The Science and Opportunity of Wildfire Risk Assessment

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1. Introduction

Wildfire management within the United States continues to increase in complexity, as the converging drivers of (1) increased development into fire-prone areas, (2) accumulated fuels from historic management practices, and (3) climate change potentially magnify threats to social and ecological values (Bruins et al., 2010; Gude et al., 2008; Littell et al., 2009). The need for wildfire risk assessment tools continues to grow, as land management agencies attempt to map wildfire risk and develop strategies for mitigation. Developing and employing wildfire risk assessment models can aid management decision-making, and can facilitate prioritization of investments in mitigating losses and restoring fire on fire prone landscapes. Further, assessment models can be used for monitoring trends in wildfire risk over space and across time.

The term risk is generally used to measure the chance of loss, as determined from estimates of likelihood and magnitude of particular outcomes. Probabilistic approaches to risk assessment estimate the expected value of the conditional probability of the even occurring and the consequence of the event given that it has occurred. Risk assessments are conducted when predicted outcomes are uncertain, but possible outcomes can be described and their likelihoods can be estimated. Wildfire risk assessment entails projecting wildfire extent and intensity, and the consequences of fires interacting with values-at-risk.

We begin by introducing a conceptual model of wildfire management (Figure 1) that considers the major drivers of wildfire risk and strategic options for mitigation. Ignition processes influence the spatiotemporal pattern of wildfire occurrence (natural and human-caused), and strategic prevention efforts can reduce the number of wildfires and associated damage (Prestemon et al., 2010). Given an ignition that escapes suppression, fuel, weather, and topography jointly drive wildfire behavior. Of these, only fuel conditions (loading, structure, continuity) can be altered to induce desirable changes in fire behavior (Agee & Skinner 2005). Suppression efforts are intended to slow the growth of active wildfires and reduce the chance of loss. Collectively these factors influence wildfire extent and intensity, which in turn determine the consequences (detrimental and beneficial) to social and ecological values. Wildfire losses can also be prevented or reduced by activities that lessen the consequences of an interaction with fire, for instance the use of fire-resistant materials in home construction.

The challenge of wildfire management is to find efficient combinations of investments in mitigation options, recognizing heterogeneity in the environmental and socioeconomic factors contributing to wildfire risk. Assessing wildfire risk and evaluating mitigation options are highly complex tasks that integrate multiple interacting components including fire simulation modeling, mapping valued resources and assets, characterizing first- and second-order fire effects, quantifying social and managerial preferences and priorities, and exploring feasible management opportunities. Wildfire risk analysis is therefore fundamentally interdisciplinary, requiring the pairing of substantive expertise (fire behavior modeling, silviculture, fire ecology, etc.) with methodological expertise (statistics, engineering, decision analysis, etc.). Improved assessment of wildfire risk in turn ideally leads to improved strategic risk management across planning scales, and ultimately to enhanced resource protection and ecosystem resiliency.

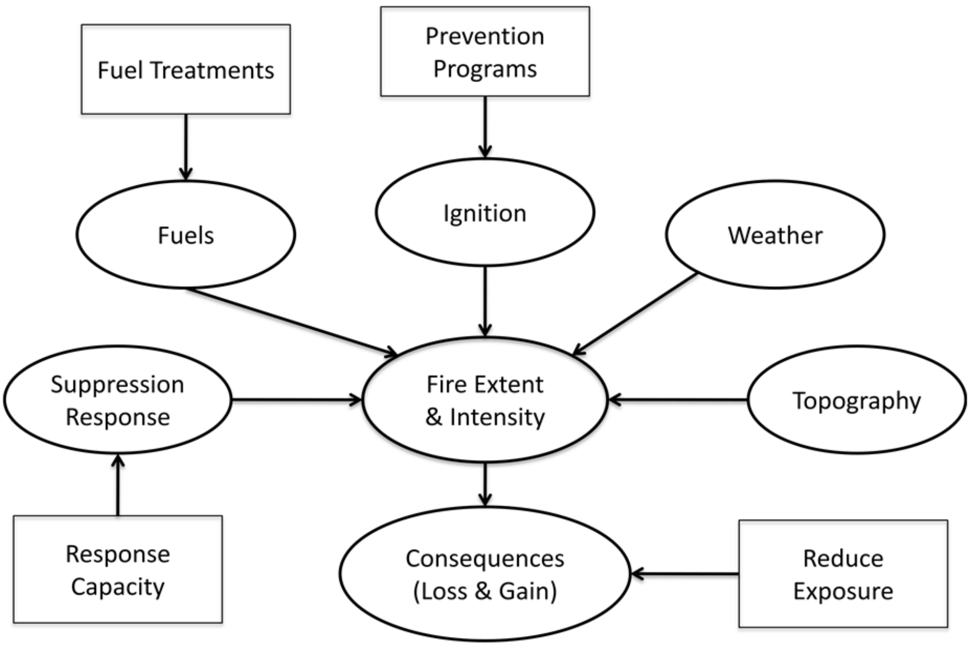

Fig. 1. Conceptual Model of Wildfire Management (Modified from Calkin et al., 2011).

The major drivers of fire extent and intensity are represented as ovals, and the major strategic options for mitigating risk are represented as rectangles.

In this chapter we review the state of wildfire hazard and risk analysis, in particular highlighting a risk assessment framework that is geospatial, quantitative, and considers multiple social and ecological values. Contextually our focus is federal wildfire management in the United States, although the framework we present has broader applicability across geographic locations and ownerships. First we review concepts of hazard and risk in the wildfire management context. Second, we describe newer developments in the application of burn probability modeling for exposure analysis, and illustrate how this modeling approach can inform fuel management and wildfire suppression efforts. Third, we discuss challenges in quantifying risk for the array of non-market values that are the primary management concern on federal lands, and how expert judgment can be used to advance wildfire effects analysis. We use examples from recent and ongoing broad scale risk assessments and describe their use for informing strategic policy. Lastly we conclude by discussing potential benefits to wildfire management and policy from embracing risk management principles.

2. Wildfire hazard and risk assessment

In is important to recognize the difference between wildfire hazard and wildfire risk, since these terms are often used interchangeably in the literature. Wildfire hazard characterizes the potential for wildfire to harm human life and safety or damage highly valued resources and assets (HVRAs) (Keane et al., 2010). Wildfire risk, by contrast, includes quantification of the magnitude of fire outcomes (beneficial and detrimental) as they relate to fire hazard (Finney, 2005). From this perspective, mapping fire hazard can reveal patterns of one component of risk, but offers less complete information to decision-makers faced with questions of how to understand and mitigate potential impacts to HVRAs.

2.1 Wildfire hazard

A variety of approaches have been adopted to characterize wildfire hazard. Typically hazard is described in relation to factors affecting the fire environment and likely fire behavior, including fuel and vegetation properties, topography, climate and weather variables, and ignition characteristics (Hessburg et al., 2007; Vadrevu et al., 2010). Conceptually, probabilistic, spatially-explicit models of wildfire hazard are most relevant for risk assessment. For instance, hazard can be described with a probability distribution for a given fire characteristic at a given location, such as fire occurrence or behavior. Fire occurrence likelihood is often estimated using logistic regression models (Brillinger et al., 2009; Finney et al., 2011a; Martínez et al., 2009; Prasad et al., 2007; Priesler & Westerling 2007). Some approaches have considered likelihood of wildfire occurrence as a separate component, and characterized hazard instead as the potential to cause harm given a wildfire occurs (i.e., hazard is measure of conditional fire behavior). Here we include wildfire likelihood in our definition of hazard, which incorporates not only the likelihood of ignition for any particular area on the landscape but also the likelihood of burning due to fire spread from remote ignitions.

Modeling fire behavior given fire occurrence typically entails estimating spread rate, flame length, fireline intensity, and crown fire activity, and involves the integration of multiple sub-models (Ager et al., 2011; Cruz & Alexander 2010). Modeling fire spread allows the computation of fire travel pathways and fire size distributions, and a robust characterization of the spatial process. Simulating fire growth across heterogeneous landscapes can identify emergent behavioral properties that may not be predictable and may not be captured with localized estimates of fire behavior (Carmel et al., 2009; Parisien et al., 2007). Modeling fire spread also allows for estimates of fireline intensity as a function of fire spread direction (flanking, heading, or backing).

Rapid advancements in geospatial data management, fire behavior modeling, and computing power have vastly improved the spatial assessment of fire impacts on HVRAs. In particular, estimation of burn probability (BP), an estimate of the likelihood of a point burning under a predefined set of assumptions about ignition and fire behavior, is now feasible for large landscapes. Explicit consideration of fire spread from remote ignitions is particularly important in parts of the western United States, where large lightning-caused fires typically spread over large distances. In other locations and in different planning environments ignition likelihood may be much more of a driver.

Simulation modeling can further produce burn probabilities for fire intensity (BP_i) as a function of the number of times a pixel burned at a given intensity level. The intensity with which a fire burns is an important variable for predicting fire effects. Fire intensity (KW/m) is typically converted to flame length to measure fire effects. Fire intensity is relative to the spread direction, and thus quantifying intensity for a particular point needs to consider all possible arrival directions and their probabilities. The conditional flame length (CFL), or the probability weighted flame length given a fire occurs (Scott, 2006; Equation 1) is used for this purpose, and is a statistical expectation, summing over burn intensity probabilities multiplied by the midpoints of the corresponding flame length category (Ager et al., 2010).

$$CFL = \Sigma BP_i FL_i \tag{1}$$

Figure 2 displays burn probability maps (a) and conditional flame lengths (b) for National Forests in the states of Oregon and Washington, in the Pacific Northwest of the United States. These estimates were derived from the large fire simulation model FSim (Finney et al., 2011a). Maps of BP and CFL differentiate regions and forests with higher relative wildfire hazard, for instance the eastern-most National Forests. Hazard is lower in the western portion of the region, where forests are generally moister and where annual rainfall is much higher.

2.2 Wildfire risk

A widely accepted ecological risk assessment framework was developed by the U.S. Environmental Protection Agency that entails four primary steps: (1) problem formulation, (2) exposure analysis, (3) effects analysis, and (4) risk characterization (U.S. Environmental Protection Agency, 1998). The two primary analytical components are exposure analysis, which explores the predicted scale and spatiotemporal relationships of causative risk factors, and effects analysis, which explores the response of HVRAs to varying levels of the risk factors (Fairbrother & Turnley, 2005). Risk characterization integrates information from exposure analysis and effects analysis to formulate a conclusion about risk. The ability to characterize risk in a common metric facilitates the integration of multiple HVRAs and allows for economic analysis of management alternatives on the basis of cost-effectiveness, although challenges exist especially for non-market resources (Chuvieco et al., 2010; Venn & Calkin, 2011).

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). In the above formulation, the components required to estimate wildfire risk are wildfire hazard maps generated from wildfire simulation models, HVRA maps, and characterization of fire effects to HVRAs. Exposure analysis intersects mapped HVRAs with spatially-explicit measures of wildfire hazard (burn probability and conditional fire intensity). Effects analysis quantitatively defines the response of the HVRA to wildfire hazard, in this case using response functions. Collectively exposure and effects analysis characterize risk to the HVRAs in question, which can be analyzed separately or aggregated using valuation techniques and/or multi-criteria decision analysis (Thompson & Calkin, 2011).

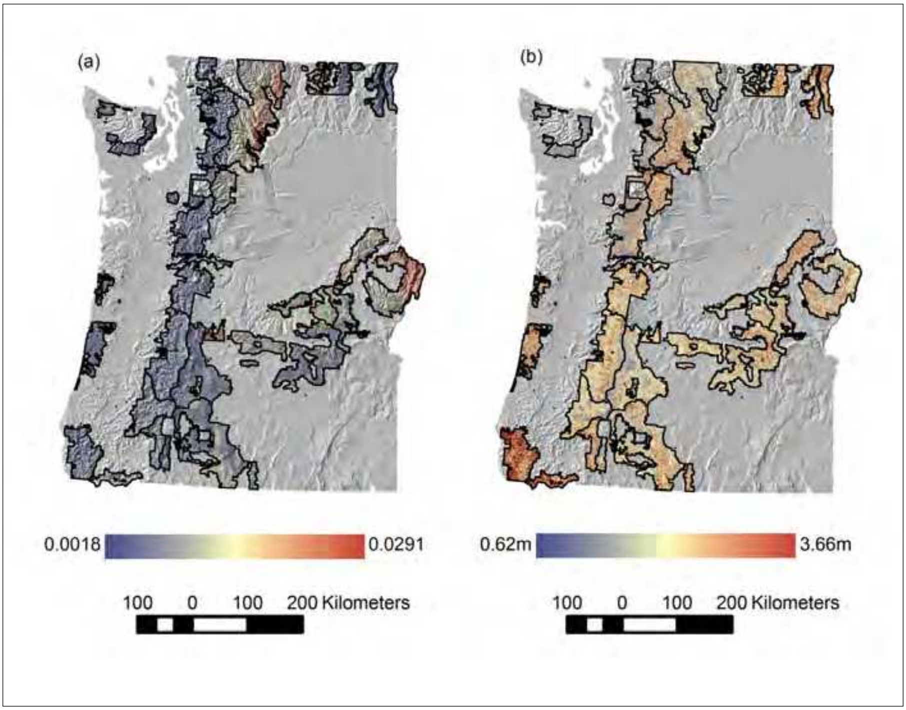

Fig. 2. Burn probability (a) and conditional flame length (b) for National Forests in the states of Oregon and Washington, in the Pacific Northwest of the United States. Figure from (Ager et al., submitted).

Figure 3 presents our conceptual model for assessing wildfire risk combining exposure and effects analysis. Here an integrated assessment is illustrated, using a representative set of HVRAs (air quality, wildlife habitat, municipal watersheds, and human communities) for which federal agencies manage. Equation 2 presents the mathematical formulation for calculating risk (Finney, 2005), where $E(NVC_i)$ is the expected net value change to resource j, and RF_i and is a "response function" for resource j as a function of fire intensity i and a vector of geospatial variables X_i that influence fire effects to resource j.

$$E(NVC_j) = \Sigma BP_i RF_j(i,X_j) \quad (2)$$

This framework quantifies risk in terms of relative net value change (NVC), or the percentage change in initial value resulting from interaction with fire. That is, response functions address relative rather than absolute change in resource or asset value. Response functions translate fire effects into NVC to the described HVRA. In response functions illustrated in Figure 3 NVC is based on fire intensity, which is a robust fire characteristic that integrates fuel consumption and spread rate, and is often used to estimate fire effects (Thompson et al. 2011a; Ager et al. 2007). In Figure 3 the response function varies according to categorical fire intensity levels, although the framework is perfectly amenable to definition of multivariate response functions incorporating additional geospatial information that influence response to fire (see Section 4).

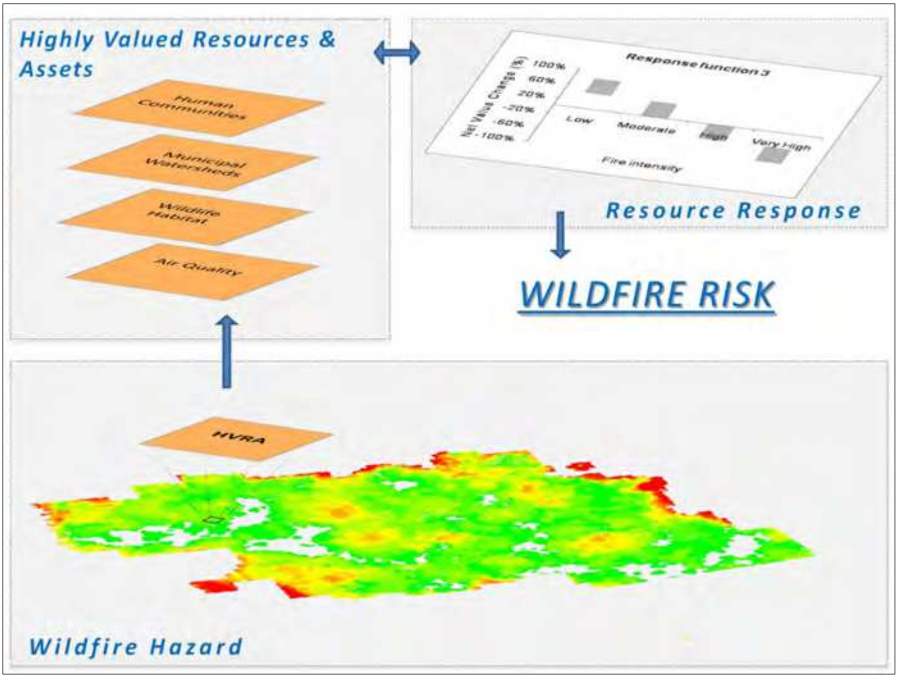

Fig. 3. Conceptual model for calculating wildfire risk (Modified from Calkin et al., 2010).

Characterizing fire effects has presented a major challenge to risk assessment, due to limited understanding of the spatiotemporal dynamics of ecological changes wrought by wildfire. Many past analyses focused on wildfire risk to commercial values, such as commercial timber (Konoshima et al. 2008), with a much more limited set focusing on broader non-market resource values and public infrastructure (Venn & Calkin 2011). There exist a variety of models that can estimate first-order fire effects such as tree mortality, soil heating, fuel consumption, and smoke production, although managers are generally more concerned with second- and third-order effects such as air quality, water quality, and habitat degradation (Reinhardt & Dickinson 2010). The management context, availability of appropriate models, and quality of spatial data will inform selection of the appropriate fire effects modeling approach (Reinhardt et al. 2001). In the absence of fire effects models, a reliance on local knowledge by resource managers is a common substitute for formal effects analyses.

3. Applications of burn probability modeling & exposure analysis

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 across multiple fire seasons. Advances in burn probability modeling have enabled increasing sophistication and analytical rigor across a variety of wildfire management applications. Researchers and practitioners are able to, for instance, project near-term fire behavior using real-time weather information (Andrews et al., 2007) or to project wildfire behavioral changes in response to fuel treatments (Kim et al., 2009). In this section we focus on application of burn probability modeling and exposure analysis to support management of wildfire incidents and to support proactive hazardous fuels reduction treatments.

3.1 Incident management

Development of suppression strategies for escaped wildland fires is subject to considerable uncertainty and complexity. Factors to balance include likely weather and fire behavior, topography, firefighter safety, and the availability and productivity of firefighting resources (ground crews, fire engines, air tankers, etc.). Of particular importance is the ability to project where and under what conditions fire is likely to interact with HVRAs. This information can help fire managers decide where aggressive fire suppression may be effectives to protect HVRAs, and where fires may have a positive impact in fire-prone ecosystems.

In the United States, all wildfires occurring on federal lands are cataloged within the Wildland Fire Decision Support System (WFDSS). WFDSS provides decision documentation and analysis functionality to describe the fire incident, create objectives and requirements, develop a course of action, validate key dependencies and evaluate risks (Noonan-Wright et al., 2011). The system combines a suite of fire behavior predictions with identification and quantification of values at risk to inform incident management considering safety, complexity, economics, and risk (Calkin et al., 2011).

The two primary risk-based analytical components within WFDSS are the Fire Spread Probability model (FSPro) and the Rapid Assessment of Values at Risk (RAVAR). FSPro calculates the probability of fire spread from a current fire perimeter or ignition point, for a specified time period. Burn probability maps are derived from simulating fire growth for thousands of statistically generated weather scenarios (Finney et al., 2011b). As implemented in WFDSS burn probabilities are mapped as probability zones, or contours, of similar burn probability; exterior contours have lower probability of fire occurrence than interior contours.

Figure 4 displays an FSPro analysis for the SQF Canyon Fire, a human-caused fire that ignited on September 20, 2010 in California in the Sequoia National Forest. The figure provides a 7-day projection of fire growth as of September 14, 2010. The fire spread probability contours, moving outward from the red center, correspond to intervals of >80%, 60-80%, 40-60%, 20-40%, 5-20%, 1-5%, and <1% of likely fire spread given the current fire location and perimeter.

The RAVAR analytic model produces two distinct map products and associated reports, inventorying mapped Critical Infrastructure (CI) and Natural and Cultural Resources (NCR). HVRAs identified in CI reports include private structures, recreation facilities, water supply systems, major power lines, pipelines, communication towers, and hazardous waste sites. NCR products focus on regionally identified natural resources and wildland management priorities, such as sensitive wildlife habitat and restoration priority areas. Table 1 provides example tabular RAVAR output quantifying the number and value of structures at risk according to FSPro Fire Spread Zones, using county tax records.

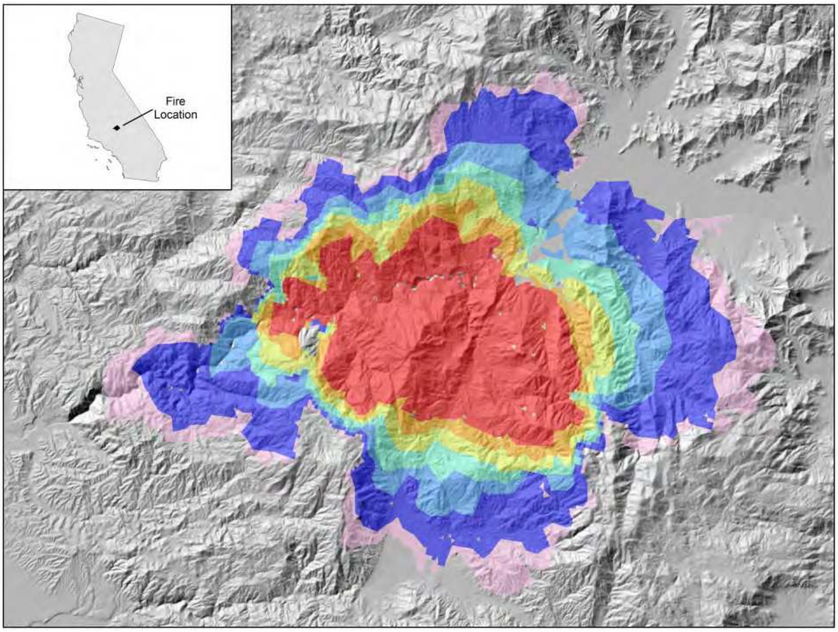

Fig. 4. FSPro run for the Canyon Fire in the Sequoia National Forest, California.

Figure 5 displays a close-up view of an FSPro-RAVAR analysis for the SQF Canyon Fire, which overlays geospatial identification of Critical Infrastructure on top of probability contours. (RAVAR maps are approximately 4′ x 3′ and are intended for poster display, generally making detailed displays on computer screens difficult.) The current fire perimeter is outlined in red, overlaid on top of associated probability contours of likely spread (see Figure 4). Threatened resources include private structures (black triangles), federal structures (green triangle), power transmission lines (inverted “T”, dashed connector), and mine sites (pick and shovel). The green line demarcates the National Forest boundary, and yellow/red dots identify “hot” points from satellite images.

Together FSPro and RAVAR provide state-of-the-art exposure analysis, linking near real time probabilistic fire spread predictions with values at risk These analytical products inform managers regarding the likelihood of fire impacting HVRAS and assist in developing target fire containment perimeters. WFDSS supports risk-informed decision making by analyzing HVRA exposure to fire, allowing local managers to evaluate the likely impacts and prioritize suppression efforts accordingly.

	Acres Threatened		**Kern County**			
Fire Spread Probability Zone	**Acres by Zone**	**Cumulative Acres**	**Count by Zone**	**Cumulative Zone**	**Value by Zone**	**Cumulative Value**
> 80 %	47,894	47,894	290	290	$43,399,080	$43,399,080
60 – 80 %	12,029	59,923	215	505	$32,175,180	$75,574,260
40 – 60 %	14,062	73,985	289	794	$43,249,428	$118,823,688
20 – 40 %	15,602	89,586	208	1,002	$31,127,616	$149,951,304
5 – 20 %	24,995	114,582	297	1,299	$44,446,644	$194,397,948
1 – 5 %	53,989	168,571	794	2,093	$118,823,688	$313,221,636
Expected Value (without suppression)		67,980		679		$101,665,338

Table 1. Estimates of Structure Values at Risk, as output by WFDSS-RAVAR, using data from Kern County, California.

3.2 Hazardous fuels management

Fuel management seeks to alter the quantity, spatial arrangement, structure, and continuity of fuels so as to induce desirable changes in fire behavior. Broadly speaking, fuel management activities are designed to reduce the risk of catastrophic fire, protect human communities, reduce the extent and cost of wildfires, and restore fire-adapted ecosystems. For a fuel treatment to function effectively it must first spatially interact with an actual wildfire, and second mitigate fire behavior according to design objectives (Syphard et al., 2011).

Recognized principles for fuels management planning (Agee & Skinner, 2005) largely relate to individual treatments and their effects on localized fire behavior. Less understood is how in aggregate fuel treatments can affect landscape-scale processes of fire spread (Hudak et al., 2011). Prospective evaluation the influence of fuel treatments requires the estimation of altered fire behavior both within and outside of treated areas (Finney et al., 2007). Spatial fire growth models and burn probability modeling have emerged as useful tools for analyzing the influence of fuel treatments on topological fire spread, and to enable risk-based analysis of fuel treatment effectiveness.

A workflow for fuel treatment planning includes identifying the purpose and need for treatments, simulating wildfire behavior across the current, untreated landscape to characterize hazard and risk, developing treatment strategies, and iteratively simulating and evaluating changes to wildfire hazard and risk stemming from the treatment. Primary variables comprising a treatment strategy include the size of individual treatment units, the placement/pattern of the treatments, the proportion of the landscape treated, and treatment longevity (Collins et al., 2010).

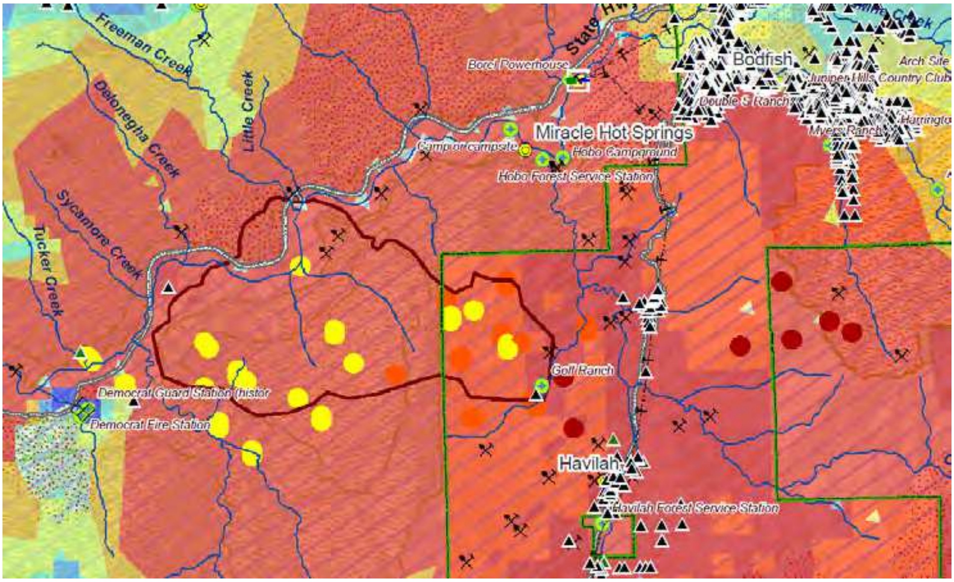

Fig. 5. Detail of RAVAR analysis for the Canyon Fire in Sequoia National Forest, California.

Ager et al. (2011) reviewed the development and use of ArcFuels, an integrated system of tools to design and test fuel treatment programs within a risk assessment framework. A number of fuel treatment case studies have employed the same basic analytical approach of comparative burn probability and intensity modeling across untreated/treated landscapes (Ager et al., 2010; Parisien et al., 2007). Figure 6 illustrates such a case study that investigated the influence of different treatment strategies on burn probability. Four scenarios, representing treating 0%, 10%, 20%, and 50% of the landscape were fed into wildfire simulation models to estimate impacts to burn and intensity probabilities.

In addition to evaluating prospective fuel treatments and informing treatment design, burn probability modeling can also be used to evaluate the effectiveness of previously implemented treatments. Field-based evaluations of fuel treatments have relied on the relatively rare occurrence of wildfires interacting with treatments. Of these treatments that have engaged wildfire, few have been subject to rigorous review to characterize treatment effectiveness (Hudak et al., 2011). Only recently has it been possible to estimate the spatial probabilities of landscape burning as a function of extant fuels treatments for real wildland fire-affected landscapes (Cochrane et al., in press). Figure 7 displays an example of burn probability modeling to analyze the impact of implemented treatments and their engagement with the School Fire. Rather than simulating the impacts of hypothetically implemented treatments, as in Figure 6, here the analysis simulates hypothetical fuel conditions had treatments not been implemented. The actual fire perimeter is outlined in red, and probability zones reflect contours of likely fire spread as output from wildfire simulations, had the treatments not been implemented. Areas of positive probability (yellow, orange, red) reflect that the treatments were effective in preventing spread. Exposure analysis intersects probability zones with mapped HVRAs including US Forest Service structures, improved structures (identified from county tax records), and bull trout (*Salvelinus confluentus*) critical habitat. Quantification of reduced exposure can inform estimates of fuel treatment effectiveness.

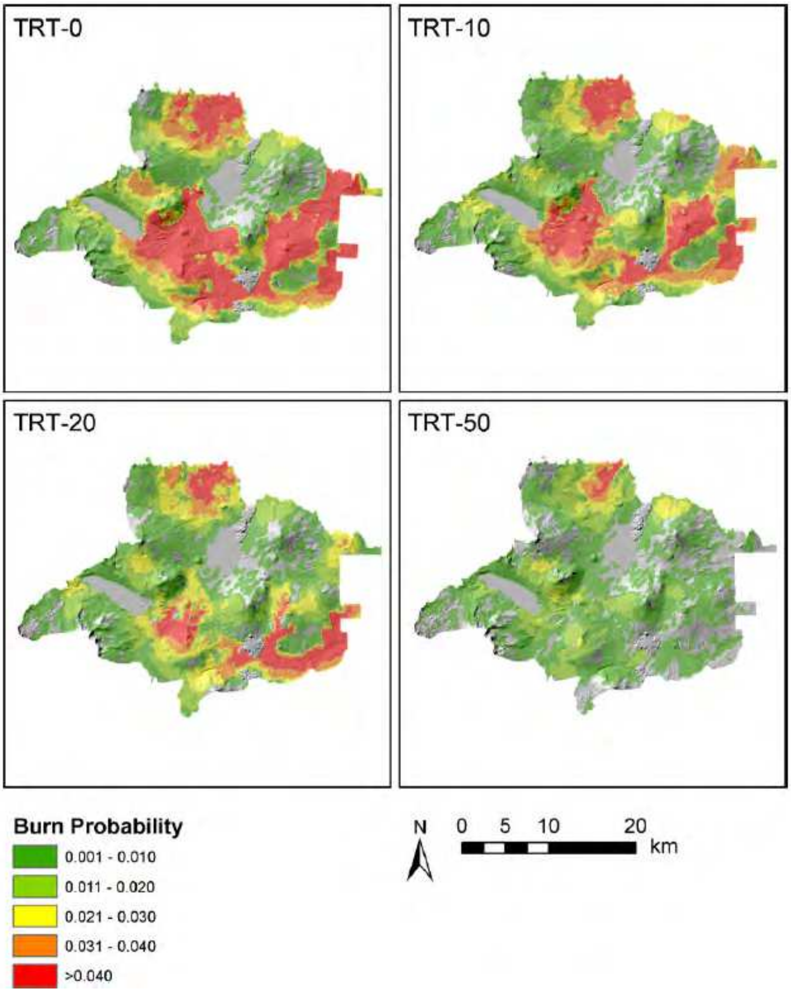

Fig. 6. Illustration of reductions in burn probability as a function of percent of the landscape treated (Ager et al., 2007). "TRT-X" refers to different modeled scenarios in which X percent of the landscape is treated.

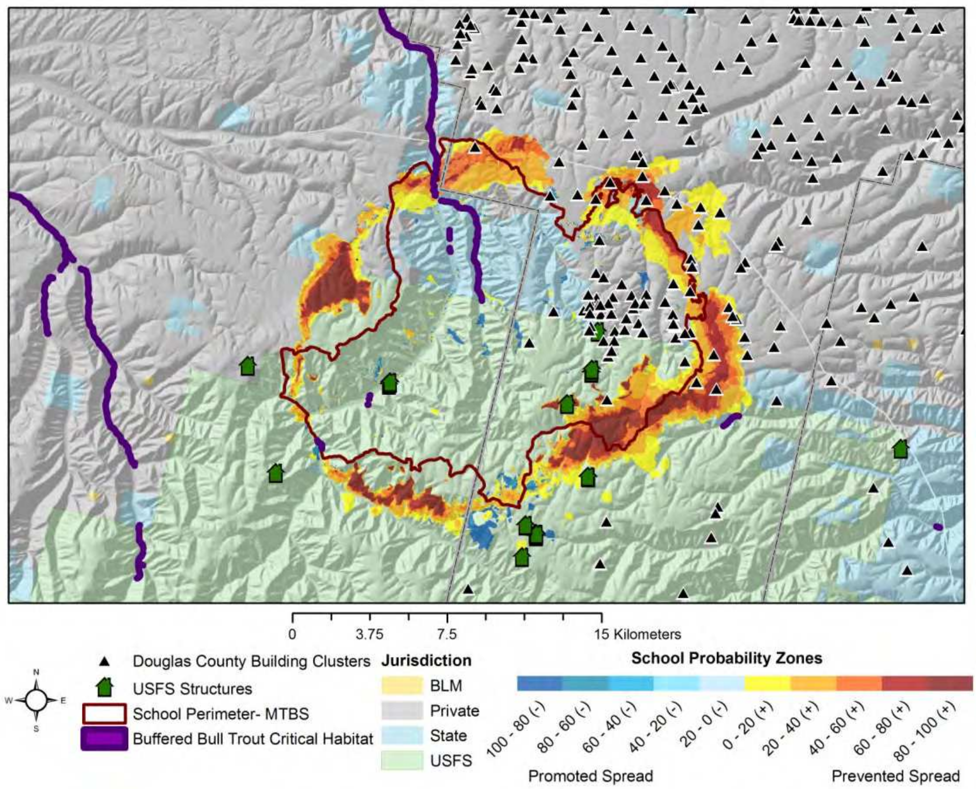

Fig. 7. Analysis for the School Fire demonstrating the impact of implemented fuel treatments. Modified from (Cochrane et al., in press).

4. Fire effects analysis & incorporation of expert judgment

Estimating resource response to wildfire is a crucial step for quantitative risk assessment (Fairbrother & Turnley, 2005), and yet is also one of the most challenging steps. Effects analysis is made difficult by the scientific uncertainty and lack of data/information surrounding wildfire effects on non-market resources; specifically in that limited scientific understanding challenges characterization of marginal ecological changes, and further in that economic methods are immature for broad scale monetization of such changes (Keane & Karau 2010; Venn & Calkin, 2011). Expert systems are commonly used in natural resource management decision-making (González et al., 2007; Hirsch et al., 2004; Kaloudis et al., 2005; Vadrevu et al., 2010), and rely on the unique expertise and judgment of professionals as a proxy for empirical data. Increasingly in a variety of natural resource management applications researchers and practitioners are adopting structured approaches for eliciting and using expert knowledge (Kuhnert et al., 2010; Martin et al., 2009). Elicitation of expert judgment is particularly useful where decisions are time-sensitive and management or policy cannot wait for improved scientific knowledge (Knol et al., 2010).

Structured Elicitation Process
1. Articulate research question
2. Identify and characterize uncertainties
3. Resolve scope and format of elicitation
4. Select experts
5. Design elicitation protocol
6. Prepare elicitation protocol
7. Elicit expert judgment
8. Feedback

Fig. 8. Eight major steps in organizing and implementing a structured elicitation of expert judgment. Modified from (Knol et al., 2010; Kuhnert et al., 2010)

Figure 8 presents a structured process for eliciting expert judgment. In the first step, a clear articulation of the research question(s) will inform the design and implementation of the study as well as the larger structure of the modeling process. This is followed by identification and characterization of uncertainties, which will influence choices regarding the type of experts and elicitation format. Resolving the scope and format of the elicitation entails identifying the number of experts to engage and the nature of the engagement (interview, group workshop, survey distribution, etc.), while considering available resources and other constraints. Selection of experts includes choices between generalists, subject matter experts, and normative experts (those with experience to support elicitation itself). Design of the protocol considers the type of information to be elicited, the most appropriate metric(s), the most appropriate elicitation mechanism, and how to clearly communicate information needs to avoid issues of linguistic uncertainty (Regan et al., 2002). Preparation of the elicitation protocol includes providing selected experts with sufficient information on the nature of the research problem and associated uncertainties, the scope and purpose of the elicitation, and the nature of the elicitation procedure itself. Lastly, the elicitation procedure is implemented, with opportunities for post-elicitation feedback and revision.

In terms of the wildfire management context, the research question generally involves assessing wildfire risk to HVRAs, potentially in a comparative risk framework to evaluate the effectiveness of alternative management actions (Figure 1). In the second step, wildfire management is subject to myriad sources of uncertainty, not all of which are necessarily best handled with expert judgment (burn probability modeling to capture environmental stochasticity, e.g.). Thompson & Calkin (2011) present a typology of uncertainties faced in wildfire management, and identify that with regard to knowledge uncertainty surrounding fire effects, expert systems are perhaps the most appropriate approach. In our past experience we have adopted group workshops, and assembled resource scientists (hydrologists, soil scientists, wildfire biologists, fire ecologists, etc.) as appropriate given the HVRAs being assessed (Thompson et al., 2011b). The elicitation protocol identifies response functions that quantitatively characterize resource-specific response functions as a function of fire intensity, and response functions are iteratively explored, justified, and updated until expert consensus is reached.

Figure 9 illustrates expert-based response functions for two HVRAs with contrasting response to fire, mapped across six fire intensity level (FIL) classes. These response functions were assigned in a group workshop format as part of a broader wildfire risk assessment conducted for the Lewis and Clark National Forest in Montana, United States. Aspen stands are highly valued because they provide habitat for a broad diversity of wildlife, and due to their relative rarity across the landscape. Aspens are reliant on wildfire for natural regeneration, and so are modeled as experiencing substantial benefit from fire at low to moderate intensities, with minor loss expected high intensity fires. For high investment infrastructure (e.g., developed campgrounds, cabins, ranger stations), damages are expected from any interaction with fire, and are expected to increase in severity as fire intensity increases.

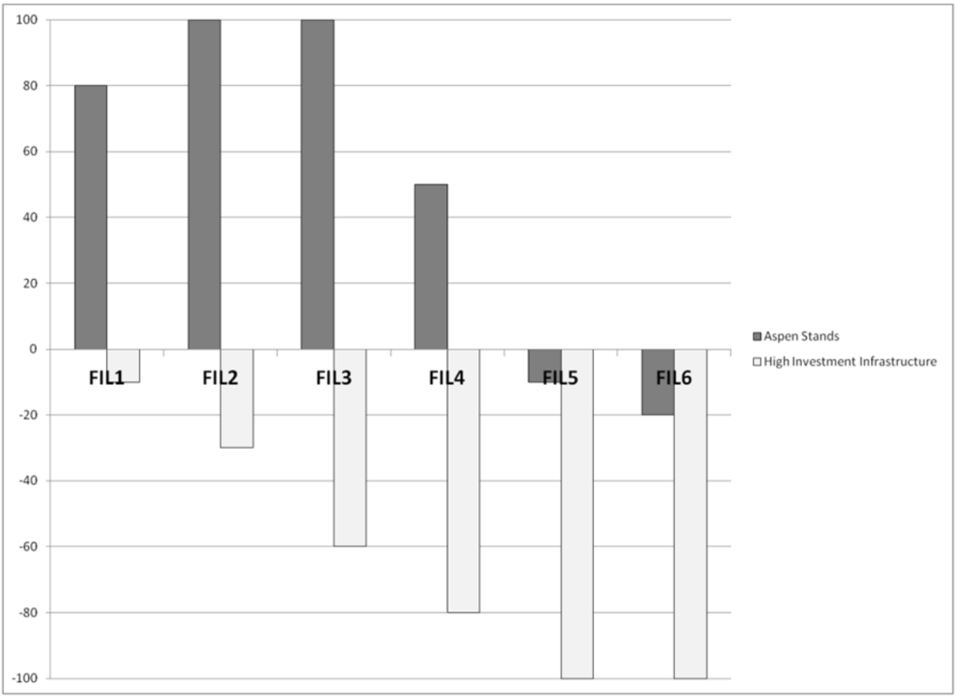

Fig. 9. Response functions plotting relative NVC (y-axis) against fire intensity level (FIL; x-axis), for stands of aspen and high investment infrastructure.

Figure 10 displays additional response functions identified as part of the wildfire risk assessment for the Lewis and Clark National Forest. This figure highlights use of an additional geospatial variable, in this case moisture conditions on the site, to further refine fire effects estimates to old growth (OG) forest stands. Dry forests typically have evolved with and tend to receive a benefit from low to moderate intensity fires. At extreme intensities, high levels of mortality and damage are expected irrespective of site moisture conditions.

5. Case study of wildfire risk

In this section we briefly review a recently published example of integrated, national-scale wildfire risk assessment (Thompson et al., 2011b). The effort leveraged tools, datasets, and expertise of the Fire Program Analysis (FPA) system, a common interagency strategic decision support tool for wildland fire planning and budgeting (http://www.fpa.nifc.gov). We aggregated results according to eight geographic areas organized largely for purposes of incident management and mobilization of suppression resources: California (CA), Eastern Area (EA), Great Basin (GB), Northern Rockies (NR), Northwest (NW), Rocky Mountain (RM), Southern Area (SA), and Southwest (SW).

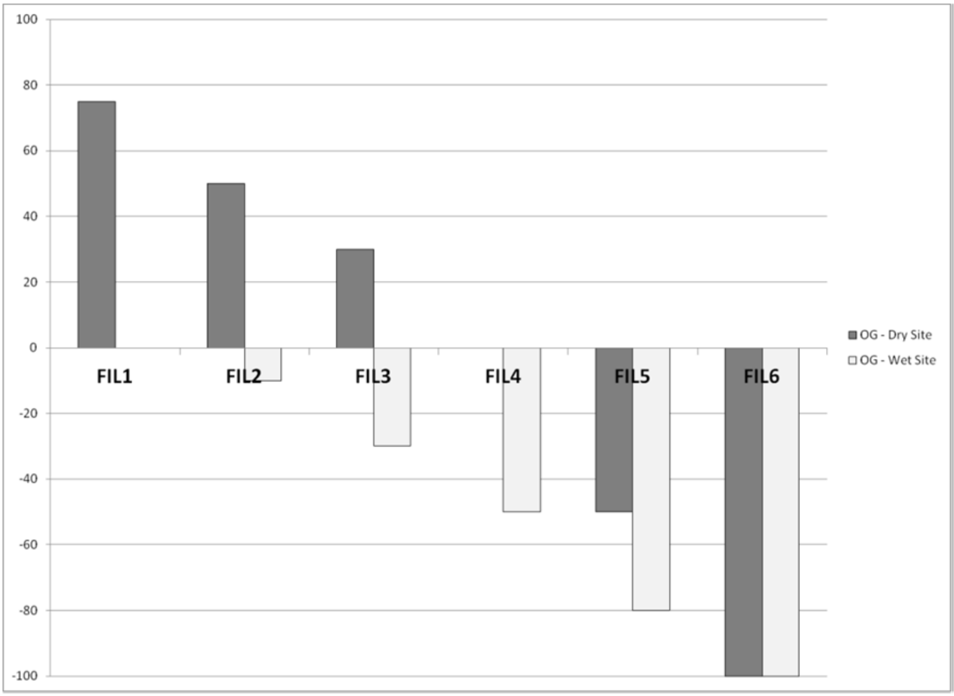

Fig. 10. Response functions plotting relative benefit/loss (y-axis) against fire intensity level (FIL; x-axis), for the Old Growth (OG) HVRA, sorted by dry/wet site.

To map wildfire hazard we used wildfire simulation outputs (burn probability and intensity) from the FSim large fire simulator (Finney et al., 2011a), mapped at on a pixel basis (270m x 270m). In cooperation with the FPA Executive Oversight Group we identified seven key HVRA themes: residential structure locations, municipal watersheds, air quality, energy and critical infrastructure, federal recreation and recreation infrastructure, fire-susceptible species, and fire-adapted ecosystems. Table 2 delineates the major HVRA themes along with identified sub-themes. We engaged ten fire and fuels program management officials from the Forest Service, National Park Service, Bureau of Land Management, Fish and Wildlife Service, and the Bureau of Indian Affairs to facilitate response function assignments.

Response functions indicated percentage NVC according to fire intensity category, as measured by flame length. As a consistent measure of NVC across HVRAs we used an area-based proxy called Total Change Equivalent (TCE). TCE effectively measures the equivalent area lost (or gained) for a particular HVRA. Since mapped pixels can support multiple HVRA layers, generation of risk estimates entailed geospatial computations for each pixel-HVRA layer combination.

HVRA Category	**HVRA Layer**	**HVRA Value Category**
Residential structure location	Low density built structures	High
	Moderate and high density built structures	Very High
Municipal watersheds	6^{th} order Hydrologic Unit Codes	Very High
Air quality	Class I areas	Moderate
	Non-attainment areas for PM 2.5 and Ozone	Very High
Energy infrastructure	Power transmission lines Oil and gas pipelines Power plant locations Cellular tower locations	High
Recreation infrastructure	FS campgrounds FS ranger stations BLM recreation sites and campgrounds NPS visitor services and campgrounds FWS recreation assets National scenic and historic trails National alpine ski area locations	High
Fire-susceptible species	Designated critical habitat National sage-grouse key habitat	High
Fire-adapted ecosystems	Fire-adapted regimes	Moderate

Table 2. HVRA layers used in national risk assessment Modified from (Thompson et al., 2011b).

Although calculating TCE in a common area-based measure does facilitate integration of multiple HVRAs and the evaluation of alternative mitigation strategies on the basis of cost-effectiveness, TCE does not capture management priorities across HVRAs. To better integrate TCE calculations we turned to multi-criteria decision analysis techniques to assign each HVRA an importance weight. First, we adopted a categorical approach using input from the fire and fuels program management officials consulted for assistance with fire effects analysis. With guidance from the experts we assigned each HVR to one of three value categories: Moderate, High, and Very High. HVRAs assigned to the Very High category related to human health and safety, specifically concerns regarding air quality, water quality, and communities at risk. We then aggregated TCE results into a single weighted risk metric (wTCE) by assuming that the ranking of value categories maintained a simple proportional relationship. With this framework a (1, 3, 9) weight vector means that HVRAs assigned in the Very High value category are 3 times as important as resources in the High value category, which in turn are 3 times as important as resources in the Moderate value category. Clearly decision-makers can experiment with alternative value category and weight vector assignments, but our purposes were primarily to illustrate joint application of multi-criteria decision analysis and risk assessment.

Table 3 summarizes TCE values by HVRA, value category, and geographic area. In the Moderate value category the Southern Area (SA) presents the greatest risk, largely to Class I areas and concerns about air quality. Across all geographic areas fire-adapted ecosystems expect to see a benefit from fire, which on balance tend to outweigh losses to other HVRAs, leading to positive values for NVC. Within the High value category fire-susceptible species were the largest contributors to risk. The Southern Area contained the largest overall area of risk to energy infrastructure, with relatively low loss expected elsewhere. Low density built structures similarly had relatively low TCE values, with higher losses associated with the Southern Area, California, and the Southwest. Within the Very High value category non-attainment areas were by far the largest contributors to risk, and especially in California. Overall California presents the largest risk in the Very High value category, followed by the Southern Area. Lastly the bottom row presents weighted TCE (wTCE) values using the (1, 3, 9) weight vector. Consistent with results from the Very High value category, California and the Southern Area appear most susceptible to wildfire-related losses. The Great Basin ranks third, due primarily to extensively mapped sage grouse habitat. Thompson et al. (2011b) present additional results including sensitivity analysis of assigned relative importance weights, and refinements regarding the temporal effects of air quality degradation and the spatial extent of mapped habitat.

HVRA Value Category	**Geographic area**							
	CA	**EA**	**GB**	**NR**	**NW**	**RM**	**SA**	**SW**
Moderate	-0.58	0.62	3.18	1.53	5.34	0.63	-4.86	2.54
High	-9.91	-1.72	-32.99	-12.70	-19.40	-7.44	-9.54	-5.57
Very High	-55.53	-2.29	-2.54	-1.25	-1.70	-1.24	-14.44	-5.97
wTCE Totals (1, 3, 9)	**-530.11**	**-25.12**	**-118.68**	**-47.82**	**-68.12**	**-32.82**	**-163.41**	**-67.86**

Table 3. Total change equivalent (TCE) in thousands of hectares for each Geographic area and Value Category.

In summary, the case study briefly explored here demonstrates application of quantitative wildfire risk assessment. The approach is scalable, in that the same integration of burn probability maps, geospatial identification of HVRAs, and resource response functions can be applied at project-level to regional to national analyses. A number of improvements can and are being pursued, such as refining the fire simulation outputs, identifying a larger and more representative set of HVRAs, introducing more structure and engaging more experts to define response functions, and using more complex multi-criteria decision analysis methods to articulate relative importance across HVRAs.

6. Conclusion

Combining quantitative fire effects analysis with burn probability and intensity maps allows for a quantitative, actuarial representation of risk in a spatial context. Risk assessment can inform the spectrum of wildfire management activities, from real-time management of incidents to proactive fuels management to reduce losses from future fires. Comparative risk assessment enables the exploration of tradeoffs across alternative investments in prevention, fuels management, and suppression response capacity, and ideally will lead to improved efficiency in pre-suppression and suppression planning. The framework we promoted here aligns with previously established ecological risk assessment frameworks, and is increasingly being adopted for federal wildfire management in the United States. The framework can be consistently applied across planning scales, is objective, repeatable, probabilistic, and spatially-explicit. A great strength is the flexibility of the framework, in that analysts can adopt alternative approaches to characterize wildfire hazard, to characterize fire effects and response functions, and further to use alternative weighting schemes to integrate risk calculations across HVRAs. A further strength is the scalability of the framework, which can be applied from project-level planning to strategic, nation-wide analysis.

Despite the strengths of this approach there remain limitations and challenges to address. Understanding current risk is not the same as projecting future risk, which requires prediction of changes in vegetation from natural growth and from other disturbances, changes in demographics and development patterns that could expose more human communities to wildfire risk, the dynamic feedbacks of wildfires changing landscape conditions, and the influences on fire regimes of a changing climate. Characterizing risk is a necessary but not sufficient component to developing, selecting, and implementing mitigation strategies. Information about management opportunities, treatment costs, and their relation to risk factors needs to be considered, as does uncertainty related to science delivery and policy direction.

A number of promising extensions to the work presented in this chapter exist. Embedding geospatial wildfire risk analysis within optimization algorithms could inform multiple applications, for instance pre-positioning aerial firefighting resources, initial attack home base locations and dispatch strategies, fuels and vegetation management, and incident management. Fuel management in particular is a promising avenue for spatially explicit optimization approaches. Increasing use of expert systems plus appropriate fire effects models will enable improved estimates of the consequences of wildfire. Increasing use of multi-criteria decision analysis techniques will enable integrated assessments of risk across social and ecological values, and will facilitate prioritization efforts. Non-market valuation studies could further assist prioritization efforts and articulation of management tradeoffs. One very important, and highly uncertain, topic is the consideration of future wildfire risk as a function of contemporary management, land use patterns, vegetative succession and disturbance, and, importantly, climate change.

7. Acknowledgement

The authors wish to recognize and thank Julie Gilbertson-Day, Mark Cochrane, Anne Birkholz, Jon Rieck, Joe Scott, and Don Helmbrecht for various contributions to figures and tables presented in this figure. The lead author is grateful for support of the Rocky Mountain Research Station and the National Fire Decision Support Center.

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