SPECIAL ISSUE

CSIRO PUBLISHING

*International Journal of Wildland Fire* **2013**, *22*, 1–14
http://dx.doi.org/10.1071/WF11114

Review

# A review of recent advances in risk analysis for wildfire management

*Carol Miller*[A,C] *and Alan A. Ager*[B]

[A]USDA Forest Service, Rocky Mountain Research Station, Aldo Leopold Wilderness Research Institute, 790 E. Beckwith Avenue, Missoula, MT 59801, USA.
[B]USDA Forest Service, Pacific Northwest Research Station, Western Wildland Environmental Threat Assessment Center, 3160 NE 3rd Street, Prineville, OR 97754, USA.
[C]Corresponding author. Email: cmiller04@fs.fed.us

**Abstract.** Risk analysis evolved out of the need to make decisions concerning highly stochastic events, and is well suited to analyse the timing, location and potential effects of wildfires. Over the past 10 years, the application of risk analysis to wildland fire management has seen steady growth with new risk-based analytical tools that support a wide range of fire and fuels management planning scales from individual incidents to national, strategic interagency programs. After a brief review of the three components of fire risk – likelihood, intensity and effects – this paper reviews recent advances in quantifying and integrating these individual components of fire risk. We also review recent advances in addressing temporal dynamics of fire risk and spatial optimisation of fuels management activities. Risk analysis approaches have become increasingly quantitative and sophisticated but remain quite disparate. We suggest several necessary and fruitful directions for future research and development in wildfire risk analysis.

**Additional keywords:** burn probability, fire likelihood, hazard, risk assessment, risk science.

Received 11 August 2011, accepted 29 June 2012, published online 14 September 2012

## Introduction

Risk analysis concerns the measurement and communication of uncertain future events of extreme consequences (Brillinger 2010). Typically, risk analysis focuses on low probability high consequence events that are stochastic in space and time. The term *risk* is generally used to describe the chance of loss, determined from estimates of likelihood and associated outcomes. Risk assessments are conducted when predicted outcomes are uncertain, but possible outcomes can be described and their likelihoods can be estimated (Haynes and Cleaves 1999). Risk analysis can help scientists and managers better understand the timing, location and potential effects of wildfires on financial values and ecological systems. Risk analysis can transparently address forest management issues and disclose tradeoffs that other analysis techniques may not account for (Hollenstein 2001).

A conference in 2005 held in Portland, OR, USA, reflected substantial interest by the wildfire science community in the application of risk analysis to fire issues (special issue of Forest Ecology and Management (FEM) 2005, volume 211). One key message was that clear and consistent definitions of risk were needed (Hardy 2005; O'Laughlin 2005), though some of the proposed terminology (Hardy 2005) differed somewhat from previous proposals (Bachmann and Allgower 2001). The conference emphasised the importance of quantifying components of risk (Fairbrother and Turnley 2005) and proposed frameworks that, compared with previous work, more closely resembled formal risk frameworks (Finney 2005; O'Laughlin 2005). These more formal frameworks defined risk as comprising three components (likelihood, intensity and effects) (Fig. 1) and used terminology consistent with the risk analysis field. Prior to the Portland conference, decision support and analysis systems self-labelled as fire risk systems were often missing key risk components.

Demand for quantitative risk-based tools has grown as wildfires have increasingly affected human and ecological resources. Globally, the growing incidence and damage from wildland fires has prompted many new efforts to build wildfire risk systems (Loboda and Csiszar 2007; Andreu and Hermansen-Báez 2008; Tolhurst *et al.* 2008; Martínez *et al.* 2009; Atkinson *et al.* 2010; Chuvieco *et al.* 2010). Current wildland fire management policy in the USA asserts 'sound risk management is a foundation for all fire management activities' (NIFC Policies, http://www.nifc.gov/policies/policies_documents/GIFWFMP.pdf, accessed 2012). Moreover, the 2009 FLAME Act requires the USA land management agencies to revise the Cohesive Wildfire Management Strategy and address concerns (GAO 2003*a*, 2003*b*, 2007, 2009) over the lack of risk-based metrics to evaluate and monitor fuel treatment programs.

In response to such demands, substantial development and improvement of tools for risk analysis have occurred in recent

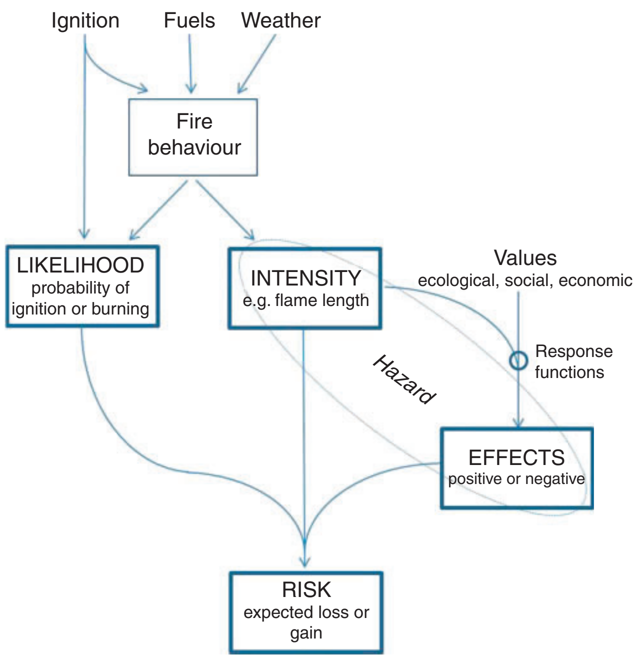


**Fig. 1.** A generalised fire risk framework with the major components of a wildfire risk analysis. Risk is a combination of likelihood, intensity and effects. Likelihood is often estimated statistically from ignition data, or simulated with fire behaviour models. Intensity is a major output of fire behaviour models. Effects may be positive or negative and can be estimated using intensity estimates and response functions. Intensity and effects together represent hazard.

years. Advances in risk assessment systems have resulted largely from improvements in software, systems integration, data availability, GIS and simulation techniques (Finney 2002, 2006; Eidenshink *et al.* 2007; Miller *et al.* 2008; Rollins 2009; and many others). Computer models can replicate spatially explicit fire growth through heterogeneous fuels (Sullivan 2009), and map fire behaviour characteristics across large landscapes (Keane *et al.* 2010). Computationally efficient algorithms have greatly increased the feasibility of simulating fire spread on large landscapes (Finney 2002). Geospatial data on important social and ecological values that are potentially affected by fire are now widely available for many regions of the world. Online weather (Zachariassen *et al.* 2003), fuel (Rollins 2009) and burn severity (Eidenshink *et al.* 2007) datasets have helped feed and validate large scale modelling efforts. All of these technological advances have facilitated the quantification of likelihood, intensity and effects at a range of spatiotemporal scales.

In this paper, we review recent advances in risk analysis approaches to address wildfire management and planning issues. We emphasise developments since the 2005 special issue of FEM. Space considerations prevent us from being fully comprehensive of contributions to the problem of analysing wildfire risk. For example, we do not cover the extensive literature concerning danger indices, short-term fire forecasting models and real time risk assessment, but we refer the reader to other papers on those subjects (Andrews *et al.* 2007; Hardy and Hardy 2007; McDaniels 2007; Vasilakos *et al.* 2007; Fiorucci *et al.* 2008; Preisler *et al.* 2009; Calkin *et al.* 2011*b*). Instead, we selected peer-reviewed papers from the last several years to illustrate one or more advances in data, models and analysis, and to discuss important differences among the approaches for their application in risk assessments. These papers quantified and mapped one or more of three wildfire risk components (likelihood, intensity and effects).

## Definitions and the components of fire risk

The wildfire professional community has variously applied the term *risk*. Disparate terminology has led to confusion, despite efforts to standardise and operationalise definitions (Bachmann and Allgower 2001; Finney 2005). We start with Society for Risk Analysis (SRA) definitions: (1) risk is the potential for realisation of unwanted, adverse consequences to human life, health, property or the environment; and (2) the estimation of risk is based on the expected value of the conditional probability of an event occurring times the consequence of the event given that it has occurred (SRA Glossary, http://www.sra.org/resources_glossary.php, accessed 2012). With these definitions, risk is the expectation of loss, and includes some assessment of three risk components: (1) likelihood of the event; (2) expected intensity and (3) one or more effects related to the expected intensity. In the context of wildfire, however, we adapt these definitions because both negative *and* positive effects can be realised. Therefore, fire risk is the expectation of loss *or* benefit, and the loss or benefit may occur to any number of social and ecological values affected by fire (Finney 2005).

The terms *risk*, *hazard*, *exposure*, *threats*, *vulnerability* and *fire danger* are frequently used but are not always defined. The term *hazard* is often incorrectly interchanged with *risk*, and technically refers to the potential for loss given a fire event, but describes nothing about the likelihood of the event occurring. It is typically calculated using fire behaviour models from fuel information and quantified in terms of flame length, potential for crowning fire behaviour or fire effects such as tree mortality. *Exposure* describes the spatial juxtaposition of values with fire behaviour in terms of likelihood and intensity, but does not explicitly describe fire effects on those values. A *threat* is an expected loss that has undesired social or ecological consequences. Almost synonymous with *risk*, the term *threat* excludes the notion that fires can have beneficial effects. *Vulnerability* is the potential effect of a threat and considers the adaptive capacity of the affected entities over time. A vulnerability assessment of a wildland–urban interface (WUI) would consider how people respond and adapt to the threat from fire via fire-proofing structures and other mitigation efforts. Finally, *fire danger* describes the short-term outlook for fire occurrence (days, weeks), typically considered over broad geographic regions, and makes use of short-term weather forecasts (Hardy and Hardy 2007; Vasilakos *et al.* 2007). Fire danger ratings may also include an assessment of fire behaviour (e.g. Haines index), but intensity and effects are not explicitly considered.

Estimates of the three primary fire risk components (likelihood, intensity and effects) and variables that drive them are needed to build fire risk models and apply them for risk assessment. As such, it is important to understand the various ways that likelihood, intensity and effects are represented in fire

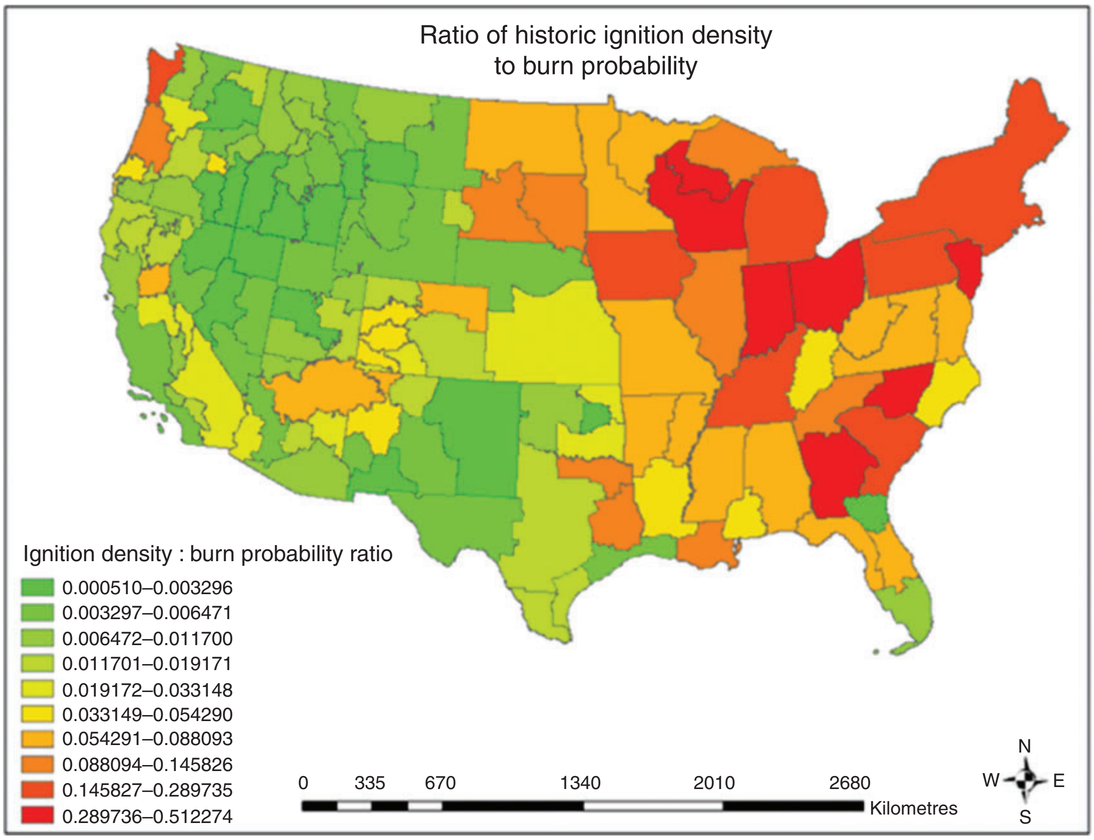


**Fig. 2.** Map of continental US quantifying the difference between ignition probability and burn probability calculated with the FSIM model (Finney *et al.* 2011*b*). Image from Calkin *et al.* (2011*c*).

risk analyses. For instance, some fire risk models and assessments represent likelihood as ignition probability, which is estimated from ignition data, whereas others use the probability of burning, which refers to the probability that a fire encounters a particular place. Although burn probability depends in part on ignition, it also depends on the subsequent spread of fire, which can be estimated from historical data on area burned or derived at finer scales using fire simulation methods.

There are also inherent assumptions in the numerous fire behaviour models used to predict fire risk (Cruz and Alexander 2010). Fire intensity is represented with a range of metrics including fireline intensity, flame length and crown fire potential. Estimates depend on the particular fire behaviour model used and assumptions about weather and fuels. For instance, flame length might be estimated by simulating fire behaviour under constant weather conditions (e.g. Finney 2007), or by averaging many estimates simulated under a range of probable weather conditions and fire spread directions (heading, flanking and backing) (e.g. Ager *et al.* 2010*b*).

The effects term in a fire risk model represents the change in ecological, social and economic values associated with fire intensity. Effects can be quantified with discrete or continuous response (loss–benefit) functions, resulting in negative or positive change in value. First-order fire effects models can be useful in effects analysis to measure ecological effects of fires in terms of tree mortality, erosion, carbon and other ecosystem properties (Reinhardt and Dickinson 2010). Structure ignition models (Mell *et al.* 2010) may be important for quantifying effects as well, although these models are not yet operational for risk mapping efforts.

Fire risk is a combination of likelihood, intensity and effects (Fig. 1). A high likelihood of fire does not necessarily connote high fire risk if fire intensity is too low to have much of an effect on a value of concern. A basic challenge in fire risk assessment is the interpretation of similar levels of risk generated from entirely different combinations of risk components. For instance, a low probability–high effect situation can have the same estimated risk as a high probability–low effect situation.

## Likelihood: wildfire occurrence and burn probability

Fire likelihood can be represented as either ignition probability or burn probability. Typically, ignition probability is statistically modelled using fire occurrence data whereas burn probability is estimated via simulation. The two representations can exhibit vastly different spatial patterns (Fig. 2), and tend to be used for different purposes. For example, estimates of ignition probability are used in initial attack simulations and burn probabilities are more often applied in fuels management planning problems.

Numerous studies have framed wildfire risk in terms of ignition and analysed spatial and temporal patterns of historic ignition data (Prestemon *et al.* 2002; Preisler *et al.* 2004; Genton *et al.* 2006; Sturtevant and Cleland 2007; Syphard *et al.* 2008; Catry *et al.* 2009; Martínez *et al.* 2009). Statistical approaches have been used to explore spatial ignition patterns, and to map the probability of ignition occurrence using human and biophysical variables. Correlations between fire ignitions and landscape features are often significant, and depend on whether ignitions are anthropogenic vs natural in origin. For instance, human-caused ignitions are typically correlated with variables such as density of agricultural and livestock activities, housing density, distance from transportation routes and facilities, and land use (Nunes *et al.* 2005; Loboda and Csiszar 2007; Martínez *et al.* 2009). Some studies have shown the importance of human variables as well as biophysical variables in predicting spatial patterns of human-caused ignitions (Syphard *et al.* 2008; Catry *et al.* 2009). In contrast, naturally caused ignitions tend to be correlated with physical environmental variables such as fuel moisture, relative humidity and temperature (Preisler *et al.* 2004).

Where human-caused ignitions dominate wildfire occurrence, the study of ignition probability can be especially valuable for managers, law enforcement and fire agencies. For example, estimates of ignition probability are used to simulate initial attack effectiveness (Fried *et al.* 2006; Haight and Fried 2007). Worldwide, human activities are responsible for most wildfire ignitions, and more than 90% of forest fires in the Mediterranean countries are caused by people (FAO 2007). Not surprisingly, therefore, many studies focus on areas where ignitions are primarily anthropogenic. Because these areas also tend to have high spatial density of social values, there is great potential for expected loss from fire. In this context, likelihood measured as ignition probability can serve as a surrogate measure of wildfire risk and be used to design prevention planning programs to reduce ignition frequency (Martínez *et al.* 2009; Prestemon *et al.* 2010). Such studies have also led to the development and formulation of comprehensive risk assessment frameworks that link ignition probability to other risk components (Loboda and Csiszar 2007).

However, in regions like the western USA where large fires often spread over long distances (e.g. 20–50 km), likelihood is better represented by burn probability. Thus, spatial ignition patterns may accurately reflect fire likelihood where fires are small (e.g. 1–10 ha), but where fires are larger, the estimates of likelihood need to account for fire spread from distant ignitions. One way to estimate spatially explicit burn probabilities is to simulate many thousands of fires with a mechanistic fire growth simulation (Miller *et al.* 2008). This approach has been used in risk assessment systems from Australia, Canada and the USA. In Australia, the Bushfire risk management model used a spread model called PHOENIX (Tolhurst *et al.* 2008) that accounts for fuel, weather and topographic conditions as a fire grows and moves across the landscape. In Canada, the spread model called Prometheus was used to construct burn probability maps (Braun *et al.* 2010). In the USA, several studies have employed fire spread models to map burn probability (Ager *et al.* 2007, 2010*b*; Parisien *et al.* 2007; Yang *et al.* 2008; Moghaddas *et al.* 2010).

Until fairly recently, however, the ability to simulate fire spread across landscapes for the purpose of estimating burn probability was limited by computational and technological barriers. Early attempts to represent landscape spread when mapping fire likelihood included GIS-based least cost path approaches that solve for the shortest travel time between pixels on a raster landscape (e.g. Miller 2003*a*) and the use of fire growth models such as FARSITE (Roloff *et al.* 2005; Schmidt *et al.* 2008; Carmel *et al.* 2009). The computational demands of using fire growth models limited the number of fires that could reasonably be simulated, making it impractical to generate burn probability for large landscapes. The reprogramming of fire spread algorithms using a minimum travel time (MTT) approach (Finney 2002) dramatically reduced computation time. Fire growth models like the original FARSITE and Prometheus simulate mechanistic fire spread as a vector wave front whereas the MTT approach solves for fire arrival time across the landscape, producing nearly identical results given constant fire weather. Taking advantage of efficient parallel computing, the MTT algorithm made it feasible to generate burn probability surfaces for very large ($>2 \times 10^6$-ha) landscapes, thus facilitating the use of wildfire likelihood in risk assessments in the USA and elsewhere (Salis *et al.* 2010), and supporting incident management and strategic landscape planning (Finney 2006; Calkin *et al.* 2010; Finney *et al.* 2011*a*, 2011*b*). Other fire spread models exist (Sullivan 2009) but have not seen the same widespread application due to their complexity and data requirements.

## Wildfire hazard: intensity and effects

We consider the latter two risk components (intensity and effects) together to represent hazard. In most models they are intertwined (e.g. Keane *et al.* 2010), making it difficult to discuss advances in one vs the other risk factor. In some cases, the effects are not quantified but instead are merely implied such as in exposure assessments that describe the juxtaposition of fire behaviour and values of concern (Ager *et al.* 2012). Therefore, we discuss studies that focus on intensity and effects under the broader category termed *hazard*.

Mapping hazard often relies on wildfire behaviour models. Models for predicting surface and crown fire rates of spread (e.g. Rothermel 1972, 1991; Forestry Canada Fire Danger Group 1992), crown fire transition and propagation (Van Wagner 1977, 1993; Scott and Reinhardt 2001), and a host of potential fire effects (e.g. tree mortality, fuels consumption, smoke emissions, soil heating and erosion), are used singly or in combination to map hazard. Various applications are available to do this, including the Canadian Forest Fire Danger Rating System (Alexander *et al.* 1996), NEXUS (Scott 1999), Fire and Fuels Extension to the Forest Vegetation Simulator (FVS-FFE) (Reinhardt and Crookston 2003), BehavePlus (Andrews 2007) and the First Order Fire Effects Model (FOFEM) (Reinhardt and Dickinson 2010). These tools were originally developed to generate point estimates of fire behaviour and associated effects, and the use of GIS approaches is necessary to enable mapping across large landscapes. In Canada, GIS tools were integrated with the fire danger rating system to map potential fire behaviour characteristics (Englefield *et al.* 2000), and in the USA the application FlamMap greatly improved the feasibility of mapping fire intensity across large landscapes (Finney 2006). FlamMap calculates the fire behaviour that would be expected under presumed weather conditions (commonly extreme fire weather) for every pixel on a rasterised landscape. Landscape scale capabilities are now being added to models like FOFEM as well (Hamilton *et al.* 2009). In general, however, wildfire hazard models do not incorporate spatiotemporal patterns of fire occurrence or probability of burning. Ignoring the geometry of fire spread, the mapped intensity for each pixel typically assumes a heading fire and therefore represents the maximum heat output. Widespread use of fire behaviour and effects models for hazard calculations has motivated numerous technical reviews and critiques (Stratton 2006; Peterson *et al.* 2007; Varner and Keyes 2009; Cruz and Alexander 2010).

A recent approach to mapping fire hazard – FIREHARM – made some notable advances in high-resolution (~100-m) effects modelling (Keane *et al.* 2010). This approach uses spatial daily historical climate (DAYMET; Thornton *et al.* 1997) to simulate daily fuel moisture, thus incorporating the historical range of temporal variability in fire weather conditions. This is distinct from many other approaches that map hazard assuming a static, and usually extreme, weather condition. FIREHARM uses daily variation in fuel moistures and existing fire behaviour and fire effects models to map probabilities of undesirable fire events. Probabilities are derived from the temporal variability in weather, not from the likelihood of ignition or fire occurrences. Ignitions and fire spread are not explicitly simulated; fire behaviour characteristics represent heading fires only. Even so, these maps can take several days to create for a large landscape because moistures and fire characteristics are simulated for every day in the climate database. An alternative 'event' mode in FIREHARM that is less computationally intensive and more typical of hazard mapping efforts may be better suited for large, regional analyses. In this mode, the hazard is mapped for a specified set of weather and fuel moisture conditions.

Fire intensity can be translated to change in value using fire effects models or 'response functions.' The latter describe how fire qualitatively or quantitatively changes the value of something. In most risk assessments, response functions are implied to be loss functions: any fire is assumed to have a negative outcome, and more intense fire behaviour is assumed to have a worse outcome. For example, a risk map created with a simple overlay of fire probability and the WUI implicitly assumes that any fire will cause a loss to WUI values (Haight *et al.* 2004; Bar Massada *et al.* 2009; Atkinson *et al.* 2010). Although complex response functions that vary fire effects with intensity have been used (Ager *et al.* 2010*a*, 2010*b*; Calkin *et al.* 2010), and a wide range of models can be used to examine fire effects (Massman *et al.* 2010; Reinhardt and Dickinson 2010), a loss is usually assumed. In the USA, this implicit assumption of loss was concordant with federal fire policy before 2009 wherein beneficial effects of wildfires managed during suppression efforts were not considered (Lasko 2010). However, fires do not necessarily result in negative effects, and fires can actually benefit resources such as fire-dependent species. Positive and negative ecological fire effects have been mapped for risk analysis, by coupling loss–benefit functions for different ecological resources with fire intensity proxies such as flame length and crown fire potential (Fig. 3) (Black and Opperman 2005; Calkin *et al.* 2010).

## Integrating likelihood and hazard

Describing fire risk requires the integration of likelihood and hazard. Two general approaches have been used for this integration: the development of risk ratings or indices, and what we call the integral risk model (IRM).

In the first approach, discrete indices describe likelihood, hazard and supporting information, which can then be combined into a composite risk score. Commonly called ratings, most of these indices do not employ burn probability modelling, but may incorporate measures of rate of fire spread. One example is a decision support system for assessing danger of severe fire and prioritising subwatersheds for fuel treatment (Hessburg *et al.* 2007). To map the likelihood of severe fire, fire behaviour characteristics were simulated with the hazard model FIREHARM under 90th percentile weather conditions and combined in a logic model with data on fuels, vegetation condition (FRCC; McNicoll and Hann 2004) and ignition risk. Ignition risk in this case was derived from vegetation greenness, drought indices and lightning strike occurrence. The output of the logic model was essentially a map of the potential for severe fire, which was then evaluated in the context of other landscape attributes. Results for a $4.8 \times 10^6$-ha landscape showed that subwatersheds in poor condition with respect to fire were not necessarily the best candidates for treatment because additional factors such as the amount of WUI needed to be considered as well. Thus, the ecological status of an area could be placed within a social values context to inform decision making. The application appears to be expandable, potentially making it applicable for strategic planning at national and regional scales, as well as tactical planning at local scales. A second example modelled the probabilities of human- and lightning-caused ignition probabilities, and combined them with indices describing fuel moisture content, rate of spread and flame length (Chuvieco *et al.* 2010). The resulting index, which integrated aspects of both likelihood and intensity, was then combined with information on socioeconomic values and the vulnerability of those values to fire. Differences in the resulting integrated risk index among four large regions in Spain were described, highlighting the importance of considering the multiple components of wildfire risk.

The risk index and rating approach has been used widely for state and regional assessments in the USA (Andreu and Hermansen-Báez 2008). These assessments serve a range of functions including the identification of areas that are most fire-prone and amenable to mitigation. They also can facilitate communication among fire management agencies and local residents to address community protection priorities. A host of indices are surrogates for risk factors, describing fire behaviour, ignition potential and fire spread rates. Likelihood is informed from ignition indices and surface and crown fire behaviour models are used to estimate fire behaviour characteristics. Fire intensity estimates assume heading fires only, and the direction of spread is not considered. Although fire events are not modelled, burned area is predicted by translating spread rates to fire size based on historical relationships.

Risk rating systems for wildfire have several inherent drawbacks. First, when creating composite indices, weights must be assigned based on assumptions about each index's

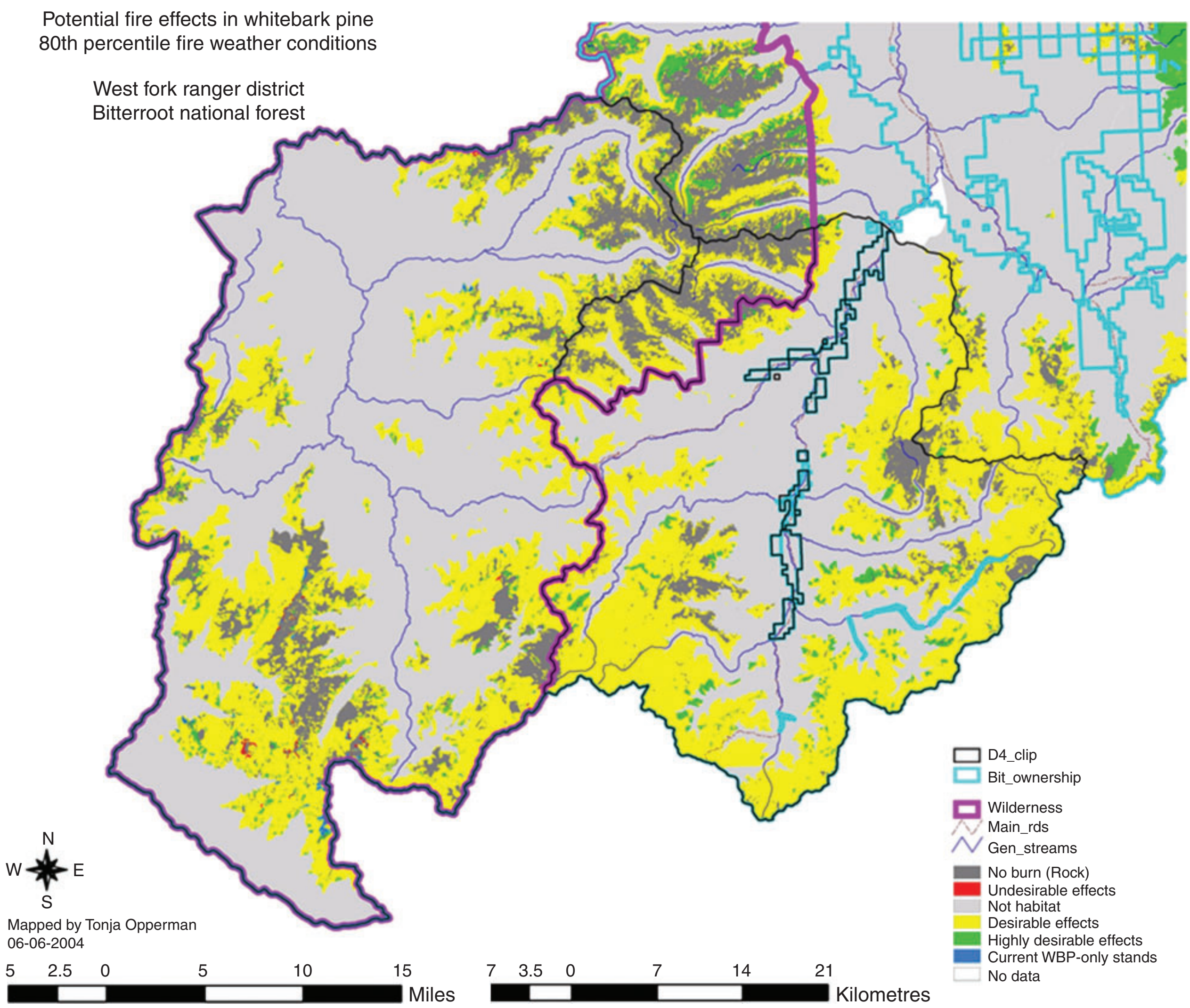


**Fig. 3.** Map of fire effects on whitebark pine generated with the Fire Effects Planning Framework (FEPF) assuming 80th percentile fire weather conditions (Black and Opperman 2005). Desirable (yellow) or highly desirable (green) fire effects on whitebark pine are predicted for most areas and undesirable (red) fire effects are predicted for only a few locations.

contribution to overall risk. Even minor adjustments to these relative weights can result in substantially different estimates of risk. Second, the somewhat idiosyncratic methods used in these rating systems make it difficult to compare across assessments. Third, composite scores are dimensionless and without measurable units, making them difficult to interpret. Finally, risk ratings are not expressed in the probabilistic terms that are consistent with the field of risk science.

An approach to integrating *likelihood* and *hazard* with fewer drawbacks is that of the Integral Risk Model (IRM). IRMs have long been a goal of the risk assessment community and incorporate likelihood and hazard to quantify expected change in value. Finney (2005) proposed a formula to seamlessly integrate likelihood, intensity and effects on multiple values as:

$$E(NVC_j) = \sum_i p(f_i)RF_j(f_i) \qquad (1)$$

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

This formula can be computed for a geographic area of any size, but is static in that it applies to a particular time period. In the IRM formulation, the expected net value change to a resource can be positive (i.e. fire confers a benefit) or negative (i.e. fire results in a loss) (Rideout and Omi 1990). Furthermore, the calculation of expected loss includes burn probability estimates for all possible fire intensities, allowing marginal probabilities of fires of different fire intensities to be considered.

An IRM was used to analyse fuel treatment effects on risk to northern spotted owl (*Strix occidentalis caurina*) habitat in central Oregon, USA (Ager *et al.* 2007). Burn probabilities were estimated by simulating 10 000 wildfires with random ignition locations and weather conditions representative of those occurring during a recent large fire within the study area. The simulations were performed with a modified version of FlamMap that generated a frequency distribution of flame lengths along with the probability of their occurrence. This allowed intensity information to be used in a different way than previous studies because model outputs also included an expectation of fire intensity (e.g. flame length) that considered whether the fire was heading, backing or flanking into the pixel. Loss functions were developed with the Forest Vegetation Simulator (Crookston and Dixon 2005) and described a threshold flame length at which fire adversely affected habitat conditions. The burn probability–flame length distributions were combined with the loss function to calculate expected loss of habitat using Eqn 1. Another study used a similar approach to calculate the effect of fuel treatment strategies on the expected loss of old growth ponderosa pine (*Pinus ponderosa*) (Ager *et al.* 2010*b*).

A drawback of the above studies is that they focussed on a small number of values, therefore failing to integrate risk across the spectrum of issues for which national forests are managed. The IRM approach has been extended to consider multiple highly valued resources and a much larger geographic scope (Calkin *et al.* 2010). The resource values were represented by social, economic and ecological attributes mapped across the continental USA. Wildfire simulation outputs were used to estimate burn probabilities and flame lengths, and stylised loss–benefit functions were applied to calculate expected net value change (NVC) for each of 12 values. The resulting framework thus accommodated multiple resources with a suite of generalised response functions that translate fire effects into economic terms based on flame length. This effort did not attempt to monetise resources, instead estimating NVC with an area-based proxy defined as the equivalent area lost or gained for a particular resource value. It was calculated by multiplying a percentage coefficient (relative NVC) for each flame length category by the probability of fire at that flame length category, which in turn was multiplied by pixel area. This approach allows a wide diversity of resources and values to be considered, such as populated areas, fire-adapted ecosystems, fire-susceptible species, energy infrastructure, recreation infrastructure, municipal watersheds and air quality. The IRM represents a significant step toward fully implementing a framework of the sort proposed at the Portland conference in 2005, combining all three components of risk into a quantitative measure.

## Advances in modelling temporal dynamics of fire risk

One important development in the arena of risk analysis has been the ability to model temporal dynamics of fire risk. Most risk studies, including those described in the preceding section, have used static response functions, considering only immediate, first-order fire effects (Reinhardt *et al.* 1997). However, response functions that describe only short-term fire effects can underestimate effects in the case of delayed tree mortality, or overestimate effects in the case of rapidly recovering vegetation. Longer term dynamics in vegetation, fuel, climate and land use change substantially affect wildfire incidence and effects (Westerling *et al.* 2006; Guzy *et al.* 2008). Several advances have been made to consider how fire risk changes through time and in response to management.

One attempt to include the post-fire recovery response in a risk assessment framework is the Fire Threat Model (FTM) (Loboda and Csiszar 2007). FTM estimates fire risk from fire danger (what we would term likelihood and intensity) and values at risk (i.e. effects), but then also considers recovery potential and fire suppression capabilities. Although details on the recovery module have not yet been published, recovery potential in FTM is estimated from the severity of the fire's effects, information on the ability of an affected resource to return to its pre-burn condition and the timeframe for the recovery to occur.

Another effort developed a statistical wildfire damage risk model that estimated an intensity-weighted risk that was, in part, a function of previous wildfires and prescribed fires (Mercer *et al.* 2007). Other variables affecting the estimates of risk included pulpwood volume, housing density and Niño-3 sea surface temperature, a proxy for drought. This statistical dynamic risk model was then used in a simulation experiment to simulate net economic outcomes from wildfire for different levels of prescribed fire over a 100-year period.

Stand-based vegetation succession models have been used to address temporal change in risk components. For example, Finney *et al.* (2007) used a custom version of FVS-FFE with a parallel processing feature to examine several different fuel treatment scenarios on fire likelihood for three western USA study areas. Scenarios included randomly and optimally placed fuel treatments (Finney 2007) with varying sizes of treatment units, rates of area treated over time and amount of area put into untreated reserves. Over the 50 years simulated, optimisation struck a balance between re-treating previous units and treating new stands. One simplification was that it assumed no random wildfire disturbances occurred during the 50-year simulation.

Landscape Fire Simulation Models (LFSMs) such as LANDIS (Scheller *et al.* 2007) simulate disturbance and succession and have been used to study the interplay between fuels management and fires. For example, Sturtevant *et al.* (2009) simulated fire, fuels management and forest dynamics for 250 years to evaluate risk mitigation strategies for a multi-owner landscape in Wisconsin, USA. Results highlighted the difficulty of maintaining fire-dependent pine and oak forest, which, without natural ignitions requires active management over the long-term. Another interesting effort used LANDIS coupled with an urban growth model to simulate risk to California coastal shrubland from WUI expansion (Syphard *et al.* 2007*a*). Risk to these habitats is largely from increased fire frequency due to increased human ignitions, and so the expansion of the WUI is of particular concern. Although it may have been feasible with this simulation approach to examine the fire risk to WUI at the same time as examining fire risk to coastal sage shrublands, this was not done.

## Advances in spatial optimisation

Another important area of development is that of spatial optimisation of fuels management activities. Risk metrics have been used to drive optimisation of fuels management with the goal of finding cost-effective timing and spatial locations of fuel treatments. However, optimisation is extremely challenging due to the spatiotemporal complexity of environmental variables in the wildfire process. Several approaches have made notable progress.

Several simulation approaches have been used to identify spatially efficient fuel treatment designs for disrupting landscape fire spread rates. In one, the MTT algorithm first was used to identify the fastest fire travel routes among nodes in a landscape (Finney 2007). Subsequently, a heuristic approach was used to locate fuel treatments to efficiently disrupt these travel routes. The method was demonstrated for a simple stylised landscape as well as for a complex landscape near Flagstaff, Arizona, but only for a selected fire weather scenario representing conditions of the 'problem fire.' A similar approach used a shortest path heuristic algorithm to find harvest locations that would disrupt fire spread and protect timber volume across a 13 000-ha landscape in Alberta, Canada (Palma *et al.* 2007).

More complex simulation approaches have considered multiple risk components in the spatial optimisation of fuel treatments. For example, one approach estimated fire risk from uniform ignition probabilities, conditional probabilities of cell-to-cell fire spread, intensity and values at risk, and then located treatments using a mixed integer programming model to minimise the sum of expected fire loss (Wei *et al.* 2008). Likelihood of fire was assumed to accumulate across the landscape in downwind directions and the effect of fire on values depended on fire intensity. This study demonstrated that the spatial allocation of treatments was much more complicated when more than one wind direction was considered because major travel routes for fire differ. Another approach combined a physical fire model with a stochastic spatial-dynamic optimisation model to locate fuel treatments that maximise timber harvest profits (Konoshima *et al.* 2010). A simplified stylised landscape with large management units was used to demonstrate the spatial tradeoffs between harvesting and fuel treatments. Initial landscape conditions, ignition locations and weather conditions were used to generate spatial patterns of fire likelihood, which were then used to find the optimal spatial allocation of fuel treatment and harvest for maximising profit. Optimal management depended on the net value of timber and the probability that value will be lost (i.e. risk). Net value was influenced by economic parameters such as stumpage prices, and fire risk was influenced primarily by the fire environment. A study by Lehmkuhl *et al.* (2007) used fire spread models and a heuristic evolutionary algorithm to simultaneously satisfy multiple objectives for fuel treatment and northern spotted owl habitat.

More recently, the temporal aspect has been considered in optimisation studies. For example, the approach by Konoshima *et al.* (2010), above, used a dynamic optimisation model to determine the spatial configuration of forest management activities that would maximise net revenue in the current time period plus the expected maximum net present value of future periods. One study used the same shortest path algorithm as the Canadian example above (Palma *et al.* 2007) to identify critical harvest stands but also used a planning model to maximise the present net worth of timber harvested over an 80 year planning horizon (Acuna *et al.* 2010). Another study examined long-term tradeoffs between profitability and fire risk for Catalonian forests (González-Olabarria and Pukkala 2011). Five 30-year planning scenarios with different objectives were evaluated in terms of their effect on net income and fire risk components in the 10 years subsequent to the planning period. The approach considered potential losses from fire, net income from different harvesting methods, and the effect of those harvesting methods on fire risk. A cellular automaton fire spread model was used to generate burn probabilities that were used by a simulated annealing optimisation algorithm to locate forest treatments. The study found that considering the potential losses from fire resulted in plans that generated more profit and lower fire risk.

Due to necessary simplifications, most optimisation efforts provide improved arrangements or scheduling of fuel treatments rather than truly optimal solutions (e.g. Finney 2007; Acuna *et al.* 2010). Treatment optimisation algorithms are computationally intensive, with computational demands increasing exponentially with the size of the landscape, number of treatment choices and degree of stochasticity included. As such, more complex formulations (e.g. Konoshima *et al.* 2010) are demonstrated on highly simplified landscapes. Progress in optimisation has been incremental and true optimisation on real landscapes with real management considerations remains an intractable problem. Early studies did not use complete measures of risk and ignored intensity, but more recent studies have incorporated response functions that depend on intensity. Notably, all of the spatial optimisation approaches we discussed estimate likelihood as some kind of spatial burn probability, thereby acknowledging the importance of landscape fire spread.

## Future directions for research and development

We expect the demand for risk-based fire management decision support to continue, and discuss several particularly necessary and fruitful areas for future research and development: (1) integrate decision environments; (2) address temporal dynamics; (3) improve resource valuation; (4) build empirical knowledge and (5) validation and communicate uncertainty.

### *Integrate decision environments*

Two decision environments can be supported with fire risk analysis. The first is the management of fuels to minimise the long-term expected loss from fire. In this strategic planning environment, decision support tools help managers decide how to alter fuels, where to place fuel treatments and how often to treat (Reinhardt *et al.* 2008). The second decision environment is the management of ignitions. In this real-time fire management environment, decision support tools and established strategic plans help managers decide whether to allow, control or suppress a fire. Depending on the timing, location and weather, fire may be deemed a desired natural process that regulates fuels and restores fire resilient forests (Noss *et al.* 2006), or it may be considered an undesired threat to social values and therefore become the target of active suppression. Most applications discussed in this paper demonstrate how quantitative risk analysis can help with the fuels management decision environment or with initial attack decisions. Only a few have demonstrated the use of risk analysis for supporting decisions to allow ignitions to burn.

Risk analysis is essential for supporting decisions to manage ignitions, especially for adopting alternatives to full suppression. Restoration of natural fire regimes is necessary to manage long-term wildfire risk (Schoennagel and Nelson 2011) and wildfire is probably the way most areas will be treated for fuel reduction. In the USA, the flexibility in current fire policy intrinsically acknowledges that fire can have negative and positive outcomes (Lasko 2010). Risk tools will need to better factor in the beneficial effects of fire so that these might be maximised while minimising losses. As fires are allowed to burn longer, risk analyses will need to consider a wider range of weather conditions and will need to consider topological relationships, such as those that extend the local effects of a treatment across larger areas (Ager *et al.* 2010*b*). Risk is also transmitted in complex ways across different land ownerships. For example, most of the significant fires that cause damage to residential structures start in vegetated areas close to the WUI where the likelihood of human-caused ignitions is high (Syphard *et al.* 2007*b*). Understanding the sources and spatial transmission of risk can help inform mitigation efforts such as preventing human-caused ignitions, reducing the potential for structure ignition (Cohen 2008), and can lead to better predictions of proposed treatment effectiveness (Finney 2007; Finney *et al.* 2007).

A decision in one of these management environments affects future decisions in the other. For example, fuel treatments may protect valued resources so that ignitions can be allowed to burn unimpeded in the future (Suffling *et al.* 2008). Although the location and timing of a wildfire cannot be planned in the same way as a prescribed burn or thinning operation, wildfire itself can be a very effective fuel treatment (Miller 2003*b*). Perhaps most salient is that fire suppression in the real-time incident management environment transfers risk to the future fuel management environment. Risk analysis needs to support both types of decisions and represent how actions taken in one decision environment transmit risk to the other. At a minimum, the framing of any risk analysis problem should acknowledge the existence of these two environments. Most efforts to date have had a narrow focus that may contribute to the misaligned incentive structure for managers lamented by Calkin *et al.* (2011*a*).

### *Address temporal dynamics*

Changes in risk as a result of any decision made about fuels, ignitions or both can extend through time and need additional attention (Calkin *et al.* 2011*a*). Models without a temporal dimension cannot be used to evaluate cumulative effects or risk management activities over most planning timeframes. The potential effects of climate change on fire regimes further reinforce the need for temporal risk tools and frameworks for decision support. A change in moisture status and fire danger will likely be accompanied by a change in the exposure to fire because of increased ignitions and longer seasons for wildfires to spread. Treatment schedules that are optimal today may not be optimal in 20 or 30 years due to changes in seedling establishment and growth rates. The current pace of climate change makes it likely that discernable changes could be seen well within the timeframe of fire risk management.

Risk tools, therefore, need to increase in complexity and account for climate-mediated vegetation and fuel dynamics. Successfully coupling the complex processes of fire and vegetation succession is non-trivial, however. Processes of fire spread and intensity have to be linked to processes of vegetation succession and then to fire effects. For example, although the stand-based FVS-FFE is already widely used in the USA for modelling succession and fire effects, it is not yet fully compatible with fire spread tools. Although LFSMs can simulate fire and vegetation dynamics (Keane *et al.* 2004), most substantially simplify fire spread processes and simulate fire effects with rule-based functions that do not depend on fire intensity. Furthermore, many LFSMs were developed and parameterised for a particular ecosystem or geographic area and may not easily be applied to other landscapes. The succession and disturbance processes in these models require substantial parameterisation and data that may not be available for many study areas. Finally, most of the vegetation dynamics models available for the landscape scale do not handle species-specific climate responses.

### *Improve resource valuation*

Risk can be analysed for a wide variety of resource values (Calkin *et al.* 2010) but simultaneously analysing risk to multiple values while considering multiple objectives is a more difficult challenge (Calkin *et al.* 2011*a*). Although risk analysis has been used to evaluate different treatment strategies for their ability to maximise net economic benefits (Mercer *et al.* 2007), and to simultaneously protect socioeconomic and ecological values (Ager *et al.* 2010*b*), fire is usually assumed to have detrimental effects. A next step will be to use risk analysis to evaluate strategies that increase the expected benefits of fire for some resource values while decreasing the expected losses to others. New response functions will be needed for assessing risk to ecological resource values, especially those that stand to benefit from fire. These response functions may not be linear or monotonic and the expected net value change in the short-term may be completely opposite to the change expected in the long-term.

We expect that the demand for quantitative risk frameworks will continue, with an increasing need to quantify resource values. Although recent efforts have demonstrated how to derive quantitative metrics that are consistent across many different types of highly valued resources (Calkin *et al.* 2010), their interpretation can quickly become obscured when aggregated or generalised. The econometric approach has great utility for illuminating the risk components that influence decisions, but a major challenge will be quantifying a diversity of non-market values using a common metric that may not be monetary. For example, in the IRM formulation, the equivalent area lost or gained used by Calkin *et al.* (2010) was a good attempt at quantifying expected NVC in a non-monetary, yet meaningful, way for ecological resources. Other metrics need to be explored for quantifying fire effects on ecological resources and communicating expected benefits along with expected losses (Black and Opperman 2005).

### *Build empirical knowledge*

Ultimately the strength of wildfire risk analysis depends on knowledge derived from empirical observations. As technology allows risk analysis tools to become increasingly complex and sophisticated, there is an ever increasing need for basic empirical data to parameterise models. Although data on fire occurrence, weather and fuels are becoming more widely available (Stocks *et al.* 2003; Zachariassen *et al.* 2003; Rollins 2009), data on fire effects are still lacking for many species and ecosystems. Information about longer-term fire effects is particularly sparse. For example, we know little of how post-fire forest structure or habitat condition changes over several years or after repeated burning. Values-at-risk are ultimately a human construct, and improvements in valuation may require a better understanding of human preferences and attitudes. Further investments in fire behaviour experimentation will be needed to support fundamental improvements to fire spread and structure ignition models, and to better understand basic processes such as those responsible for the stopping or slowing of fire spread.

### *Validation and communicate uncertainty*

Validation of risk analyses typically involves the examination of individual risk components in relation to empirical data. For example, individual likelihood and hazard indices were compared with observed fire occurrence data in Spain (Chuvieco *et al.* 2010). Modelled burn probabilities can be compared with historic burn probabilities if adequate fire history data exist (Finney *et al.* 2011*b*). In addition, we suggest that verification tests and sensitivity analyses are useful approaches to evaluating risk models, whereby input parameters are systematically varied to generate a suite of model outputs. The goal of a verification test is to ensure that the model behaves as intended, and can be used to establish the domain of applicability of the model. The goal of a sensitivity analysis is to determine which model parameters have the greatest influence on model output; ideally these are parameters whose values are known with a high of degree of certainty.

Several sources and types of uncertainty currently limit the use of risk analyses for fire management (Thompson and Calkin 2011). Risk analyses characterise the uncertainty associated with the variability inherent in fire occurrence patterns, fire behaviour, fire effects and even the monetary or non-monetary value of an affected resource. The expected NVC computed in the IRM formulation is not exact because it has been computed using imperfect models that contain imperfect assumptions and imperfectly known functional relationships, and that are parameterised with imperfect and limited data. These uncertainties propagate as models get increasingly complex. Conceptually, there is a confidence interval around the expected NVC that could communicate these uncertainties but has not yet been quantified.

## Conclusions

The fire research and management communities have come a long way in the development and application of wildfire risk concepts in 10 years. Prior to 2000, there was little evidence of a common language or definition. Several risk frameworks that have emerged recently employ a common definition of risk that includes likelihood and hazard. The IRM, in particular, sets the stage for future developments. It is a robust framework that exemplifies and incorporates the more promising advances we have discussed. Its ability to evaluate multiple resource values under variable weather conditions in a quantitative framework is powerful information for policy makers, budget planners and land managers.

As risk assessment tools become increasingly quantitative, they will likely supplant the use of qualitative (e.g. Chuvieco *et al.* 2010) indices. This trend should also facilitate the application of risk to optimisation problems. These increasingly quantitative frameworks are already supporting a wide range of fire and fuels management planning scales, from that of the individual incident or fuel treatment project, to the national or subcontinental scale. For example, burn probability modelling and related risk analysis tools have moved from the research domain to centralised management systems in federal land management agencies in the USA to strategically plan budgets (Fire Program Analysis FPA http://www.fpa.nifc.gov, accessed 2012), support wildland fire and fuels management decisions (e.g. Calkin *et al.* 2011*b*) and monitor trends in hazard and risk over time (Calkin *et al.* 2010).

Progress in risk assessment approaches has not been logical or linear. Existing fire risk tools are continually modified with new features, linked and hybridised with other tools and applied to new management problems. Developers of tools have tended to focus on one risk factor at a time, often improving the ability to model the single factor, while simplifying the other two. The research and development community remains fragmented in this area. To simplify the daunting complexity of natural resource management issues, many fire risk tools have been developed and applied to narrowly defined problems and decision environments. As a result, the application of risk analysis to address numerous ecological and policy questions has lagged. Additional case studies are needed at a range of spatial and temporal scales that are more broadly framed to inform critical issues of concern in wildfire management.

## Acknowledgements

We thank the USDA Forest Service Fire and Aviation Management for financial support to the risk management research program at the Western Wildland Environmental Threat Assessment Center, as well as the National Fire Plan and Joint Fire Science Program for supporting risk management research.

## References

Acuna MA, Palma CD, Cui W, Martell DL, Weintraub A (2010) Integrated spatial fire and forest management planning. *Canadian Journal of Forest Research* **40**, 2370–2383. doi:10.1139/X10-151

Ager AA, Finney MA, Kerns BK, Maffei H (2007) Modeling wildfire risk to northern spotted owl (*Strix occidentalis caurina*) habitat in Central Oregon, USA. *Forest Ecology and Management* **246**, 45–56. doi:10.1016/J.FORECO.2007.03.070

Ager AA, Finney MA, McMahan A, Cathcart J (2010*a*) Measuring the effect of fuel treatments on forest carbon using landscape risk analysis. *Natural Hazards and Earth System Sciences* **10**, 2515–2526. doi:10.5194/NHESS-10-2515-2010

Ager AA, Vaillant NM, Finney MA (2010*b*) A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. *Forest Ecology and Management* **259**, 1556–1570. doi:10.1016/J.FORECO.2010.01.032

Ager AA, Vaillant NM, Finney MA, Preisler HK (2012) Analyzing wildfire exposure and source-sink relationships on a fire-prone forest landscape.

*Forest Ecology and Management* **267**, 271–283. doi:10.1016/J.FORECO.2011.11.021

Alexander ME, Stocks BJ, Lawson BD (1996) The Canadian Forest Fire Danger Rating System. *Initial Attack* **1996**(Spring), 6–9.

Andreu A, Hermansen-Báez LA (2008) Fire in the South 2: the southern wildfire risk assessment. A report by the Southern Group of State Foresters. Available at http://www.southernwildfirerisk.com/reports/FireInTheSouth2.pdf [Verified 20 August 2012]

Andrews PL (2007) BehavePlus fire modeling system: past, present, and future. In 'Proceedings of 7th Symposium on Fire and Forest Meteorological Society,' 23–25 October 2007, Bar Harbor, ME. Paper J2.1. (American Meteorological Society: Boston, MA) Available at https://ams.confex.com/ams/pdfpapers/126669.pdf [Verified 20 August 2012]

Andrews PL, Finney MA, Fischetti M (2007) Predicting wildfires. *Scientific American* **297**(2), 46–55. doi:10.1038/SCIENTIFICAMERICAN0807-46

Atkinson D, Chladil M, Janssen V, Lucieer A (2010) Implementation of quantitative bushfire risk analysis in a GIS environment. *International Journal of Wildland Fire* **19**, 649–658. doi:10.1071/WF08185

Bachmann A, Allgower B (2001) A consistent wildland fire risk terminology is needed! *Fire Management Today* **61**(4), 28–33.

Bar Massada AB, Radeloff VC, Stewart SI, Hawbaker TJ (2009) Wildfire risk in the wildland–urban interface: a simulation study in northwestern Wisconsin. *Forest Ecology and Management* **258**, 1990–1999. doi:10.1016/J.FORECO.2009.07.051

Black A, Opperman T (2005) Fire effects planning framework: a user's guide. USDA Forest Service, Rocky Mountain Research Station, General Technical Report GTR-RMRS-163WWW. (Fort Collins, CO)

Braun WJ, Jones BL, Lee JSW, Woolford DG, Wotton BM (2010) Forest fire risk assessment: an illustrative example from Ontario, Canada. *Journal of Probability and Statistics* **2010**, 823018. doi:10.1155/2010/823018

Brillinger DR (2010) Some examples of the communication of risk and uncertainty. *Environmetrics* **21**, 719–727. doi:10.1002/ENV.1040

Calkin DE, Ager AA, Gilbertson-Day J (2010) Wildfire risk and hazard: procedures for the first approximation. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-235. (Fort Collins, CO)

Calkin DC, Finney MA, Ager AA, Thompson MP, Gebert KM (2011*a*) Progress towards and barriers to implementation of a risk framework for US federal wildland fire policy and decision making. *Forest Policy and Economics* **13**, 378–389. doi:10.1016/J.FORPOL.2011.02.007

Calkin DE, Thompson MP, Finney MA, Hyde KD (2011*b*) A real-time risk-assessment tool supporting wildland fire decision-making. *Journal of Forestry* **109**(5), 274–280.

Calkin D, Ager A, Thompson M (2011*c*) A comparative risk assessment framework for wildland fire management: the 2010 cohesive strategy science report. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-262. (Fort Collins, CO)

Carmel Y, Paz S, Jahashan F, Shoshany M (2009) Assessing fire risk using Monte Carlo simulations of fire spread. *Forest Ecology and Management* **257**, 370–377. doi:10.1016/J.FORECO.2008.09.039

Catry FX, Rego FC, Bação FL, Moreira F (2009) Modeling and mapping wildfire ignition risk in Portugal. *International Journal of Wildland Fire* **18**, 921–931. doi:10.1071/WF07123

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

Cohen JD (2008) The wildland-urban interface fire problem: a consequence of the fire exclusion paradigm. *Forest History Today* **2008**, 20–26.

Crookston NL, Dixon GE (2005) The forest vegetation simulator: a review of its structure, content, and applications. *Computers and Electronics in Agriculture* **49**, 60–80. doi:10.1016/J.COMPAG.2005.02.003

Cruz MG, Alexander ME (2010) Assessing crown fire potential in coniferous forests of western North America: a critique of current approaches and recent simulation studies. *International Journal of Wildland Fire* **19**, 377–398. doi:10.1071/WF08132

Eidenshink J, Schwind B, Brewer K, Zhu ZL, Quayle B, Howard S (2007) A project for monitoring trends in burn severity. *Fire Ecology* **3**, 3–21. doi:10.4996/FIREECOLOGY.0301003

Englefield P, Lee BS, Suddaby RM (2000) Spatial fire management system. In 'ESRI International User Conference 2000', 26–30 June 2000, San Diego, CA. Paper 489. (ESRI: San Diego, CA) Available at http://training.esri.com/bibliography/index.cfm?event=general.recordDetail&ID=8648 [Verified 20 August 2012]

Fairbrother A, Turnley JG (2005) Predicting risks of uncharacteristic wildfires: application of the risk assessment process. *Forest Ecology and Management* **211**, 28–35. doi:10.1016/J.FORECO.2005.01.026

FAO (2007) Fire management – global assessment 2006. A thematic study prepared in the framework of the Global Forest Resources Assessment 2005. UN Food and Agriculture Organization, Forest Management Division, Forest Paper 151. (Rome, Italy) Available at http://www.fao.org/docrep/009/a0969e/a0969e00.htm [Verified 20 August 2012]

Finney MA (2002) Fire growth using minimum travel time methods. *Canadian Journal of Forest Research* **32**, 1420–1424. doi:10.1139/X02-068

Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management* **211**, 97–108. doi:10.1016/J.FORECO.2005.02.010

Finney MA (2006) An overview of FlamMap fire modeling capabilities. In 'Fuels Management-How to Measure Success: Conference Proceedings', 28-30 March 2006, Portland, OR. (Eds PL Andrews, BW Butler) USDA Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-41, pp. 213–220. (Fort Collins, CO)

Finney MA (2007) A computational method for optimising fuel treatment locations. *International Journal of Wildland Fire* **16**, 702–711. doi:10.1071/WF06063

Finney MA, Seli RC, McHugh CW, Ager AA, Bahro B, Agee JK (2007) Simulation of long-term landscape-level fuel treatment effects on large wildfires. *International Journal of Wildland Fire* **16**, 712–727. doi:10.1071/WF06064

Finney MA, Grenfell IC, McHugh CW, Seli RC, Trethewey D, Stratton RD, Brittain S (2011*a*) A method for ensemble wildland fire simulation. *Environmental Modeling and Assessment* **16**, 153–167. doi:10.1007/S10666-010-9241-3

Finney MA, McHugh CW, Grenfell IC, Riley KL, Short KC (2011*b*) A simulation of probabilistic wildfire risk components for the continental United States. *Stochastic Environmental Research and Risk Assessment* **2011**, 1–28.

Fiorucci P, Gaetani F, Minciardi R (2008) Development and application of a system for dynamic wildfire risk assessment in Italy. *Environmental Modelling & Software* **23**, 690–702. doi:10.1016/J.ENVSOFT.2007.05.008

Forestry Canada Fire Danger Group (1992) Development and structure of the Canadian Forest Fire Behavior Prediction System. Forestry Canada, Fire Danger Group and Science and Sustainable Development Directorate, Information Report ST-X-3. (Ottawa)

Fried JS, Gilless JK, Spero J (2006) Analysing initial attack on wildland fires using stochastic simulation. *International Journal of Wildland Fire* **15**, 137–146. doi:10.1071/WF05027

GAO (2003*a*) Forest Service: information on decisions involving fuels reduction activities. US General Accountability Office, GAO-03-689R. (Washington, DC) Available at http://www.gao.gov/assets/100/91867.pdf [Verified 20 August 2012]

GAO (2003*b*) Wildland fire management: additional actions required to better identify and prioritize lands needing fuels reduction. US General Accountability Office, GAO-03-805. (Washington, DC) Available at http://www.gao.gov/assets/240/239308.pdf [Verified 20 August 2012]

GAO (2007) Wildland fire management: better information and a systematic process could improve agencies' approach to allocating fuel reduction funds and selecting projects. US General Accountability Office, GAO-07-1168. (Washington, DC) Available at http://www.gao.gov/assets/270/267638.pdf [Verified 20 August 2012]

GAO (2009) Wildland fire management: federal agencies have taken important steps forward, but additional action is needed to address remaining challenges. US General Accountability Office, GAO-09-906T (Washington DC) Available at http://www.gao.gov/assets/130/123076.pdf [Verified 20 August 2012]

Genton MG, Butry DT, Gumpertz ML, Prestemon JP (2006) Spatio-temporal analysis of wildfire ignitions in the St Johns River Water Management District, Florida. *International Journal of Wildland Fire* **15**, 87–97. doi:10.1071/WF04034

González-Olabarria J-R, Pukkala T (2011) Integrating fire risk considerations in landscape-level forest planning. *Forest Ecology and Management* **261**, 278–287. doi:10.1016/J.FORECO.2010.10.017

Guzy MR, Smith CL, Bolte JP, Hulse DW, Gregory SV (2008) Policy research using agent-based modeling to assess future impacts of urban expansion into farmlands and forests. *Ecology and Society* **13**(1), 37.

Haight RG, Fried JS (2007) Deploying wildland fire suppression resources with a scenario-based standard response model. *INFOR: Information Systems and Operational Research* **45**(1), 31–39. doi:10.3138/INFOR.45.1.31

Haight RG, Cleland DT, Hammer RB, Radeloff VC, Rupp TS (2004) Assessing fire risk in the wildland-urban interface. *Journal of Forestry* **102**(7), 41–48.

Hamilton D, Bramel J, Helmbrecht D, Jones J, Hann W (2009) First Order Fire Effects Model Mapping Tool (FOFEMMT) for ArcGIS 9.2–9.3 (version 1.1.0). National Interagency Fuels, Fire, & Vegetation Technology Transfer. Available at http://www.fire.org/niftt/released/FOFEMMT_090407.pdf [Verified 20 August 2012]

Hardy CC (2005) Wildland fire hazard and risk: problems, definitions, and context. *Forest Ecology and Management* **211**, 73–82. doi:10.1016/J.FORECO.2005.01.029

Hardy CC, Hardy CE (2007) Fire danger rating in the United States of America: an evolution since 1916. *International Journal of Wildland Fire* **16**(2), 217–231. doi:10.1071/WF06076

Haynes R, Cleaves D (1999) Uncertainty, risk, and ecosystem management. In 'Ecological Stewardship, Volume III'. (Eds WT Sexton, AJ Malk, RC Szaro, NC Johnson) pp. 413–429. (Elsevier Science Ltd: Oxford, UK)

Hessburg PF, Reynolds KM, Keane RE, James KM, Salter RB (2007) Evaluating wildland fire danger and prioritizing vegetation and fuels treatments. *Forest Ecology and Management* **247**, 1–17. doi:10.1016/J.FORECO.2007.03.068

Hollenstein K (2001) Risk analysis as a tool for policy evaluation: a multi-level comparison example. In 'Risk Analysis in Forest Management', pp. 75–112. (Kluwer Academic: Dordrecht, the Netherlands)

Keane RE, Cary GJ, Davies ID, Flannigan MD, Gardner RH, Lavorel S, Lenihan JM, Li C, Rupp TS (2004) A classification of landscape fire succession models: spatial simulations of fire and vegetation dynamics. *Ecological Modelling* **179**, 3–27. doi:10.1016/J.ECOLMODEL.2004.03.015

Keane RE, Drury SA, Karau EC, Hessburg PF, Reynolds KM (2010) A method for mapping fire hazard and risk across multiple scales and its application in fire management. *Ecological Modelling* **221**, 2–18. doi:10.1016/J.ECOLMODEL.2008.10.022

Konoshima M, Albers HJ, Montgomery CA, Arthur JL (2010) Optimal spatial patterns of fuel management and timber harvest with fire risk. *Canadian Journal of Forest Research* **40**, 95–108. doi:10.1139/X09-176

Lasko R (2010) Implementing federal wildland fire policy–responding to change. *Fire Management Today* **70**(1), 6–8.

Lehmkuhl JF, Kennedy M, Ford ED, Singleton PH, Gaines WL, Lind RL (2007) Seeing the forest for the fuel: Integrating ecological values and fuels management. *Forest Ecology and Management* **246**, 73–80. doi:10.1016/J.FORECO.2007.03.071

Loboda T, Csiszar IA (2007) Assessing the risk of ignition in the Russian Far East within a modeling framework of fire threat. *Ecological Applications* **17**, 791–805. doi:10.1890/05-1476

Martínez J, Vega-García C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention planning in Spain. *Journal of Environmental Management* **90**, 1241–1252. doi:10.1016/J.JENVMAN.2008.07.005

Massman WJ, Frank JM, Mooney SJ (2010) Advancing investigation and physical modeling of first-order fire effects on soils. *Fire Ecology* **6**, 36–54. doi:10.4996/FIREECOLOGY.0601036

McDaniels J (2007) WFDSS: taking decision support into the 21st century. *Advances in Fire Practice* **2007(**Fall), 1–4. (Wildland Fire Lessons Learned Center) Available at http://wildfirelessons.net/SearchResults.aspx?q=taking%20decision%20support%20into%20the%2021st%20century [Verified 20 August 2012]

McNicoll CH, Hann WJ (2004) Multi-scale planning and implementation to restore fire-adapted ecosystems and reduce risk to the wildland/urban interface in the Box Creek watershed. In 'Proceedings of the 22nd Tall Timbers Fire Ecology Conference: Fire in Temperate, Boreal, and Montane Ecosystems', 15–18 October 2001, Kananaskis, AB. (Eds KEM Galley, WJ de Groot) pp. 294–316. (Tall Timbers Research Station: Tallahassee, FL)

Mell WE, Manzello SL, Maranghides A, Butry D, Rehm DB (2010) The wildland-urban interface fire problem: current approaches and research needs. *International Journal of Wildland Fire* **19**, 238–251. doi:10.1071/WF07131

Mercer DE, Prestemon JP, Butry DT, Pye JM (2007) Evaluating alternative prescribed burning policies to reduce net economic damages from wildfire. *American Journal of Agricultural Economics* **89**(1), 63–77. doi:10.1111/J.1467-8276.2007.00963.X

Miller C (2003a) The spatial context of fire: a new approach for predicting fire occurrence. In 'Proceedings of Fire Conference 2000: The First National Congress on Fire Ecology, Prevention and Management', 27 November–1 December 2000, San Diego, CA. (Eds KEM Galley, RC Klinger, NG Sugihara) pp. 27–34. (Tall Timbers Research Station: Tallahassee, FL)

Miller C (2003b) Wildland fire use: a wilderness perspective on fuel management. In 'Fire, Fuel Treatments, and Ecological Restoration: Conference Proceedings', 16–18 April 2002, Fort Collins, CO. (Eds PN Omi, LA Joyce) USDA Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-29, pp. 379–385. (Fort Collins, CO)

Miller C, Parisien M-A, Ager AA, Finney MA (2008) Evaluating spatially explicit burn probabilities for strategic fire management planning. In 'Modelling, Monitoring, and Management of Forest Fires'. (Eds J De las Heras, CA Brebbia, D Viegas, V Leone) pp. 245–252. (WIT Press: Boston, MA)

Moghaddas JJ, Collins BM, Menning K, Moghaddas EEY, Stephens SL (2010) Fuel treatment effects on modeled landscape-level fire behavior in the northern Sierra Nevada. *Canadian Journal of Forest Research* **40**, 1751–1765. doi:10.1139/X10-118

Noss RF, Beier P, Covington WW, Grumbine RE, Lindenmayer DB, Prather JW, Schmiegelow F, Sisk TD, Vosick DJ (2006) Recommendations for integrating restoration ecology and conservation biology in ponderosa pine forests of the Southwestern United States. *Restoration Ecology* **14**(1), 4–10. doi:10.1111/J.1526-100X.2006.00099.X

Nunes MCS, Vasconcelos MJ, Pereira JMC, Dasgupta N, Alldredge RJ, Rego FC (2005) Land cover type and fire in Portugal: do fires burn land cover selectively? *Landscape Ecology* **20**, 661–673. doi:10.1007/S10980-005-0070-8

O'Laughlin J (2005) Conceptual model for comparative ecological risk assessment of wildfire effects on fish, with and without hazardous fuel treatment. *Forest Ecology and Management* **211**, 59–72. doi:10.1016/J.FORECO.2005.01.028

Palma CD, Cui W, Martell DL, Robak D, Weintraub A (2007) Assessing the impact of stand-level harvests on the flammability of forest landscapes. *International Journal of Wildland Fire* **16**(5), 584–592. doi:10.1071/WF06116

Parisien M, Junor DR, Kafka VG (2007) Comparing landscape-based decision rules of placement of fuel treatments in the boreal mixedwood of western Canada. *International Journal of Wildland Fire* **16**, 664–672. doi:10.1071/WF06060

Peterson DL, Evers L, Gravenmier RA, Eberhardt E (2007) A consumer guide: tools to manage vegetation and fuels. USDA Forest Service, Pacific Northwest Research Station, General Technical Report PNW-GTR-690 (Portland, OR)

Preisler HK, Brillinger DR, Burgan RE, Benoit JW (2004) Probability based models for estimating wildfire risk. *International Journal of Wildland Fire* **13**, 133–142. doi:10.1071/WF02061

Preisler HK, Burgan RE, Eidenshink JC, Klaver JM, Klaver RW (2009) Forecasting distributions of large federal-lands fires utilizing satellite and gridded weather information. *International Journal of Wildland Fire* **18**, 508–516. doi:10.1071/WF08032

Prestemon JP, Pye JM, Butry DT, Holmes TP, Mercer DE (2002) Understanding broadscale wildfire risks in a human-dominated landscape. *Forest Science* **48**, 685–693.

Prestemon JP, Butry DT, Abt KL, Sutphen R (2010) Net benefits of wildfire prevention education efforts. *Forest Science* **56**, 181–192.

Reinhardt ED, Crookston NL (2003) The fire and fuels extension to the forest vegetation simulator. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-116 (Ogden, UT)

Reinhardt ED, Dickinson MB (2010) First-order fire effects models for land management: overview and issues. *Fire Ecology* **6**(1), 131–142. doi:10.4996/FIREECOLOGY.0601131

Reinhardt ED, Keane RE, Brown JK (1997) First order fire effects model: FOFEM 4.0, user's guide. USDA Forest Service, Intermountain Research Station, General Technical Report INT-GTR-344. (Ogden, UT)

Reinhardt ED, Keane RE, Calkin DE, Cohen JD (2008) Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. *Forest Ecology and Management* **256**, 1997–2006. doi:10.1016/J.FORECO.2008.09.016

Rideout DB, Omi PN (1990) Alternative expressions for the economic theory of forest fire management. *Forest Science* **36**(3), 614–624.

Rollins MG (2009) LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire* **18**, 235–249. doi:10.1071/WF08088

Roloff GJ, Mealey SP, Clay C, Barry J, Yanish C, Neuenschwander L (2005) A process for modeling short- and long-term risk in the southern Oregon Cascades. *Forest Ecology and Management* **211**, 166–190. doi:10.1016/J.FORECO.2005.02.006

Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service, Intermountain Research Station, Research Paper INT-RP-115. (Ogden, UT)

Rothermel RC (1991) Predicting behavior and size of crown fires in the northern Rocky Mountains. USDA Forest Service, Intermountain Research Station, Research Paper INT-438. (Ogden, UT)

Salis M, Arca B, Bacciu V, Spano D, Duce P, Santoni P, Ager A, Finney M (2010) Application of wildfire spread and behavior models to assess fire probability and severity in the Mediterranean region. *Geophysical Research Abstracts* **12**(EGU2010), 12991.

Scheller RM, Domingo JB, Sturtevant BR, Williams JS, Rudy A, Gustafson EJ, Mladenoff DJ (2007) Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. *Ecological Modelling* **201**, 409–419. doi:10.1016/J.ECOLMODEL.2006.10.009

Schmidt D, Taylor AH, Skinner CN (2008) The influence of fuels treatment and landscape arrangement on simulated fire behavior, Southern Cascade range, California. *Forest Ecology and Management* **255**, 3170–3184. doi:10.1016/J.FORECO.2008.01.023

Schoennagel T, Nelson CR (2011) Restoration relevance of recent National Fire Plan treatments in forests of the western United States. *Frontiers in Ecology and the Environment* **9**, 271–277. doi:10.1890/090199

Scott JH (1999) NEXUS: a system for assessing crown fire hazard. *Fire Management Notes* **59**(2), 21–24.

Scott JH, Reinhardt ED (2001) Assessing crown fire potential by linking models of surface and crown fire behavior. USDA Forest Service, Rocky Mountain Research Station, Research Paper RMRS-RP-29. (Fort Collins, CO)

Stocks BJ, Mason JA, Todd JB, Bosch EM, Wotton BM, Amiro BD, Flannigan MD, Hirsch KG, Logan KA, Martell DL, Skinner WR (2003) Large forest fires in Canada, 1959–1997. *Journal of Geophysical Research* **108**, 8149. [Published online early 20 December 2002] doi:10.1029/2001JD000484

Stratton RD (2006) Guidance on spatial wildland fire analysis: models, tools, and techniques. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-183. (Fort Collins, CO)

Sturtevant BR, Cleland DT (2007) Human and biophysical factors influencing modern fire disturbance in northern Wisconsin. *International Journal of Wildland Fire* **16**, 398–413. doi:10.1071/WF06023

Sturtevant BR, Miranda BR, Yang J, He HS, Gustafson EJS, Scheller RM (2009) Studying fire mitigation strategies in multi-ownership landscapes: balancing the management of fire-dependent ecosystems and fire risk. *Ecosystems* **12**, 445–461. doi:10.1007/S10021-009-9234-8

Suffling R, Grant A, Feick R (2008) Modeling prescribed burns to serve as regional firebreaks to allow wildfire activity in protected areas. *Forest Ecology and Management* **256**, 1815–1824. doi:10.1016/J.FORECO.2008.06.043

Sullivan AL (2009) Wildland surface fire spread modelling, 1990–2007: 3. Simulation and mathematical analogue models. *International Journal of Wildland Fire* **18**, 387–403. doi:10.1071/WF06144

Syphard AD, Clarke KC, Franklin J (2007*a*) Simulating fire frequency and urban growth in southern California coastal shrublands, USA. *Landscape Ecology* **22**, 431–445. doi:10.1007/S10980-006-9025-Y

Syphard AD, Radeloff VC, Keely JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB (2007*b*) Human influence on California fire regimes. *Ecological Applications* **17**, 1388–1402. doi:10.1890/06-1128.1

Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008) Predicting spatial patterns of fire on a southern California landscape. *International Journal of Wildland Fire* **17**, 602–613. doi:10.1071/WF07087

Thompson MP, Calkin DE (2011) Uncertainty and risk in wildland fire management: a review. *Journal of Environmental Management* **92**(8), 1895–1909. doi:10.1016/J.JENVMAN.2011.03.015

Thornton PE, Running SW, White MA (1997) Generating surfaces of daily meteorological variables over large regions of complex terrain. *Journal of Hydrology* **190**, 214–251. doi:10.1016/S0022-1694(96)03128-9

Tolhurst K, Shields B, Chong D (2008) Phoenix: development and application of a bushfire risk management tool. *The Australian Journal of Emergency Management* **23**(4), 47–54.

Van Wagner CE (1977) Conditions for the start and spread of crown fires. *Canadian Journal of Forest Research* **7**, 23–34. doi:10.1139/X77-004

Van Wagner CE (1993) Prediction of crown fire behavior in two stands of jack pine. *Canadian Journal of Forest Research* **23**, 442–449. doi:10.1139/X93-062

Varner JM, Keyes CR (2009) Fuels treatments and fire models: errors and corrections. *Fire Management Today* **69**(3), 47–50.

Vasilakos C, Kalabokidis K, Hatzopoulos J, Kallos G, Matsinos Y (2007) Integrating new methods and tools in fire danger rating. *International Journal of Wildland Fire* **16**, 306–316. doi:10.1071/WF05091

Wei Y, Rideout D, Kirsch A (2008) An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. *Canadian Journal of Forest Research* **38**, 868–877. doi:10.1139/X07-162

Westerling AL, Hidalgo HG, Cayan DR, Swetnam TW (2006) Warming and earlier spring increase Western US forest wildfire activity. *Science* **313**(5789), 940–943. doi:10.1126/SCIENCE.1128834

Yang J, He HS, Shifley SR (2008) Spatial controls of occurrence and spread of wildfires in the Missouri Ozark Highlands. *Ecological Applications* **18**, 1212–1225. doi:10.1890/07-0825.1

Zachariassen J, Zeller KF, Nikolov N, McClelland T (2003) A review of the Forest Service remote automated weather station (RAWS) network. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-119. (Fort Collins, CO)