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Case Study

Integrated Wildfire Risk Assessment: Framework Development and Application on the Lewis and Clark National Forest in Montana, USA

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ABSTRACT

The financial, socioeconomic, and ecological impacts of wildfire continue to challenge federal land management agencies in the United States. In recent years, policymakers and managers have increasingly turned to the field of risk analysis to better manage wildfires and to mitigate losses to highly valued resources and assets (HVRAs). Assessing wildfire risk entails the interaction of multiple components, including integrating wildfire simulation outputs with geospatial identification of HVRAs and the characterization of fire effects to HVRAs. We present an integrated and systematic risk assessment framework that entails 3 primary analytical components: 1) stochastic wildfire simulation and burn probability modeling to characterize wildfire hazard, 2) expert-based modeling to characterize fire effects, and 3) multicriteria decision analysis to characterize preference structures across at-risk HVRAs. We demonstrate application of this framework for a wildfire risk assessment performed on the Little Belts Assessment Area within the Lewis and Clark National Forest in Montana, United States. We devote particular attention to our approach to eliciting and encapsulating expert judgment, in which we: 1) adhered to a structured process for using expert judgment in ecological risk assessment, 2) used as our expert base local resource scientists and fire/fuels specialists who have a direct connection to the specific landscape and HVRAs in question, and 3) introduced multivariate response functions to characterize fire effects to HVRAs that consider biophysical variables beyond fire behavior. We anticipate that this work will further the state of wildfire risk science and will lead to additional application of risk assessment to inform land management planning. Integr Environ Assess Manag 2013;9:329–342. © 2012 SETAC

Keywords: Wildfire   Ecological risk assessment   Environmental management   Simulation   Expert judgment   Multicriteria decision analysis

INTRODUCTION

The financial, socioeconomic, and ecological impacts of wildfire continue to challenge federal land management agencies in the United States (Thompson et al. 2012; Bruins et al. 2010). In recent years, policymakers and managers have increasingly turned to the field of risk analysis to better manage wildfires and to mitigate losses to highly valued resources and assets (HVRAs). This trend is evident, for instance, in the widespread adoption of the Wildland Fire Decision Support System (Calkin, Thompson et al. 2011; Noonan-Wright et al. 2011), in the design and delivery of decision support tools for fuels management (Ager et al. 2011), in the development and implementation of the National Cohesive Wildland Fire Management Strategy (Calkin, Ager et al. 2011), and in recent and ongoing efforts at strategic, integrated risk assessment (Thompson, Calkin, Finney et al. 2011). Use of wildfire risk assessment models can facilitate decision making across the fire management spectrum, with application to fire prevention, hazardous fuels management, fire detection, initial attack dispatch, and large fire suppression (Martell 2007).

Wildfire risk analysis is fundamentally interdisciplinary, requiring the pairing of substantive expertise in the biophysical sciences with methodological expertise in the decision sciences. Assessing wildfire risk entails the interaction of multiple components, including geospatial integration of wildfire simulation outputs with HVRAs (exposure analysis), and the further characterization of fire effects to HVRAs (effects analysis). For planning purposes it is critical that assessment results be both spatial and quantitative (Thompson and Calkin 2011). Spatially explicit characterizations of wildfire risk are necessary to reflect variability in topography, vegetation conditions, ignition density, burn probability, fire intensity, and spatial patterns of HVRAs. Quantifying risk facilitates analysis of tradeoffs across HVRAs, and enables cost-effectiveness analysis as a basis for evaluating risk mitigation options.

Spatial burn probability modeling enables robust analysis of HVRA exposure to wildfire, yet lagging behind fire modeling efforts is a comprehensive understanding of the socioeconomic and ecological consequences of fire (Keane et al. 2008; Venn and Calkin 2011). This knowledge deficit is manifest in terms of limited or inadequate empirical observations, a lack of predictive models, and limited understanding of complex ecological processes. Models to estimate first-order fire effects (e.g., tree mortality, soil heating, fuel consumption, and smoke emissions) do exist, although some level of inference is still necessary to characterize the broader effects (e.g., habitat

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loss) in which managers are typically more interested (Reinhardt and Dickinson 2010). Despite these challenges, it remains critical to characterize likely wildfire-related losses (and benefits) to assess risk and to prioritize mitigation efforts accordingly.

In such cases characterized by complexity and uncertainty, a formal recognition of uncertainty and reliance of expert judgment is often the most suitable approach (Borchers 2005). Formal elicitation and application of expert judgment is one of the only options to synthesize available scientific knowledge for time-sensitive policy or managerial decisions and can provide increased rigor relative to reliance on intuition, rules of thumb, or other proxies (Krueger et al. 2012). The application of expert knowledge in ecology and natural resource management is common (Failing et al. 2004, 2007; Cheung et al. 2005; Marvin et al. 2009; Murray et al. 2009; Runge et al. 2011; Marcot et al. 2012), due largely to the fact that the types of questions being proposed are characterized by uncertainty and a lack of data, and because management decisions based on ecological risk assessment often cannot afford to delay for further study and analysis (Kuhnert et al. 2010). Application in the wildfire literature is extensive, including related but simpler and less formal work on fire effects analysis (Thompson, Calkin, Gilbertson-Day et al. 2011), estimation of aerial suppression effects on wildfire containment time (Plucinski et al. 2011), comparative assessment of prefire versus during-fire management actions (Penman et al. 2011), multicriteria analysis exploring the causative factors of fire (Vadrevu et al. 2009), calibration and critique of fuel models to design landscape fuel treatment strategies (Bahro et al. 2007), analysis of forest stand vulnerability to fire based on structural characteristics (González et al. 2007), estimation of initial attack crew productivity (Hirsch et al. 2004), and estimation of aerial retardant fireline production rates (Mees et al. 1994).

Further challenging integrated risk assessment is a lack of a common currency across market and nonmarket HVRAs. Previous quantitative wildfire risk analyses have tended to focus on assessing risk to commercial resources and assets such as timber (Konoshima et al. 2010), with little applicability to the natural, cultural, and ecological values for which federal agencies must manage. Time and resource constraints, limited studies of nonmarket HVRAs, limited applicability of benefit transfer approaches, and other factors often prohibit the use of nonmarket valuation in wildfire risk assessment (Venn and Calkin 2011). Fortunately, multicriteria decision analysis techniques can be used to help resource managers balance and quantify tradeoffs and to articulate preferences and relative importance of HVRAs (Kiker et al. 2005; Ananda and Herath 2009).The establishment of relative importance (RI) weights across HVRAs enables the integrated presentation of risk, allows for simpler mapping and visualization, and can facilitate prioritization decisions. The establishment of RIs further makes clear the delineation between knowledge and preferences, which is necessary for transparency and rigor in decision processes (Gregory and Long 2009).

In this article, we demonstrate the application of a systematic, integrated wildfire risk assessment framework carried out for the Lewis and Clark National Forest, Montana, United States. Our framework entails 3 primary analytical components: 1) stochastic wildfire simulation and burn probability modeling to characterize wildfire hazard, 2) expert-based modeling to characterize fire effects, and 3) multicriteria decision analysis to characterize Forest leadership preference structures. We embed these components within a spatial, quantitative risk assessment framework that allows for the portrayal of risk to individual HVRAs and for an aggregated portrayal of risk across HVRAs with a unitary metric. In particular we devote attention to our approach to eliciting and encapsulating expert judgment, in which we: 1) adhered to a structured process for using expert judgment in ecological risk assessment, 2) used as our expert base local resource scientists and fire/fuels specialists who have a direct connection to the specific landscape and HVRAs in question, 3) introduced multivariate response functions to characterize fire effects to HVRAs that consider biophysical variables beyond fire behavior. We anticipate that this work will further the state of wildfire risk science and will lead to additional application of risk assessment to inform land management planning.

METHODS

A framework for quantifying wildfire risk

Figure 1 presents the overall risk assessment framework, its 3 primary analytical components, and its outputs. The overall process entails collaboration with different types of Forest staff at different points in the process. Line officers (i.e., Forest leadership: Forest Supervisor and District Rangers) are asked to provide guidance regarding assessment endpoints and relevant land and fire management plan objectives. Principally this entails the identification of HVRAs to be included in the assessment (Component 2), and further the articulation of relative HVRA importance in the context of fire protection and/or restoration (Component 3). In different planning contexts or with different governance structures, the composition of the group providing value-based information may differ. Resource specialists, by contrast, are asked to provide science-based information regarding the possible effects of fire to the identified set of HVRAs (Component 2).

This framework provides spatially resolved estimates of wildfire risk on a per-pixel basis, quantified as expected net value change (NVC), building on work originally proposed by Finney (2005). We use NVC rather than expected loss to explicitly recognize possible ecological benefits of fire; thus terms "hazard" and "risk" should be interpreted in that context throughout this article. Value change is expressed in relative terms on a percentage basis, as defined by expert-based loss/gain functions (e.g., complete loss $= -100\%$). These "response functions" output a common measure of risk, and a given pixel on the landscape can present risk to multiple (or zero) HVRAs. Equation 1 provides the formula for calculating $E(\mathrm{NVC}_j)_k$, the expected net value change to HVRA j on landscape pixel k. BP_{ik} is the probability of pixel k burning with fire intensity class i, and RF_{ijk} the response function for HVRA j on pixel k at fire intensity class i. To provide an integrated measure of risk across HVRAs, the relative importance of each HVRA (RI_j) can be derived using multicriteria decision analysis techniques. Equation 2 displays how to calculate risk across HVRAs for a given landscape pixel k. The weighting factor α_j captures both the relative importance and the relative extent of mapped HVRA pixels, where N_j is the count of total mapped pixels (Eqn. 3). Incorporating the relative extent of HVRAs will tend to distribute relative importance across HVRAs with a large number of mapped pixels, and to concentrate relative

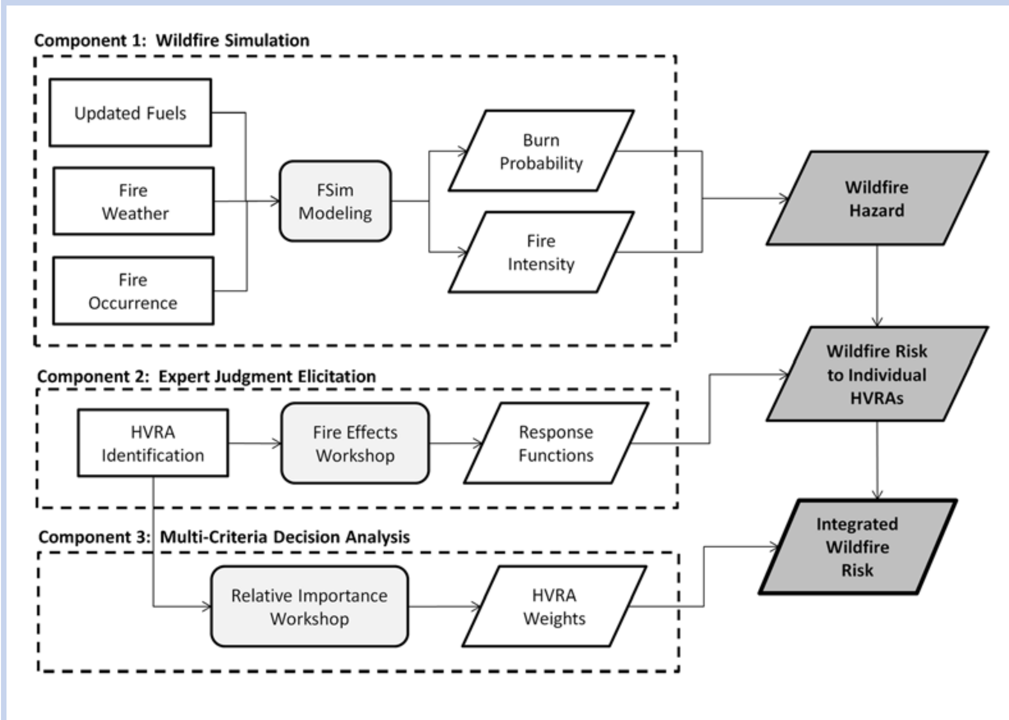

Figure 1. Flowchart for integrated wildfire risk assessment process, with 3 primary analytical components identified. The light gray boxes indicate key processes, and the dark gray boxes indicate modeled outputs.

importance for rare HVRAs. That is, HVRAs with few mapped pixels will have a high importance per pixel. Finally, expected net value change across all HVRAs and the entire landscape can be derived as in Equation 4.

$$E(NVC_j)_k = \sum_i BP_{ik} RF_{ijk} \quad (1)$$

$$E(NVC)_k = \sum_j E(NVC_j)_k * \alpha_j \quad (2)$$

$$\alpha_j = \frac{RI_j}{N_j} \text{ and} \quad (3)$$

$$E(NVC) = \sum_k E(NVC)_k \quad (4)$$

Study area

The study area is known as the Little Belts Assessment Area, comprising 363 678 hectares in the areas around the Little Belts mountain range (Figure 2). The Little Belts range is within the Lewis and Clark National Forest (LCNF) in central Montana, United States. Four Ranger Districts lie within the study area: Belt Creek, Judith, Musselshell, and White Sulphur Springs. Relative to other locations in the mountainous west of the United States, the Little Belts Assessment Area has a low historic occurrence of large fire, although large fires do occur, and there exists concern over increasing wildfire hazard with insect infestations and a changing climate. Historically, large fires ($\geq$121 hectares; agency reporting standards) within the assessment area have accounted for approximately 2.5% of all fires, while accounting for approximately 95% of all area burned. Thus it is critical to examine those rare fires that grow large rather than all ignitions. Across a broader assessment area known as a Fire Planning Unit, 80 197 hectares burned out of 2 724 390 hectares of burnable area over the period of 1992 to 2009, which results in a nonspatial, average annual large fire burn probability of 0.00164. This estimate can serve as a useful guide for evaluating wildfire simulation outputs, although the limited historical record may not fully capture the potential for large fire on this landscape.

Wildfire simulation modeling

A prerequisite step for modeling wildfire growth and behavior is mapping the vegetative and fuel conditions across the landscape. Generating this ''fuelscape'' required critiquing and updating LANDFIRE version 1.0.5 data (http://www.landfire.gov) to reflect local knowledge of wildfire behavior and changes to fuel and vegetation characteristics from recent insect infestation and wildfire burn severity. A local critique and update workshop was held with LCNF vegetation and fire management resource specialists to accomplish this task, an approach consistent with the expert-driven development of LANDFIRE data products (Rollins 2009). The LCNF resource specialists recommended modification of the surface fire behavior fuel model (Scott and Burgan 2005) in some areas of the Forest to better reflect the expected fire behavior. We used data of relative overstory canopy loss to update forest canopy characteristics for recent insect infestation and then LCNF resource specialists developed rules for mapping post-insect disturbance surface and canopy fuel. The relative overstory canopy loss data was developed by the USFS Region 1 Geospatial Services Group using a change detection process that assessed LANDSAT imagery from 2000 and 2009 and reference data interpreted

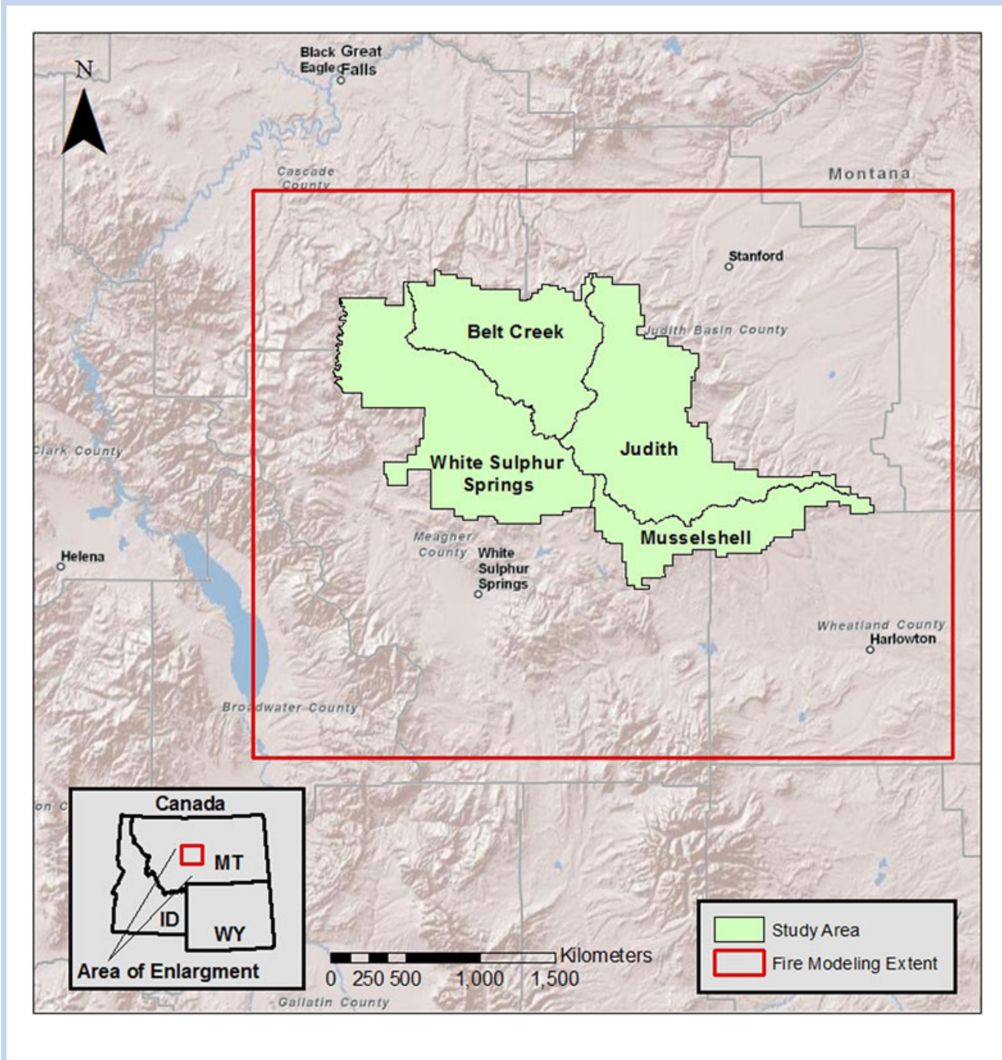

Figure 2. Ranger Districts and Little Belts Assessment study area, located in central Montana.

from 2009 color infrared NAIP imagery. Rules to update surface and canopy fuel for recent wildfires not captured in the LANDFIRE version 1.0.5 data were developed by the LCNF resource specialists based on burn severity and time since disturbance as captured in data from the USFS Monitoring Trends in Burn Severity program (http://www.mtbs.gov).

To produce spatially resolved burn probabilities, we turned to the wildfire simulation system FSim (Finney, McHugh et al. 2011), which combines a number of submodels related to weather influences, ignition probability, fire spread, and containment success. FSim simulates fire occurrence and growth on a daily basis for tens of thousands of fire seasons to generate estimates of wildfire likelihood given current landscape conditions. FSim belongs to a family of fire models built largely off the FARSITE (Finney 1998) fire modeling system, with broad application in wildfire risk analysis (Ager et al. 2011; Finney, Grenfell et al. 2011; Noonan-Wright et al. 2011). In addition to geospatial data on burnable vegetation, the FSim model is parameterized with data from a local weather station to generate relevant fire weather streams, and with local historic fire occurrence data in the form of a spatial ignition density grid and parameters for a stochastic large-fire occurrence submodel.

The spatial resolution for this modeling effort was a pixel size of 90 m (0.81 ha), for which FSim outputs pixel-specific burn probabilities partitioned according to 1 of 6 fire intensity classes. Annual burn probabilities are calculated as the number of times a pixel burns (at any intensity) divided by the total number of simulated fire seasons. The spatial pattern of burn probability is influenced by local ignition likelihood and by spread potential from remote ignitions. The distribution of burn probability among the fire intensity classes is influenced by local fuel type, the simulated wind speed and fuel moisture at the time the pixel burns, and the orientation of the flame front with respect to the heading direction (the flanking and backing portions of a wildfire are less intense than the heading portion). Collectively the geospatial mapping of burn probability and fire intensity characterize wildfire hazard and provide the foundation for exposure and effects analysis.

HVRA identification and definition

We asked Forest leadership to identify a suite of priority HVRA layers with potential to be impacted by wildfire. The identification process proceeded hierarchically, with 5 primary HVRAs identified followed by articulation of a series of

Table 1. Set of HVRAs and sub-HVRAs, and total mapped area, included in the Little Belts Assessment

HVRA	Sub-HVRA	Mapped area (Ha)
Green Trees	Tenderfoot Creek Experimental Forest	3516
	Visual quality	19 039
	Timber base	84 542
Wildlife habitat	Aspen	484
	Old growth	30 385
	Riparian Habitat	19 556
	Sagebrush Steppe	9221
	Ungulate Winter Range	55 088
	Whitebark pine	10 700
Infrastructure	High Investment Infrastructure	301
	General Investment Infrastructure	771
	Power lines	2628
	Electronic sites	16
Watersheds	Municipal watersheds	2841
	Westslope cutthroat trout stream	84 767
WUI	—	81 377

HVRA = highly valued resources and assets; WUI = wildland urban interface.

sub-HVRAs. Table 1 presents the entire set of HVRAs and sub-HVRAs, as well as their mapped area within the Little Belts Assessment area, and Figure 3 provides the HVRA locations within the study area. The Green Trees HVRA consists of an experimental forest dedicated to long-term research, popular recreation areas and scenic corridors that have not been impacted by recent insect or wildfire disturbance, and commercial timber resources. The Wildlife Habitat HVRA corresponds to various vegetation and plant communities that provide habitat for a diversity of important wildlife species. The Infrastructure HVRA includes a variety of fire-susceptible structures or developed areas, including rental cabins, campgrounds, fire lookouts, power lines, etc. The Watersheds HVRA includes municipal watersheds, which provide drinking water, and habitat for the Westslope cutthroat trout, a native species classified as sensitive. Lastly, the Wildland Urban Interface (WUI) HVRA consists of areas near residential structures. Upon identifying the list of HVRAs and, critically, ensuring sufficiency of geospatial data to map all HVRAs, we were able to proceed to engage experts and to assign response functions.

Expert Judgment and Response Function Workshop

Factors influencing implementation of expert-based approaches include identification of the type of information to be elicited, of the most appropriate experts, of the best way to encapsulate expert information, and of the best way to elicit expert information. Further driving many applications are practical considerations relating to available resources and timelines. For our purposes we defined an 8-step process for eliciting expert judgment, premised largely on frameworks presented by Knol et al. (2010) and Kuhnert et al. (2010). Below we briefly review each step in the context of the Little Belts Assessment.

1. *Articulate the research question*: Our specific problem was how to characterize wildfire effects to HVRAs and how to integrate that information with wildfire simulation modeling outputs to characterize wildfire risk.
2. *Identify and characterize relevant uncertainties*: The primary source of uncertainty is knowledge-based (Ascough et al. 2008), relating to lack of data and predictive models regarding fire effects to the suite of HVRAs considered.
3. *Resolve the scope and format of elicitation*: We opted to establish and align expert subgroups based on relevant expertise with HVRAs. In essence, we modeled our approach off an application of the Delphi process detailed by MacMillan and Marshall (2006), in that we sought to use multiple experts, sought expert consensus, and provided multiple opportunities to refine HVRA-specific response function definitions.
4. *Select the experts*: Our expert pool included 17 members, a balance of resource generalists and specialists. In this context generalists span a range of professions, including fire management officers, fuels specialists, and foresters. Specialists, by contrast, are HVRA-specific, including wildlife biologists, fisheries biologists, soil scientists, and forest hydrologists.
5. *Design the expert judgment elicitation protocol*: Our elicitation design used a generic template wherein response functions output NVC as a function of flame length. Additionally the protocol included a number of improvements over earlier approaches (Thompson, Calkin, Gilbertson-Day et al. 2011), including the definition of HVRA-specific response functions rather than the assignment of HVRAs to predefined stylized response functions, and the allowance of multivariate response functions.
6. *Prepare the elicitation protocol*: We created and distributed to experts a 4-page brochure, and distributed surveys to HVRA subgroups that asked experts to discuss the factors affecting how each HVRA responded to wildfire. Surveys specifically queried experts regarding 3 key factors: wildfire characteristics, HVRA characteristics, and landscape characteristics. The surveys served to introduce experts to the mental process of evaluating fire effects, and further to help identify potential variables to include in response function definitions.
7. *Elicit expert judgment*: Our elicitation protocol occurred in a 1-day group workshop format at the Forest headquarters, involved multiple individuals who varied by nature of expertise (generalist versus subject-matter experts), and was premised on consensus-based definition of quantitative HVRA-specific response functions. We began the workshop by reviewing the definition of HVRA layers, the initial feedback from survey responses, and the role of response functions in the risk assessment framework. We then broke the larger group into HVRA subgroups, assigned to define response functions for every HVRA sublayer and to document rationales behind response functions.

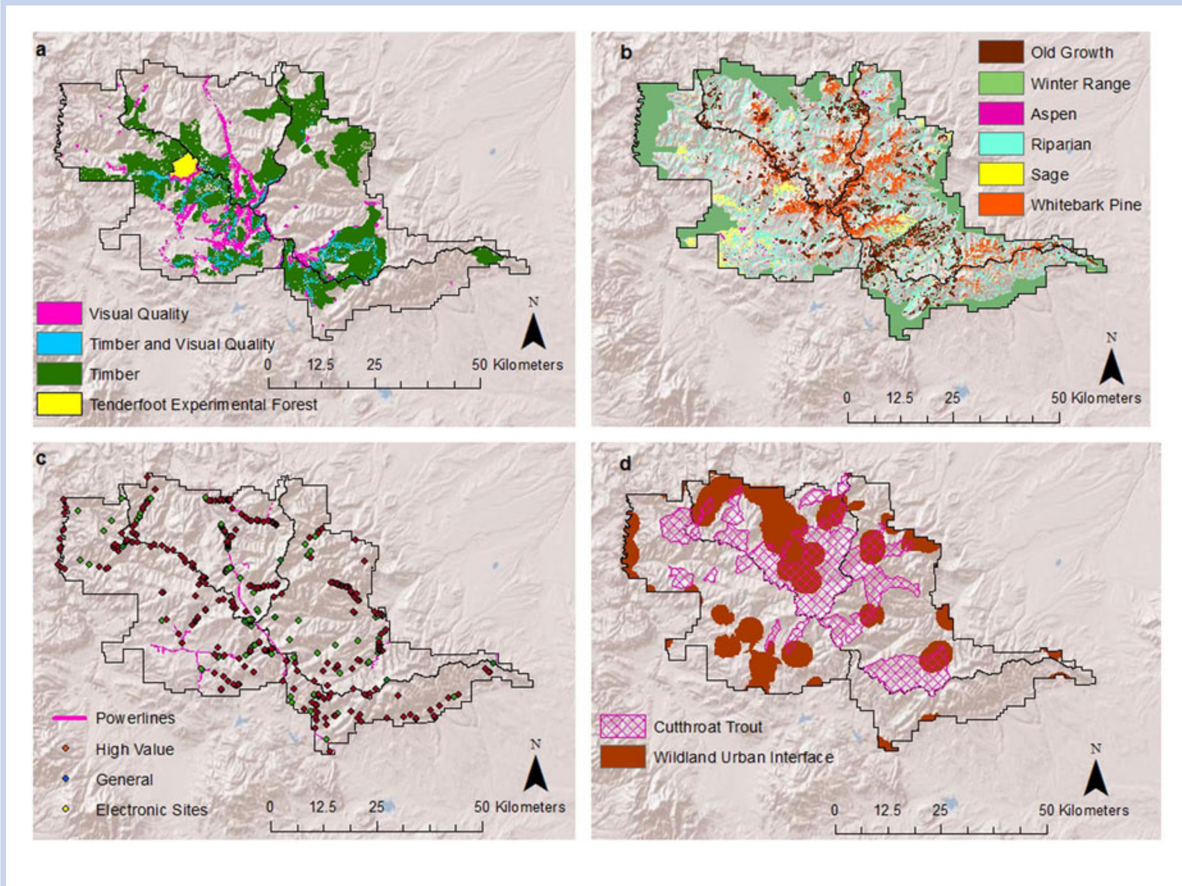

Figure 3. Mapped locations for (**A**) Green Trees Sub-HVRAs, (**B**) Wildlife Habitat Sub-HVRAs, (**C**) Infrastructure Sub-HVRAs, and (**D**) the Cutthroat Trout Sub-HVRA (high value watersheds) and the Wildland Urban Interface HVRA. The municipal watersheds sub-HVRA (high value watersheds) is not mapped for security reasons.

8. *Provide feedback and refine*: On conclusion of the HVRA subgroup meetings we rejoined all subgroups together, and asked each subgroup to present their response function definitions and justifications. We encouraged objective critique and debate, which ultimately did lead to modification of a small subset of response function definitions.

Establishing relative importance across HVRAs

In parallel with the response function workshop, we asked Forest Leadership to participate in a relative importance elicitation workshop. The purpose of the workshop was to establish quantitative weights that differentiate importance of HVRAs. The workshop entailed the use of multi-criteria decision analysis, in effect the Simple-Multi Attribute Rating Technique (Kajanus et al. 2004). Our application was premised on 3 key principles: the explicit inclusion of expert judgment (here the expertise relating to established managerial priorities), the search for group consensus, and iterative refinement of stated preference. We assigned weights according to a 4-step process (below), which proceeded first across HVRA categories, and then hierarchically across sub-HVRAs within an HVRA category:

1. Rank HVRAs (or sub-HVRAs) according to importance to Forest.
2. Provide qualitative justification for rankings, and their relation to existing guidance, doctrine, or policy (e.g., Forest Management Plans, USDA Strategic Plan)
3. Assign top-ranked HVRA (sub-HVRA) a score of 100; assign all other HVRAs (sub-HVRAs) relative importance scores on scale of 0–100. Relative importance scores were also converted into percentages of overall importance across HVRAs and across sub-HVRAs within a given HVRA category.
4. Review, critique, and refine scores (iterative for both HVRAs and sub-HVRAs).

RESULTS

Wildfire hazard

Figure 4 presents maps of annual burn probability and mean fireline intensity, clipped to the assessment area. The highest burn probabilities are concentrated in the southwest corner, primarily in the White Sulphur Springs Ranger District as well as along the western periphery of the Musselshell District. These areas of high burn probability are characterized by grass and grass-shrub fuelbeds capable of high spread rates. Burn probabilities are significantly lower elsewhere, although there is a pocket of higher burn probability and intensity in Belt Creek, corresponding to Belt Park, an open grassland where fire can spread rapidly. The

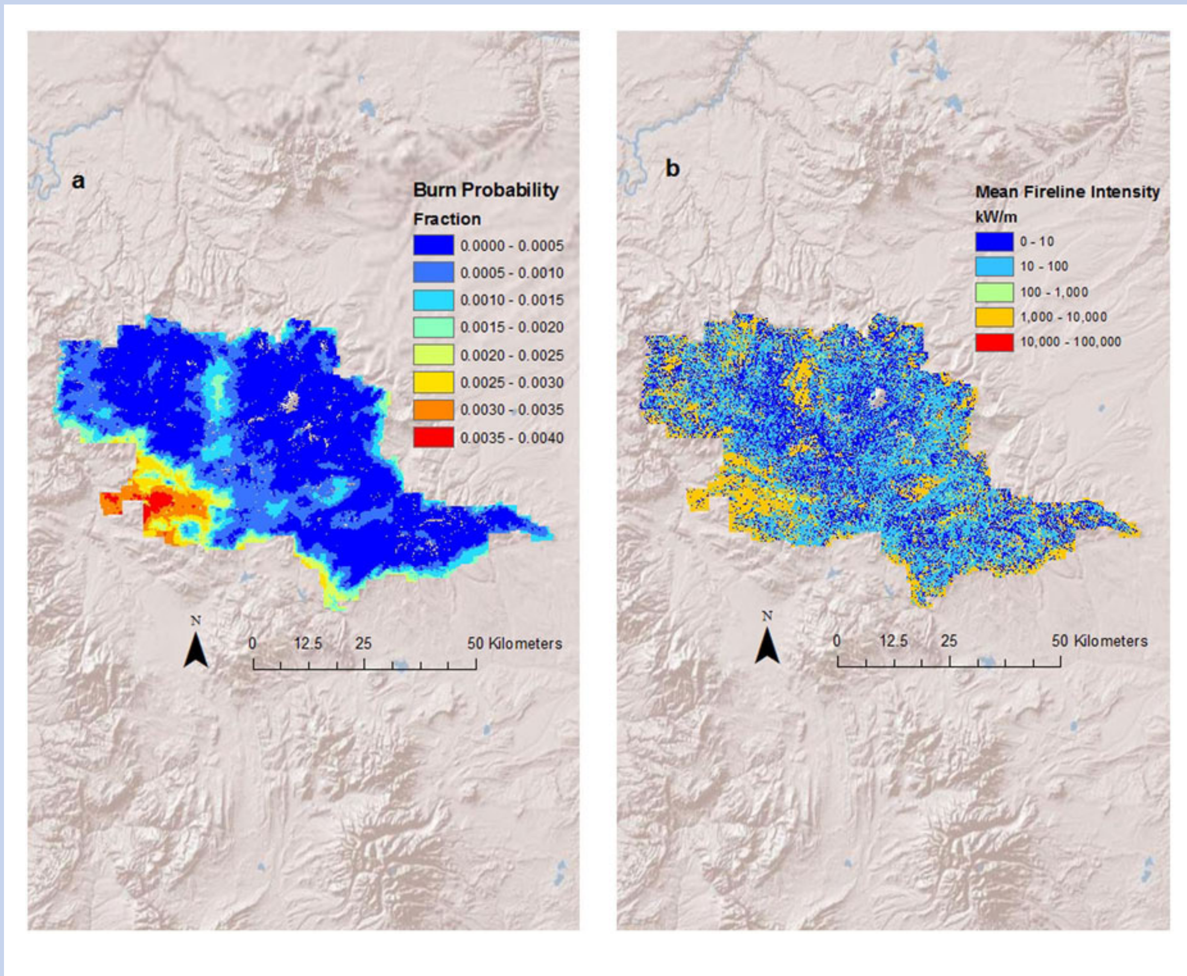

Figure 4. Burn probability and mean fireline intensity across study area.

spatial patterns of mean fireline intensity tend to align with areas of high burn probability, because both are influenced by rate of spread. Burn probabilities throughout the study area provide a range around the nonspatial historical burn probability average, with most of the area below the average, and a few areas of high burn probability well above the average.

Response functions

Table 2 presents response function definitions for all sub-HVRAs included in the Little Belts Assessment. Justifications provided by the experts are available from the authors on request. A wide range of responses to fire are exhibited, from strongly positive (Aspen Sub-HVRA) to universally negative (Tenderfoot Creek Experimental Forest Sub-HVRA), with significant implications for landscape-scale wildfire management. Responses for the Experimental Forest are strongly negative to reflect possible invalidation of experiments and loss of research data and equipment. The experts anticipated ecologically beneficial effects from low-to-moderate intensity fire to multiple Wildlife Habitat Sub-HVRAs, to Green Tree Dry Forest Sub-HVRAs, and to Westslope cutthroat trout streams. The Aspen and Whitebark pine Sub-HVRAs in particular evinced a strong positive response to fire, related to evolutionary adaptation to fire as well as fire-related mortality to competing species. These 2 Sub-HVRA response functions are also notable for their nonmonotonic functional form, which was not presented as a stylized functional form for earlier efforts described in the introduction. The experts anticipated damages for certain fire-susceptible habitat and forest or timber types, municipal watersheds, and to infrastructure and the WUI, presuming that susceptibility of loss increases with flame length. At maximum fire intensities most Sub-HVRAs experience near total loss, with the exceptions of Aspen, and watersheds where slope steepness $<35\%$.

In total, the experts defined 10 multivariate Sub-HVRA response functions, incorporating additional landscape variables relating to forest type and slope steepness. Forest type is based largely on species composition, forest structure, and moisture conditions. Dry forest types evolved with more frequent, low-intensity fires, which can remove hazardous fuels and prevent more catastrophic events and thereby incur a net ecological benefit. Thus response functions for dry forest Sub-HVRAs differ significantly, with benefits anticipated for low-to-moderate intensity fires. Slope steepness is an indicator of erosion potential, with higher slopes having increased likelihood of sediment delivery to water bodies. Thus it is mostly areas with steep slopes and high fire intensities with potential for water quality degradation.

Table 2. Response functions across all HVRA and Sub-HVRAs

HVRAs and Sub-HVRAs	Covariate	FIL 1	FIL 2	FIL 3	FIL 4	FIL 5	FIL 6
Green Trees							
Tenderfoot Creek Experimental Forest	—	−100	−100	−100	−100	−100	−100
Visuals	Juniper, PP, and DF	50	30	10	−50	−70	−100
Visuals	Other	10	−20	−40	−80	−80	−90
Timber	Douglas-fir and Ponderosa pine types	40	10	−20	−80	−100	−100
Timber	Other	−10	−30	−70	−90	−90	−100
Wildlife habitat							
Aspen	—	80	100	100	50	−10	−20
Old growth	Dry-site	75	50	30	0	−50	−100
Old growth	Wet-site	0	−10	−30	−50	−80	−100
Riparian Habitat	—	20	0	−20	−50	−80	−100
Sagebrush Steppe	—	−10	−30	−50	−90	−100	−100
Winter range	—	20	10	−30	−50	−80	−100
Whitebark pine	—	80	100	80	−30	−80	−100
Infrastructure							
High Investment Infrastructure	—	−10	−30	−60	−80	−100	−100
General Investment Infrastructure	—	0	−10	−40	−70	−90	−90
Power lines	—	0	−10	−20	−40	−80	−80
Electronic sites	—	0	−10	−20	−40	−60	−80
High value watersheds							
Westslope cutthroat trout stream	<35% slope	20	20	10	0	−30	−50
Westslope cutthroat trout stream	>35% slope	20	20	−10	−30	−50	−80
Municipal watersheds	<35% slope	0	0	0	−10	−20	−40
Municipal watersheds	>35% slope	0	0	−10	−30	−50	−80
WUI	—	−10	−30	−60	−80	−100	−100

Response functions are defined on the basis of 6 flame length categories: <2 ft (0.6 m); 2–4 ft (0.6–1.2 m); 4–6 ft (1.2–1.8 m); 6–8 ft (1.8–2.4 m); 8–12 ft (2.4–3.7 m); >12 ft (3.7 m). FIL = fire intensity level; HVRA = highly valued resources and assets; WUI = wildland urban interface.

Relative importance

Table 3 presents the RI scores as assigned for all HVRA and Sub-HVRAs. As with the response functions, justification for rankings provided by forest leadership can be made available from the authors. WUI is the most important HVRA (RI = 100), followed by Infrastructure (RI = 90), Watersheds (RI = 70), Wildlife Habitat (RI = 50), and Green Trees (RI = 30). The ''% RI'' column presents normalized importance scores as a percentage of the total RI among all HVRAs, representing each HVRA's share of overall importance. Sub-HVRAs are ranked according to Sub-RI scores, with a similar interpretation for the column ''% Sub-RI.'' The ''% Overall'' column presents the importance of HVRA/Sub-HVRA relative to all HVRAs/Sub-HVRAs, and is calculated as the product of the ''% RI'' and ''% Sub-RI'' columns. The top 3 rankings—WUI HVRA (29.4%), the High Investment Infrastructure Sub-HRVA (11.0%), and the Municipal Watersheds Sub-HVRA (10.8%)—collectively comprise over 50% of total importance. This result in part reflects agency policy prioritizing protection of life and property.

Risk calculations

Table 4 presents expected net value change across all HVRAs and Sub-HVRAs, summed across Ranger Districts. These calculations integrate burn probabilities, response functions, relative importance, and relative extent (Eqns. 1–4). To reiterate, values presented are total net effects. Thus where certain HVRAs exhibit a net benefit they still may incur negative effects at certain intensities (and vice versa). Looking first at HVRAs, the greatest loss is expected for the

Table 3. HVRA and Sub-HVRA RI weight assignments, sorted according to RI and Sub-RI

HVRA	RI	% RI	Sub-HVRA	Sub-RI	% Sub-RI	% Overall
WUI	100	29.4	—	—	—	29.4
Infrastructure	90	26.5	High Investment Infrastructure	100	41.7	11.0
			General Investment Infrastructure	60	25.0	6.6
			Power lines	50	20.8	5.5
			Electronic sites	30	12.5	3.3
			Sub-HVRA RI total	240	100	26.5
Watersheds	70	20.6	Municipal watersheds	100	52.6	10.8
			Westslope cutthroat trout stream	90	47.4	9.8
			Sub-HVRA RI total	190	100	20.6
Wildlife habitat	50	14.7	Aspen	100	21.3	3.1
			Riparian Habitat	100	21.3	3.1
			Whitebark pine	100	21.3	3.1
			Sagebrush Steppe	80	17.0	2.5
			Old growth	50	10.6	1.6
			Ungulate winter range	40	8.5	1.3
			Sub-HVRA RI total	470	100	14.7
Green trees	30	8.8	Tenderfoot Creek Experimental Forest	100	52.6	4.6
			Timber base	50	26.3	2.3
			Visual quality	40	21.1	1.9
			Sub-HVRA RI total	190	100	8.8
HVRA RI total	340	100				100

HVRA = highly valued resources and assets; RI = relative importance; WUI = wildland urban interface.

WUI. Infrastructure comes next in terms of expected loss, the magnitude of which is approximately 52% of the loss to WUI. Expected losses to Green Trees are 9% of WUI losses. Both High Value Watersheds and Wildlife Habitat are anticipated to benefit from fire. The overall magnitude of beneficial impacts to habitat is approximately 15% of the magnitude of negative impacts to WUI. Within certain HVRA categories, there exists significant variation in wildfire effects across Sub-HVRAs. This variation can manifest in terms of the magnitude of likely fire-related impacts, for instance the steeper loss to High Investment Infrastructure relative to Electronic Sites (Infrastructure HVRA). Variation is also evident in the direction of impacts, for instance with significant benefits for Aspen and significant loss for Sagebrush Steppe (Wildlife Habitat HVRA).

Figure 5 presents expected losses and benefits to all HVRAs and Sub-HVRAs, expressed relative to WUI, which has the greatest expected loss. The High Investment Infrastructure Sub-HVRA has the second greatest expected loss (27% of WUI), and the Sagebrush Steppe Sub-HVRA the third greatest expected loss (23% of WUI). Conversely, Aspen (32% of WUI), and Whitebark Pine (11%) are likely to experience net benefits from wildfire. Using 10% loss/benefit as an arbitrary ''significant fire impact'' threshold, only 7 of 16 HVRAs and Sub-HVRAs would be significantly impacted by fire (5 negative, 2 positive). Because risk calculations already incorporate relative importance and relative extent, this type of information could be a useful filter for discerning mitigation priorities.

The White Sulphur Springs Ranger District comprises by far the largest share of overall wildfire risk, more than the other 3 districts combined (Table 4). This result is influenced by several factors. First, high burn probabilities and mean fire intensities are found within the White Sulphur Springs Ranger District (Figure 4). Second, highly susceptible HVRAs (WUI, Infrastructure, Sagebrush Steppe, and Tenderfoot Creek Experimental Forest) are exposed to that hazard (Figure 3). Also, the White Sulphur Springs Ranger District is slightly larger than the others. If risk per unit area were uniform across the study area, White Sulphur Springs would still have the largest share of overall risk due merely to its larger size.

The Belt Creek Ranger District has the second highest expected loss, driven primarily by WUI and Infrastructure. This district has pockets of high burn probability largely coincident with HVRAs (WUI and Infrastructure). By

Table 4. E(NVC) across all HVRAs and Sub-HVRAs

HVRAs and Sub-HVRAs	Net response (by Ranger District)				HVRA and Sub-HVRA totals
	Belt Creek	Judith	Musselshell	White Sulphur Springs	
Green Trees	−0.02	−0.01	0	−0.33	−0.36
Tenderfoot Creek Experimental Forest	−0.01	0	0	−0.33	−0.34
Visual quality	0	0	0	0.03	0.03
Timber base	−0.01	−0.01	0	−0.03	−0.05
Wildlife habitat	0.13	0.2	0.02	0.23	0.58
Aspen	0.05	0.06	0.17	0.99	1.27
Old growth	0.02	0.04	0.02	0.02	0.1
Riparian Habitat	−0.02	−0.02	−0.02	−0.15	−0.21
Sagebrush Steppe	−0.02	−0.07	−0.14	−0.68	−0.91
Ungulate Winter range	−0.01	−0.01	−0.03	−0.04	−0.09
Whitebark pine	0.11	0.2	0.02	0.09	0.42
Infrastructure	−0.45	−0.26	−0.37	−0.99	−2.07
High Investment Infrastructure	−0.28	−0.14	−0.22	−0.44	−1.08
General Investment Infrastructure	−0.1	−0.07	−0.11	−0.14	−0.42
Power lines	−0.07	−0.04	−0.03	−0.4	−0.54
Electronic sites	0	−0.01	−0.01	−0.01	−0.03
Watersheds	0.08	0.05	0	0.03	0.16
Municipal watersheds	−0.01	0	0	0	−0.01
Westslope cutthroat trout stream	0.09	0.05	0	0.03	0.17
WUI	−0.91	−0.39	−0.16	−2.51	−3.97
Ranger District totals	−1.17	−0.41	−0.51	−3.57	−5.66

E(NVC) = expected (net value change); HVRA = highly valued resources and assets; WUI = wildland urban interface.

contrast areas within the Judith Ranger District tend to have lower burn probabilities and fire intensities, and so expected losses are far smaller in magnitude, with benefits anticipated to Whitebark Pine.

The distribution of overall wildfire risk among ranger districts (or any geographic area) is potentially useful for allocating risk mitigation resources among the ranger districts (e.g., funding for fuel treatments). Alternatively, instead of the sum, as we show here, the mean wildfire risk per unit area (total area, burnable area, or area with 1 or more HVRAs) can be calculated for geographic units within each ranger district (watersheds, for example). Mean wildfire risk by watershed is potentially useful for prioritizing watersheds within each ranger district.

DISCUSSION

The value of incorporating exposure, effects, and relative importance

Figure 6 illustrates how the primary components (wildfire hazard, response functions, and relative importance) jointly influence wildfire risk calculations. Specifically, the figure illustrates the value of incorporating response functions and relative importance, and how this information might lead to alternative mitigation strategies relative to strategies informed by exposure analysis alone. Figure 6A displays exposure analysis, mapping each HVRA/Sub-HVRA according to mean burn probability and mean fireline intensity. Burn probabilities and fireline intensities evince a strong positive correlation, reflective of their relation to rate of spread. The Aspen Sub-HVRA is an interesting exception. Fuel conditions within the Aspen Sub-HVRA—light surface fuel with no potential for crown fire—produce only low fireline intensities. The Aspen stands are small and scattered (Figure 3B) so their BPs are influenced by the conditions around them more than within them, and many of the stands are located near fast-spreading sagebrush-grasslands, resulting in relatively high BPs.

Figure 6B incorporates response functions across the distribution of flame lengths, but absent burn probabilities, hence presenting conditional net value change. The product of the *x*- and *y*-axes in Figure 6B represents expected net value change for each HVRA/Sub-HVRA. If fire effects were directly proportional to mean fireline intensity, the general

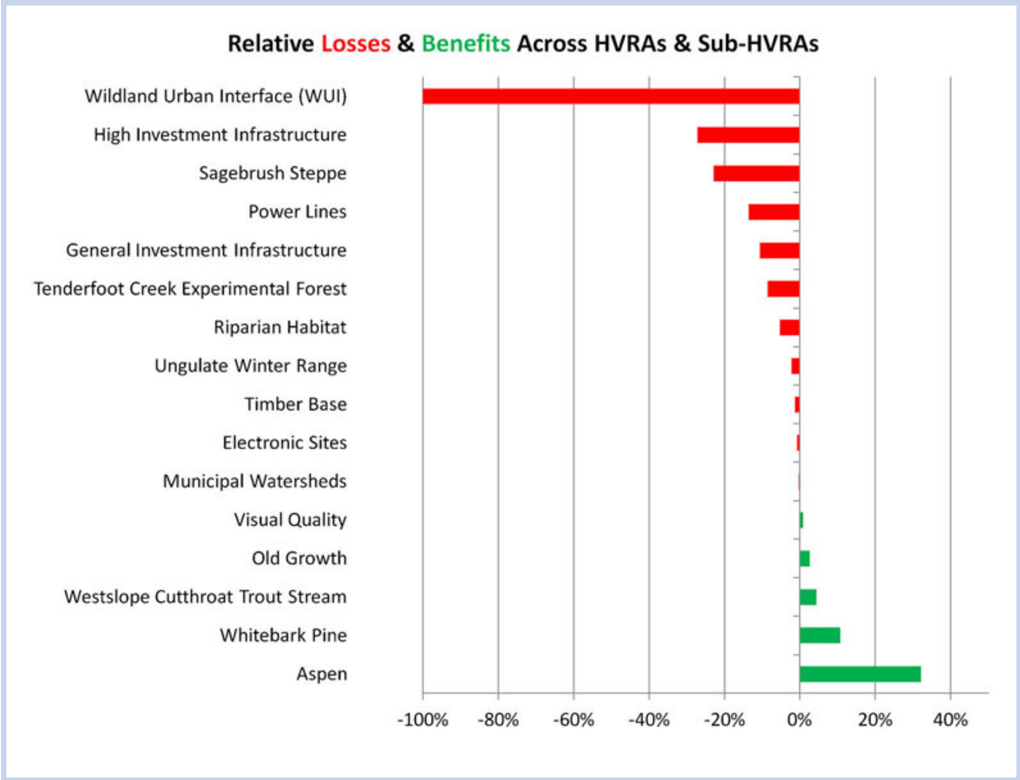

Figure 5. Summary of relative losses and benefits across all HVRAs and Sub-HVRAs, inclusive of all Ranger Districts on the Little Belts Landscape.

pattern in Figure 6A would be similar to that in Figure 6B. By contrast, Figure 6B shows a wide range of responses to fire, with multiple HVRA/Sub-HVRAs evincing strong positive and negative responses to fire.

Figure 6C further incorporates relative importance weights (see Eqns. 2 and 3), which serves to broaden the spread across HVRA/Sub-HVRAs on the y-axis. This panel presents expected loss on a per unit area basis. Electronic Sites (Elec) and High Investment Infrastructure (High), in particular, show strong weighted negative response, due not only to their relative importance but also their scarcity on the landscape (relative extent; Table 1).

Last, Figure 6D plots weighted conditional net response against expected annual area burned. Figure 6D, in effect, presents the information on net response per unit area from Figure 6C multiplied by the total mapped area. Although the weighted net response of the WUI HVRA is orders of magnitude less than the weighted net response of High Investment Infrastructure, for example, the WUI still presents significantly higher overall risk (Figure 5), due to the larger mapped area (Table 1) and expected annual area burned. Thus this Figure 6D highlights how the areal extent of an HVRA/Sub-HVRA can influence risk calculations.

Absent information on fire effects or relative importance, Figure 6A might lead to, for instance, the presumption that the Tenderfoot Experimental Creek Forest (TCEF) is the lowest mitigation priority. Figure 6B, however, indicates that the TCEF Sub-HVRA has a strong negative response to fire despite low fireline intensities, reflecting the response function where fire of any intensity is considered negative (Table 2). Additionally, Figure 6C can highlight ''low hanging fruit'' for risk mitigation strategies. Treating fuels in a relatively small area proximal to High Investment Infrastructure, for example, could yield significant reductions in expected loss. That is, Figure 6C can help highlight areas where treatments are likely to be cost-effective. Figure 6D further helps illustrate how risk is allocated across HVRAs, which can be useful for higher-level allocation of mitigation investments.

The value of integrated risk assessment

Assessing wildfire risk is a crucial component to mitigation planning. A spatial, quantitative approach to characterizing wildfire risk allows for clear identification of areas on the landscape where aggressive treatment might be cost-effective, or alternatively where fire may play a benign or even beneficial role and could be promoted. The definition of HVRA response as a function of fire behavior can facilitate the design of fuel treatments to target desired fire intensities and HVRA responses. The addition of landscape variables resulted in very different response function definitions, enabling improved targeting of high-risk landscape areas. The integration of relative importance weights allows for comparison of landscape areas with a common currency. Our reliance on formality and documentation in the elicitation of expert input enables transparency and future external review of risk assessment results (Otway and von Winterfeldt 1992). Furthermore, the explicit separation of fire effects from management priorities avoids previously highlighted pitfalls of reliance on expert judgment in risk analyses that do not clearly distinguish expressions of knowledge from expressions of preference (Maguire 2004).

A number of potential extensions to the wildfire risk assessment framework are presented here. Response functions could be extended to accommodate multiple fire behavior

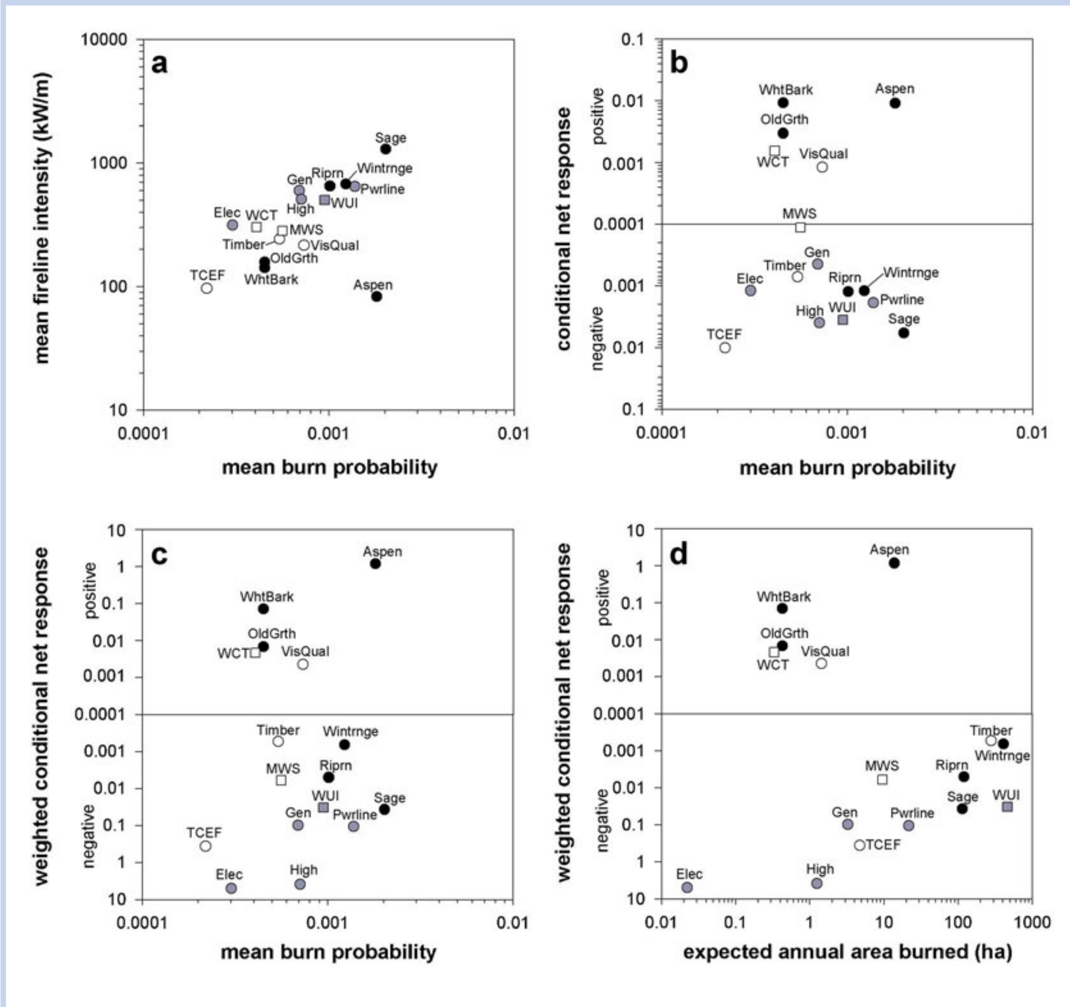

Figure 6. Illustration of how wildfire hazard, response functions, and relative importance jointly influence evaluation of wildfire risk to HVRAs. (**A**) Illustrates exposure analysis, mapping each HVRA/Sub-HVRA according to mean burn probability and mean fireline intensity. (**B**) Response functions are incorporated; the *y*-axis displays conditional net response (NVC), i.e., the net effects across fire intensity distributions without incorporating burn probability. (**C**) Further incorporates relative importance and relative extent, where the *y*-axis presents the weighted, conditional net response. (**D**) presents the same *y*-axis as (C), plotted against the expected annual area burned.

metrics, for instance fractional area burned of an HVRA in addition to fire intensity. The set of input variables could be extended to include output from other models, for instance predicted postfire erosion rates (Miller et al. 2011). Characterizing risk to human communities could incorporate structure fire modeling (Mell et al. 2010), and socioeconomic and demographic data could be used to distinguish vulnerability across at-risk communities (Gaither et al. 2011). The structure of response functions could also be modified, to include Bayesian approaches, multicriteria hierarchies, or fuzzy logic. A much more expansive modification could model longer-term temporal dynamics, considering the roles of multiple disturbance processes, vegetation succession, climatic changes, and even population growth.

Adherence to these recommendations in future applications will depend, in part, on research and development efforts but critically on the level of resources committed and the sufficiency and availability of scale-appropriate geospatial data. A fundamental component of the assessment framework is geospatial analysis, and in our experience, a necessary first step is to establish clear and consistent definitions of geospatial data (fire and fuels data in addition to HVRA data). Only then can the assessment proceed to wildfire modeling, HVRA fire effects analysis, and HVRA relative importance articulation. Including information from other sources creates tradeoffs to consider surrounding the cost of obtaining information, uncertainties, and the value of additional information (in terms of improving decision making). The use of additional models for instance entails work on parameterization, critique, and validation, and may require the recruitment of other experts. For large scale assessments the broad assignment of response functions and the use of off-the-shelf models may be appropriate, whereas for smaller assessments the inclusion of local expertise is likely necessary.

We acknowledge several potential limitations of our approach to eliciting expert judgment. Our use of a consensus approach presented no opportunity to estimate the uncertainty surrounding elicitations. We did, however, provide multiple opportunities for feedback and refinement of response functions, and disagreement across experts was minimal. Mental heuristics and biases could also influence results, which we hoped to minimize through the use of straightforward response function structure and through a separate process for establishing relative importance scores.

It might be fruitful in future efforts to devote additional time for preworkshop training to familiarize experts with the process of defining response functions.

Because of the complexity of the risk calculations it can be difficult to analyze model sensitivities, uncertainties, and errors. Nevertheless, resource managers will want to explore the potential impacts of various assumptions and to examine how those impacts may influence fire management decisions. It is a straightforward exercise to vary response function definitions to see how risk to individual HVRAs may change, and further to vary relative importance weights to see how weighted risk values change. In our experience, risk calculations are quite robust to changes in response functions and relative importance scores, insofar as changes are largely marginal (e.g., the response to fire at a given intensity level does not switch from strongly positive to strongly negative; an HVRA does not switch from most to least important). Spatial variability in fire likelihood and intensity is a strong driver of results, for which assessment of model uncertainty and error is more complex. In many cases a limited fire history against which to compare model results presents challenges to model validation. Uncertainties and errors in fire modeling systems can stem from multiple sources: data quality and availability (fire history, terrain, fuels, weather, etc.), user error, model error, and propagated error. Current models have been shown to underpredict crown fire behavior in certain circumstances (Cruz and Alexander 2010), and a comprehensive analysis of how uncertainties in fuel types, fuel moistures, wind speeds, wind directions, etc., could affect modeled fire behavior has not been carried out. Because FSim uses ensemble forecasting, however, it does provide a mechanism to capture uncertainty surrounding input conditions and parameters, in particular fire weather, and allows for probabilistic predictions of fire behavior. Ultimately, results are contingent on careful calibration and critique of fire and fuels models to minimize potential errors and uncertainties (Stratton 2009; Thompson and Calkin 2011; Scott et al. 2012).

CONCLUSIONS

In this article, we detailed a structured process for eliciting expert judgment of fire effects to highly valued resources and assets and illustrated its integration into a wildfire risk assessment performed for a National Forest in Montana. Our aim was to use expert knowledge in a transparent and credible manner to inform ecological models and to support real-world natural resource and conservation decision making. A major strength of the risk framework is its generality—the geospatial intersection of wildfire behavior metrics with mapped HVRAs and response functions—and therefore its amenability to alternative characterizations of wildfire hazard and fire effects. The response function approach in particular is suitable for encapsulating data, models, and expert judgments in a number of ways, as we described. A further strength is the scalability of the framework, which can be applied to facilitate local project planning all the way to national-scale strategic assessments. Our work supports the incorporation of risk management principles into federal land management, and aligns well with ongoing and emerging lines of research into wildfire modeling, comparative wildfire risk assessment, and fuel treatment and firefighting effectiveness, ultimately promoting efficient wildfire risk mitigation planning. Future work entails continued expansion of our risk assessment and response function framework, application of the framework to support planning within federal land management agencies, and integration of the assessment into a broader structured decision process for efficient prefire planning efforts. Ideally these efforts will promote cost-effective budgetary allocations across the wildfire management spectrum, critical at a time of increasing fiscal austerity.

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