Stoch Environ Res Risk Assess (2011) 25:761–780
DOI 10.1007/s00477-011-0461-0

ORIGINAL PAPER

# Integrated national-scale assessment of wildfire risk to human and ecological values

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Published online: 8 March 2011


**Abstract** The spatial, temporal, and social dimensions of wildfire risk are challenging U.S. federal land management agencies to meet societal needs while maintaining the health of the lands they manage. In this paper we present a quantitative, geospatial wildfire risk assessment tool, developed in response to demands for improved risk-based decision frameworks. The methodology leverages off recent and significant advancements in wildfire simulation models and geospatial data acquisition and management. The tool is intended to facilitate monitoring trends in wildfire risk over time and to develop information useful in prioritizing fuels treatments and mitigation measures. Wildfire risk assessment requires analyzing 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. This effort is designed to support strategic planning by systematically portraying how fire likelihood and intensity influence risk to social, economic, and ecological values at the national scale. We present results for the continental United States, analyze high risk areas by geographic region, and examine how risk evaluations changes under different assumptions with sensitivity analysis. We conclude by discussing further potential uses of the tool and research needs.

**Keywords** Wildfire risk assessment · Fire simulation · Non-market values

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## 1 Introduction

The spatial, temporal, and social dimensions of wildfire risk are challenging U.S. federal land management agencies to meet societal needs while maintaining the health of the lands they manage. The Office of Management and Budget, General Accounting Office, Office of Inspector General, and Congress have critiqued these agencies for their inability to document the effectiveness of fire management programs, and have called for risk-based performance measures (e.g., United States General Accounting Office 2007). Critiques in particular have been directed at the U.S. Department of Agriculture Forest Service (Forest Service), responsible for approximately 70% of all wildfire suppression expenses. As a matter of policy, the Forest Service has embraced a risk-informed management paradigm (Fire Executive Council 2009).

In this paper we present a quantitative, geospatial wildfire risk assessment tool, developed in response to demands for improved risk-based decision frameworks. The tool is intended to facilitate monitoring trends in wildfire risk over time and to develop information useful in prioritizing fuels treatments and mitigation measures. In addition the framework we develop provides a platform for comparative risk assessment, enabling evaluation of how risk to valued resources may change in response to alternative management scenarios. Implementation of the tool was made possible by leveraging off of significant advancements in fire behavior modeling (e.g., Miller et al. 2008; Finney 2002; Finney et al. 2011), and geospatial data acquisition and management for fuel layers (e.g., LANDFIRE, Department of Interior Geological Survey 2009) and highly valued resources (e.g., Calkin et al. accepted).

Wildfire risk assessment requires analyzing 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). These steps are often referred to as exposure analysis and effects analysis, respectively (Fairbrother and Turnley 2005). In our formulation, the components required to generate wildfire risk estimates are burn probability maps generated from wildfire simulation models, spatially identified resources, and response functions describing the impact of fire on the resource(s) in question. Equation 1 presents the mathematical formulation for calculating risk, which is quantified in terms of net value change (NVC).

$$E\left(NVC_j\right) = \sum_i p(f_i)RF_j(f_i) \tag{1}$$

where $E\left(NVC_j\right)$ is the expected net value change to resource $j$; $p(f_i)$ the probability of a fire at intensity level $i$; and $RF_j(f_i)$ is the "response function" for resource $j$ as a function of fire intensity level $i$.

Our work builds upon related research efforts at mapping wildfire hazard and risk (e.g., Braun et al. 2010; Chuvieco et al. 2010; Carmel et al. 2009; Hessburg et al. 2007; O'Laughlin 2005; Roloff et al. 2005; Neuenschwander et al. 2000), and similar environmental assessments in different contexts that use geospatial analyses to map areas of high concern (e.g., Eroglu et al. 2010; Masoudi et al. 2007). For our purposes we distinguish between measures of fire hazard, that focus more on fire occurrence and/or behavior, and measures of fire risk, that additionally consider the chances of fire interactions with valued resources. From this perspective, the mapping of fire hazard (e.g., Vadrevu et al. 2010; Syphard et al. 2008; Loboda and Csiszar 2007; Dickson et al. 2006), can nicely reveal patterns of one component of risk, but offers less complete information to decision-makers faced with questions of how to understand and mitigate risk (e.g., Ager et al. 2010; Chuvieco et al. 2010; Thompson et al. 2010).

By employing the actuarial definition of risk (Finney 2005), our model considers both the stochastic nature of fire occurrence and spread as well as fire effects upon valued resources. This information is useful for prioritizing fuel reduction treatments across the landscape. The information is also helpful for developing incident-specific suppression strategies; where few valued resources are at risk, managers may opt for less aggressive treatments or may even allow fires to burn under favorable weather conditions in order to enhance ecosystem values.

Notable applications of wildfire risk assessment have considered air quality (Rigg et al. 2000), salmonid populations (O'Laughlin 2005), owl habitat (Ager et al. 2007; Despain et al. 2000), commercial timber (Konoshima et al. 2008), structures in the wildland–urban interface (Bar Massada et al. 2009), old-growth trees (Ager et al. 2010), and landscape-scale indices of ecological condition (Keane and Karau 2010). Many of these works share a commonality with our approach pairing burn probabilities with some measure of resource response to fire, although other approaches exist. Zhijun et al. (2009), for instance, calculated a composite grassland fire disaster risk index that combined information on grassland fire hazard, regional exposure, vulnerability, and emergency response and recovery capacity.

The work we present in this paper expands upon many of the above efforts in that it simultaneously considers risk to many of the myriad values for which federal agencies are mandated to manage. Earlier efforts that similarly considered multiple resources include Roloff et al. (2005), who estimated fire effects on water temperature, stream flow, habitat suitability, and landslide potential in the southern Oregon Cascades, Ohlson et al. (2006), who considered wildfire risk to timber, property, landscape-level biodiversity, local air quality, and release of greenhouse gases in southeastern British Columbia, and Chuvieco et al. (2010), who considered wildfire risk to properties, wood products, hunting revenues, recreational and tourist resources, carbon stocks, soil and vegetation condition, and intrinsic landscape value for several regions of Spain.

Previous work demonstrated proof of concept of this integrated wildfire risk assessment framework with a case study of the state of Oregon (Calkin et al. 2010; Thompson et al. 2010), using an expert systems approach to describe resource response to fire and to establish relative management priority across resources. Rideout et al. (2008) similarly considered multiple values at risk and employed an expert panel, but did not separate fire effects analysis from preference articulation. The modeling approach we describe here increases transparency by uncoupling fire effects analysis and prioritization, thereby better aligning with ecological risk assessment paradigms (Fairbrother and Turnley 2005).

In this paper we demonstrate and present results of an integrated wildfire risk assessment framework that extends the scope of analysis to the continental United States. This effort is designed to support strategic planning by systematically portraying how fire likelihood and intensity influence risk to social, economic, and ecological values at the national scale. This integrated wildfire risk assessment necessitated a large-scale geospatial data collection effort, and the development of a suite of resource response functions. Our approach to analyzing resource exposure to wildfire entailed use of FSim, a wildfire simulation system. The specifics of FSim, including details on how fire behavior is modeled, how variable weather conditions influence fire spread, and validation efforts, are described in a companion paper (Finney et al. 2011). In terms of methodological discussion therefore we focus more on the remaining components of integrated risk assessment: geospatial identification of highly valued resources, fire effects analysis, development of performance measures, and integration of risk across resources. To the authors' knowledge this effort represents one of the most comprehensive, quantitative wildfire risk assessments performed to date within the United States.

## 2 Methods

### 2.1 Fire Program Analysis, Geographic Area Coordination Centers, and Forest Planning Units

The Fire Program Analysis (FPA) system is a common interagency strategic decision support tool for wildland fire planning and budgeting (http://www.fpa.nifc.gov). Much of the data, models and methods we employed derive from prior and ongoing FPA analyses. To facilitate interagency planning, the continental United States is divided into multiple Geographic Area Coordination Centers (GACCs) for the purposes of incident management and mobilization of resources (http://gacc.nifc.gov). For reporting purposes our analyses slightly modified these GACCs (combining Southern and Northern California, and the West and East Basin) to result in the following eight geographic areas: California (CA), Eastern Area (EA), Great Basin (GB), Northern Rockies (NR), Northwest (NW), Rocky Mountain (RM), Southern Area (SA), and Southwest (SW). FPA analyses further divide the landscape into Forest Planning Units (FPUs), the number of which varies by Geographic Area (Fig. 1). FPUs were defined for the purpose of cooperative fire management planning and implementation. Within each FPU, wildfire simulations were output and highly valued resources (HVR) were mapped at the pixel basis, with each pixel approximately 270 × 270 m (~7.3 ha).

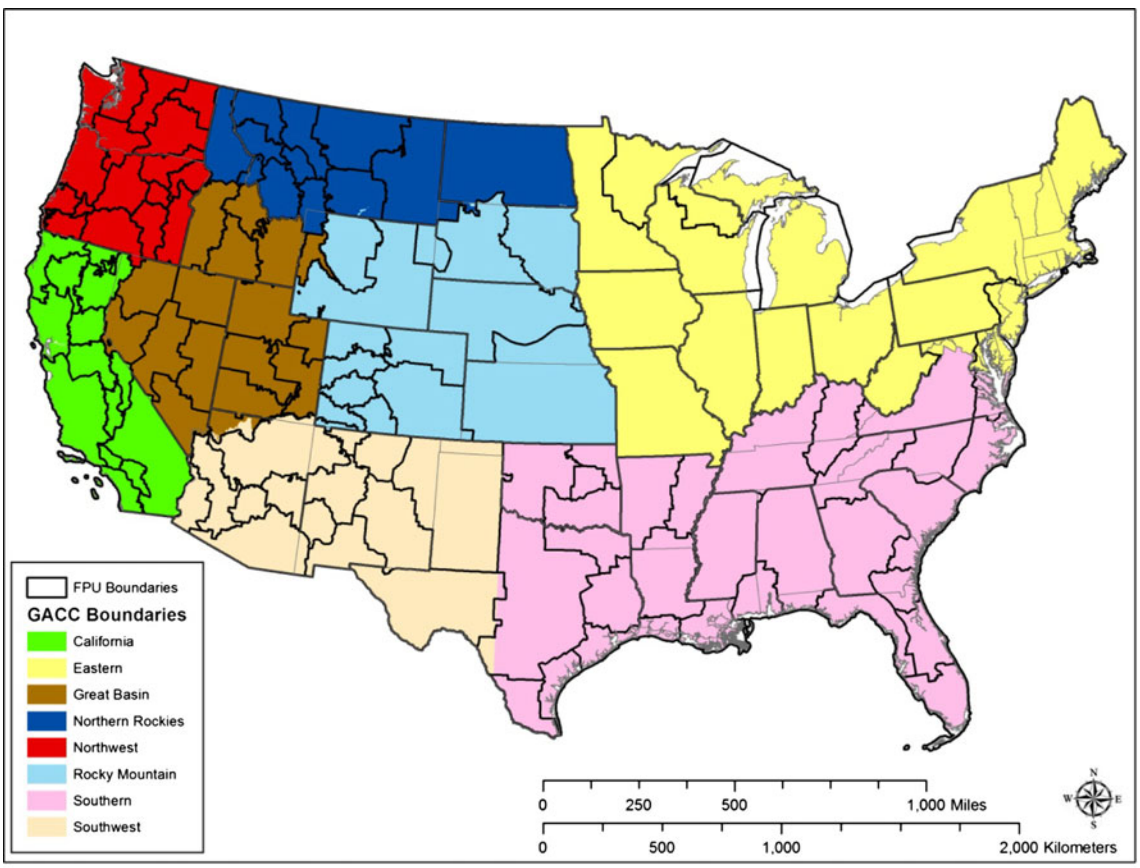



**Fig. 1** Forest Planning Unit (FPU) boundaries, along with Geographic Area Coordination Center (GACC) boundaries (with East and West Basin grouped as Great Basin, and Southern and Northern California grouped as California)

### 2.2 Mapping burn probability

The wildfire simulation model FSim (Finney et al. 2011) produced estimates of burn probability and fire intensity distribution for each pixel. FSim uses the Minimum Travel Time fire spread algorithm (Finney 2002), which facilitates processing large numbers of fires. The algorithm models the spread of fire according to Fermat's principle, which produces fire growth by searching for the fastest straight-line travel paths from burning to unburned nodes. The implementation makes the standard assumption that fires spread as elliptical waves (Andre et al. 2006; Anderson et al. 1982). For the MTT algorithm, the orientation, size and eccentricity of the ellipse is constant within each cell of the landscape. The simulations were completed on a bank of computers located at the U.S. Geological Survey Earth Resources Observation and Science Data Center located in Sioux Falls, SD.

Simulations were performed individually for each FPU, and were parameterized to reflect differences in historical fire management activities as well as climatic and ignition variability. Results output from the model can be compared against historical average burn probabilities and fire size distributions to ensure that simulation outputs are realistic. More details on the simulation process can be found in Finney et al. (2011). The annual burn probability and the conditional probability of fire intensity (as measured by flame length) were then calculated for each pixel. Burn probability (BP) is an estimate of the likelihood of a pixel burning, given a random ignition within the pixel or spread from adjacent pixels. As shown in Eq. 2, $BP$ is a function of the number of times the pixel burned, $F$, and the number of simulated fires, $n$.

$$BP = \frac{F}{n} \tag{2}$$

Flame lengths were sorted into categories defined as 0–0.61 m (Low), greater than 0.61–1.83 m (Moderate), greater than 1.83–3.66 m (High), and greater than 3.66 m (Very High).[1] Higher flame lengths increase the likelihood of crown fire, which can result in tree mortality. The Minimum Travel Time algorithm (Finney 2002) outputs flame lengths based upon (1) the different weather conditions occurring at the time the fire burns each pixel, and (2) the direction the fire encounters a pixel relative to the major direction of spread (i.e., heading, flanking, or backing fire). For each pixel, the wildfire simulation also outputs a vector of conditional flame length probabilities, $BP_i$, representing the $i$th flame length category (Low, Moderate, High, and Very High). $BP_i$ is a measure of the probability that a fire of a given flame length will occur, conditioned on a fire occurring within the pixel. Put another way, $BP_i$ is a measure of the number of times a pixel burns with a given flame length.

Finney et al. (2011) performed a validation exercise comparing predicted fire size distributions with historical data from all FPUs. The national and regional maps suggest some sharp burn probability transitions along FPU boundaries. This appearance is produced because a single Remote Automated Weather Station (RAWS) is used to generate weather for each FPU and because ignition probabilities were random and uniform across the FPU based on historical records of ignition probability and numbers of ignitions (Finney et al. 2011). The combined effect created a "stair-step" exaggeration of the burn probability differences across neighboring FPUS, which we minimized by normalizing the modeled probabilities by the historical burn probabilities calculated with historic fire size data.

### 2.3 Geospatial mapping of highly valued resources (HVRs)

Table 1 enumerates the HVR layers and sub-layers included in the risk assessment, which were identified with

**Table 1** HVR layers acquired for first approximation of national risk assessment

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

[1] These flame length categories correspond to 0–2 ft (low), greater than 2–6 ft (Moderate), greater than 6–12 ft (High), and greater than 12 ft (Very High). These flame length categories are collapsed versions of six fire intensity levels output by FSim: 0–2, 2–4, 4–6, 6–8, 8–12, and 12+ ft.

assistance from the FPA Executive Oversight Group. In total we identified seven key HVR themes, or layers: residential structure locations, municipal watersheds, air quality, energy and critical infrastructure, federal recreation and recreation infrastructure, fire-susceptible species, and fire-adapted ecosystems. Data for these layers were acquired from multiple sources, such as enterprise databases, data clearinghouses and servers, and local data aggregated to the national scale. Data layers were selected largely based on availability and/or suitability for mapping at a national scale. Figure 2 displays conceptually how all HVRs are overlaid onto the landscape, such that a given pixel could house multiple HVR layers.

Our HVR layer for fire-susceptible species is comprised of two datasets: federally designated critical plant and wildlife habitat, and key sage-grouse habitat as defined by the Bureau of Land Management National Sage-Grouse Mapping Team. The first dataset was built by the Conservation Biology Institute and the Remote Sensing Applications Center, who combined several hundred individual layers from the U.S. Fish and Wildlife Service Critical Habitat Portal (http://crithab.fws.gov). With assistance from Jack Waide (Research Coordinator for Conservation Science, National Wetlands Research Center, USGS), we identified 41 vertebrate, invertebrate, and plant species as fire-susceptible species (or species most likely to be negatively impacted by fire) through review of many recovery plans and critical habitat designations. The 41 species included in the model are thought to broadly represent the general geographic distribution of listed taxa. Although the sage-grouse is not a federally listed threatened or endangered species, we included mapped habitat for the purpose of informing wildfire decision making.

Our fire-adapted ecosystems layer represents areas where fire historically played an important role in a nonlethal way to maintain the ecosystem, and where the management goal can be reintroduction of fire on the landscape. The data are derived using fire regime and fire return interval data products from LANDFIRE (http://www.landfire.gov). Our definition of fire-adapted ecosystems included cells that had fire regime groups 1 or 3 (fire return interval of less than 200 years and low to mixed severity) and the percent of low severity fire was greater than 50 percent (codes 11–20); this definition is based in large part on concepts provided by Robert Keane (Research Ecologist, Rocky Mountain Research Station, US Forest Service).

The subset of HVR layers included here are, admittedly, insufficient for a truly comprehensive analysis. Many potential data layers were necessarily omitted due to issues with data availability, quality, etc. Biological data sets for ecoregions with high species richness and rarity

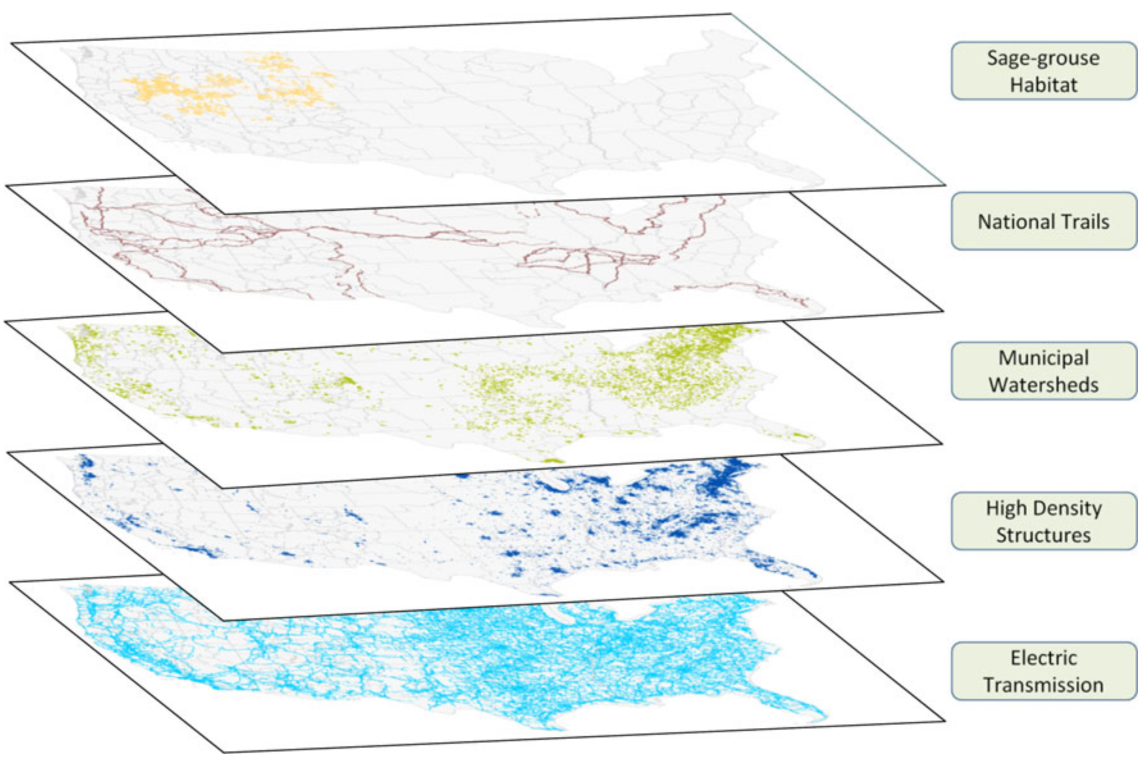



**Fig. 2** Conceptual representation of geospatial overlay of human and ecological values at the national scale. Each pixel can support multiple resources. For example, in the layers depicted below, a given pixel in the Northwest might simultaneously house sage-grouse habitat, municipal watersheds, high-density built structures, and electric transmission lines

(World Wildlife Fund), critical watersheds for conserving biodiversity (NatureServe), and international biological hotspots (Conservation International), for instance, were discarded because of overly coarse spatial resolution. Priority conservation areas (The Nature Conservancy), national wetlands inventory (U.S. Fish and Wildlife Service), and GAP species richness (U.S. Geological Survey) were omitted because of incomplete map extents. Calkin et al. (2010) describes in more detail many of the challenges and issues associated with acquiring geospatial HVR datasets at the national scale, and lists the data sources for included layers. Interested readers are also referred to Jones et al. (2004) and Agumya and Hunter (1999), who discuss the use and limitations of geospatial data, including the importance of understanding the uncertainty surrounding the data and the necessity to use particular datasets despite their inherent uncertainty due to the lack of suitable alternatives.

### 2.4 Defining and assigning resource response functions

Estimating resource response to wildfire (i.e., effects analysis) is a crucial step for quantitative risk assessment (Fairbrother and Turnley 2005). Effects analysis is made difficult by the scientific uncertainty and lack of data/information surrounding wildfire effects on non-market resources (Venn and Calkin 2009; Keane and Karau 2010). An expert systems approach was, therefore, adopted to deal with the scientific uncertainty (e.g., Vadrevu et al. 2010; González et al. 2007; Kaloudis et al. 2005; Hirsch et al. 1998, 2004). Expert systems rely on the best judgment of experts as a proxy for empirical data. Ten fire and fuels program management officials from the Forest Service, National Park Service, Bureau of Land Management, Fish and Wildlife Service, and the Bureau of Indian Affairs consulted with the authors to facilitate response function assignments.

We defined a suite of generalized response functions that translate fire effects into NVC for each HVR, based upon flame length category. Basing resource response on a measure of fire intensity, such as flame length, is a common approach in wildfire risk assessment (e.g., Ager et al. 2007, 2010). We defined these functions so as to reflect the different ways in which the various HVRs might respond to fire of different intensities (e.g., fire-adapted ecosystems see a beneficial effect from low intensity fire, but losses are anticipated from high intensity fire). Table 2 presents response function quantitative definitions, qualitative descriptions, and HVR assignments as identified by the queried experts.

The response functions indicate relative NVC as a percentage of initial resource value, for each flame length category. NVC is estimated using an area-based proxy called Total Change Equivalent (TCE). TCE aggregates pixel-based outputs and is defined as the equivalent area lost (or gained) for a particular HVR, measured in acres. TCE is calculated by multiplying a percentage coefficient (relative NVC) for each flame length category by the conditional flame length probability, which in turn is multiplied by pixel area. As an example, consider a pixel on the landscape that contains designated critical habitat for a fire susceptible species (e.g., the northern spotted owl). Assume the wildfire simulation model indicates the following conditional flame length probability vector: (1, 1, 0.5, and 0.25%). The assigned response function, RF7, predicts 10% loss, 60% loss, 70% loss, and 80% loss, corresponding to the flame length categories Low, Moderate, High, and Very High, respectively. TCE for this specific HVR on this specific pixel would therefore be calculated as $\{7.28 \text{ ha} * [(0.01 * -0.1) + (0.01 * -0.6) + (0.005 * -0.7) + (0.0025 * -0.8)]\} = -0.09$ ha.[2] As pixels and the national landscape support multiple HVR layers, generation of risk estimates entailed computations for each pixel-HVR layer combination.

### 2.5 Integrating risk calculations

TCE as a measure of risk enables commensurability, facilitating integration of the multiple assets and resource values we consider here. This allows for the evaluation of alternative mitigation strategies on the basis of cost-effectiveness to inform comparative risk assessment. Another benefit of a common measure like TCE is a significantly reduced cognitive burden relative to balancing multiple, non-commensurate measures, thereby reducing the likelihood of users adopting mental shortcuts that can systematically bias decision-making (Maguire and Albright 2005). Further, use of TCE enables additive evaluations of risk, for instance to identify regions with higher quantities of expected loss to a suite of HVRs. However, TCE does not capture management priority or social worth ascribed to each HVR, prompting the consideration of various alternatives for incorporating information related to preferences.

First, we adopt a categorical approach using input from the fire and fuels program management officials consulted for assistance with fire effects analysis. With guidance from the experts we assigned each HVR to a generic "value category"—Moderate, High, and Very High. Within the Moderate value category, experts assigned Class 1 areas, recreation sites and campgrounds, national trails, and fire-adapted ecosystems. Within the high value category, low-density built structures, electronic transmission lines, oil and gas pipelines, energy generation plants, cellular phone towers, ski areas, and critical habitat for fire-susceptible species. Within the Very High category, non-attainment areas, moderate- and high-density built structures, and municipal watersheds. Assigning value

[2] 18 acre pixel; net expected loss of 0.225 acres.

**Table 2** Response function (RF) quantitative definitions, descriptions, and HVR assignments

| RF | % NVC by flame length category | | | | Description | HVR layer/sub-layers assigned |
|---|---|---|---|---|---|---|
| | L | M | H | VH | | |
| 1 | +60 | +20 | −20 | −60 | Strong benefit at low fire intensity decreasing to a strong loss at Very High fire intensity | Fire-adapted ecosystems |
| 2 | +30 | +10 | −10 | −30 | Moderate benefit at low fire intensity decreasing to a moderate loss at Very High fire intensity | National alpine ski area locations (recreation infrastructure) |
| 3 | 0 | −10 | −20 | −30 | Mild increasing loss from slight benefit or loss at low intensity to a moderate loss at Very High intensity | Class I areas (air quality); recreational sites and campgrounds (recreation infrastructure) |
| 4 | −10 | −30 | −50 | −80 | Moderate increasing loss from mild loss at low intensity to a strong loss at Very High intensity | Municipal watersheds |
| 5 | 0 | 0 | 0 | −50 | Slight benefit or loss at all fire intensities except a moderate loss at Very High intensity | National scenic and historic trails (recreation infrastructure) |
| 6 | −80 | −80 | −80 | −80 | Strong loss from fire at all fire intensities | Residential structure location |
| 7 | −10 | −60 | −70 | −80 | Loss increases from slight loss at low intensity to strong loss at Very High intensity | Non-attainment areas (air quality); fire-susceptible species |
| 8 | 0 | 0 | −80 | −80 | Slight benefit or loss from fire at low and moderate intensities and a strong loss from fire at High and Very High intensities | Energy infrastructure |

Each response function expresses percent NVC as a function of flame length category (Low, Moderate, High, and Very High). Fire and fuels program management officials assigned each HVR to the most appropriate response function

categories to HVR layers implies that HVRs in the same category have relative social values of a similar magnitude. A more detailed justification for these value category assignments can be found in Calkin et al. (2010).

Clearly, further articulation of preferences would provide better information on the relative importance of each HVR and its associated TCE. There exists the temptation to monetize all resources to provide a common measure that encapsulates relative worth. Often however price-based approaches do not adequately account for wildfire effects to non-market resources (Brillinger et al. 2009). According to Venn and Calkin (2009), the current state of non-market valuation is insufficient to credibly monetize all resource values considered in this study, presenting a challenge to reporting and quantifying risk to multiple, overlapping resources at both pixel and landscape scales.

To move forward in the absence of a monetization approach we turn to ratio-scale preference models, common to many decision support techniques such as the Analytic Hierarchy Process (Saaty 1980). We aggregated TCE results into a single weighted risk metric by presuming that the ranking of value categories maintained a simple proportional relationship. Equation 3 displays how weighted TCE (wTCE) is calculated, where $\alpha_i$ is the weight assigned to the value category associated with HVR $i$, and where $n$ is the number of HVR layers.

$$wTCE = \sum_{i=1}^{n} \alpha_i TCE_i \tag{3}$$

We evaluated three weight vectors: (1, 2, 4), (1, 3, 9), and (1, 4, 16), reflecting value differential factors of 2, 3, and 4, respectively. For example, the (1, 3, 9) weight vector assumes resources in the Very High value category are three times as important as resources in the high value category, which in turn are three times as important as resources in the Moderate value category. If normalized to sum to 1.00, our weight vectors become (0.14, 0.29, 0.57), (0.08, 0.23, 0.69), and (0.05, 0.19, 0.76). This approach is similar to previous work overlaying user-defined weighting schemes with geospatially identified landscape variables (e.g., Rideout et al. 2008; Southern Sierra Geographic Information Cooperative 2003).

Clearly, decision-makers can experiment with various weight vectors and value category assignments to explore how changes affect the proportion of risk assigned to various HVR layers, how risk is spatially distributed across Geographic Areas and FPUs, and how monitoring and treatment priorities may change in response. The interaction of value category assignments and the weights assigned to each value category may have a significant influence on risk estimates. These expressions of preference therefore require careful consideration to ensure they reflect relative national priorities.

## 2.6 Geo-processing risk

Calculating TCE risk values combined fire simulation flame length probability files, geospatial resource layers, and response functions. These computations were automated in the Python programming language within ArcMap (www.esri.com). Specifically, three sequential modules were written to batch-process data for each FPU. All processing was conducted on a PC with ESRI ArcGis 9.3 software with the Spatial Analyst extension. Figure 3 outlines the major steps in the computation of risk estimates. The first two modules, "Import FPA 2 Raster" and "FLC_HVR," prepare the data for processing by the third module, "BL_Calc," which calculates the percent change in value (TCE) for each HVR-pixel combination. All input data were in the Albers USGS NAD83 projection.

The module "Import FPA 2 Raster" operates on text files output from the wildfire simulation model FSim. Each file contains probabilities of wildfire by flame length under specified fuel moisture and weather conditions analyzed at the FPU level. The text files contain (X,Y) coordinate information and flame lengths as point locations on each 270 m pixel. These points are converted to an intermediate database (dbf) file; in this conversion process flame lengths are collapsed into four flame length categories (FLCs). The database file is then converted to an intermediate (X,Y) event table, and a raster file for each FPU-FLC combination is created.

The "FLC_HVR" module processes each FPU-FLC file, which contain FLCs for all pixels within the FPU. This module masks these input FPU-FLC files so that only those pixels containing HVRs are output. The "BL_Calc" module then calculates, on a pixel by pixel basis, benefits and losses to each HVR layer within that pixel, according to the HVR's assigned response function and the probabilities associated with each FLC. Total Change Equivalent (TCE) is calculated by multiplying a percentage coefficient for each FLC (response function) by the conditional FLC probability, which in turn is multiplied by pixel area.

Output from the "BL_Calc" module is a raster file of percent change, for the HVR, for each of the FLCs. These output pixels are then summed by HVR, producing a raster file of total percent change for the HVR across all FLCs. The third output is a sum of these total percent change values for all HVRs assigned to a particular HVR value category. On top of this latter output we overlaid weight vectors to output singular, weighted TCE values mapped at the pixel scale across the continental United States.

## 3 Results

### 3.1 Summary statistics

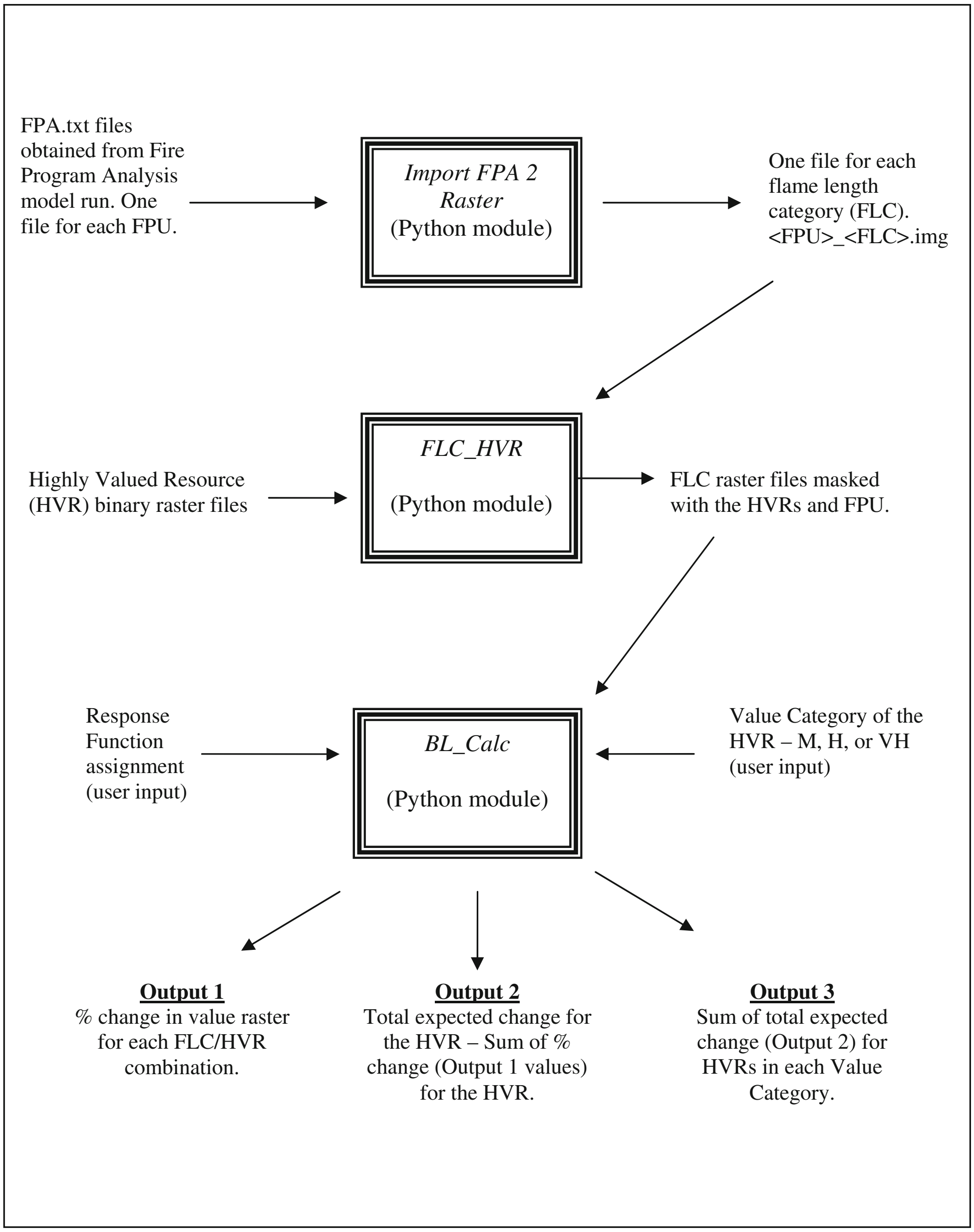
Table 3 displays total mapped hectares and TCE (expected NVC measured in hectares) for each HVR layer, sorted by value category. Independent of value category, the HVRs with the greatest expected loss are, in order, non-attainment areas (−54,467 ha), sage-grouse key habitat (−51,933 ha), and critical habitat (−35,321 ha), moderate and high density built structures (−16,891 ha), watersheds (−13,416 ha), class I areas (−8,819 ha), low density built structures (−8,069 ha), and energy infrastructure (−3,953), with minimal expected impact to recreation infrastructure. Fire-adapted ecosystems are expected to see substantial beneficial impacts associated with fire (+17,396 ha).

Tables 4, 5 and 6 further break down results from Table 3 by Geographic Area and value category. We address each value category and associated HVR layers in turn, starting with the Moderate value category (Table 4). For Class I areas the Southern Area (−5,322 ha) and Northern Rockies (−1,331 ha) stand out. Across all regions fire-adapted ecosystems are expected to see a benefit associated with fire, in particular the Northwest (5,832 ha), Great Basin (3,420 ha), Southwest (3,018 ha), and Northern Rockies (2,867 ha). Fire impacts to national recreation trails/campgrounds/sites are expected to be minimal. California (−581 ha) and especially the Southern Area (−4,858 ha) anticipate losses to Moderate HVRs associated with wildfire. Other Geographic Areas anticipate net beneficial impacts to Moderate HVRs, especially the Northwest (5,337 ha), the Great Basin (3,178 ha), the Southwest (2,543 ha), and the Northern Rockies (1,532 ha).

Fire-susceptible species were the largest contributors to risk within the High value category (Table 5). With respect to designated critical habitat, most Geographic Areas have expected habitat loss approximately in the range 4,000–10,000 ha. The comparatively low TCE values for critical habitat in the Eastern Area and Rocky Mountains reflect in large part lack of mapped fire-susceptible species in these regions, as well as lower wildfire hazard in parts of the east. The Northern Rockies comprise the largest share of TCE for critical habitat in large part due to extensive Canada lynx habitat. The Great Basin (−28,404 ha), Northwest (−13,415) and Rocky Mountain (−6,443) Geographic Areas house large areas of expected loss to key sage-grouse habitat. TCE values for energy infrastructure were relatively low across all Geographic Areas, with an exception in the Southern Area (−2,004 ha), which also contained the largest overall area of energy infrastructure. Low density built structures similarly had relatively low TCE values, with higher losses associated with the Southern Area (−3,512 ha), California (−1,245 ha), and the Southwest (−1,073 ha). As with other recreation infrastructure (Table 4), impacts to ski area locations are expected to be minimal.

Non-attainment areas were by far the largest contributors to risk within the Very High value category (Table 6). Air quality factors very prominently in California, which has an expected TCE of −45,191 ha that is an order of magnitude larger than any other Geographic Area. Overall

**Fig. 3** Analysis flow for calculating risk. Modified from Calkin et al. (2010)




California appears to dominate the picture of risk in the Very High value category (−55,534 ha), with the highest risk by far associated with non-attainment areas, the second highest risk associated with moderate/high density built structures, and the highest risk associated with watersheds. The Southern Area is the clear runner-up (−14,438 ha), with the second highest risk associated with non-attainment areas and watersheds, and the greatest risk associated with moderate/high density built structures. The Southwest region ranks third (−5,996 ha), largely due to risk associated with non-attainment areas.

In summary, we see that some areas appear more susceptible to wildfire-related loss than others, in particular California and the Southern Area. However it is difficult to describe the degree to which one Geographic Area may constitute greater risk than another area without considering the relative priority across value categories. We therefore turn to our three weight vectors (described above) to understand how our assessment of overall risk may change as a function of value category and weight assignments. Before doing so however we first address some issues related to our TCE calculations.

### 3.2 TCE adjustments: spatial and temporal extent

Our results exhibit a moderate association between total hectares and TCE, as might be expected when using an area-based measure of risk (Table 3). This association is

**Table 3** Total hectares and TCE hectares by HVR category/layer at the national scale, as sorted by value category

| Value category | HVR category | HVR layer | Total hectares | TCE hectares |
|---|---|---|---|---|
| Moderate | Air quality | Class I areas | 12,463,691 | −8,819 |
| | Fire-adapted ecosystems | Ecosystems | 29,888,286 | 17,396 |
| | Recreation infrastructure | National trails/camps/sites | 1,924,290 | −181 |
| | Total | | 44,276,267 | 8,396 |
| High | Built structures | Low density | 16,628,505 | −8,069 |
| | Energy/Infrastructure | Energy/infrastructure | 38,173,961 | −3,953 |
| | Fire-susceptible species | Critical habitat | 23,963,834 | −35,321 |
| | | Sage-grouse key habitat | 20,398,842 | −51,933 |
| | Recreation infrastructure | Ski area locations | 363,071 | 23 |
| | Total | | 99,165,142 | −99,253 |
| Very High | Air quality | Non-attainment areas | 79,065,444 | −54,467 |
| | Built structures | Mod/High density | 53,405,009 | −16,891 |
| | Watersheds | Watersheds | 61,804,897 | −13,416 |
| | Total | | 194,275,350 | −71,371 |

**Table 4** Total change equivalent (TCE) in hectares by HVR layer for each Geographic Area: Moderate value category

| | Geographic Area | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CA | EA | GB | NR | NW | RM | SA | SW |
| Class I areas | −871 | −40 | −237 | −1,331 | −488 | −59 | −5,322 | −471 |
| Ecosystems | 336 | 659 | 3,420 | 2,867 | 5,832 | 686 | 578 | 3,018 |
| National recreation | −46 | 0 | −5 | −4 | −7 | −1 | −114 | −4 |
| Total | −581 | 619 | 3,178 | 1,532 | 5,337 | 626 | −4,858 | 2,543 |

**Table 5** Total change equivalent (TCE) in hectares by HVR layer for each Geographic Area: High value category

| | Geographic Area | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CA | EA | GB | NR | NW | RM | SA | SW |
| Critical habitat | −6,078 | −854 | −4,048 | −10,336 | −5,585 | −273 | −4,023 | −4,123 |
| Sage-grouse | −1,749 | 0 | −28,404 | −1,922 | −13,415 | −6,443 | 0 | 0 |
| Energy | −831 | −176 | −208 | −51 | −102 | −208 | −2,004 | −374 |
| Low density | −1,245 | −693 | −336 | −397 | −300 | −513 | −3,512 | −1,073 |
| Ski area locations | −3 | 4 | 6 | 7 | 4 | 2 | 2 | 0 |
| Total | −9,906 | −1,719 | −32,990 | −12,699 | −19,398 | −7,435 | −9,537 | −5,570 |

**Table 6** Total change equivalent (TCE) in hectares by HVR layer for each Geographic Area: Very High value category

| | Geographic Area | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CA | EA | GB | NR | NW | RM | SA | SW |
| Non-attainment areas | −45,191 | −1,027 | −1,134 | −106 | −4 | −155 | −3,615 | −3,234 |
| Mod/High density | −5,211 | −1,105 | −488 | −428 | −550 | −404 | −6,851 | −1,853 |
| Watersheds | −4,952 | −155 | −921 | −716 | −1,142 | −679 | −3,972 | −879 |
| Total | −55,534 | −2,287 | −2,543 | −1,250 | −1,696 | −1,238 | −14,438 | −5,966 |

especially evident for fire-susceptible species. The spatial extent of key sage-grouse habitat in particular stands out, nearly equaling the total area and exceeding the total TCE of federally designated critical habitat for the 40 other species considered in our analysis. Within the critical habitat HVR Canada lynx comprises nearly 47% of total critical habitat area and 43% of TCE. The Northern Spotted Owl (13% of total habitat, 15% of TCE) and Mexican Spotted Owl (17/12%) also exert a significant influence on overall TCE calculations.

These observations call into question relationships between spatial extent of HVRs, TCE values, and relative scarcity. For a HVR such as structure locations, the greater the TCE value the greater the likelihood of wildfire interacting with human development, and risk is appropriately increased. With respect to habitat however a greater TCE does not necessarily indicate greater susceptibility of species loss. In other words, 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. If we instead consider the likely portion of habitat lost (i.e., TCE hectares/total hectares), the relative ranking of most at-risk fire-susceptible species changes dramatically (Table 7).

Considering only TCE, the 10 most at-risk species are (1) sage-grouse, (2) Canada lynx, (3) Northern spotted owl, (4) Mexican spotted owl, (5) Cape Sable Seaside Sparrow, (6) Marbled Murrelet, (7) Desert Tortoise, (8) Coastal California Gnatcatcher, (9) Peninsular Bighorn Sheep, and (10) Quino checkerspot butterfly. As seen in Table 7, when looking instead at portion of habitat loss many of these species lose salience relative to other species with smaller habitat extents but greater likelihood of loss. The two most influential species, sage-grouse and Canada lynx, end up falling to ranks 15 and 25, respectively. The Cape Sable Seaside Sparrow by contrast increases in salience, geographically ascribing high risk to areas of interior southern Florida with frequent fire.

Arguably these results suggest decoupling fire-susceptible species from the integrated TCE calculations and presenting information on expected habitat loss separately. Instead of TCE we consider percent of expected habitat loss as our measure of risk. Table 8 summarizes the results of risk to fire-susceptible species by Geographic Area. California (9.26%), the Southern Area (5.40%), and the Southwest (1.21%) comprise the largest contributions. Whereas in the Southern Area these results are driven by a particular at-risk species (Cape Sable Seaside Sparrow), in the other areas risk is elevated due to multiple species. Take for instance California, which houses critical habitat for a multitude of species including the Mountain Yellow-legged Frog, San Bernardino Mountains bladderpod, Quino checkerspot butterfly, Vail Lake ceanothus, and Arroyo Toad.

Another possible issue with our TCE calculations relates to the temporal extent of air quality impacts. Although we recognize that smoke issues are very important and can result in significant health and economic impacts (Kochi et al. 2010), particularly in highly populated areas, smoke impacts last only a short duration (days to weeks) relative to the impacts to other resource types. Omission of this temporal component may inflate the risk associated with wildfire in non-attainment areas and class I areas. To explore changes to TCE values, we adjusted results by a factor of 1/52, based on the rationale that the human health and safety issues associated with smoke only last for, on average, 1 week per year. Table 9 presents the collective changes to TCE values due to excluding fire-susceptible species and applying the air quality temporal adjustment factor.

### 3.3 Integrated risk: weighted TCE values

Given the above discussion of issues related to management priority, spatial extent of fire-susceptible species, and temporal extent of air quality impacts, we perform a sensitivity analysis that presents weighted TCE (wTCE) values for a range of assumptions. Our analysis explores how the relative ranking of Geographic Areas may change as wTCE changes. Table 10 presents results in four quadrants, distinguished by two factors: (1) whether fire-susceptible species are included in wTCE calculations, and (2) whether the temporal adjustment factor is applied to air quality HVRs. Within each quadrant we present results for our three ratio-scale weight vectors, thereby arriving at a total of 12 scenarios to analyze.

An immediately apparent trend is the prominence of California and the Southern Area, which in 11 of 12 examined scenarios constitute the two Geographic Areas with the greatest degree of risk. The one exception occurs where fire-susceptible species are included, where air quality is adjusted, and with the weight vector that places the most importance on moderate and high HVRs (especially fire-susceptible species) relative to Very High HVRs (1, 2, 4); under these conditions the Great Basin comprises the greatest risk due to extensive sage-grouse key habitat (see Table 7). The Southern Area is ranked first where fire-susceptible species are excluded and where air quality is adjusted, both of which reduce expected loss for California.

Another notable trend is the seeming *unimportance* of the weight vectors. Within each quadrant, rankings across weight vectors remain remarkably consistent. This finding is very encouraging, suggesting our results are robust and should not substantially differ under alternative preferences. However should initial value categories be defined differently these results may change.

With respect to the inclusion/exclusion of fire-susceptible species (comparison across upper and lower halves of Table 10), the exclusion of fire-susceptible species tends to skew overall risk towards California and the Southern Area while decreasing risk everywhere else. Without fire-susceptible species the Southwest area moves up in rank to a consistent 3rd, a logical result as SW ranks 3rd in both the High and Very High value categories (independent of

**Table 7** Total hectares, TCE hectares, and percent of total habitat lost by species

| Rank | Species | Total hectares | TCE (hectares lost) | % Habitat lost |
|---|---|---|---|---|
| 1 | Cape Sable Seaside Sparrow | 79,920 | 4,005 | 5.01 |
| 2 | Mountain Yellow-legged Frog | 3,455 | 48 | 1.39 |
| 3 | San Bernardino Mountains bladderpod | 401 | 5 | 1.16 |
| 4 | Quino checkerspot butterfly | 69,503 | 677 | 0.97 |
| 5 | Vail Lake ceanothus | 87 | 1 | 0.86 |
| 6 | Arroyo Toad | 42,275 | 345 | 0.82 |
| 7 | Thread-leaved brodiaea | 2,566 | 21 | 0.81 |
| 8 | Mexican flannelbush | 95 | 1 | 0.65 |
| 9 | Coastal California Gnatcatcher | 151,042 | 756 | 0.50 |
| 10 | Spruce-fir moss spider | 3,886 | 15 | 0.38 |
| 11 | New Mexico Ridge-nosed Rattlesnake | 1,232 | 4 | 0.35 |
| 12 | Cushenbury buckwheat | 2,726 | 10 | 0.35 |
| 13 | Cushenbury oxytheca | 1,276 | 4 | 0.31 |
| 14 | Sonora Chub | 29 | 0 | 0.30 |
| 15 | Sage grouse | 20,398,842 | 51,933 | 0.25 |
| 16 | California Red-legged Frog | 181,907 | 419 | 0.23 |
| 17 | Parish's daisy | 1,837 | 4 | 0.21 |
| 18 | Peninsular Bighorn Sheep | 330,412 | 691 | 0.21 |
| 19 | Gila chub | 4,556 | 9 | 0.20 |
| 20 | Cushenbury milk-vetch | 1,735 | 3 | 0.19 |
| 21 | Southwestern Willow Flycatcher | 48,799 | 92 | 0.19 |
| 22 | Wenatchee checkermallow | 26,186 | 46 | 0.17 |
| 23 | Northern Spotted Owl | 3,193,647 | 5,472 | 0.17 |
| 24 | Marbled Murrelet | 1,573,656 | 2,200 | 0.14 |
| 25 | Canada Lynx | 11,217,932 | 15,044 | 0.13 |
| 26 | Purple amole | 642 | 1 | 0.13 |
| 27 | Alameda Whipsnake | 62,577 | 70 | 0.11 |
| 28 | Mt Graham Red Squirrel | 744 | 1 | 0.11 |
| 29 | Mexican Spotted Owl | 3,994,052 | 4,324 | 0.11 |
| 30 | Bay Checkerspot Butterfly | 9,710 | 9 | 0.09 |
| 31 | Colorado butterflyplant | 1,494 | 1 | 0.08 |
| 32 | Bull Trout | 290,332 | 216 | 0.07 |
| 33 | Zayante band-winged grasshopper | 4,534 | 3 | 0.07 |
| 34 | Preble's Meadow Jumping Mouse | 12,612 | 5 | 0.04 |
| 35 | Desert Tortoise | 2,611,103 | 816 | 0.03 |
| 36 | Inyo California towhee | 882 | 0 | 0.01 |
| 37 | Houston Toad | 34,219 | 3 | 0.01 |
| 38 | Oregon silverspot butterfly | 87 | 0 | 0.00 |
| 39 | Kincaid's lupine | 204 | 0 | 0.00 |
| 40 | Fender's blue butterfly | 1,196 | 0 | 0.00 |
| 41 | Willamette daisy | 284 | 0 | 0.00 |

*Note*: Zeros represent fractional hectares or percentages of habitat lost

air quality adjustment). The Eastern Area also moves up in rank, but this information must be evaluated alongside the observation that in the Eastern Area wildfire poses little to no risk to critical habitat (0.01% expected habitat loss; Table 8). As expected, the Great Basin, Northwest, and Northern Rockies all move down in rank due to substantial reductions in High value category TCE.

With respect to unadjusted/adjusted air quality (comparison across left and right halves of Table 10), the most obvious change resulting from the adjustment is the

**Table 8** Total expected habitat loss as a percent of total habitat, summed across fire-susceptible species within each Geographic Area

| Geographic Area | Total % habitat loss |
|---|---|
| CA | 9.26 |
| SA | 5.40 |
| SW | 1.21 |
| NW | 0.50 |
| GB | 0.19 |
| RM | 0.15 |
| NR | 0.13 |
| EA | 0.01 |

significant reduction in weighted TCE values for California. This was expected due to the 5-fold reduction in Very High TCE for California (Table 9). The distribution of risk across Geographic Areas is significantly less skewed, and weighted risk values for California and the Southern Area are nearly identical after the adjustment. When evaluated in concert with exclusion of fire-susceptible species (lower-right quadrant), the Southern Area switches rank with California to comprise the greatest area of overall risk.

Figure 4 displays the relative contributions of each HVR to national weighted TCE for the baseline (fire-susceptible included, air quality unadjusted; upper-left quadrant in Table 10) and fully modified (fire-susceptible excluded, air quality adjusted; lower-right quadrant in Table 10) scenarios. In the modified scenario the role of non-attainment areas is significantly diminished. Smoke impacts are now less of a driver to risk than all other HVRs related to human health (built structures and watersheds), and are roughly on par with energy and critical infrastructure. Figures 5 and 6 compare Geographic Area share of national weighted TCE for the baseline and modified scenarios, respectively. Both are calculated using the (1, 3, 9) weight vector. The primary difference is between California and the Southern Area, largely due to the air quality adjustment. In the modified scenario the Great Basin and Northwest comprise a smaller share of national risk due to the exclusion of fire-susceptible species. To reiterate the information presented in the modified scenario should be evaluated simultaneously with the information on fire-susceptible species presented in Table 8. The top three Geographic Areas by wTCE (SA, CA, and SW, Fig. 6) are also the top three areas of high expected loss to fire-susceptible species (although not exactly by rank, Table 8), providing an aligned picture of integrated risk.

Figures 7 and 8 display TCE values for all FPUs within the California and Northwest Geographic Areas, respectively. For economy of presentation we display just two illustrative examples of the output provided for all Geographic Areas. In the case of California, we see that significant losses to resources within the Very High value category are expected, in particular within the San Diego Area and Riverside Area FPUs. This elevated risk is due in part to high population densities in fire-prone areas. By contrast, the Northwest GACC has relatively few resources of similar value category at risk, and significant benefits to fire-adapted ecosystems are anticipated in the Central Oregon and Southeast Oregon FPUs. Analysis of these outputs facilitates prioritization across and within GACCs.

## 4 Discussion

This assessment provides a framework within which to estimate the relative contributions of various highly valued resources to national risk. The framework also provides a platform for comparative risk assessment, insofar as risk mitigation efforts can be modeled. A clear opportunity is fuel treatment evaluation, in which fire simulations can be run on landscapes with modeled treatments to see subsequent impacts on fire behavior and associated reductions in risk (e.g., Ager et al. 2010). It may be possible to model other mitigation measures, such as fire-wise investments, by changing response function definitions. A key additional variable for comparative risk assessment is management opportunity, i.e., where can we actively seek to mitigate

**Table 9** Total change equivalent (TCE) in hectares for each Geographic Area across value categories, with baseline calculations as well as TCE adjustments

| | Geographic Area | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CA | EA | GB | NR | NW | RM | SA | SW |
| Moderate | −581 | 619 | 3,178 | 1,532 | 5,337 | 626 | −4,858 | 2,543 |
| Mod. adj. | 273 | 658 | 3,410 | 2,837 | 5,816 | 684 | 362 | 3,005 |
| High | −9,906 | −1,719 | −32,990 | −12,699 | −19,398 | −7,435 | −9,537 | −5,570 |
| High adj. | −2,079 | −865 | −538 | −441 | −398 | −719 | −5,514 | −1,447 |
| Very High | −55,534 | −2,287 | −2,543 | −1,250 | −1,696 | −1,238 | −14,438 | −5,966 |
| V.H. adj. | −11,032 | −1,280 | −1,431 | −1,146 | −1,692 | −1,086 | −10,893 | −2,794 |

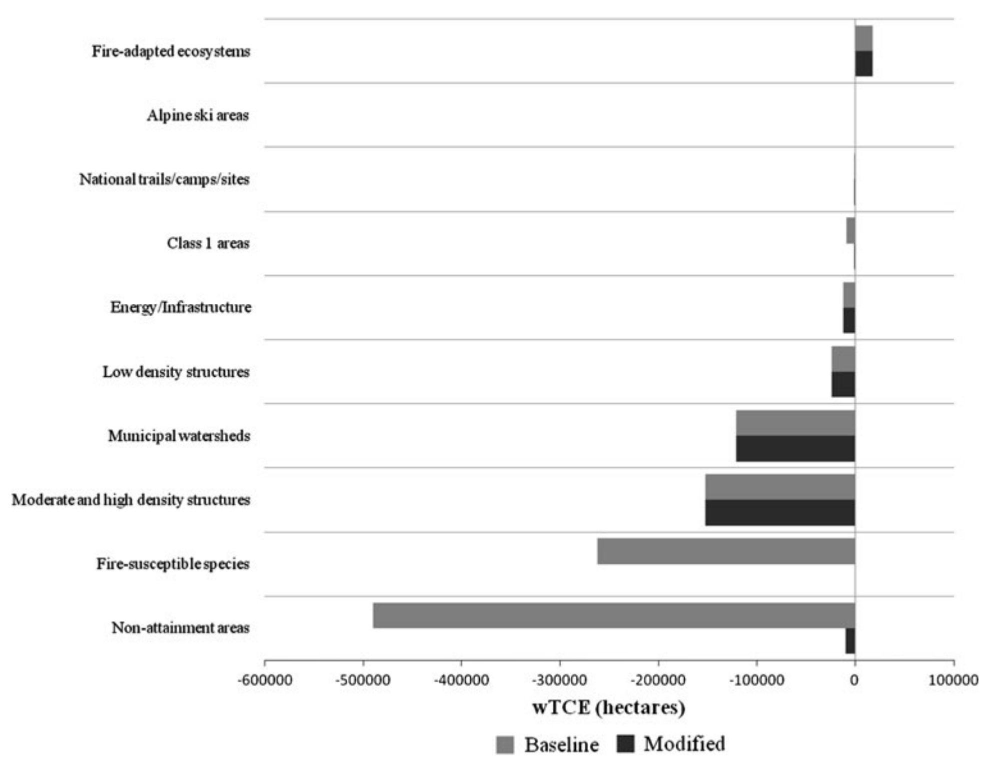
Moderate and Very High value category TCEs are adjusted by the air quality temporal factor. High value category TCEs are adjusted to exclude fire-susceptible species

**Table 10** Geographic Areas ranked by weighted TCE values (and % of overall weighted TCE)

| Rank | Air quality *unadjusted* | | | Air quality *adjusted* | | |
|---|---|---|---|---|---|---|
| | Weight vector | | | Weight vector | | |
| | (1, 2, 4) | (1, 3, 9) | (1, 4, 16) | (1, 2, 4) | (1, 3, 9) | (1, 4, 16) |
| Fire-susceptible species *included* | | | | | | |
| 1 | CA (45.69%) | CA (50.22%) | CA (53.06%) | GB (22.25%) | CA (22.87%) | CA (24.48%) |
| 2 | SA (15.43%) | SA (15.53%) | SA (15.70%) | CA (20.75%) | SA (22.43%) | SA (24.05%) |
| 3 | GB (13.79%) | GB (11.28%) | GB (9.71%) | SA (20.29%) | GB (19.26%) | GB (17.18%) |
| 4 | NW (7.60%) | NW (6.47%) | SW (6.60%) | NW (12.95%) | NW (12.01%) | NW (11.21%) |
| 5 | SW (6.13%) | SW (6.45%) | NW (5.70%) | NR (8.85%) | NR (8.10%) | NR (7.52%) |
| 6 | NR (5.46%) | NR (4.54%) | NR (3.97%) | SW (6.29%) | SW (6.90%) | SW (7.26%) |
| 7 | RM (3.63%) | RM (3.12%) | RM (2.80%) | RM (6.04%) | RM (5.58%) | RM (5.27%) |
| 8 | EA (2.26%) | EA (2.39%) | EA (2.46%) | EA (2.57%) | EA (2.84%) | EA (3.03%) |
| Fire-susceptible species *excluded* | | | | | | |
| 1 | CA (63.76%) | CA (63.88%) | CA (64.08%) | SA (40.97%) | SA (37.93%) | SA (36.79%) |
| 2 | SA (20.76%) | SA (19.14%) | SA (18.48%) | CA (36.27%) | CA (34.95%) | CA (34.65%) |
| 3 | SW (6.83%) | SW (7.02%) | SW (7.07%) | SW (8.36%) | SW (8.79%) | SW (8.92%) |
| 4 | EA (2.89%) | EA (2.85%) | GB (2.84%) | EA (4.68%) | EA (4.47%) | EA (4.37%) |
| 5 | GB (2.28%) | GB (2.70%) | EA (2.82%) | RM (3.85%) | RM (3.74%) | NW (4.29%) |
| 6 | RM (1.63%) | RM (1.60%) | NW (1.68%) | GB (2.56%) | GB (3.68%) | GB (4.06%) |
| 7 | NR (1.23%) | NW (1.41%) | RM (1.58%) | NR (1.99%) | NW (3.52%) | RM (3.67%) |
| 8 | NW (0.63%) | NR (1.40%) | NR (1.45%) | NW (1.32%) | NR (2.92%) | NR (3.24%) |

Sensitivity analysis is performed across three weight vectors, whether fire-susceptible species are included in TCE calculations, and whether the temporal adjustment to air quality TCE calculations is applied

**Fig. 4** Contribution of each HVR layer to wTCE at the national scale, for the baseline and modified scenarios



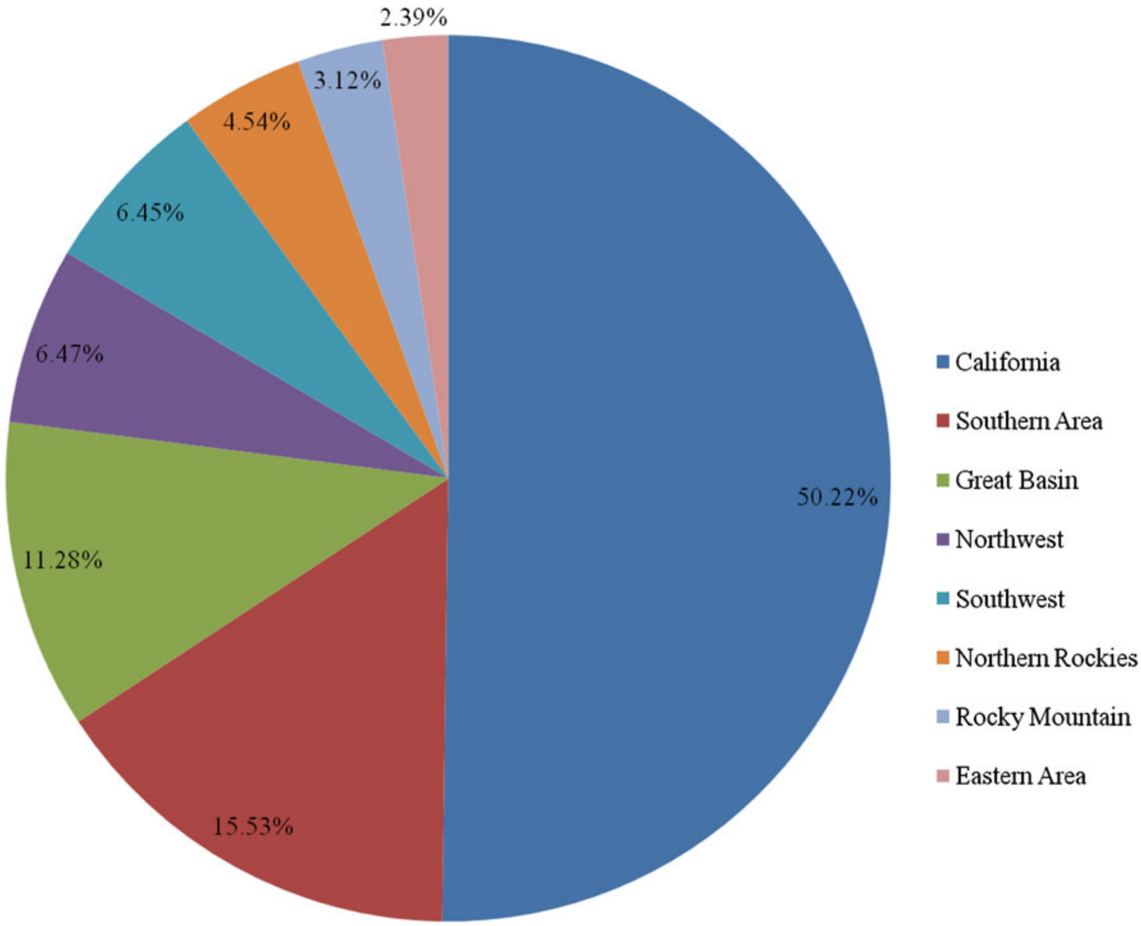



**Fig. 5** Geographic Area share of national weighted risk (wTCE), for the baseline scenario, using the (1, 3, 9) weight vector

risk. Raw risk values inform risk mitigation planning and prioritization, but this information needs to be augmented with information on where treatments are likely to be effective, and to what degree risk can be reduced. The types of risk-based outputs from our framework can dovetail well with proposed decision analytic approaches for integrated, multi-attribute fuel management planning (Stockmann et al. 2010; Hyde et al. 2006; Ohlson et al. 2006).

This risk assessment framework that pairs fire modeling with fire effects analysis is scalable, meaning the same approaches can be employed from the project (e.g., Ager et al. 2007) to the national scale (which we demonstrate here). Currently the Beaverhead-Deerlodge National Forest in Montana is employing very similar techniques as part of an integrated fire and fuels risk assessment. Highly valued resources considered in that assessment include isolated threatened and endangered fish population, recreation infrastructure, wildland–urban interface, municipal watersheds, streams listed as water quality limited under the Clean Water Act, utility infrastructure, and wildlife habitat.

We performed a sensitivity analysis regarding several important questions—how to handle wildfire risk to habitat with a spatial proxy for risk, how to account for the short duration of smoke impacts relative to other HVRs, and how to incorporate relative importance across HVRs. Both the temporal adjustment factor and the initial value category assignment could be subjects of further sensitivity analysis as well. The issue of temporal dynamics of resource response is not unique to air quality. This exploration we leave for future work.

We stressed the utility of our approach to quantification of risk (TCE), which provides an objective, transparent, and commensurate measure of risk across human and ecological values. TCE reduces the cognitive burden of balancing a large quantity of information, and enables cost-effectiveness analysis of alternative mitigation strategies. However, aggregating results across HVRs into a single metric could forfeit some information, hence our thorough presentation of results before applying weight vectors. Further, we identified problems with the use of TCE to represent risk to critical habitat, and resorted to an

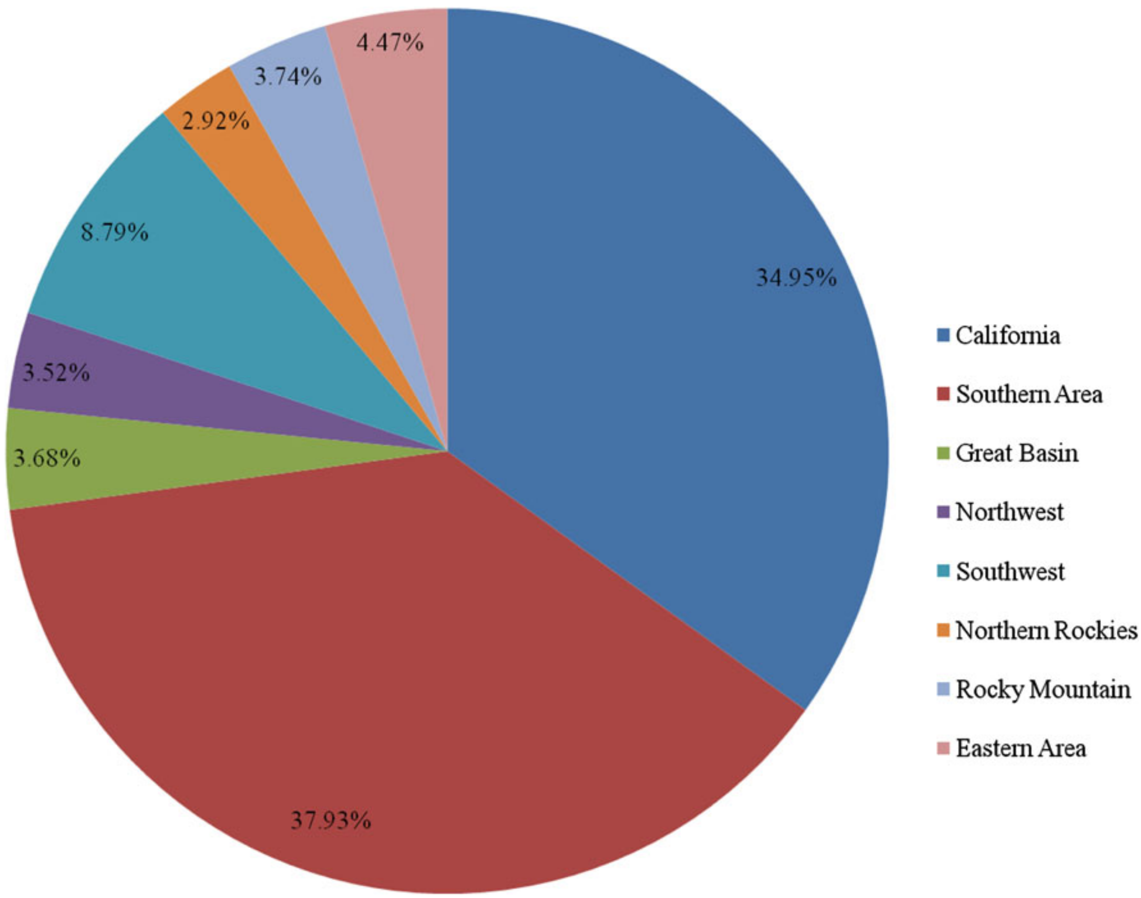



**Fig. 6** Geographic Area share of national weighted risk (wTCE), for the modified scenario, using the (1, 3, 9) weight vector

alternative measure based on expected proportion of habitat lost. Thus there are tradeoffs to consider related to definition of a single measure to describe risk—the benefits may be offset where risk to the resource in question is mischaracterized.

The framework we promote here is a composite of multiple models, and the potential exists for propagation of uncertainty. We are confident in the quality of many inputs, including LANDFIRE data and the FSim simulation model, although both systems are actively being revised and improved. While input data layers for HVRs could certainly be refined, by and large the general modeling approach interacting fire with resources is fundamentally sound, and forms the basis of most contemporary applications of wildfire risk assessment. Clearly fire effects analysis comprises the largest source of uncertainty, and modeling efforts should evolve to reflect new information as it becomes available.

Further critiques of our approach can be directed towards our sole reliance on quantitative information. While the notion that quantitative assessments will lead to a "right" answer is attractive, a map of qualitative risk or values can also be a very effective decision support and planning tool, allowing decision makers to see where impacts might occur and to weigh tradeoffs accordingly. Exposure and effects analyses do not necessarily have to be quantitative to be useful (e.g., Black and Opperman 2005; O'Laughlin 2005). In fact, a danger inherent in quantifying risk is that the user will ignore those things that are not measurable. One could look for guidance from the work of Chuvieco et al. (2010), who in their risk assessment approach employ a variety of quantitative and qualitative techniques across a suite of market and non-market resources.

## 5 Conclusion

This analysis demonstrates a national-scale, quantitative wildfire risk assessment. TCE calculations for HVRs are based on the integration of burn probability maps, geospatial identification of resource presence, and expert-defined

**Fig. 7** Risk calculations (TCE) for the California Geographic Area, classified according to FPU and value category

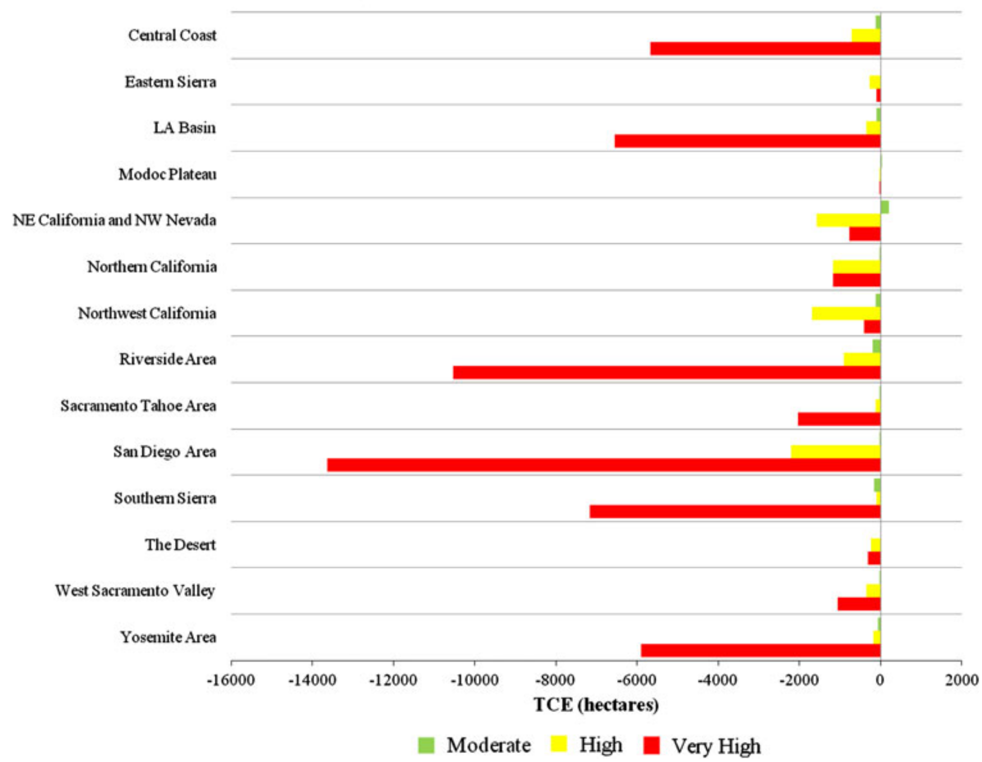
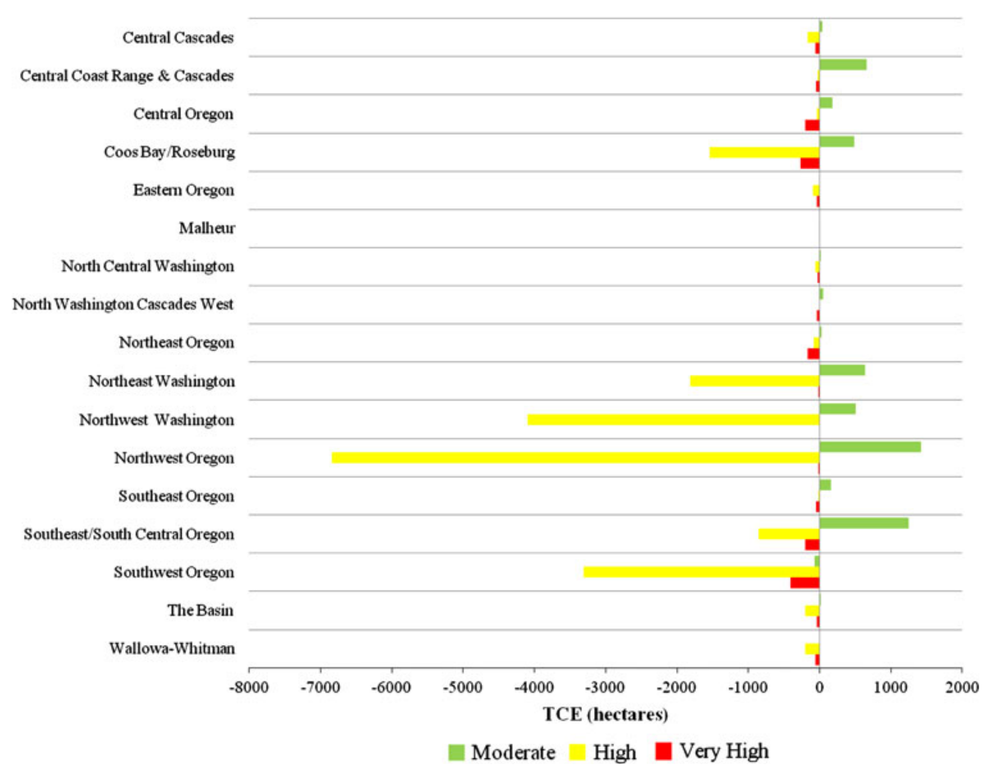



**Fig. 8** Risk calculations (TCE) for the Northwest Geographic Area, classified according to FPU and value category




resource response functions. The methodology leverages off recent and significant advancements in wildfire simulation models and geospatial data acquisition and management. Resource response functions are appropriately assigned using an expert systems approach. The approach is similar to many other wildfire risk assessments that have appeared in recent literature, but greatly expands the scope of analysis to include a suite of human and ecological values at risk from wildfire across the continental United States.

Results indicate that California and the Southern Area are the Geographic Areas with the highest expected losses. The interaction of wildfire with human development in the Very High value category (moderate/high density built structures and municipal watersheds) drove the elevated risk in these areas. This result was robust across various scenarios examined in our sensitivity analysis. The next most at-risk Geographic Area varies with assumptions, but the Southwest generally appears to be third. Beneficial impacts to fire-adapted ecosystems are anticipated across the west, in particular in the Northwest. More detailed analysis of FPU-level risk, although possible with our data and results, is beyond the scope of this paper.

In subsequent iterations, there is a need for resource experts and fire management experts to re-prioritize HVR layers within value categories, to refine response function definitions and assignments, to improve upon data layers, and to consider the variable impact of alternative weighting schemes on national priorities. With respect to fire modeling, future analyses will improve the granularity of FPU-level fire behavior modeling by increasing the number of weather stations used for generating artificial weather data. Spatial correlation in ignition processes could also be considered.

Fire effects analysis could be extended to include fire-level impacts, where the spatial pattern and topology of fire severity is important. This would entail modification of the wildfire simulation model to preserve the landscape pattern of severity for individual fires. Doing so would enable more robust analysis for some fire effects, such as watershed-level sedimentation response, where the landscape scale burn severity pattern is an important component. The present implementation is a pixel-level approach, which assumes that fire effects are spatially independent of pixel context within the overall pattern of effects that each fire produces across a landscape.

The issue of how to prioritize across resources will remain a challenge. Our coarse approach to define three value categories (Moderate, High, Very High) is a useful first step, but should be refined in subsequent analyses. Our initial results appear robust in that they do not appear highly susceptible to alternative weighting schemes. To move further towards integrated risk calculations requires some form of multi-criteria analysis, with relevant experts and stakeholders queried to develop a reasonable priority ranking. Multi-criteria analysis involves a systematic approach to analyze relative worth and to assign a weight to each HVR (or each HVR value category).

Future research could include a number of promising directions. Other factors to bring into the analysis could include community natural resource dependence, biomass utilization facilities, wood products markets, and existing transportation networks. Risk calculations could be used as input for operations research analyses determining optimal fuel reduction treatment combinations, or allocations of suppression resources. Other risk factors, such as invasive species and climate change, could be brought into the analysis. A temporal component that considers landscape condition change through time, in response to a changing climate and disturbances, would also benefit strategic planning.

The authors anticipate that the integrated wildfire risk assessment methods developed in this paper will continue to be refined and will inform decision-makers moving forward.

**Acknowledgments** We would like to thank Claire Montgomery, Jim Menakis, Miles Hemstrom, Joe Scott, Charles Shrader-Patton, Tom Quigley, James Strittholt, Jeff Kaiden, Robert Keane, Jack Waide, Tim Sexton, Rick Prausa, Rich Lasko, Peter Teensma, John Segar, Fred Wetzel, Erik Christiansen, Roy Johnson, Dan Buckley, and Dennis Dupuis. Thanks also to the editors and three anonymous reviewers.

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