother and Turnley, 2005). Thus most previous efforts have limited analysis to resources for which response to fire is better understood and more easily quantified, such as commercial timber (e.g., Konoshima et al., 2010). Conceptual models have been proposed that consider values at risk and the sensitivity of values to fire, but do not demonstrate actual implementation of risk assessment or quantification of effects (e.g., Bonazountas et al., 2007; Loboda and Csiszar, 2007; Kaloudis et al., 2005). Others have modeled first order effects such as fuel consumption and tree mortality without explicitly identifying a resource or value at risk (e.g., Keane et al., 2010). In general, selection of the appropriate fire effects modeling approach will depend on the management context and the quality and quantity of data available (Reinhardt et al., 2001). At landscape scales expert judgment may be best approach to handle the myriad sources of uncertainty given data and knowledge limitations (Thompson et al., 2010).

In recent years, however, the state of wildfire risk assessment incorporating both exposure and effects analysis has seen significant advancements. Researchers have employed a variety of techniques to model and quantify fire effects to a variety of resources.

Table 2
Selected examples of exposure analysis on real-world landscapes. Approaches are broken down by whether they adopt probabilistic or non-probabilistic methods. Within each sub category references are sorted in order of date published with more recent manuscripts appearing first, a rough proxy for increasing complexity. Probabilistic methods generally entail simulation and logistic regression, although researchers have used other methods such as Poisson processes. Non-probabilistic models instead employ variety of approaches that generally fall under the umbrella of artificial intelligence and expert systems, with fuzzy logic and/or fuzzy set theory probably the most common.

Meta-approach	Approach & context	Location	Reference
Probabilistic			
Logistic regression & simulation	FSim model maps burn probabilities and fire behavior distributions at the pixel-scale, given artificially generated weather streams and ignition locations and using the minimum travel time algorithm (Finney, 2002). Weather streams generated by pairing time-series analysis of energy release component (ERC) with historic distributions of wind speed and direction. The location and frequency of ignitions were generated based on 1) a logistic regression model that predicted the likelihood of at least one large fire, and 2) and empirical distribution function to predict the number of large fires given a fire occurs. Model used to develop a large fire risk assessment system for the contiguous land area of the United States.	Contiguous United States	Finney et al. (in press)
Logistic regression & simulation	Burn-P3 (Parisien et al., 2005) and fire growth sub-model Prometheus (Tymstra et al., 2009) identify the likelihood that a landscape pixel will be burned, given multiple ignition locations and weather streams. Stochasticity introduced via random draws for "spread event days," number of escaped fires, and weather streams. Authors define Fire Susceptibility Index (FSI) as relative rating of likelihood of burning. Also used logistic regression analysis to predict probability of high or extreme FSI values at a given location, using a set of explanatory variables related to fire environment and fire regime characteristics.	West central Alberta, Canada	Beverly et al. (2009)
Simulation	Multiple FARSITE (Finney, 1998) runs, with calendar date, fire length, ignition location, climatic data and other parameters randomly drawn from known distributions. Distance from road used as proxy for ignition likelihood (80% of ignitions occurred within buffer around roads and trails). Maps of fire distribution from simulations overlaid to identify areas of high and low fire frequency.	Mt. Carmel, Israel	Carmel et al. (2009)
Logistic regression	Investigation into human factors associated with high fire risk. Ignition danger index used as metric for "high" or "low" occurrence of forest fires. Logistic regression model predicted high or low occurrence of forest fires, based on explanatory variables related to agricultural landscape fragmentation, agricultural abandonment and development processes.	Peninsular Spain and Balearic Islands	Martínez et al. (2009)
Logistic regression	Remote sensed data of biophysical and anthropogenic variables along with fire count data sets used to assess the underlying cause of fires. Explanatory variables included topography, vegetation, climate, anthropogenic and accessibility factors. Logistic regression model estimated the probability of fire presence.	Deccan Plateau, India	Prasad et al. (2007)
Logistic regression	Authors used logistic regression techniques to generate 1-month-ahead wildfire-danger probability maps in western U.S. Maps spatially forecast probabilities of large fire (>400 ac) events, mapped at 1° lat/long grid. Explanatory variables included monthly average temperature and lagged Palmer drought severity index.	Western U.S.	Preisler and Westerling (2007)
Simulation	Used BEHAVE (Andrews, 1986) and FARSITE (Finney, 1998) to simulate fire behavior under different weather conditions and ignition locations. Assessed the fire potential in an ecological reserve in the savannas (cerrado) of central Brazil. Identified modeling issues associated with fire behavior in savannas.	Central Brazil	Mistry and Berardi (2005)
Non-probabilistic			
Fuzzy-AHP	Integration of GIS with fuzzy-logic-based implementation of AHP (Saaty, 1980). Authors developed a hierarchy of biophysical and socioeconomic factors thought to influence fire risk, then used an expert systems approach to assign weights to criteria using fuzzy set theory. Fuzzy measure of fire risk quantified and mapped using GIS.	Southern India	Vadrevu et al. (2009)
Fuzzy Logic	Developed Fire Threat Model to quantitatively assess wildland fire occurrence based on remote sensed data. Risk of ignition is quantified using fuzzy logic as a spatial multi-criteria function of proximity to major roads, railroads, settlements, terrain, and land cover/land use.	Russian Far East	Loboda and Csiszar (2007)
Fuzzy Logic	EMDS (Reynolds et al., 2003) logic model used to asses "fire danger" as multi-criteria fuzzy membership function of fire hazard, fire behavior, and ignition risk. Fire hazard was a function of surface fuels, canopy fuels, and fire regime condition class; fire behavior a function of spread rate, flame length, fireline intensity, and crown fire potential; and ignition risk a function of Palmer drought severity index, Keetch-Byram drought index, NDVI Relative Greenness Index, and lightning strike probability.	Utah, U.S.	Hessburg et al. (2007)
Fuzzy logic & neural network	Developed simulation tool to be used in operational decision support system. Paired fuzzy logic with neural network to estimate fire spread as a function of terrain characteristics, vegetation type and density and meteorological conditions.	Attica, Greece	Vakalis et al. (2004a,b)

Bar Massada et al. (2009), for instance, intersected maps of structure locations with burn probability maps generated using FARSITE (Finney, 1998) and MTT (Finney, 2002), as implemented in FlamMap (Finney, 2006), in order to estimate the expected number of structures lost due to wildfire. Atkinson et al. (2010) similarly paired a probabilistic wildfire model with maps of urban residences in Hobart, Tasmania. Ager et al. (2007) used FlamMap to streamline fire behavior modeling and simulation with FVS-FFE (Reinhardt and Crookstontech, 2003) to model northern spotted owl habitat loss as a function of altered stand structure and composition. Other salient examples include contingent valuation to estimate existence value of the Leadbeater's possum (Spring and Kennedy, 2005), expert judgment to analyze stand vulnerability to fire based on structural characteristics (González et al., 2007), and simulation with TELSA (Kurz et al. 2002) to measure dissimilarity (Euclidean Distance) from desired landscape composition (Miller, 2007). Metrics of fire

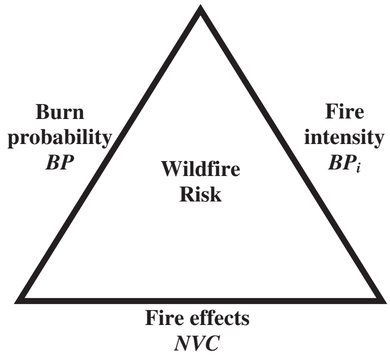

Fig. 1. Wildfire risk triangle (modified from Scott, 2006). Risk is a quantitative measure defined in the actuarial sense as a probabilistic expectation of net value change (Finney, 2005). Risk is a function of burn probability (BP), conditional fire intensity (BP_i), and fire effects (NVC). For informing effects analysis fire intensity is frequently measured in terms of flame length (e.g., Ager et al., 2007).

response can include monetary value (e.g., Brillinger et al., 2009; Crowley et al., 2009; Konoshima et al., 2008; Spring et al., 2008; Butry et al., 2001), structure loss (e.g., Bar Massada et al., 2009), species richness (Lindenmayer et al., 2008), relative abundance index (Kennedy and Fontaine, 2009), and landscape-scale ecological indices based on historic range and variability (Keane and Karau, 2010). More complicated approaches have sought to simultaneously assess wildfire risk to a multitude of market and non-market resources (e.g., Calkin et al., 2010; Thompson et al., 2010; Ohlson et al., 2006; Roloff et al., 2005).

3.4. Risk characterization

Risk characterization integrates "information from the problem formulation, exposure, and effects components to synthesize an overall conclusion about the risk that is complete, informative, and useful in decision-making processes" (Sikder et al., 2006, p. 240). The ability to quantify risk in a common metric facilitates the integration of multiple resource values, and allows for cost-effectiveness and/or cost-benefit analyses. Where multiple values are simultaneously considered characterizing risk becomes a difficult exercise, especially where non-market resources are involved. Ideally such a characterization would reflect the relative social value of each resource, and would monetize marginal changes in resource values as a measure of marginal social welfare change. The nominal economic model for federal wildfire management in the United States adopts this approach with the cost plus net value change (C + NVC) model. The model seeks to minimize the sum of fire-related costs and net value change to resources (Donovan and Rideout, 2003a). Within the C + NVC model, damages and benefits to resources are assumed known and quantifiable in monetary terms.

Broadly accepted and credible means to monetize damages and benefits to non-market resources remain an open question (e.g., Keane and Karau, 2010; Venn and Calkin, 2009; Calkin et al., 2008; Fairbrother and Turnley, 2005; Spring and Kennedy, 2005), thereby limiting the utility of the C + NVC model and similar approaches that rely on monetization.[1] Brillinger et al. (2009, p. 618), for example, state that, "many economic price-based models that assess wildfire management and economic impact typically fail to adequately account for effects on non-marketed resources such as recreation, flora and fauna, air quality, soil, water quality, or cultural heritage. Furthermore, these models require a considerable amount of information, which in many cases is unavailable. Because of these restrictions, there still exists a substantial gap in the scientific understanding of the overall social cost associated with wildfires." To paraphrase, significant knowledge uncertainty results in a lack of resource value measures to guide prioritization across fires and resources at risk.

Rideout et al. (2008) is a notable example from the wildfire economics literature that addresses preference uncertainty surrounding protection of market and non-market resources. The authors developed an expert-based, consensus-driven method based on the theory of marginal rate of attribute substitution in order to estimate implicit prices for wildland–urban interface, Sequoia groves, commercial timber, non-commercial forested areas, rangeland, and roadless areas. In application the method is quite similar to tools from the decision sciences literature, such as the analytic hierarchy process and the simple multi-attribute rating technique, in that relative preferences are elicited via pair-wise, ratio-scale comparisons, and in that all attributes are scored relative to a "numeraire" attribute assigned a score of 1.0 on a (0, 1) scale. Implicit prices for fire protection were derived to prioritize areas for protection. Experts were asked to establish different sets of implicit prices for different fire intensity levels, meaning that fire effects were only implicitly taken into account. A more transparent approach would uncouple fire effects analysis and valuation, and would thereby better align with the ecological risk assessment paradigm promoted here.

4. Risk-based decision support for wildfire management

In this section we review salient applications of risk-based wildfire decision support. Not all applications adopt the same actuarial definition of risk, but do in some capacity adhere to the basic risk assessment framework that considers exposure and effects analyses. Decision support efforts span a range of planning scales, including incident-level analyses to inform operational suppression decision-making (e.g., Keane and Karau, 2010), landscape-scale fuel treatment strategy development (e.g., Ager et al., 2010a), and strategic allocation and location of firefighting resources (e.g., Dimopoulou and Giannikos, 2004). Some approaches are more conceptual, intending to advance general comprehension and the theory of decision support tools (e.g., Konoshima et al., 2010; Crowley et al., 2009; Spring and Kennedy, 2005), whereas others are more oriented on applied research to inform actual management (e.g., Calkin et al., in press; Bar Massada et al., 2009). In the case of the former, many authors have greatly simplified either the landscape or the representation of fire behavior (or both) in order to reduce the computational burden of optimization approaches (e.g., Donovan and Rideout, 2003b).

Here it would be appropriate to reinforce the notion that risk assessments in and of themselves are decision support tools. Two recent applications (Thompson et al., in press; Chuvieco et al., 2010) reflect advanced landscape-scale integrated wildfire risk assessment. The approaches, although disparate, share many important commonalities. First, both define risk as the intersection of fire danger (exposure) and resource response (effects), and consider risk to a suite of human and ecological values. Second, both methods stress the importance of establishing a common risk metric to inform management (characterization), while recognizing the inherent uncertainty of doing so. Third, both methods are scale-independent, applicable to local, regional, and national scales. Table 3 describes both applications in more detail.

[1] This statement is not meant to suggest that monetization approaches are under all circumstances inappropriate, but rather that their applicability is limited in many circumstances, especially where considering a multitude of resources, and especially at landscape-scale analyses. Readers are referred to Venn and Calkin (2009) and Rideout et al. (2008) for discussions of outstanding issues related to non-market valuation techniques and their applicability to wildfire management.

4.1. Commercial timber loss

Many risk-based analyses of fire management have focused on the effect of fire with regard to commercial timber management. Forest economists have modeled fire risk to timber values at the stand level and analyzed the impact of fire risk on optimal timber management decisions, generally assuming spatial independence across stands (e.g., Yoder, 2004; Reed, 1987, 1984). Hyytiäinen and Haight (2009), for instance, evaluate even- and uneven-aged management systems for a single stand, using static annual burn probabilities and without considering possible impacts to adjacent stands. Savage et al. (2010) embedded a non-spatial fire simulation model within a linear program harvest schedule model.

Efforts that have identified optimal harvest decisions under spatially explicit fire threat have used simplified theoretical landscapes (e.g., Konoshima et al., 2008, 2010). Other timber-related applications have increased complexity by simultaneously considering multiple management objectives, while retaining simplistic models of fire or theoretical landscapes. Examples include Amacher et al. (2005), who considered a generic non-timber benefit function in addition to timber revenue, and Spring et al. (2008), who incorporated objectives for cavity-nesting species in mountain ash forests. Stainback and Lavalapati (2004) considered the risk of fire and other disturbances affecting carbon sequestration credits.

4.2. Fuel treatment effectiveness

Evaluating fuel treatment effectiveness is another common arena of risk-based research, subject in particular to knowledge uncertainty regarding how to best achieve ecological goals (Lehmkuhl et al., 2007). Early efforts were constrained by computational capabilities, limiting analyses to the conceptual arena or to simpler models of fire behavior (e.g., Calkin et al., 2005; Hummel and Calkin, 2005; Bevers et al., 2004). More recent approaches to develop fuel treatment optimization models have also, in general, relied on simplifications. Though computational advancements now allow for robust simulation of fire movement across realistic landscapes and for spatially explicit optimization of forest management activities, coupling the two still presents computational challenges. In some cases simplifications are manifested in models of fire behavior. Wei et al. (2008), for instance, used a piecewise linear approximation of fire occurrence and spread within a mixed integer programming model to allocate fuel treatments across a 15,522 ha landscape in California. Kim et al. (2009) used a spatially explicit heuristic optimization algorithm to schedule fuel management activities in different spatial patterns across the landscape in order to achieve volume objectives, and only then examined resulting changes in fire behavior using FARSITE (Finney, 1998). Their analysis considered 15 simulated fires per harvest pattern. Lehmkuhl et al. (2007) similarly considered only a few ignitions (5), although their model did simulate fire behavior within iterations of the optimization algorithm.

Thus, a clear tradeoff exists between computational requirements for wildfire simulation models and optimization algorithms. With optimization approaches the number of treatment alternatives that can be considered is much higher, at the expense of the number of fires that can be simulated. Because of this, approaches that focus less on seeking "optimal" fuel treatments are able to model exposure analysis and effects analysis more robustly. Ager

Table 3
Selected examples of integrated wildfire risk assessment considering human and ecological values. Both methods share a common objective of deriving spatially explicit assessment of fire risk conditions, in order to monitor trends in wildfire risk over time and to help inform decision makers prioritize pre-fire and mitigation measures. Both methods are also scalable, able to be applied to inform operational management and strategic planning.

Approach	Location	Reference
Exposure Analysis: Burn probability maps generated with stochastic simulation model FSim (Finney et al. in press). Resources considered included populated areas, municipal watersheds, air quality, energy infrastructure, federal recreation and recreation infrastructure, fire-susceptible species, and fire-adapted ecosystems. Minimum mapping unit fixed at 270 m^2. *Effects Analysis:* Expert systems approach defined resource response to fire as a function of fire intensity. Ten fire and fuels program management officials from federal land management agencies consulted with the authors to facilitate response function assignments. A suite of generalized response functions translated fire effects into net value change (NVC) to the resource in question. NVC was estimated using an area-based proxy called Total Change Equivalent (TCE), which aggregates pixel-based outputs and is defined as the equivalent area lost (or gained) for a particular resource, measured in acres. *Risk Characterization:* Coarse-filter approach assigned resources into qualitative "value categories." The highest value category was reserved for resources related to human health and safety (e.g., populated areas and municipal watersheds). Additional layer of analysis assigned weights to each value category using ratio-scale weight vectors. Risk to critical habitat was also examined independently from TCE with an alternative spatial proxy defined as expected percent of habitat lost.	United States	Thompson et al. (in press)
Exposure Analysis: Fire occurrence probability was quantified as a multi-criteria function of human and lightning caused ignition (predicted with logistic regression), live and dead fuel moisture content (derived from remote sensed data), and propagation (modeled with BEHAVE (Andrews and Chase, 1990)). Resources considered included properties, wood products, hunting revenues, recreational and tourist resources, carbon stocks, soil and vegetation condition, and intrinsic landscape value. Minimum mapping unit fixed at 1 km^2. *Effects Analysis:* Damage to socioeconomic resources estimated using average fire intensity and expert opinion. Vulnerability of ecological resources to fire similarly estimated using expert judgment, cross-tabulating short- and medium-term impacts considering soil erodibility, water limitations, and vegetation community. *Risk Characterization:* The authors did not derive a common risk scale for all input variables. "Tangible" socioeconomic resources (e.g., properties, wood products) were quantified using market prices and standard financial analyses. "Intangible" socioeconomic resources (e.g., recreation, wildlife conservation) were monetized using travel-cost models and contingent valuation. Ecological resources were instead qualitatively categorized into four ordinal groups (low, medium, high and extreme).	Spain	Chuvieco et al. (2010)

et al. (2010a), for instance, simulated the growth of 10,000 fires across a 16,343 ha landscape in northeast Oregon, for ten treatment scenarios. The work examined tradeoffs between protecting the wildland urban interface and preserving old forest structure. Using FVS-FFE (Reinhardt and Crookston, 2003) the authors quantitatively projected expected mortality to large trees, by species. Recognizing the complexity of processes guiding structure ignition (Cohen, 2008), the authors opted not to estimate structure loss and instead provided scatter plots of burn probability and conditional flame length to identify relative wildfire risk among structures. Similar work examining the effects of fuel treatments by simulating thousands of fires has considered risk to spotted owl habitat (Ager et al., 2007).

Interest in investigating the carbon flux implications of hazardous fuels reduction treatments (e.g., Hurteau and North, 2010; Wiedinmyer and Hurteau, 2010) appears to be increasing. Campbell et al. (2009), for instance, examined how thinning treatments affected carbon dynamics in mature ponderosa pine stands. In other analyses the focus expands to examine how future wildfire emissions may change in response to fuel treatments. Ager et al. (2010b) caution that such analyses ought to model fire spread across the landscape in order to capture off-site effects, and consider the probability of the treatment actually interacting with fire (i.e., pre- and post-treatment analyses cannot simply assume a fire will occur with probability of 1.0).

4.3. Active fire management

Risk-based decision support efforts have been directed toward management of active fires, in particular for initial attack to contain fires quickly before they can grow large and possibly cause damage. MacLellan and Martell (1996) modeled airtanker deployment as a queuing system with airtankers as servers and fires as customers, and developed an optimization model to identify home-basing strategies to minimize the average annual cost of satisfying daily airtanker deployment demands. Some authors have adopted maximal covering models, which seek to provide coverage to demand areas within a time or distance limit (e.g., Dimopoulou and Giannikos, 2002; Hodgson and Newstead, 1978). Expansions to these models include simulation with scenario analysis to allow for uncertainty in model parameters (e.g., Haight and Fried, 2007; Dimopoulou and Giannikos, 2004).

Most approaches designed to facilitate management of active fires use some form of simulation, comparing the rate of spread of the fire (either using simple elliptical equations or more complex fire behavior simulations) to the productive capacity of firefighting resources (e.g., Ntaimo et al., 2008; Fried et al., 2006; Fried and Gilless, 1999; Islam and Martell, 1998; Fried and Fried, 1996). In earlier, simpler models, when the constructed length of fireline equaled the fire perimeter, the fire was contained. In addition to fireline length, Mees et al. (1994) modeled fireline width as a random variable that influenced the probability of containment. Fried and Fried (1996) improved upon initial attack simulation by accounting for the interaction between fireline production and fire growth. Efficacy of production is often negatively adjusted to account for factors such as fire weather index, rate of spread, or fuel type. The CFES2 simulation model allows for the diversion of resources for structure protection, at rates based upon population density and dispatch level (Fried et al., 2006). Some authors have elicited expert judgment to inform modeling of initial attack crew and/or airtanker productivity (Hirsch et al., 2004, 1998; Mees et al., 1994; Mees and Strauss, 1992).

Providing decision support for escaped large wildland fires is a more complex problem, in large part because of substantial uncertainty surrounding the effectiveness of various firefighting resources and tactics on containment. For example, Finney et al. (2009, p. 249) state that “the effectiveness of suppression efforts on the progress or containment of large fires has not been modeled or even characterized, and it is presently not known what or how different factors are related to successful containment.” Podur and Martell (2007) attempted to model containment of large fires, using fireline production rates from Hirsch et al. (2004) for crews and the deterministic simulation system LEOPARDS (McAlpine and Hirsch, 1999) to model airtanker efficacy. The authors did not account for alternative uses of airtankers such as point protection, and highlighted the uncertainty surrounding extended attack. Earlier approaches (e.g., Hof et al., 2000) relied on even simpler models of fire and suppression effectiveness.

The Wildland Fire Decision Support System[2] (WFDSS) may constitute the most advanced tool for management of escaped wildland fires (Calkin et al., in press). Recognizing the limited understanding of suppression efficacy, the tool does not attempt to model the effectiveness of various combinations of firefighting resources or suppression tactics, leaving those evaluations to experts in the field. Rather, the tool provides state-of-the-art exposure analysis, linking in real-time spatial fire threat with values at risk. The two primary decision support analysis components, FSPro (Fire Spread Probability model, see Finney et al., 2010) and RAVAR (Rapid Assessment of Values at Risk), identify where the fire is likely to spread, mapped as probability contours, overlaid with geospatial identification of human and ecological values. Outputs from the analysis are two distinct map products and associated reports. Critical Infrastructure reports identify private structures, public infrastructure, public reserve areas, and hazardous waste sites that are within the current or projected fire perimeters. Natural and Cultural Resources reports instead focus on regionally identified natural resource priorities, and include sensitive wildlife habitat, recreation zones, and restoration priority areas. WFDSS is now used by all federal land management agencies with wildfire responsibility within the United States. Use of the tool facilitates management decisions of where and when aggressive fire suppression is required to protect resource values, and when fire may be allowed to burn to protect and enhance ecosystem values.

4.4. Long-term planning: mitigation and adaptation

Lastly, we address applications that consider long-term spatiotemporal dynamics and especially the implications of a changing climate. Projecting into the future requires the simultaneous consideration of human development (including land use and land cover change), vegetative succession, species migration, disturbance dynamics, climate change, and feedbacks therein (Balshi et al., 2009). This is the least mature area of risk-based analysis within the wildfire literature, and is subject to the greatest degree of knowledge uncertainty. Key research questions include: 1) how might climate change impact wildfire (and other disturbance) regimes (Running, 2008); 2) how might we alter management today in order to mitigate climate change (Canadell and Raupach, 2008); and 3) how might we develop adaptation strategies to reduce future social and ecological losses to wildfire (Kilpeläinen et al., 2010).

With respect to the first question, climate change is predicted to affect the frequency, intensity, duration and timing of fires, including extreme wildfire events, and could lead to wildfires being the primary agents of change in some ecosystems (Hanewinkel et al., 2010; Littell et al., 2010; Kurz et al., 2008; Dale et al., 2001).

[2] http://wfdss.usgs.gov/wfdss/WFDSS_Home.shtml.

Predictions of increased droughts and longer fire seasons have led to predictions of increased wildfire activity, magnified threats to human and ecological values, and possible climate feedbacks though increased emissions (Running, 2006; Westerling et al., 2006). Examples of predictions from around the globe include an increased occurrence of wildfires in the northern UK (Albertson et al., 2010), increased area burned in Canada and more broadly across the circumboreal forests (Balshi et al., 2009; Flannigan et al., 2009a), increased area burned in the western United States (Littell et al., 2009), increased number of potential large fire ignition days in south-eastern Australia (Bradstock et al., 2009), and an increased number of fire alarm days in southern Finland (Kilpeläinen et al., 2010). For other regions of the globe, however, such as Africa, South America, and South Asia, we have a more limited understanding of possible impacts to wildfire regimes from climate change (Flannigan et al., 2009b).

Climate change mitigation strategies associated with wildfire management include reducing emissions via fuel reduction treatments and improving prevention and suppression efforts, and using removed biomass to replace fossil fuels for energy production (Canadell and Raupach, 2008; Malmsheimer et al., 2008; Silverstein et al., 2006). Bond-Lamberty et al. (2007) assert that past successful suppression operations in Canada may have underappreciated carbon flux benefits, suggesting enhanced suppression could provide benefits in the future. However, the prospect of even greater emissions from larger fires in the future due to fuel accumulation (Arno and Brown, 1991) needs to be considered, as does the notion that additional investments in suppression response capacity may be inefficient or ineffective where fires are driven largely by weather independent of suppression effort (Finney et al., 2009). Caution is also warranted to avoid an overly narrow focus on carbon flux dynamics as a proxy for climate issues (Thompson et al., 2009). There is a need to better incorporate other biogeophysical processes that can exert possibly countervailing influences of wildfire on climate, such as evapotranspiration and albedo (Bonan, 2008). Randerson et al. (2006), for instance, found that future increases in fire in boreal forests may not accelerate global warming, because increased snow exposure led to increased albedo resulting in a cooling effect.

Identifying future management and adaptation strategies requires coupling projections of climate and wildfire dynamics with our understanding of how management influences wildfire activity, both of which are subject to significant uncertainty. Nevertheless such studies remain highly important for informing future risk management and reducing social and ecological losses to wildfire (Kilpeläinen et al., 2010). Crookston et al. (2010), for instance, augmented a tree growth model to incorporate climate data (Climate-FVS) that can allow managers to investigate possible future effects on forested ecosystems. Fried et al. (2008) projected an increase in the number of fires escaping initial attack in California, then examined "what-if" scenarios with additional firefighting resources and found only modest augmentations to existing capacity would be sufficient to compensate for increased wildfire activity. Albertson et al. (2010) suggests active management on a number of fronts in response to an increase in wildfire occurrence in the northern UK, including fuel reduction, increased detection effort, and investment in awareness programs. Podur and Wotton (2010) suggest that future fires in Canada may exceed existing suppression capacity, and recommend further research into the effect of increased suppression capacity and into adaptation options. Littell et al. (2009) note that adaptation strategies should depend on ecosystem specific variables, with some ecosystems more suitable for mitigation and resiliency treatments than others.

5. Discussion

5.1. Overview

Assessing and managing wildfire risk requires analyzing exposure to risk factors (i.e., fire occurrence, spread, and intensity) and fire effects. In this paper we promoted a quantitative definition of risk, with the rationale that improved transparency and objectivity can better inform decision-making. Use of a common measure can entail a significantly lower cognitive burden than balancing multiple non-commensurate measures, and thus can reduce the likelihood of reliance on mental shortcuts or heuristics that can bias decision-making (Maguire and Albright, 2005). However, expressing risk as a probabilistic expectation does have potential pitfalls, for instance not capturing the variability around the expectation, or possibly equating low-likelihood, high-magnitude events with high-likelihood, low-magnitude events (Hanewinkel et al., 2010). Further, use of qualitative information can augment quantitative analyses, can be useful for capturing expert opinion, and can reduce the likelihood that the user will ignore what is not measured.

Exposure analysis is arguably where current wildfire science is most advanced, leveraging increased modeling capabilities with expanded use of remote sensing technologies. Recent improvements in computing power enable massive geo-processing, rapid simulations and the projection of fire behavior across planning scales. Improved geospatial data acquisition and management provides increased resolution and accuracy regarding fuel conditions (e.g., Department of Interior Geological Survey, 2009; Rollins et al., 2006) and valued resources. Continued technological advancements may allow for the use of more computationally intensive fully physical models in the near future (Sullivan, 2009a). Applications of exposure analysis include informing real-time suppression decision-making (e.g., Calkin et al., in press), prospective fuel treatment planning (e.g., Ager et al., 2010a; Kim et al., 2009), and assessing wildfire risk to a variety of resources (e.g., Chuvieco et al., 2010; Bar Massada et al., 2009; Roloff et al., 2005).

Still, multiple sources of uncertainty remain with regard to modeling exposure analysis. Cruz and Alexander (2010) identify a significant under-prediction bias for assessing crown potential common to many fire modeling systems, and challenge the fire modeling community to better evaluate model performance against independent datasets and empirical observations. Atkinson et al. (2010) note that fire modeling results can be highly influenced by the quality of input data and models. Models of fire spread are critical, and yet the basic methods of simulating wildfire spread have not substantially changed in decades (Sullivan, 2009c). There is a need to improve our fundamental scientific understanding, requiring investments into basic fire physics and chemistry. There is also a need to better understand how uncertainty and errors propagate through models (Sullivan, 2009c). Ironically, there is even uncertainty about how best to reduce current scientific uncertainty (i.e., where to measure, how long to measure, how to correlate measurements with observations) (Sullivan, 2009b). Another component to consider is ignition occurrence. FSim (Finney et al. in press) assume a uniform distribution of ignitions, which is more appropriate for simulating fire occurrence in geographic areas that are characterized by relatively few large fires and burned areas may be geographically distant from ignition sources. Carmel et al. (2009) employed a proxy of distance to road to consider likelihood of ignition. Similar models where fire is primarily driven by anthropogenic actions (e.g., Chuvieco et al., 2010) have employed more sophisticated ignition models. Continued empirical research (e.g., Baeza et al., 2002) should help inform and validate exposure analysis efforts.

A major remaining roadblock to strategic wildland fire planning is our limited ability to characterize, and therefore effectively manage, non-market resource values at risk. With respect to non-market resources at risk there are two major sources of uncertainty at play: a limited scientific understanding of ecological response to wildfire (knowledge uncertainty), and unknown social preferences/values to inform prioritization and resource allocation (decision uncertainty). That is, we face a "…lack of information about both disturbance effects on non-market resources and the social welfare implications of resource change for many non-market values, making full social cost-benefit analysis for large disturbance events very challenging" (Venn and Calkin, 2009, p. 52). These uncertainties challenge integrated wildfire risk assessment, especially for public lands or other ownerships with management objectives beyond industrial timber production.

5.2. Knowledge uncertainty

In terms of assessing ecological response to fire, current decision support efforts appear to be moving in the right direction for managing knowledge uncertainty. Generally speaking, this entails the design and application of some form of an expert system, augmented to the degree possible by empirical evidence. Efforts at synthesizing anticipated resource response to wildfire (e.g., Keane et al., 2008; Kennedy and Fontaine, 2009; Moody and Martin, 2009), and empirical investigation into fire effects (e.g., Cassady et al., 2010; Meigs et al., 2009; Hyde et al., 2007; Gottfried et al., 2007) can reduce the scope and magnitude of this knowledge uncertainty.

The possible ecologically beneficial role of large fire needs to be better understood (Keane et al., 2008), as do the hydrological and geomorphological influences of wildfire (Shakesby and Doerr, 2006). Vulnerability analysis, which considers the sensitivity and resiliency of the value(s) at risk, (Turner et al., 2003) could also be expanded within wildfire risk assessments (e.g., Gaither et al., 2011).

How to manage wildfire risk is another area of knowledge uncertainty. Clearly there is a need to better understand the effect of management actions, both pre-fire and suppression, on fire occurrence and behavior. This would necessarily entail multiple field studies at multiple sites across multiple scales, evaluating a number of research questions ranging from post-treatment stand development to tracking and evaluating retardant drops. Improved decision support technology could also help reduce knowledge uncertainty in the planning environment. Martell (2007) offers interesting insights for future applications of operations research methodologies, including maximal coverage and stochastic vehicle routing for fire detection, and spatially explicit stochastic integer programming for fuel treatment planning. He suggests fuel treatment optimization needs to consider uncertainty surrounding fire ignition and spread, initial attack success, and large fire growth. For many applications of operations research methodologies, such as optimal timber and fuel treatment, there is a need to better integrate algorithms with real landscapes and realistic models of fire spread. Advances in computation, such as parallel processing and improved heuristic development, should prove fruitful in this arena.

Another key area of knowledge uncertainty is modeling the spatiotemporal dynamics of wildfire regimes and climate change. Many analyses to date have relied in some way on simplifications due to knowledge gaps or for computational purposes, at the possible expense of model reliability and accuracy (e.g., Fried et al., 2008). Projecting future wildfire regimes is confounded by uncertainty surrounding other dynamic processes. For instance ascertaining accurate projections of plant distribution shifts entails significant uncertainty regarding the interaction of land cover, carbon dioxide fertilization, biotic interactions, and dispersal mechanisms (Hanewinkel et al., 2010; Thuiller et al., 2008). Though next-generation dynamic vegetation models can better represent the dynamics of disturbance and succession, they too are still subject to significant knowledge uncertainty (Fisher et al., 2010). Flannigan et al. (2009b) highlight a number of avenues of future research, including improved global fire data collection, and continued modifications to global models to better account for dynamics of weather, vegetation, people, and disturbances. In summary, modeling limitations, knowledge gaps, and other uncertainties pose a significant challenge for addressing spatiotemporal dynamics (in particular climate change) within the quantitative risk assessment framework described within this paper. An exhaustive review of the relevant literature and uncertainties inherent to climate change and wildfire is well beyond the scope of this paper. Readers interested in a more thorough review of uncertainty surrounding the science of climate change are encouraged to read Morgan et al. (2009). Notably, this document similarly advocates the identification, characterization, and quantification of sources of uncertainty. Flannigan et al. (2009b) is an excellent synthesis of current state of understanding of how global wildfire dynamics may be impacted by a changing climate.

5.3. Decision uncertainty

In contrast to managing knowledge uncertainty and increased reliance on appropriate decision support methods (i.e., expert systems), with respect to managing decision uncertainty results are more mixed. Of the relatively few efforts that do explicitly attempt to value non-market resources (e.g., Chuvieco et al., 2010; Spring and Kennedy, 2005) even fewer address known issues related to preference articulation methods. Particularly challenging are efforts at integrating multiple values, such as large-scale prioritization across a suite of valued resources; those that have attempted integrated prioritization (e.g., Thompson et al., 2010) have by necessity adopted coarse-filter approaches.

The fields of decision science and environmental economics will need to be brought to bear in future applications. Despite known issues with non-market valuation techniques, moving forward they remain an important method to generate estimates of value if carefully designed. In concert with research efforts seeking to improve methodologies, there is a need to implement additional studies to better understand social preferences. Venn and Calkin (in press) recommend a suite of choice modeling studies distributed across heterogeneous communities. Additional investigation into low-quality preference information could address promising areas such as group decision-making techniques (Diaz-Balteiro and Romero, 2008) and voting mechanisms (Kangas et al., 2006). Researchers could also look further into the development of hybrid decision support tools, as recommended by Mendoza and Martins (2006) and Kangas and Kangas (2005). Moving forward, we should seek to use and design preference elicitation methods that recognize our cognitive limitations (Holmes and Boyle, 2005) and don't require the many assumptions regarding rationality (Reiskamp et al., 2006). Issues related to preference uncertainty are, of course, not unique to wildfire economics, and so researchers may be able to leverage off of advancements made by ecological and environmental economists in related fields.

5.4. Looking ahead

A natural question arises as to how best to balance and prioritize investments in research to reduce and better manage uncertainty. The answer to this question will vary with relevant stakeholders and predominant management objectives, and is by its nature subject to some degree of preference uncertainty. Location-specific variables, such as land use, land cover, fire regime, the ecological role of fire, the spatial pattern of values at risk, etc., will also influence research priorities. As an example compare wildfire risk management in the western United States and in the Mediterranean basin of southern Europe. In the case of the former, important areas of research include how to better understand the beneficial role of large fires on the landscape and how to better manage naturally ignited wildfires for resource benefit. In the case of the latter, where population densities and rates of human-caused fires are higher, research into improving the effectiveness of prevention programs and rapid-response suppression operations might be prioritized much higher.

The temporal nature of the problem at hand also influences how to prioritize research investments. Questions of a more immediate nature, such as employing risk-based analyses to determine the optimal allocation of firefighting resources across a given region, will necessarily rely more heavily on expert judgment in the absence of time and resources to perform more in-depth analysis. Longer term questions, such as preparing for climate change, require establishing a vision, research direction, acquisition of resources, etc. The onus lies with domain experts (fire ecologists, economists, wildfire biologists, climatologists, etc.) to collectively identify and help prioritize research directions. Increased communication across disciplines, across professional arenas (e.g., industry, academia, government), and across geographic location is recommended to promote learning, collaboration, and synergy. Within the realms of decision science and economics we would recommend increased use of systematic and structured processes to elicit expert judgment (e.g., Knol et al., 2010), a greater incorporation of behavioral psychology and cognitive science into non-market valuation techniques (e.g., Brown et al., 2008), investigation into the value of information to help prioritize learning (e.g., Kangas et al., 2010), increased pairing of fire simulation models with optimization models (e.g., Rytwinksi and Crowe, 2010), and in general a broader adoption of principles of decision-making under uncertainty within economic analyses.

We would also recommend that researchers and practitioners take care to align the complexity of the decision support tool with the nature of the decision-making environment. Decision makers can become quickly overwhelmed by decision support systems that try to describe all of the relevant effects and tradeoffs. Decision support tools therefore need to achieve a balance between providing information to guide decisions and allowing relevant experts to ultimately make decisions (see for instance the WFDSS tool referenced earlier in Section 4.3). What constitutes decision support tools is broader than just computerized aids, including checklists, templates, and training and education (MacGregor and Haynes, 2005). "Soft" operations research approaches, which seek acceptable rather than normatively optimal solutions, may better incorporate expert judgment and facilitate bottom-up planning, and could be explored further (Mendoza and Martins, 2006). MacGregor and Gonzalez-Caban (2008) echo that sentiment in part by recommending improved and increased use of local knowledge for active wildfire management. The Millennium Challenge '02, the largest and most expensive war game ever conducted by the Pentagon, provides an example of the challenges of centralized decision-making with excessive reliance on complicated decision support tools (Gladwell, 2005). In this exercise, a team with low-technology military and intelligence resources with decentralized decision-making routed a team with superior numbers and equipped with high-technology military and intelligence resources, and the best available decision support tools to facilitate centralized decision-making. After the simulation, the commander of the winning team commented that the losing team's information systems and mechanistic decision-making processes were useful when planning for engagement, but were cumbersome and useless after engagement when rapid decision-making was required to counter unexpected changes in the simulation environment.

6. Conclusion

Strategic wildland fire planning is subject to myriad sources of uncertainty, which upon classification can be addressed and managed using various decision support tools. Informed decision-making requires an integrated evaluation of multiple uncertainty types. Using an uncertainty typology from the decision-making literature we described sources of linguistic, variability, knowledge, and decision uncertainty within the wildland fire context. We reviewed approaches to managing fire-related uncertainty, and described illustrative examples of risk-based analyses. We assessed the state of wildfire risk analysis to identify trends and remaining research needs.

A key challenge is a better characterization of non-market resources at risk, both in terms of their response to fire and also how society values those resources. Our findings echo earlier literature identifying wildfire effects analysis and value uncertainty as the primary challenges to integrated wildfire risk assessment and wildfire management. Research needs remain in both the biophysical and social sciences, including basic fire science, fire spread models, fire effects models, and social preferences. Spatio-temporal dynamics and the consequences of climate change also remain key areas of research, and the degree of uncertainty present in projections of alternative futures will no doubt influence how we characterize and prioritize future risk mitigation efforts.

As a matter of transparency and objectivity, risk assessments should identify and characterize all uncertainties. The scope of uncertainty is likely to vary with the scale of the analysis. At landscape levels mapping of fuels and valued resources may be coarse by necessity, but can be refined as the planning scale decreases. Social valuation of resources can also be scale-dependent, for instance in circumstances where communities have strongly held values that may not be transferrable elsewhere. By contrast some uncertainties are largely scale-independent, for instance conceptual understanding of fire effects and treatment efficacy. This research focused on utilizing decision support frameworks to improve our ability to manage human and ecological values at risk to wildland fire. We stress the importance of characterizing uncertainties in order to better quantify and manage them. Leveraging the most appropriate decision support tools can facilitate wildfire risk assessment and ideally improve decision-making. The authors are most familiar with the state of wildfire research in the United States, in particular the arena of public land management. We attempted a thorough exploration of the literature and of the risk management approaches being adopted around the world, although inevitably we may have overlooked high quality analyses. It is our hope this paper stimulates additional research into integrated risk assessment and decision-making under uncertainty, and ultimately improves our ability to manage wildfire with imperfect information.

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