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Advancing effects analysis for integrated, large-scale wildfire risk assessment

Matthew P. Thompson · David E. Calkin · Julie W. Gilbertson-Day · Alan A. Ager

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Abstract In this article, we describe the design and development of a quantitative, geospatial risk assessment tool intended to facilitate monitoring trends in wildfire risk over time and to provide information useful in prioritizing fuels treatments and mitigation measures. The research effort is designed to develop, from a strategic view, a first approximation of how both fire likelihood and intensity influence risk to social, economic, and ecological values at regional and national scales. Three main components are required to generate wildfire risk outputs: (1) burn probability maps generated from wildfire simulations, (2) spatially identified highly valued resources (HVRs), and (3) response functions that describe the effects of fire (beneficial or detrimental) on the HVR. Analyzing fire effects has to date presented a major challenge to integrated risk assessments, due to a limited understanding of the type and magnitude of changes wrought by wildfire to ecological and other nonmarket values. This work advances wildfire effects analysis, recognizing knowledge uncertainty and appropriately managing it through the use of an expert systems approach. Specifically, this work entailed consultation with 10 fire and fuels program management officials from federal agencies with fire management responsibilities in order to define quantitative resource response relationships as a function of fire intensity. Here, we demonstrate a proof-of-concept application of the wildland fire risk assessment tool, using the state of Oregon as a case study.

Keywords Wildfire risk · Risk assessment · Effects analysis · Expert system · Uncertainty

M. P. Thompson (✉) · D. E. Calkin
Rocky Mountain Research Station,
USDA Forest Service, Missoula, MT, USA
e-mail: mpthompson02@fs.fed.us

J. W. Gilbertson-Day
College of Forestry and Conservation,
University of Montana, Missoula, MT, USA

A. A. Ager
Western Wildland Environmental Threat Assessment Center, USDA Forest Service, Prineville, OR, USA

Introduction

In recent years, various federal oversight agencies and expert panels have sought to identify causal factors of unprecedented fire suppression costs and to suggest possible modifications to federal fire management policy and strategies (USDA Office of Inspector General 2006; Government Accountability Office 2007, 2009). A common thread that emerged is the perceived inability of federal agencies with wildland fire responsibilities to quantify the value of fire management activities in terms of reducing wildfire risk to social, economic, and ecological values. In response, researchers with the Rocky Mountain Research Station and the Western Wildland Environmental Threat Assessment Center of the USDA Forest Service designed and developed a quantitative, geospatial risk assessment tool to facilitate monitoring trends in wildfire risk over time and to develop information useful in prioritizing fuels treatments and mitigation measures.

Risk assessments are decision support tools that integrate information regarding the likelihood and magnitude of resource response to risk factors, in order to synthesize a conclusion about risk that can inform decision making (Sikder et al. 2006). Two key steps in risk assessment are exposure analysis and effects analysis (U.S. EPA 1998). Exposure analysis explores the predicted scale and spatial/temporal relationships of the causative risk factors, whereas effects analysis explores the response of valued resources to varying levels of the risk factors (Fairbrother and Turnley 2005). Assessing wildfire risk therefore requires an understanding of the likelihood of wildfire by intensity level and the magnitude of potential beneficial and negative effects to valued resources from fire at different intensity levels (Finney 2005).

At root, integrated wildfire risk assessment is subject to multiple sources of uncertainty. Of primary importance here are uncertainty with respect to fire occurrence and behavior and uncertainty with respect to the response of various

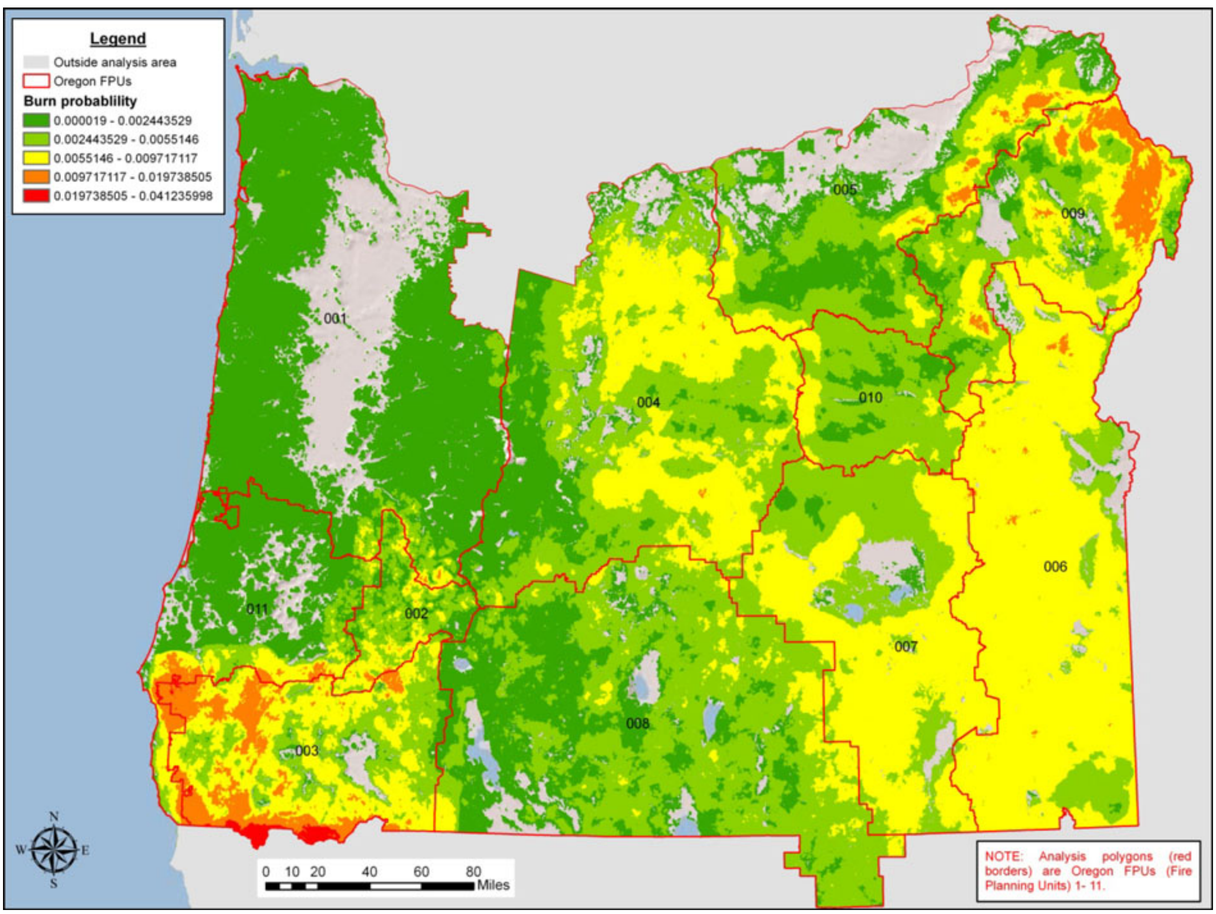

Fig. 1 Map of Oregon FPUs showing burn probability outputs from the FSim model. Values represent estimates of annual burn probability

valued human and ecological resources to fire. In broader terms, these types of uncertainty can be characterized as variability uncertainty (the inherent variability that manifests itself in natural systems) and knowledge uncertainty (limits of our knowledge and/or scientific understanding), respectively (Ascough et al. 2008). To the extent that these types of uncertainty can be quantified, they can be incorporated into a quantitative risk framework. Addressing variability uncertainty, such as modeling fire occurrence and/or behavior, can be handled with probabilistic approaches (e.g., Finney et al. 2007; Wei et al. 2008; Amacher et al. 2005. Addressing knowledge uncertainty, by contrast, is best handled using non-probabilistic approaches (Kangas and Kangas 2004). Without a quantitative framework, attempts at objective exposure and effects analyses will be limited.

Robust exposure analysis is made possible by advancements in fire simulation tools, such as development of the minimum travel time algorithm (Finney 2002) that allows for realistic modeling of fire behavior across real-world landscapes (Finney et al., in review). These tools output spatially explicit burn probability information, a crucial input to strategic fire and fuels management planning (Miller et al. 2008). Thus, managers are able, for example, to project near-term fire behavior using real-time weather information to inform suppression decision making (Andrews et al. 2007) or to examine how simulated wildfire

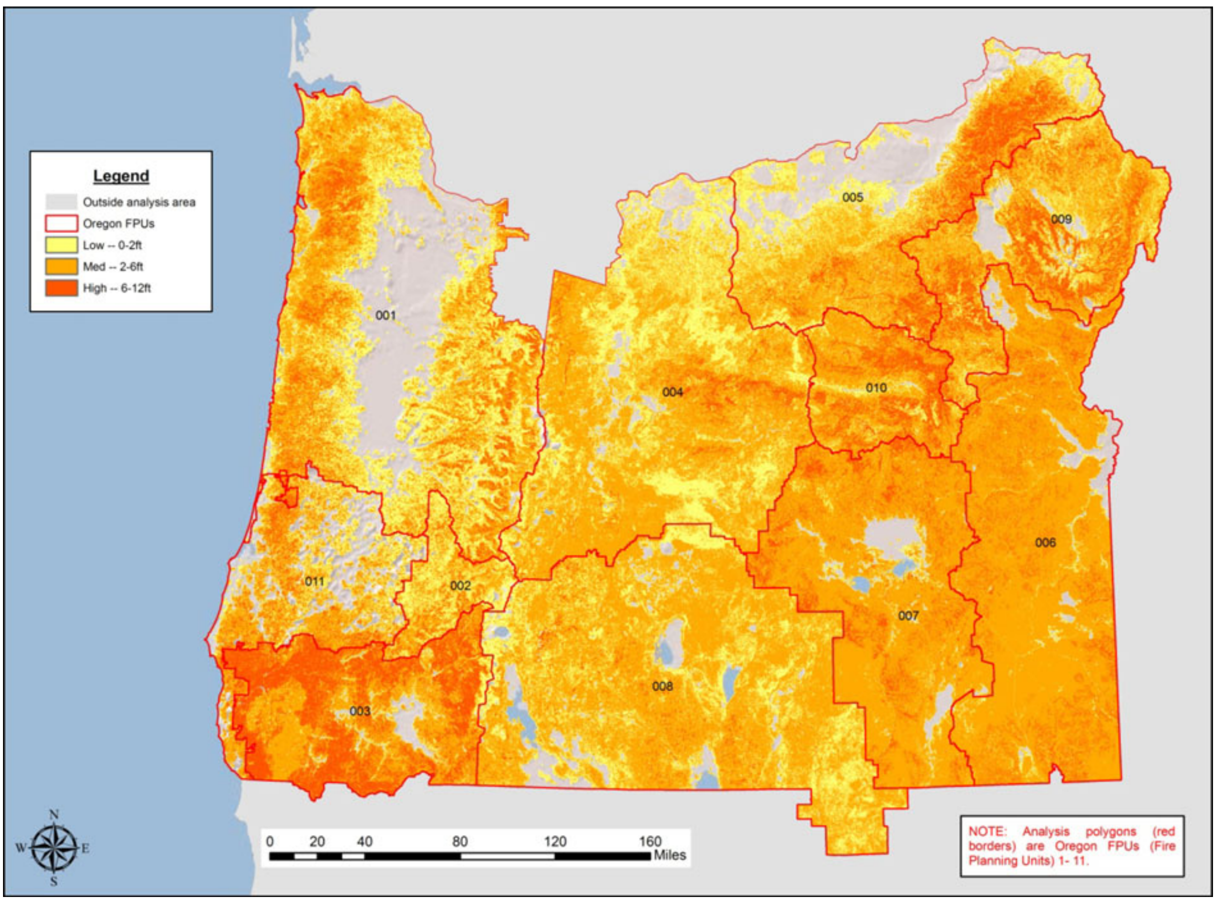

Fig. 2 Map of Oregon FPUs showing wildland fire hazard results from the FSim program. Fire hazard is defined as the average flame length of the fire. The Very High hazard class (flame length > 12 feet) was not predicted to occur in any FPU and is, therefore, excluded from the legend

behavior changes in response to fuel management activities (e.g., Kim et al. 2009).

Effects analysis, however, has to date presented a major challenge to integrated risk assessments, due to a limited understanding of the type and magnitude of changes wrought by wildfire to ecological and other nonmarket values (Fairbrother and Turnley 2005; Venn and Calkin, in press). Thus, most previous efforts have limited analysis to resources for which response to fire is better understood and more easily quantified, such as commercial timber (e.g., Konoshima et al. 2008), or have instead generated estimates of fire danger or hazard rather than risk (e.g., Hessburg et al. 2007). Others have proposed conceptual models that consider values at risk and the sensitivity of values to fire but did not demonstrate implementation of integrated risk assessment (e.g., Calkin et al. 2005; Kaloudis et al. 2005; Bonazountas et al. 2007).

Integrated exposure analysis for wildfire risk assessment is, therefore, challenged by significant knowledge uncertainty. Efforts at synthesizing anticipated resource response to wildfire (e.g., Keane et al. 2008; Kennedy and Fontaine 2009; Moody and Martin 2009), and empirical investigation into fire effects (e.g., Hyde et al. 2007) can reduce the scope and magnitude of this knowledge uncertainty. In the meantime, however, in absence of improved information, decision-makers must look to appropriate decision support techniques to address this knowledge uncertainty. Most common is use of an expert system, based on the premise that the best judgment of experts is likely the most appropriate substitute for perfect information (e.g., Vadrevu et al. 2009; González et al. 2007;

Table 1 HVR data layers acquired for risk assessment, identified according to HVR theme, sub-layer within theme, and data source

HVR theme	Sub-layer within theme	Source
Energy infrastructure	Power transmission lines	Homeland Security Infrastructure Program
	Oil and gas pipelines	National Pipeline Mapping System
	Power plant locations	Homeland Security Infrastructure Program
	Cellular tower point locations	Federal Communication Commission http://wireless.fcc.gov/geographic/index.htm
Federal recreation and recreation infrastructure	FS Campgrounds	USDA Forest Service (FS), FSGeodata Clearinghouse- Vector Data Gateway http://svinetfc4.fs.fed.us/vectorgateway/index.html
	Ranger stations	ESRI Data and Maps 9.3
	BLM recreation sites and campgrounds	GeoCommunicator http://www.geocommunicator.gov/GeoComm/index.shtm
	NPS visitor services and campgrounds	National Park Service (NPS) Data Store http://www.nps.gov/gis/data_info
	FWS recreation assets	USDI Fish and Wildlife Service (FWS)
	National scenic and historic trails	NPS Data Store http://www.nps.gov/gis/data_info
	National Alpine ski area locations	National Operational Hydrologic Remote Sensing Center http://www.nohrsc.noaa.gov/gisdatasets/
Fire-susceptible species	Designated critical habitat	U.S. Fish and Wildlife Service Critical Habitat Portal http://crithab.fws.gov/
	National sage-grouse key habitat	Bureau of Land Management (BLM)
Air quality	Class I airsheds	NPS Air Resources Division http://www.nature.nps.gov/air/maps/receptors/index.cfm
	Non-attainment areas for PM 2.5 and ozone	Environmental Protection Agency downloaded from www.myfirecommunity.net
Municipal watersheds	Sixth-order hydrologic unit codes	Natural Resource Conservation Service
Fire-adapted ecosystems	Fire-adapted regimes	LANDFIRE map products http://www.landfire.gov/
Residential structure location	Pixels identified as containing built structures	LandScan USA

Hessburg et al. 2007; Nadeau and Englefield 2006; Kaloudis et al. 2005; Hirsch et al. 1998, 2004).

Ongoing research within the USDA Forest Service is advancing the development of wildfire risk analysis tools that employ expert systems approaches to perform integrated effects analysis. This work entails linking spatially explicit information regarding probabilities of fire and fire intensity with expert-defined resource benefit and loss functions. That is, this line of research pairs probabilistic (i.e., fire occurrence and behavior) with non-probabilistic (i.e., resource response) techniques to handle uncertainty. Ager et al. (2007), for instance, quantified fuel treatments effectiveness in terms of reduced wildfire risk to spotted owl habitat within the Deschutes National Forest by developing loss functions with the Forest Vegetation Simulator. A similar risk analysis approach was used to measure the effects of fuel treatments on the expected loss of old growth (Ager et al. 2010a) and carbon (Ager et al., in press). Expanding these detailed analyses to regional and national scales to provide consistent risk assessment processes is complicated by the required data specificity and difficulty in developing benefit–loss functions for a broad range of human and ecological values.

The research effort described in this paper is designed to develop, from a strategic view, a first approximation of how both fire likelihood and intensity influence risk to social, economic, and ecological values at regional and national scales. The approach uses a quantitative risk framework that approximates expected losses and benefits from wildfire to highly valued resources (HVR). This work advances wildfire effects analysis, recognizing knowledge uncertainty and appropriately managing it through the use of an expert systems approach. Specifically, this work entailed consultation with 10 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. The risk assessment framework we present relies

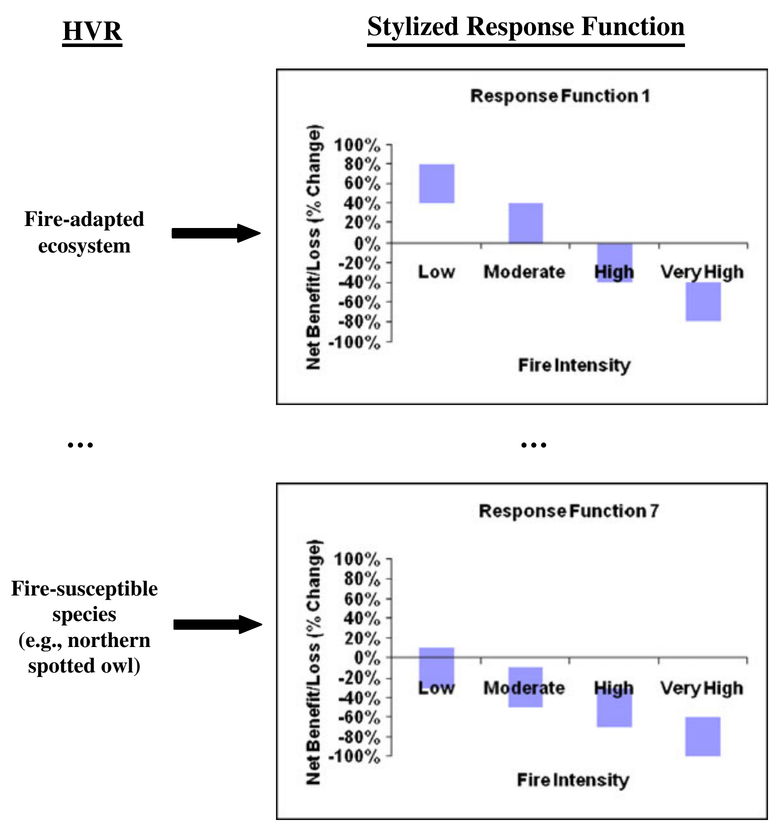

Fig. 3 Conceptual model of expert system approach. Fire and fuels program management officials mapped each HVR to the most appropriate response function. The *bars* indicate a range of relative net value change; the *midpoint of the bar* was used in the risk calculations (see Table 2)

upon expert judgment to define quantitative resource response relationships as a function of fire intensity.

In this article, we describe the design, development, and application of a large-scale wildfire risk assessment decision support tool. We demonstrate a proof-of-concept analysis for the state of Oregon. Although the state of Oregon is not the only suitable prototype, the range of identified resource values provides adequate opportunity to assess wildfire risk across diverse ecosystems. Provinces in the state of Oregon vary widely ranging from mixed-conifer and alpine forests to coniferous forest-tundra to semi-desert (as defined by the Bailey et al. (1994) ecoregion classification system). Oregon hosts abundant plant and wildlife species, some with sensitive habitats potentially at risk of wildfire. Additionally, developed resources occur in areas ranging from densely populated cities to wildland–urban interfaces bordering forested landscapes. These national forests and public lands offer abundant recreation opportunities and also represent areas where fuels treatments may mitigate wildfire risk to identified resources. A more detailed presentation, including issues associated with data acquisition and model design and an expanded discussion of results, can be found in Calkin et al. (2010). We begin with a mathematical definition of risk, then describe the major components of the risk assessment model, next provide preliminary results, and lastly offer some concluding remarks including future research directions.

Wildfire risk assessment

Three main components are required to generate wildfire risk outputs: (1) burn probability maps generated from wildfire simulations, (2) spatially identified HVR, and (3) response functions that describe the impact of fire on the HVR. The components are combined in a risk framework modified from Finney (2005) to calculate a probabilistic expectation of net value change (NVC) to the resource in question. Equation 1 presents the mathematical formulation for calculating NVC.

$$E\left(\mathrm{NVC}_j\right) = \sum_i p\left(f_i\right) \mathrm{RF}_j\left(f_i\right) \tag{1}$$

Table 2 Summary characteristics of the eight response functions assigned by experts

Response function	Description	Relative net value change by flame length class (percent)			
		L	M	H	VH
1	Strong benefit at low fire intensity decreasing to a strong loss at very high fire intensity.	+60	+20	−20	−60
2	Moderate benefit at low fire intensity decreasing to a moderate loss at very high fire intensity.	+30	+10	−10	−30
3	Mild increasing loss from slight benefit or loss at low intensity to a moderate loss at very high intensity.	0	−10	−20	−30
4	Moderate increasing loss from mild loss at low intensity to a strong loss at very high intensity.	−10	−30	−50	−80
5	Slight benefit or loss at all fire intensities except a moderate loss at very high intensity.	0	0	0	−50
6	Strong loss from fire at all fire intensities.	−80	−80	−80	−80
7	Loss increases from slight loss at low intensity to strong loss at very high intensity.	−10	−60	−70	−80
8	Slight benefit or loss from fire at low and moderate intensities and a strong loss from fire at high and very high intensities.	0	0	−80	−80

Values indicate the expected net value change (percent of initial value) for the four flame length classes where:

$E(\mathrm{NVC}_j)$	expected net value change to resource j
$p(f_i)$	probability of a fire at intensity level i
$\mathrm{RF}_j(f_i)$	"response function" for resource j as a function of fire intensity level i

Thus, risk is the product of burn probability at a given fire intensity and the resulting change in resource value, summed over all possible fire intensities. Calculating risk at a given location requires spatially defined estimates of the likelihood and intensity of fire interacted with identified HVR (i.e., exposure analysis). This interaction is quantified through the use of a response function that estimates expected benefits and losses to the specified resource at the specified fire intensity (i.e., effects analysis). Characterizing wildfire risk to HVR in this manner allows for an objective risk monitoring framework and can inform prioritization decisions.

The first component in the risk assessment model is the generation of spatially explicit burn probability maps. We used wildfire simulation outputs from the Fire Program Analysis (FPA) system to quantify wildfire likelihood and intensity. The FPA system is a common interagency strategic decision support tool for wildland fire planning and budgeting (www.fpa.nifc.gov). FPA wildfire simulations include geospatial data, which provide the means to map levels of wildfire risk to lands analyzed within this study. The risk assessment was conducted on a pixilated landscape made up of 886 × 886 ft (approximately 270 × 270 m; 18 acres; 7.3 ha) pixels, consistent with methodology developed for the FPA project. Analyses were conducted at the individual Fire Planning Unit (FPU), and results were developed for the 11 FPUs contained in Oregon. The wildfire simulation model FSim (Finney et al., in review) was used to estimate annual burn probability for each pixel. Figure 1 displays the burn probability map for all FPUs in Oregon.

Figure 2 displays the wildfire hazard map for all FPUs in Oregon. The interaction of burn probability (Fig. 1) and conditional fire intensity (Fig. 2) is a key driver of resource response to wildfire and is, therefore, a key driver of our risk calculations. Wildfire hazard was defined here as the average flame length of all simulated fires that burned a given pixel. Hazard was calculated as the probability weighted flame length among the flame length intervals output from the FSim program. The

Table 3 Assignment of response functions to the HVR included in the study

HVR theme	HVR	Response function (% value change by intensity)
Fire-susceptible species	Bull trout	7 (−10, −60, −70, −80)
	Fender's blue butterfly	7 (−10, −60, −70, −80)
	Greater sage-grouse	7 (−10, −60, −70, −80)
	Kincaid's lupine	7 (−10, −60, −70, −80)
	Marbled murrelet	7 (−10, −60, −70, −80)
	Northern spotted owl	7 (−10, −60, −70, −80)
	Oregon silverspot butterfly	7 (−10, −60, −70, −80)
	Willamette daisy	7 (−10, −60, −70, −80)
Watershed	Municipal watershed	4 (−10, −30, −50, −80)
Energy infrastructure	Communication towers	8 (0, 0, −80, −80)
	Electric transmission lines	8 (0, 0, −80, −80)
	Power plants	8 (0, 0, −80, −80)
	Oil and gas transmission	8 (0, 0, −80, −80)
Recreation infrastructure	Rec. sites and campgrounds	3 (0, −10, −20, −30)
	Ski areas	2 (+30, +10, −10, −30)
	National trails	5 (0, 0, 0, −50)
Air quality	Non-attainment areas	7 (−10, −60, −70, −80)
	Class I Airsheds	3 (0, −10, −20, −30)
Ecosystem	Fire-adapted ecosystems	1 (+60, +20, −20, −60)
Built structures	Low density	6 (−80, −80, −80, −80)
	Moderate and high density	6 (−80, −80, −80, −80)

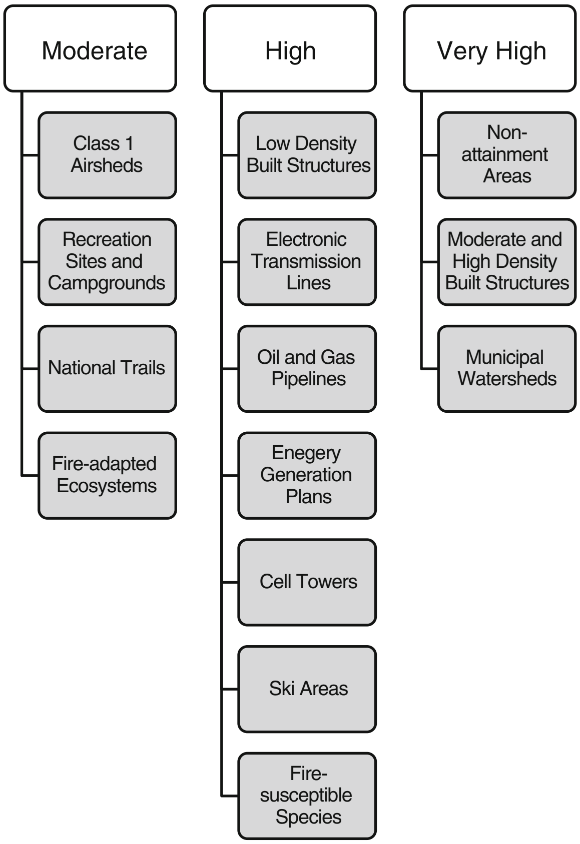

Fig. 4 HVR value class assignments

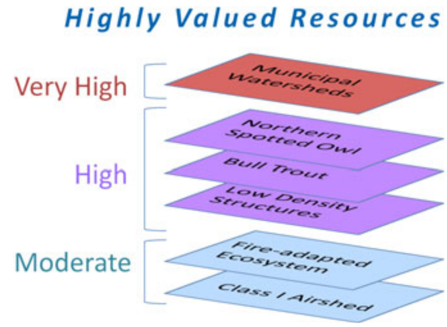

Fig. 5 Hypothetical landscape pixel housing HVRs assigned to various value classes

outputs were then placed into categories corresponding with the response function flame length categories of Low (0 to 2 ft), Moderate (greater than 2 to 6 ft), High (greater than 6 to 12 ft), and Very High (greater than 12 ft). Variation in flame length among simulated fires is caused by a number of factors including wind speed, fuel moisture, and the direction of fire arrival relative to the maximum spread direction.

In general, high hazard values were observed within all FPUs and were associated with higher elevation mixed conifer forests distributed among the various mountain ranges in Oregon (Fig. 2). Averaged across all FPUs, 13% of the total burnable area[1] was assigned to the High hazard category (greater than 6 to 12 ft flame length), 62% to the Moderate hazard category, and 24% to the Low hazard category. None of the burnable area in Oregon was in the Very High hazard category. The Southwest Oregon FPU contained the largest area on both a percentage and total area basis in the High hazard category (47%). The Central Oregon and Southeast/South FPUs show relatively minor area within the High hazard category (4% and 2%, respectively). Nearly all the burnable area in the Southwest, Southeast, and Eastern Oregon FPUs were in the Moderate and High hazard categories. The Northwest and Central Coast FPUs had the largest percentage of area in the Low hazard category, reflecting relatively moderate weather and fuel moisture conditions.

The second component of the risk assessment model involved identification of HVR data layers. With assistance from the FPA Executive Oversight Group, a total of seven HVR categories were identified: energy infrastructure, Federal recreation infrastructure, fire-susceptible species, air quality, municipal watersheds, fire-adapted ecosystems, and built structures. For fire-susceptible species, we mapped designated critical habitat for federally listed threatened or endangered species, with the additional inclusion of key sage-grouse habitat. This key habitat layer was compiled by the BLM National Sage-Grouse

[1]Burnable areas by definition have a non-zero burn probability from the FSim simulation output. Variation existed in the burnable area among the FPUs due to different proportions of non-burnable fuels. In particular, large areas of the Northwest Oregon FPU are considered urban and nonburnable (27%) in a wildfire context. Nonburnable area covered 25% of the Northeast Oregon FPU and 29% of the Coos Bay-Roseburg FPU because each contained large agricultural areas, rock, and other non-burnable land types.

Table 4 Area of fire-susceptible species per Oregon FPUs (acres)

FPU		Bull trout	Fenders blue bfly	Sage-grouse	Kincaids lupine	Marbled murrelet	N. Spotted owl	Oregon silverspot bfly	Willamette daisy
1	Northwest Oregon	15,726	2,954	0	504	891,494	1,647,739	180	703
2	Central Coast Range	0	0	0	0	0	269,886	0	0
3	Southwest Oregon	0	0	0	0	420,014	889,206	0	0
4	Central Oregon	9,295	0	765,180	0	0	95,888	0	0
5	Northeast Oregon	38,262	0	0	0	0	0	0	0
6	Southeast Oregon	8,881	0	4,322,888	0	0	0	0	0
7	Eastern Oregon	3,585	0	3,188,061	0	0	0	0	0
8	Southeast/South	31,777	0	2,333,784	0	0	84,287	0	0
9	Wallowa–Whitman	61,067	0	7,494	0	0	0	0	0
10	Malheur	1,261	0	4,918	0	0	0	0	0
11	Coos Bay/Roseburg	0	0	0	0	226,652	563,369	0	0
Total		169,854	2,954	10,622,324	504	1,538,160	3,550,376	180	703

Mapping Team and was provided to this group for the purpose of informing wildfire decision making. Within these categories, data layers were chosen based on availability at a national scale and HVR representation upon which fire management decisions are made. These categories are not intended to represent the full suite of resource layers considered to be of importance but rather were chosen based on available data to make a first attempt at approximating regional and national HVR datasets.

Data collected for this exercise were obtained from a combination of sources, including enterprise databases, data clearinghouses and servers, and local data aggregated to the national scale. Many of the datasets required augmentation from other sources, while others appeared to require relatively little, if any, processing. Table 1 displays the list of HVR layers included in this monitoring exercise. Despite wide interest in these specific data for many other wildland fire assessment projects, there remain significant challenges to acquire, assemble, and reconcile these data for national wildfire risk analyses. Some ecological data sets, for instance, had to be discarded due to issues with overly coarse spatial resolution or incomplete map extent. Calkin et al. (2010) discuss many of the challenges and issues associated with HVR data acquisition at the national scale.

Response functions are the third component in the risk assessment framework employed in this study. Identifying response functions is critical to enable effects analysis. These functions translate fire effects into NVC to the described resource. In each response function, NVC is based on the flame length of the fire and represents both beneficial and adverse effects to the resource. Although fire outcomes could be related to any fire characteristic, response is typically related to some measure of fire intensity such as flame length (Ager et al. 2007; Finney 2005). Fire intensity is a robust fire characteristic because it integrates two important fire characteristics—fuel consumption and spread rate. The fire modeling results described in the previous section produced burn probability by flame length class for each pixel. Accordingly, we developed response functions to correspond to these same wildfire hazard classes: Low, Moderate, High, and Very High.[2]

The approach used here quantified NVC to a given resource as the percentage change in the initial resource value resulting from a fire at a given flame length. That is, response functions address relative rather than absolute change in resource or asset value. Specifically, risk was quantified as the expected annual relative NVC on a pixel-by-pixel basis. The value of the resource represents the value derived from the resource in this and

[2]Although the study area of Oregon had no burnable area in the Very High hazard class, we nevertheless included this hazard class in response function development for completeness and for future modeling efforts with extensions to broader scales.

all future periods; therefore, NVC was inclusive of future resource value changes including potential recovery or deterioration over time. For example, if a low flame length fire occurred in an area that reduced the immediate values of critical habitat but resulted in less adverse affects (or even positive effects) in subsequent years, the overall response may be less adverse than the initial response because it integrates the future outcomes of the fire.

Initially, a suite of 14 stylized response functions were defined, after considering the different ways in which the various HVRs under consideration might respond to fire of different intensities. The general response functions indicate a range of relative NVC as a percentage of initial resource value for the four flame length classes. National leaders were engaged in order to assign each HVR to a response function. Figure 3 displays the conceptual expert systems approach, which to reiterate relies on expert judgment to map specific resources to the most appropriate stylized response function. In total, eight response functions were retained for assignment to HVRs. Table 2 summarizes each of these response functions, and Table 3 presents the response function assignment for HVRs considered in the analysis of Oregon.

Generating wildfire risk outputs

Quantifying risk in a common unit of measurement facilitates the integration of multiple assets and resource values into a general risk assessment framework. In some cases, it may be possible to monetize benefits and losses. Collapsing integrated risk calculations into a common monetary measure simplifies trend monitoring and allows for fire and fuels management strategies to be objectively evaluated with cost–benefit analysis. However, for a multitude of reasons, our ability to monetize value change to nonmarket resources due to wildfire is severely constrained (Venn and Calkin 2010), limiting the applicability of nonmarket valuation methods for national scale assessments.

Despite the difficulties in monetizing net fire-caused change across multiple HVR value classes,

Table 5 Total Change Equivalent (TCE) by HVR per Oregon PUs

FPU	Energy (Plants)	Energy (Gas)	Energy (ElecTrans)	Energy (Cell)	Rec (Camp)	Rec (Trails)	Rec (Ski)	Fire-Sus species[a]	Air quality (NAA)	Air quality (Airsheds)	Watershed	Fire ecos	Built structures[b]
1 Northwest Oregon	0	0	−2	0	0	0	0	−489	−1	−8	−132	6	−37
2 Central Coast Range	0	–	−4	–	–	0	–	−496	–	0	−100	35	−9
3 Southwest Oregon	0	−7	−92	−1	−8	−2	1	−7981	–	−153	−751	−10	−384
4 Central Oregon	0	−3	−11	0	0	−1	0	−1974	–	−8	−273	3083	−354
5 Northeast Oregon	–	−1	−7	0	0	0	−1	−26	–	–	−115	393	−38
6 Southeast Oregon	0	−6	−15	0	0	0	–	−16851	–	–	−21	3509	−79
7 Eastern Oregon	–	–	−22	0	–	0	–	−10077	–	–	–	1263	−31
8 Southeast/South	0	−1	−9	0	0	0	1	−4448	−8	−8	–	1576	−68
9 Wallowa–Whitman	0	−1	−25	0	0	−1	1	−140	–	−341	−401	420	−53
10 Malheur	–	–	−5	0	–	0	–	−7	–	−33	−81	142	−22
11 Coos Bay/Roseburg	–	0	−2	0	0	0	–	−148	–	0	−67	2	−15
Total	0	−19	−195	−1	−8	−6	2	−42,636	−9	−551	−1,942	10,420	−1,090

Zeros represent fractional acres while dashes indicate no HVR present or no change

[a]Includes sage-grouse

[b]Consolidated across low, moderate, and high density for economy of presentation

a general aggregation of HVR may be informative. In the absence of any such aggregation, a meaningful interpretation of national wildfire risk would be quite difficult given the myriad resources to consider and their non-commensurate measures. We adopted a geospatial proxy measure that aggregates pixel-based risk outputs into an overall measure referred to as Total Change Equivalent (TCE). TCE is the equivalent area lost (gained) assuming 100% loss (gain) for a particular HVR, as measured in acres. For a given HVR, therefore, the response function outputs equivalent area change, providing a common risk measure across HVRs.

Although TCE does provide a common measure of anticipated HVR response to wildfire, it does not provide information regarding social preferences or values. Even in the absence of monetization approaches, the relative values of various socioeconomic and environmental resources may still be estimated. In such cases, multi-criteria analysis can be helpful (Diaz-Balteiro and Romero 2008). For this first approximation, we adopted a coarse-filter approach that assigns each HVR a generic value class—Moderate, High, and Very High (Fig. 4). Value class assignment proceeded with assistance from fire and fuels managers, reflecting in part current

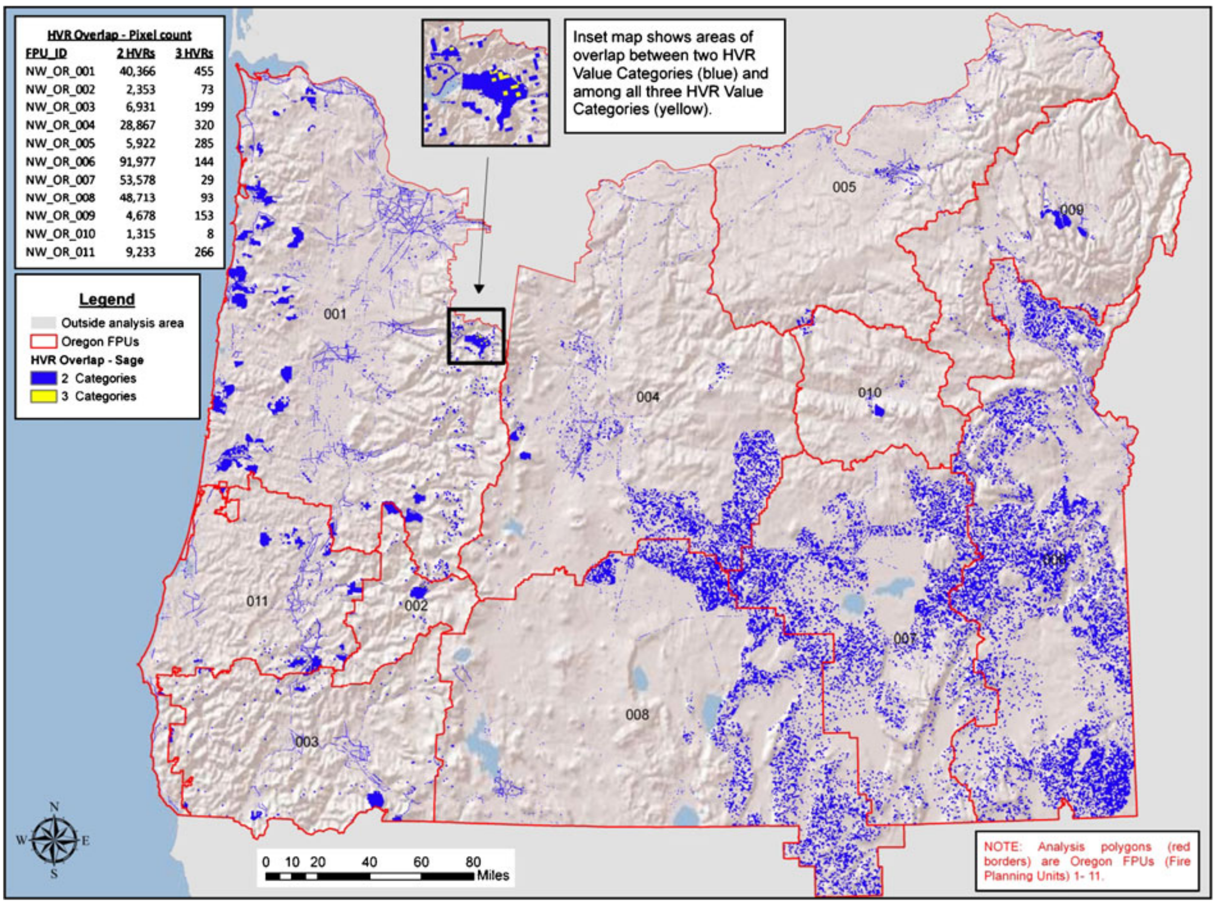

Fig. 6 Map of Oregon FPUs that demonstrates overlapping pixels among HVR value categories, with sage-grouse key habitat included. *Blue pixels* represent areas of overlap between two HVR value categories and *yellow pixels* represent overlapping pixels among three HVR categories. The *black box* and *inset* map highlight an area of high overlap (among three HVR categories). Counts of overlapping pixels by FPU are shown in the table *inset* above

management priorities (see Appendix 1). Because this project addresses only highly valued resources, a “low value” category was not included, thereby excluding all areas not identified as having an HVR. Categorizing the HVR themes implies that HVRs in the same category presumably have values of a similar magnitude. Therefore, the relative risk values are additive within each value category. We made no attempt to weight the relative value or importance of the three value categories to produce an overall weighted wildfire risk TCE value. As a result, Eq. 1 must be calculated separately for each HVR value class.

TCE values were calculated for each pixel and integrated across value categories. To illustrate, consider the hypothetical pixel depicted in Fig. 5. This portion of the landscape houses multiple HVRs spanning all value classes. Within a value class, TCE values are additive, i.e. $TCE_{Moderate}$ is aggregated across Class 1 airsheds and fire-adapted ecosystems, and TCE_{High} is aggregated for low density structures, bull trout critical habitat, and northern spotted owl critical habitat. TCE for a given HVR, say critical habitat for the northern spotted owl, can be calculated as follows. Assume that this 18-acre pixel of critical habitat (Resource Response Function 7; Table 3) had a 0.5% chance of burning with high fire intensity (70% loss in value) and a 1% chance of burning with very high fire intensity (80% loss in value).

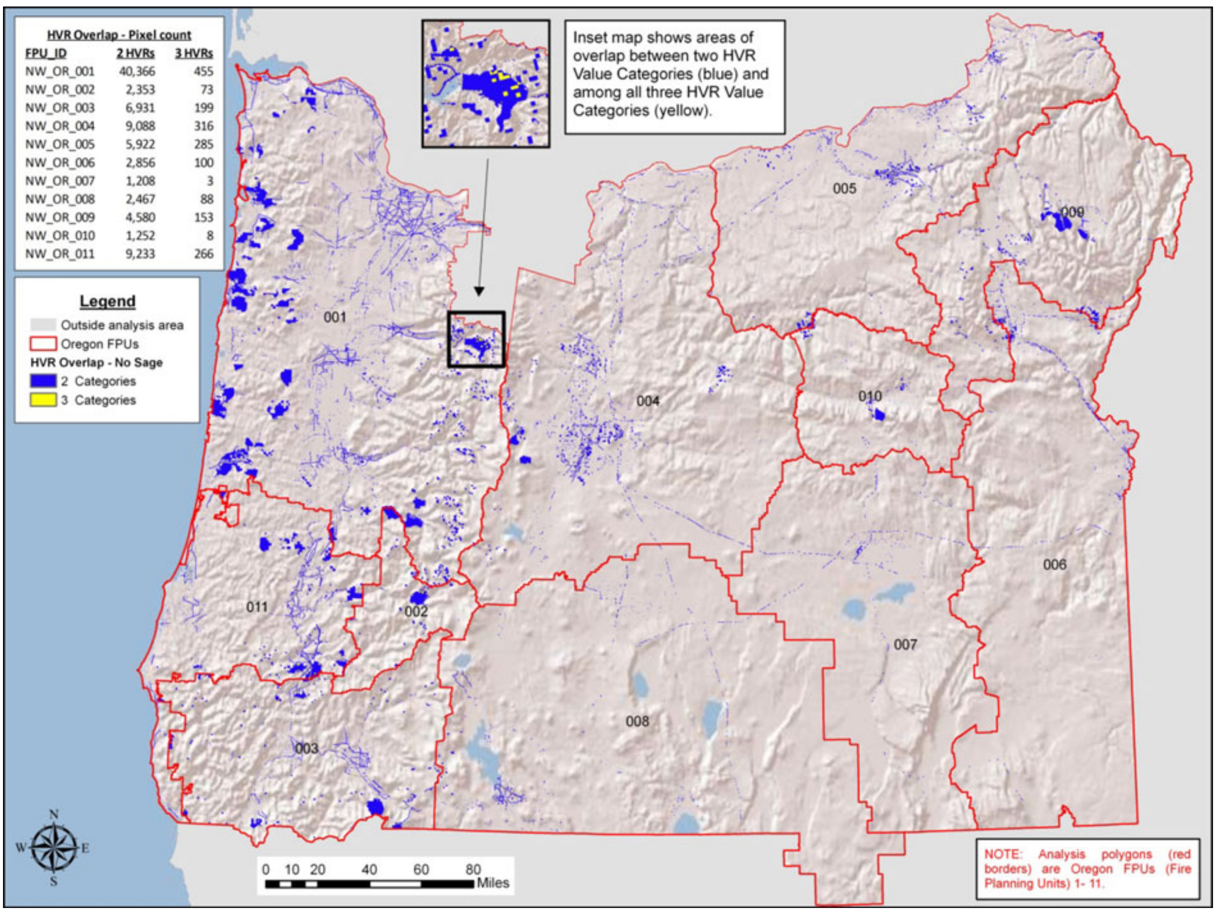

Fig. 7 Map of Oregon FPUs that demonstrates overlapping pixels among categories, *without* sage-grouse key habitat. *Blue pixels* represent areas of overlap between two HVR value categories and *yellow pixels* represent overlapping pixels among HVR categories. The *black box* and *inset* map highlight an area of high overlap (among three categories). Counts of overlapping pixels by FPU are shown in the table *inset* above

The contribution of this specific HVR to TCE_{High} would equal -0.207 acres $[(0.005 \times -0.7 \times 18 \text{ acres}) + (0.01 \times -0.8 \times 18 \text{ acres})]$. TCE_{High} for bull trout critical habitat, which shares the same response function, would be identical.

Results

The results we present here apply only to the study area across the state of Oregon; future analyses will describe risk at the national scale. Fire-susceptible species comprised the largest area (15.7 million acres) among the HVR themes, primarily due to sage-grouse habitat within FPUs Southeast Oregon, Eastern Oregon, and Southern Oregon, and because of northern spotted owl and marbled murrelet habitat in the Northwest Oregon FPU. In particular, sage-grouse habitat comprised more than half of the total area of all fire-susceptible species (Table 4). Fire-adapted ecosystems comprised 9.4 million acres, mostly distributed east of the Cascade Mountains. Municipal watersheds and built structure density were next largest at 5 and 2.1 million acres, respectively. The air quality theme made up 1.6 million acres, energy related utilities covered more than 1.2 million acres, and the recreation theme comprised the lowest total area at approximately 217,000 acres. It should be noted that all HVR were represented as 886 × 886 ft (approx. 270 × 270 m) pixels so the area of linear features like trails and transmission lines were represented by a buffer and probably cover less area than estimated. Ski area locations were represented as 1 mile (1.6 km) buffered points because actual area polygons were unavailable.

The percent area covered by at least one HVR on burnable area varied from 19% to 91% among the 11 FPUs and averaged 58% over the entire

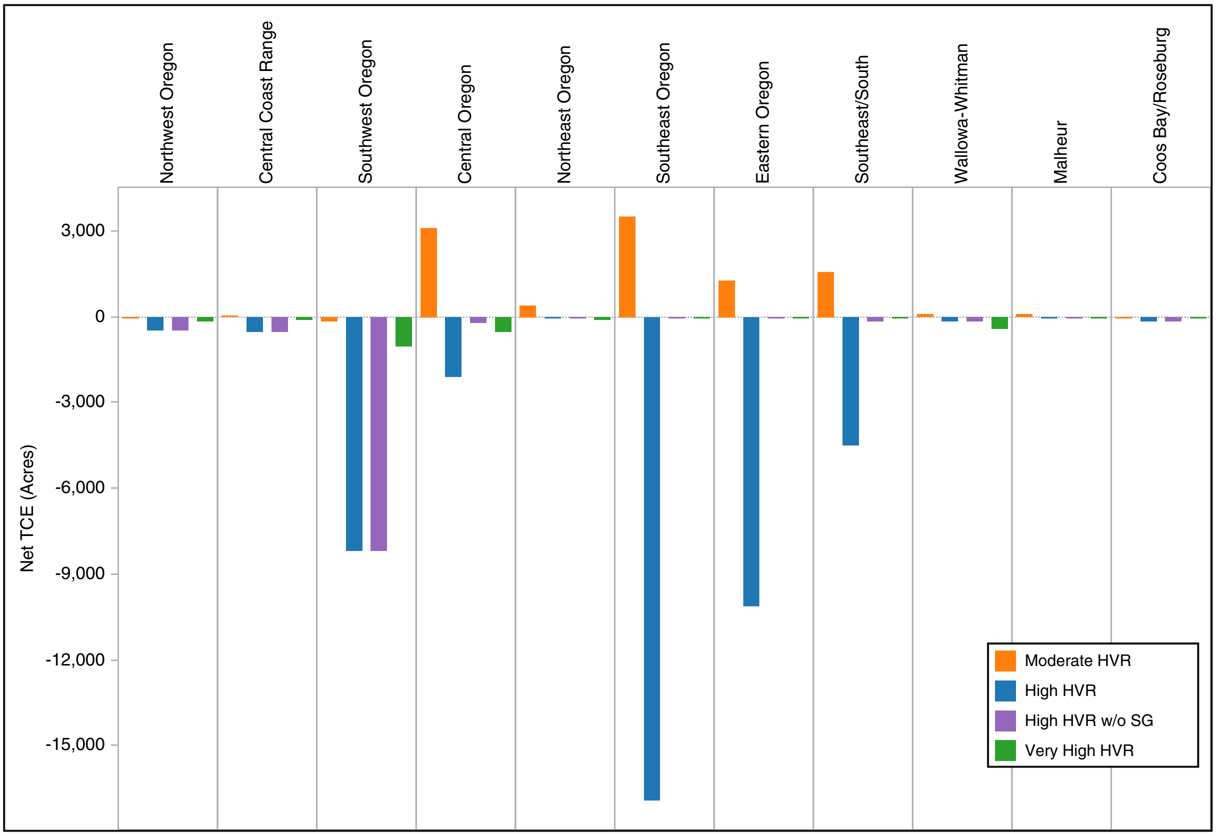

Fig. 8 Total Change Equivalent (TCE) by HVR value category for the Oregon FPUs. The High HVR category shown here includes sage-grouse key habitat

Table 6 Total Change Equivalent (TCE) by FPU and HVR category

FPU		TCE (acres)			
		M	H (w/ SG)	H (w/o SG)	VH
1	Northwest Oregon	−2	−500	−500	−161
2	Central Coast Range	35	−504	−504	−106
3	Southwest Oregon	−173	−8,192	−8,192	−1,026
4	Central Oregon	3,075	−2,105	−224	−510
5	Northeast Oregon	392	−55	−55	−132
6	Southeast Oregon	3,507	−16,922	−76	−52
7	Eastern Oregon	1,261	−10,120	−56	−11
8	Southeast/South	1,569	−4,492	−158	−40
9	Wallowa–Whitman	80	−194	−175	−424
10	Malheur	108	−23	−18	−93
11	Coos Bay/Roseburg	2	−155	−155	−73
Total		9,854	−43,263	−10,113	−2,627
Average		896	−3,933	−919	−239

Values represent annual change. The M (Moderate) value category contains both positive and negative values because some FPUs had beneficial effects from fire that outweighed the negative effects—principally due to the response function for fire-adapted ecosystems. Results for the H (High) value category are shown with and without sage-grouse habitat for comparison

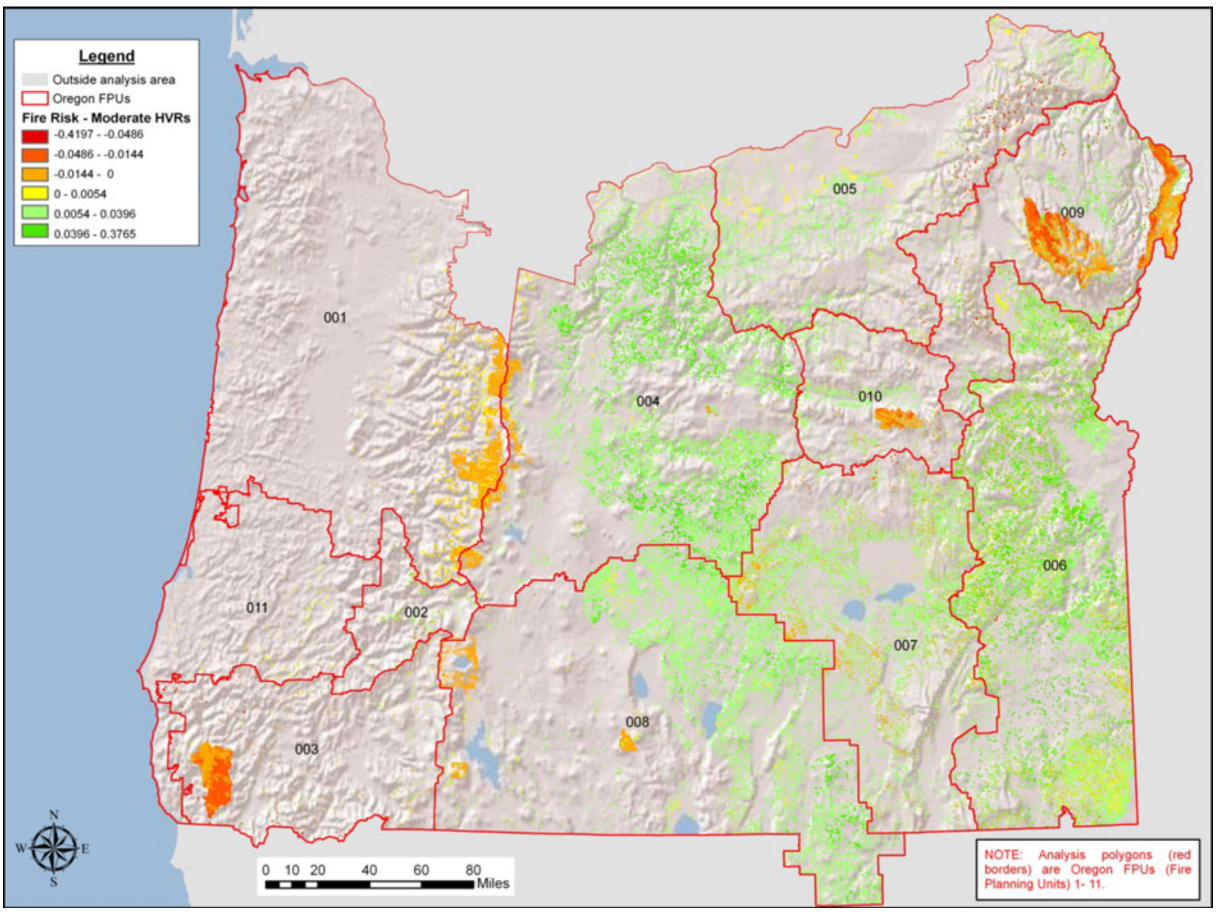

Fig. 9 TCE of HVRs in the moderate value category for the Oregon FPUs

study area. Southeast and Eastern Oregon FPUs had the highest percentage of HVR within their boundaries primarily due to sage-grouse key habitat. The Coos Bay/Roseburg and Northwest Oregon FPUs had the highest percentage of area in the Very High category (17% and 21%, respectively) primarily due to human population as indicated by the built structure data.

Table 5 displays TCE by HVR for all FPUs in Oregon. This information shows how each resource responds to the simulated wildfire conditions across the state prior to aggregating results across value categories. Fire-susceptible species in particular evince a negative response to fire, although this relates to the spatial extent of sage-grouse habitat (see discussion below). Municipal watersheds, built structures, Class 1 airsheds, and electronic transmission lines, in descending order, also appear susceptible to damage by wildfire. Fire-adapted ecosystems by contrast are expected to incur a net ecological benefit due to the presence of wildfire on the landscape (see also Fig. 9); this information could be useful for developing fire management plans that allow more fires to burn under favorable conditions.

The broad spatial extent of the sage-grouse habitat could bias risk calculations to overemphasize certain FPUs with large areas of identified habitat. One possible interpretation is that the key sage-grouse habitat was delineated more coarsely than other fire-susceptible species layers. Subsequently, we evaluated risk with and without the sage-grouse habitat included in the analysis. With the sage-grouse key habitat included, there

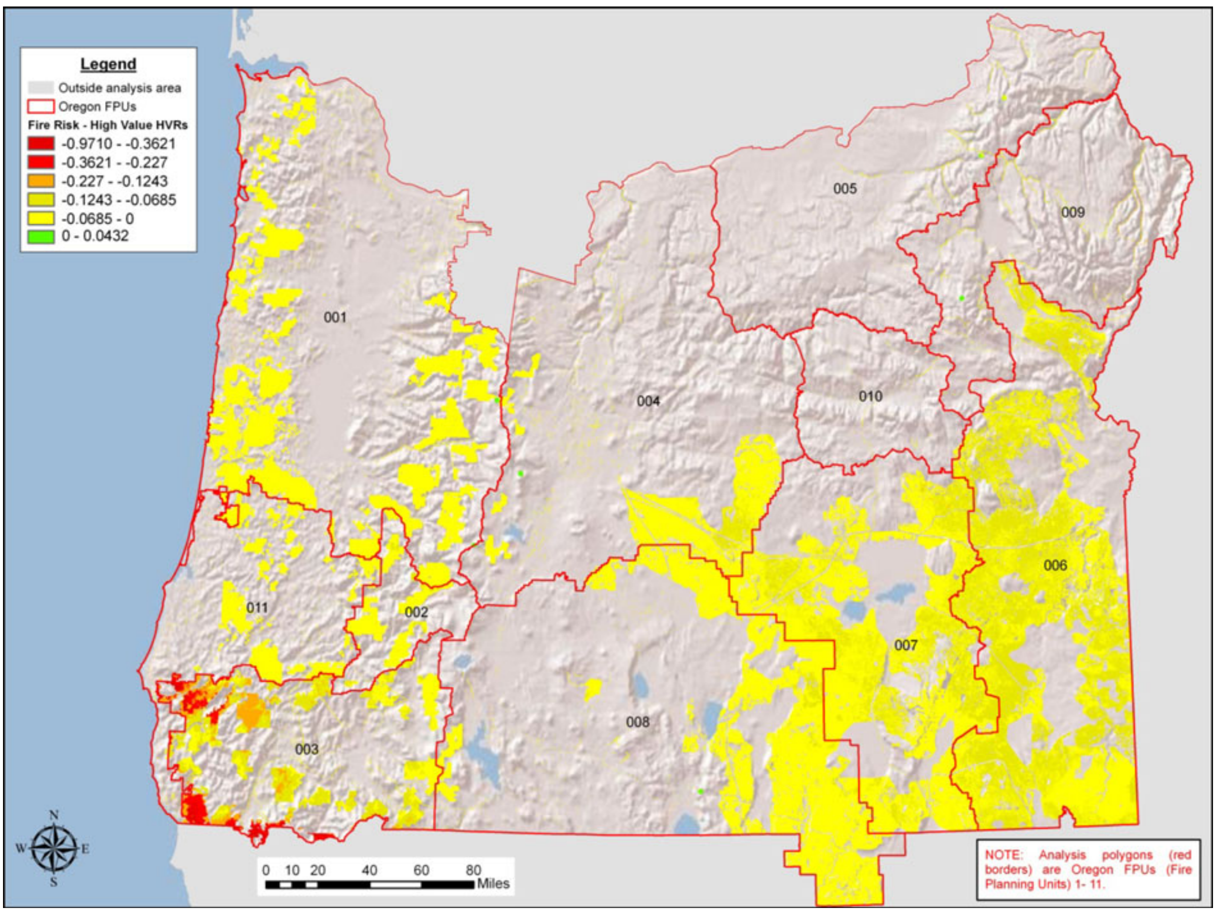

Fig. 10 TCE of HVRs in the high value category for the Oregon FPUs *with* sage-grouse

was considerable overlap among the HVR value categories (Fig. 6). When sage-grouse key habitat is removed from the analysis, the amount of HVR value category overlap significantly declines (Fig. 7). The majority of the overlap exists between two value categories while relatively little overlap occurs among all three value categories.

Figure 8 displays TCE by value category for all FPUs in Oregon. In general, TCE estimates were relatively low, reflecting low burn probabilities for individual pixels. The positive values for $TCE_{Moderate}$ reflect beneficial effects of fire for fire-adapted ecosystems. Large negative TCE_{High} values are observed in Southeast Oregon, Eastern Oregon, and Southeast/South due to extensive sage-grouse habitat. When calculated, absent sage-grouse habitat, TCE_{High} values within those same FPUs are significantly lower. TCE_{High} values within the Southwest Oregon FPU are not sensitive to sage-grouse habitat, as that FPU instead houses critical habitat for the northern spotted owl and the marbled murrelet.

TCE averages (Table 6) across all FPUs were +896 acres (Moderate-value category), −3,933 acres (High-value category, with sage-grouse), −919 acres (High-value category, without sage-grouse), and −239 acres (Very-High-value category). Projected loss was largest for the High-value category whether sage-grouse was included or not. The total HVR area by category had a strong influence on the TCE estimates—the more HVR area within an FPU, the higher the loss estimate for TCE given a constant burn probability, flame length, and response function. Spatial

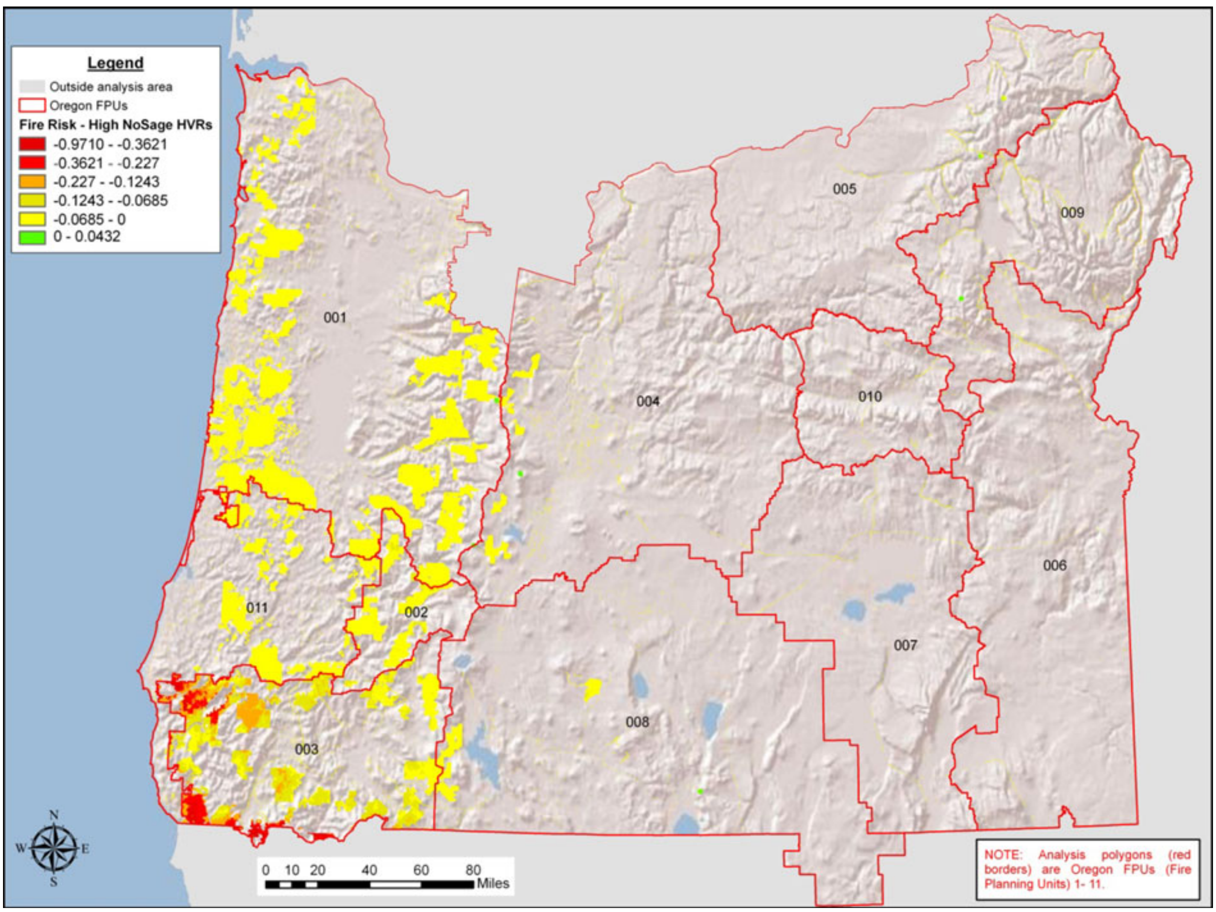

Fig. 11 TCE of HVRs in the high category for the Oregon FPUs *without* sage-grouse

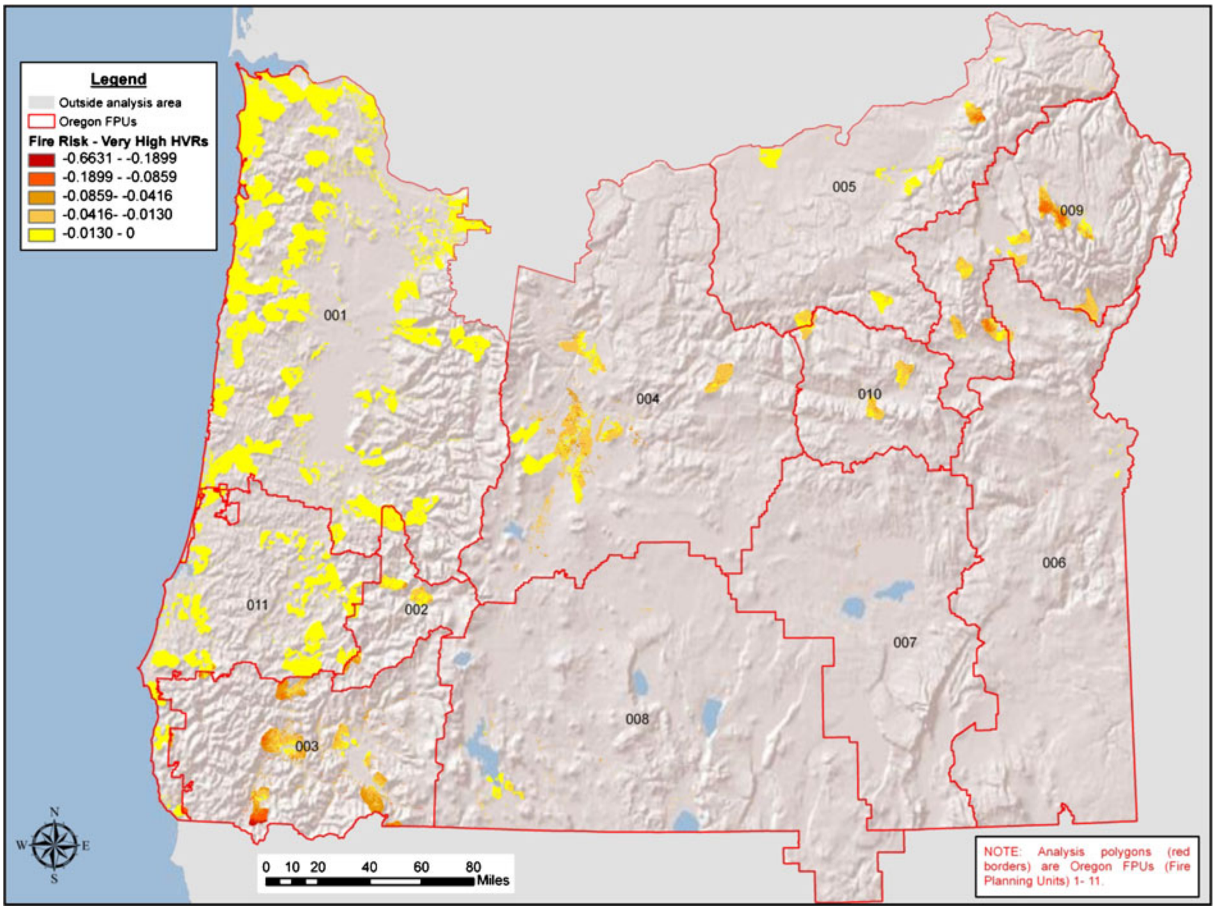

Fig. 12 TCE of HVRs in the very high value category for the Oregon FPUs

patterns of TCE largely reflected the distribution of HVR (Figs. 9, 10, 11, and 12).[3] In Fig. 9, much of central and eastern Oregon is green (positive net value change), which again reflects beneficial effects to fire-adapted ecosystems. Figures 10 and 11 illustrate the significant degree to which key sage-grouse habitat influences risk calculations for TCE_{High} and tend to suggest a modest level of risk to resources distributed across the Cascade and Coast ranges, with higher risk levels in the Southwest Oregon FPU. Figure 12 indicates that there is no expectation of benefit to resources in the Very-High-value category, that moderate loss is anticipated across Northwest Oregon and the Central Coast Range, and that the Southwest Oregon and Central Oregon FPUs have the largest degree of relative risk (see also Fig. 8).

The largest negative TCE was observed for the Southeast Oregon FPU for the High-value category at −16,922 acres (only −76 acres without sage-grouse). The Southwest Oregon FPU exhibited the largest negative TCE for the Very-High-value category, at −1,026 acres. The large negative TCEs for the High (with sage-grouse) category in the Eastern Oregon and Southeastern Oregon FPUs resulted from a combination of high burn probabilities and large areas of key sage-grouse habitat. The large negative TCE in the

[3]Note that the color-mapped values in the legends in Figures 9-12 are not consistent across value categories, in order to better distinguish the relative risk within rather than across value categories. That is, a mapped pixel of red (indicating high relative risk of loss) in Fig. 9 for $TCE_{Moderate}$ does not necessarily represent the same TCE value for a pixel mapped red in Fig. 10 for TCE_{High}.

High category in the Southwestern FPU resulted from large areas of northern spotted owl and marbled murrelet critical habitat combined with high burn probabilities. Positive TCE and APC were realized in the Moderate category in many of the FPUs due to the positive benefits realized from low and moderate intensity fires in fire-adapted ecosystems (Table 3; Response Function 1). The Central and Southeast FPUs have the largest projected benefit from wildfire at 3,075 and 3,507 acres, respectively.

In aggregate, these results suggest prioritizing the Southwest Oregon FPU, as it presents the greatest risk to valued resources within both the High- and Very-High-value categories. Depending upon the relative worth of the value categories, one might next prioritize Central Oregon with the second largest negative value for $TCE_{Very-High}$, followed by the Wallowa–Whitman FPU. With sage-grouse excluded from the analysis, the Southeast Oregon, Eastern Oregon, and Southeast/South Oregon FPUs appear to present the least amount of risk and even offer expected benefits to fire-adapted ecosystems.

Discussion and concluding remarks

This paper presented methods to incorporate wildfire spread, fire intensity, and change in value for a range of human and ecological values into a risk framework. The spatial, temporal, and social dimensions of the wildfire risk problem are challenging the Federal land management agencies to meet societal needs while maintaining the health of the lands they manage. Recent fire management data and modeling developments, such as LANDFIRE, FPA, and Wildland Fire Decision Support System, among others, allow a level of analysis and assessment that were, until very recently, impossible. These developments pose opportunities to analyze, communicate, and implement a more risk-informed fire management policy that can reduce Federal fire management costs and improve land condition. Extensions of these efforts, such as the one described in this paper, demonstrate the potential of a national risk assessment framework. This study is scalable from local project planning to national assessments and can accommodate a broad range of fire management activities such as fuel treatment scheduling, fire planning, suppression decisions support, and fire resource budgeting.

Here, we demonstrated a proof-of-concept application of the wildland fire risk assessment decision support tool. Risk assessment requires the identification of valued resources at risk, as well as the integration of information regarding both the likelihood of fire and the magnitude of resource response to fire (i.e., exposure and effects analysis). Few efforts to date have incorporated analysis of fire effects, due in part to substantial uncertainty regarding resource response and relative value of resources. Our review of the literature and of current planning tools revealed that significant knowledge uncertainty was limiting efforts at quantitative effects analysis. For this large-scale wildfire risk assessment, we employed the most appropriate decision support tool, an expert systems approach to handle knowledge uncertainty. The authors engaged experts and senior leadership in the wildland fire community for assistance in valuing resources and interpreting fire effects on resources, in order to adequately assign response functions.

The information gathered in this study can be summarized in tabular and map formats at many different scales. The overall purpose of the analysis is to provide a base line of current conditions for monitoring trends in wildfire risk over time, and to develop information useful in prioritizing where fuels treatments and mitigation measures might be proposed to address significant wildfire risk. Future analyses would be used to determine trends and changes in response to fuel reduction investments, climate shifts, and natural disturbance events (e.g., bark beetles) between the timeframes analyzed. Monitoring data could be used to address national and regional questions regarding changes in fire risk and hazard as a result of investment strategies or changing conditions. The tool directly responds to critiques by Office of Management and Budget, General Accounting Office, and Congress that call for risk-based performance measures to document the effectiveness of fire management programs.

Managing federal lands requires the integration of multiple social, economic, and ecological values. With respect to the relative social value of the HVRs, for this first approximation, we adopted only a coarse-filter approach that categorized HVRs as Moderate, High, or Very High in value. Refinements in data quality will facilitate value class assignment. We identified expert disagreement on the need to assign a single value class to national level data when there was desire to assign a different value to assets within a national aggregate class. For instance, there was a desire to assign well-developed campground sites in major National Parks a High value compared to small campgrounds with few amenities that would be assigned a Moderate value. However, the attribution for all Federal campgrounds was not equally descriptive and further separation by value classes is not feasible at this time.

Future work could delve deeper into multi-criteria analysis to better approximate the relative social values across HVRs. In this example, we relied on a priori, cardinal expressions of preference. Although we recommended a sensitivity analysis of the weights, more robust techniques exist to statistically assess the uncertainty surrounding expressions of cardinal preferences (e.g., Alho and Kangas 1997). Preference uncertainty can be significant; Kurtilla et al. (2009) for instance identified preference uncertainty as the dominant form of uncertainty in the development of forest management plans involving multiple criteria. Some research offers concepts such as dynamic learning or preference discovery, suggesting that with experience individuals' ability to articulate preferences improves (e.g., Brown et al. 2008; Braga and Starmer 2005; Holmes and Boyle 2005). Participatory decision making approaches that incorporate multiple stakeholders and incorporate "soft" methods are increasingly methods are increasingly popular tools for deriving social weights (Diaz-Balteiro and Romero 2008; Mendoza and Martins 2006). Interactive, iterative preference articulation could allow decision-makers to gain experience with the process and to better understand their preferences.

Beyond multi-criteria approaches, nonmarket valuation techniques could also be brought to bear to articulate social weights across HVRs. Translating response functions into monetary values is likely to be more readily understood and communicated across different forest officials, policy makers, and other stakeholders. Venn and Calkin (in press) review a variety of approaches that have been employed in the wildfire management context, including hedonic pricing, travel-cost models, benefit transfer, contingent valuation, and choice modeling. The authors highlight a number of challenges with existing methods, and recommend a suite of regional choice modeling studies moving forward to inform management of public lands. Brillinger et al. (2009, p. 618) echo the sentiment relating to a lack of valuation information, citing a "substantial gap in the scientific understanding of the overall social cost associated with wildfires." We should note that even without explicitly adopting monetization approaches, by assigning quantitative weights across HVRs where a given resource does have commercial value effectively means that all resources have been priced (e.g., Rideout et al. 2008).

Future work will also be required to improve input data quality, refine response functions by engaging resource specialists, and to better handle the temporal nature of resource response to disturbance. The coarse nature of identified key sage-grouse habitat, for instance, tended to inflate risk in southeastern Oregon beyond what would be considered reasonable. To illustrate this inflation, we performed a with/without analysis, although this should not be interpreted to mean we suggest key sage-grouse habitat should altogether be removed from analyses. More recent efforts at national-scale assessments have identified similar issues with other species, such as the Canada lynx. That fire-susceptible species with broader distributions of habitat increase rather than decrease risk is counter to the more intuitive notion of relative scarcity influencing risk. The issue of spatial overrepresentation of critical habitat or other resources leads to concerns about strategic gaming to influence prioritization (e.g., Rideout et al. 2008). Efforts are underway to identify agency leads, prioritize resource data layers, and in some cases, identify appropriate financial resources to address the need for nationally consistent natural resource data layers. The first steps following identification of priority data layers will be to develop data standards and request data input from the appropriate agencies.

Response function assignments in the future will be better tailored to specific resources of interest, and risk calculations will be formulated so as to account for the role of time. In this first approximation, expert opinion differed on assigning response functions to nonattainment areas, Class I airsheds, and fire-adapted ecosystems. Differences largely centered on the desire to alter the response function through different time horizons. For example, smoke from current wildfires is initially harmful; however, smoke from future fires in the area will likely be lessened due to the reduction in fuels. We intend to involve more input from the scientific and research communities in subsequent exercises to better inform management decisions related to fire effects on resources and sensitive species. This input is critical to accurately interpret model results.

The application of annual value change to quantify risk to HVRs creates additional challenges because some of the identified HVRs are proxies for the real underlying value at risk. For example, considering the Critical Habitat layer, its role in preventing extinction is what is most important. If the entire habitat is destroyed in the short term, it will not matter if it recovers quickly because the species that depend on it may become extinct in the meantime. If half the habitat is destroyed now and then recovers, but the other half is destroyed later, the species may survive. These are two very different outcomes for the same aggregate value change. Because of the potential biases created by the current state of spatial data and challenges in assigning value to modeled resources, the authors recommend caution in utilizing these results to distribute budgets and prioritize large areas for fuel treatment and mitigation efforts.

An awareness and understanding of the limitations of our approach is important for other practitioners seeking to apply similar methodologies in other management contexts. As we have made clear, wildfire risk assessments are subject to knowledge uncertainty surrounding the effects of fire on valued resources and the preference uncertainty surrounding the relative valuation of market and nonmarket resources. Our approach of defining response functions, assigning social weights, and outputting expected value change provides a quantitative framework for integrated risk assessment but does not fully capture important issues such as the variability around statistical expectations and the spatiotemporal dynamics of resource response to fire. Other researchers may opt to define resource-specific response functions rather than our generalized ones or to use resource-specific social weights rather than value classes. As planning scales decrease, the ability to further stratify analyses according to questions of fire effects and valuation improves. The intent for this prototype was to demonstrate the methodology for national applications.

Though we believe the use of expert judgment to be the most suitable approach to managing knowledge uncertainty, caution and attention to detail are warranted. Due diligence requires a critical review of information gleaned, for instance by ensuring the appropriate experts were queried and cross-checking expert opinions with available scientific literature. The expert panel we employed was comprised of fire and fuels program management officials from the US Department of Agriculture and the US Department of Interior. While these individuals are relatively homogenous in the positions they hold as senior leadership in Federal agencies, they represent agencies with diverse management objectives, and each provides a different perspective to the resource response discussion. As a group, their opinions may reflect viewpoints consistent with wildfire policy and management, where interactions with resource specialists (as intended in future efforts) would likely provide resource-focused response functions, further refining effects analysis.

At present, researchers with the Forest Service are working to scale up the analysis to the national level and deliver results to decision makers. We believe this first approximation demonstrates that it is now possible to represent and quantify risk at the broad scale of the sub-regions of the USA using the best available data. We also believe this first approximation has identified future efforts that could make this framework more applicable to fire management resource distribution efforts. Existing models' analytical capabilities could be enhanced by incorporating the effects of fire on HVR, and engaging with more resource experts is a clear next step in advancing effects analysis. The authors are encouraged by the efforts that Federal fire management officials and agencies have made to date and we believe the potential payoffs from this focus far outweigh the costs.

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Appendix 1: Justification of HVR value class and response function assignments

All critical plant and wildlife habitat layers were placed in the High-value category due to the rarity of critical habitat and the inability or length of time required to replace them if lost or damaged by fire. Critical habitat of fire-susceptible species was assigned to Response Function 7 (RF7; Table 3) based on the assumption that low flame length fire results in mild loss, but greater flame length fire results in substantial net reduction of habitat value.

Municipal watersheds were placed in the Very-High-value category due to the direct implication to human health and welfare. It was assumed that low flame length fire generally corresponds to lower fuel consumption and lower severity and would, therefore, have a less adverse impact on the watershed and water quality value. This was assigned to RF4, indicating a small value reduction at low flame length, which would increase to substantial reduction of value at high flame length.

All energy infrastructure HVR were placed in the High-value category because of their importance to the function of modern society. Although these assets are replaceable if damaged or destroyed, loss can cause significant disruption over the short and medium term. All energy infrastructure HVR were assigned to RF8 based on the assumption that only high to very high flame length causes damage to these assets, but that damage, when it occurs, is generally substantial.

For recreation infrastructure, the recreation sites and national trails HVR were placed in the Moderate-value category (the lowest value category used in this project, which addresses only highly valued resources). Ski areas were placed in the High-value category due to their relative scarcity and to the difficulty of replacing them because of site requirements. Recreation sites were assigned to RF3 on the assumption that their value reduction is proportional to flame length; however, sites may remain functional even after high severity fire. Ski areas were assigned to RF2 on the assumption that low flame length fire may confer a net benefit by accomplishing routine vegetation management and reducing the likelihood of a future, more damaging fire. We also assumed that high flame length fire would significantly, but not completely, reduce the value of the ski area. National trails were assigned to RF5 on the assumption that only very high fire severity would adversely affect the value of these trails; lower flame length fires would have little effect on trail value. Furthermore, the net value reduction at the highest fire flame length class is not 100% because these trails can typically be reconstructed as needed.

Non-attainment areas were placed in the Very High-value category due to the direct implication to human health and welfare. Non-attainment areas were assigned to RF7 because they have the potential for slight loss from low flame length fires, but would likely experience substantial loss at all flame lengths above low. Class I Airsheds were assigned to RF3 and the Moderate-value category, which assumes that fires of increasing flame length class would be increasingly damaging to the visibility and air quality within the airshed.

Fire-adapted ecosystems were placed in the Moderate-value category because fire is important in these ecosystems and is necessary to maintain healthy and functioning environments. Fire-adapted ecosystems were assigned to RF1 on the assumption that low flame length fire would confer a substantial net benefit, but higher flame length fires would result in increasing loss.

Finally, pixels identified as containing built structures were assigned to one of two categories: (1) High initial value for low density cells that were estimated to contain only one built structure (one or two projected persons per cell) and (2) Very High for cells that were estimated to contain more than one built structure (three or more persons per cell). Both built structure categories were assigned to RF6, assuming that any fire had the potential to result in a substantial loss.

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