Assessing Risks to Multiple Resources Affected by Wildfire and Forest Management Using an Integrated Probabilistic Framework

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Abstract

The tradeoffs that surround forest management are inherently complex, often involving multiple temporal and spatial scales. For example, conflicts may result when fuel treatments are designed to mediate long-term fuel hazards, but activities could impair sensitive aquatic habitat or degrade wildlife habitat in the short term. This complexity makes it hard for managers to describe and communicate the conditional nature of risk and to justify planned activities to stakeholders. In addition, our understanding of how proposed activities will affect resources of concern is often limited owing to informational shortcomings and imprecise models. To be robust and transparent, a risk assessment framework needs to reveal these limitations while quantifying the probable outcomes of project effects to multiple resources of concern. In this analysis, we describe the effects of fuel treatments using such a planning framework called CRAFT (Comparative Risk Assessment Framework and Tools). CRAFT provides a platform from which diverse ancillary models and other relevant information can be transparently integrated and evaluated.

We conducted our case study in the southwestern Klamath Mountains of California. As is typical of most montane forests of California, this area has experienced decades of fire suppression, and severe effects from wildfire are a concern. Working with managers, we identified a range of measurable objectives involving the wildland urban interface, fire behavior, fire effects, and sensitive wildlife. We then developed a conceptual model describing how components of the system interrelate. From this, we developed a probabilistic framework, using Bayesian belief networks, in which we employed existing fire models to address how expected fire behavior varies across different burning scenarios. Our framework provides decisionmakers and stakeholders with insights into the condition probability that management alternatives will be successful.

Keywords: Bayesian belief network, comparative risk analysis, CRAFT, fire effects, objectives, tradeoffs.

Introduction

Forest management decisions are often difficult because ecosystems are inherently complex, and the system's response to management is uncertain. Management tradeoffs typically involve very different objectives that can be difficult to compare or model across spatial and temporal scales. In addition, future conditions are often dependent on stochastic variation in the system that can be difficult to predict. One way for managers to address this complexity is to consider outcomes as conditioned on a range of influential factors that are assessed in terms of how likely they are to occur. This approach is more comprehensive than the single-scenario analyses that are commonly used in forest planning today, and it provides key information for decisionmakers and stakeholders.

Traditional risk assessment approaches were developed to reduce the likelihood of catastrophe such as engineering failures, insurance-related loss, or environmental contamination. These approaches may provide a poor model for forest risk assessments because management activities and nonactivities may influence a wide array of values across space and time. When something could happen that is unambiguously bad, such as a nuclear plant meltdown, the failure of a critical aircraft part, or a toxic spill, prevention is a clear and high-priority objective. In forest management, disturbances may be both a threat to the system and a critical requirement for the long-term viability of the system. For example, frequent fires may reduce surface

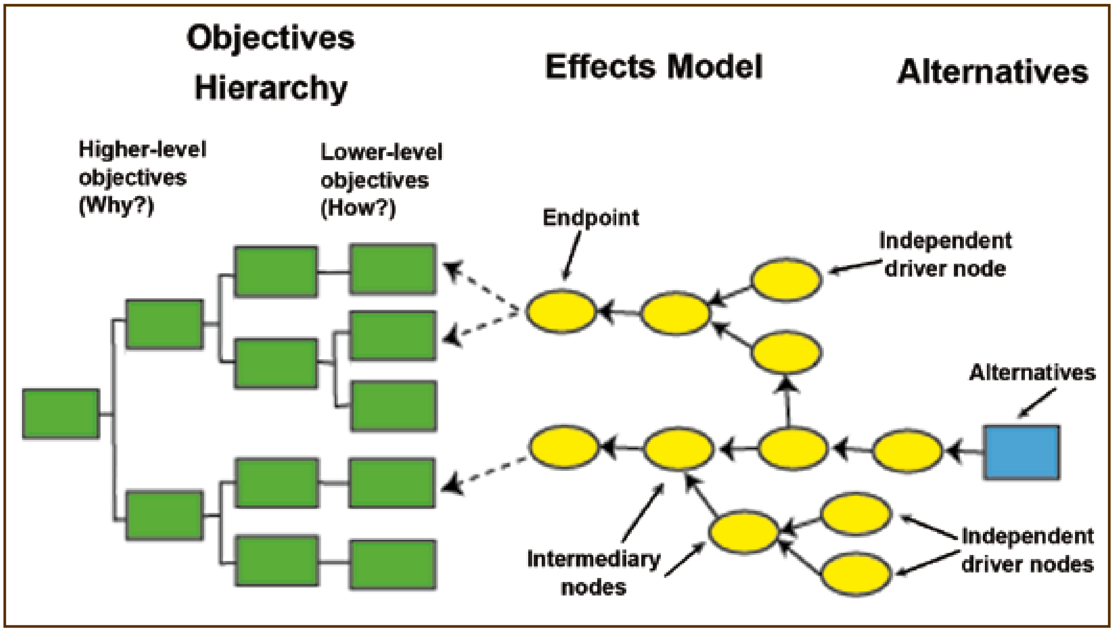

Figure 1—Overview of the Comparative Risk Assessment Framework and Tools process showing how increasingly specific objectives (in green) from left to right tier to risk assessment endpoints. The effects of different management alternatives (in blue) and scenarios are modeled using a probabilistic belief network (in yellow).

fuels and increase the resilience of old trees, yet they may also spread invasive species, reduce air quality, and threaten homes in the surrounding wildland-urban interface. Rather than decide how to prevent fire, forest managers increasingly must decide where, when, and how to conduct fire and fuel management to balance competing tradeoffs and diverse stakeholder values. Unlike risks associated with an unambiguous catastrophe, the risks and tradeoffs associated with forest management are better viewed comparatively. In this analysis, we introduce a comparative risk assessments framework and tools called CRAFT that was developed to address the tradeoffs associated with forest management decisions. A more detailed discussion of CRAFT can be found at: http://www.fs.fed.us/psw/topics/fire_science/craft/. [Date accessed unknown].

Study Area

We selected a 3000-km^2 area located in the Klamath Mountains of northwestern California centered on the town of Hayfork. The majority of the landscape is under Federal management and includes portions of the Shasta-Trinity and Six Rivers National Forests. Private inholdings are common and contribute to wildland-urban interface management problems that are characteristic of the West. These include issues related to wildland fire, air quality, and biodiversity management. Both national forests fall under the Northwest Forest Plan, a 1994 regional plan designed to maintain sustainable forest products and to sustain species. As part of that plan, areas were allocated for different purposes. The primary land allocations present in the study area include late successional reserves that were set aside for old-growth species, including the northern spotted owl, and the Hayfork Adaptive Management Area set aside for experimentation and learning.

The vegetation of the study area consists of a diverse array of conifers, hardwoods, shrublands, and grassy meadows. Douglas fir (*Pseudotsuga menziesii* (Mirb.) Franco) forests dominate a large portion of the area, but forests of ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) occur on dry sites, and Jeffrey pine (*Pinus jeffreyi* Gred. & Baif.) and incense-cedar (*Calocedrus decurrens* Torr.) dominate forests on ultramafic soils. Mixed-conifer forests are found where pine, Douglas fir, white fir (*Abies concolor* (Gord. & Glend.) Lindl. ex Hildebr.), and incense-cedar co-occur and typically include various species of hardwoods in

Upper Level Objectives ——————————————— Lower Level Objectives

I. Protect communities
- A. Minimize structural loss from wildfire
  - 1. Prevent wildfire from entering the community
    - a. Limit surface fuel accumulation on public lands within a half mile of the wildland-urban interface (WUI)
  - 2. Minimize fire severity within the WUI
    - b. Increase use of fire-safe landscaping and building materials
  - 3. Maintain fire suppression effectiveness
    - a. Maintain first-response capability within local communities
    - b. Minimize reliance on distance resources
- B. Maimtain air quality
    - a. Limit smoke production from wildland fire

II. Maintain forest health
- C. Restore resilient and sustainable forests
  - 1. Minimize conditions that increase uncharacteristic fire effects
    - a. Raise the canopy base height (ladders) in key areas
    - b. Reduce and restore fuel loads
  - 2. Limit the need for future high-cost/effort maintenance
    - a. Maintain canopy cover above 70 percent in key protection areas
    - b. Check the spread of invasive species
- D. Protect viable wildlife populations
  - 1. Protect threatened and endangered wildlife
    - a. Maintain or increase spotted owl habitat
    - b. Maintain spotted owl population viability
- E. Maintain investments in historical plantations
  - 1. Accelerate regrowth
    - a. Thin stands to maintain desired growth
    - b. Reduce ladder and surface fuels

Figure 2—A partial objectives hierarchy for the Hayfork study area. Upper level objectives (left) suggest general goals, whereas lower level objectives (right) can be formulated into specific risk assessment endpoints, monitoring endpoints, or specific management activities.

the canopy or understory. The most common hardwoods include tanoak (*Lithocarpus densiflorus* (Hook. & Arn. Rehd.), canyon live oak (*Quercus chrysolepis* Liebm.), black oak (*Quercus kelloggii* (Newb.) and chinquapin (*Chrysolepis chrysophylla* (Hook.) Hjelmqvist). Surface and live fuel composition and structure have been altered from their historical condition by 20th-century fire suppression and logging. Wildfires occur on a regular basis, but extensive, long-burning wildfires have only occurred in 1987 and 1999.

The CRAFT Process

The CRAFT planning process leads managers through four stages involving (1) objective setting and problem conceptualization, (2) alternatives design, (3) probabilistic modeling of effects, and (4) synthesis. In this analysis, we emphasize steps 1 and 3 to show how objectives can be incorporated within a single modeling framework and then considered in terms of their uncertainties. Figure 1 provides a graphical overview of the CRAFT process.

Specifying and Structuring Objectives

A critical first step in CRAFT is to fully understand the problems at hand. It is easy to sidestep this step by jumping to alternatives or even modeling, but a thoughtful, interdisciplinary exploration of the objectives and the problems is needed before specific modeling tools and data sets are considered. Existing information and familiar models may be ill suited for the specific problems at hand.

In CRAFT, problem formulation is addressed using two planning tools: (1) an objectives hierarchy that helps planners and stakeholders focus on specific measurable objectives rather than on overarching goals, and (2) by a cause-and-effect model that provides a transparent documentation of how the system is thought to operate. In addition to documenting values and beliefs, these tools serve to identify potential tradeoffs for the comparative assessment of risk.

Objectives hierarchies have been used for a variety of planning purposes, but they are rarely used by public agencies in the United States (Clemen and Reilly 2001, Keeney 1992). An objectives hierarchy simply separates intangible objectives (the upper levels) from detailed, measurable objectives (the lower levels) and structures them within a hierarchy. Specific lower level objectives suggest how upper level objectives might be achieved. This structure ensures that planners have formulated explicit lower level objectives that will be translated into risk assessment endpoints. Detailed objectives may also serve as appropriate monitoring endpoints as part of a broader forest management strategy. We show a partial Objectives Hierarchy for our study area in Figure 2.

From an agency perspective, an objectives hierarchy simplifies risk assessments by providing focus, context, and clarity. Upper level objectives often correspond to general forest mandates, whereas lower level objectives may relate to the extension of statutes to specific instances or locations. For example, although maintaining biodiversity is mandated by a number of statutes, the specific requirements for maintaining viable habitat and populations for individual species often reflect regulatory policy.

From a stakeholder perspective, objectives hierarchies can be powerful tools for involvement. Stakeholder values differ in terms of their specificity, and, by using an objectives hierarchy, stakeholders are more likely to see how their values fit with those of the agency. Comprehensive objectives hierarchies can also suggest opportunities for stakeholder-agency collaboration. As examples, the protection of homes from wildfire and invasive species control both require agency and stakeholder involvement to ultimately be successful. Perhaps, most valuably, an objectives hierarchy can provide a common vision for what a managed ecosystem could look like. Stakeholders are more likely to remain engaged when they can imagine desired future conditions. Once future objectives are clarified, specific management choices and tradeoffs can be considered through a separate process.

Conceptualizing Cause and Effect

Following the identification of measurable objectives in CRAFT, cause-and-effect models are developed that identify the factors that are known to influence relevant lower level objectives of concern. A conceptual model consists of a bubble-arrow diagram and supportive text that explains the relationship in detail (U.S. Environmental Protection Agency 1998). Conceptual models help managers identify the key reasons why a particular management objective may or may not be met. Causes and effects can be established across spatial and temporal scales so that the interconnectedness of the ecosystem is apparent. This step is designed to be conceptually inclusive and unrestrained by the availability of local data or existing supportive models that have been used in the past. Later on, when a quantitative effects model is being developed, ancillary models, data, and expert opinion are more likely to be used appropriately when a clear conceptual model exists. Cause-and-effect relationships may be based on existing research, ancillary models, or expert opinion.

From an agency perspective, this task transparently documents the factors that were considered beyond those that are carried forward in the formal risk modeling step that follows. Conceptual models also provide a transparent venue for group involvement by describing the problem in a way that both interdisciplinary team members and stakeholders can dispute and ultimately come to agreement.

At some point, the cause-and-effect model will likely suggest specific management activities. In CRAFT, as with National Enviromental Policy Act, these activities are then combined into formal management alternatives.

Effects Modeling

A formal effects model results from careful restructuring of lower level objectives and the conceptual model. Two key decisions are (1) the selection of suitable risk assessment endpoints, and (2) how cause and effect will be analyzed and integrated.

Risk assessment endpoints tier to lower level objectives, and they must be place and time specific. For example, a well-focused wildland-urban interface endpoint may be to prevent any wildfire from entering within 1.0 mi of the town of Hayfork indefinitely. This specificity allows management alternatives to be tailored to real places. Further, spatial and temporal needs will influence the structural type of effects model used.

The effects modeling platform can incorporate an assortment of ancillary models, available data, and expert opinion. In CRAFT, that integrative platform is a Bayesian belief network that reveals assumptions, uncertainties, and likelihoods. Belief networks have been used for a range of natural resource planning issues (e.g., Lee and Irwin 2005, Marcot and others 2001). Belief networks have strict structural limitations that require a careful translation from the conceptual model. Relationships between parent and child nodes in the network can be calculated using multiple runs of deterministic ancillary models, analyses of existing data sets, or expert opinion. Each set of relationships provides a scenario that is defined by the model assumptions. The relative importance of each scenario in the model is then conditioned on the specified probability distributions of the nodes that have no parent nodes (i.e., the driver nodes). Importantly, the model can provide information even if no distributions are specified. Decisionmakers can readily explore the sensitivity of outcomes to different assumptions of the driver nodes.

The Hayfork Effects Model—

During the conceptual modeling phase, wildfire behavior was identified as a key node that was critical for wide ranging objectives of concern. To illustrate how variability in fire behavior can be implemented in a belief network, we defined a number of vegetation-related variables and varied two others—fire weather and wind direction.

Fire behavior can be modeled by a wide array of models, but relatively few are useful for characterizing how fire behavior is likely to vary across the landscape. Landscape modeling is especially important in mountainous terrain such as our Klamath study area because patterns of vegetation and fuel, fire behavior, and winds are strongly influenced by topography. We used FlamMap (Finney 2006) to describe spatial patterns of fire behavior. FlamMap is not a dynamic fire spread model, and we did not calculate fire behavior using real-time fire weather or results that are conditional on spread from discrete ignition points. We essentially burned the entire landscape under fixed scenarios to limit the number of permutations and to transparently represent the assumptions used in our belief network.

The spatial information used in FlamMap includes slope, aspect, canopy cover, and surface fuel model. To model crown fire, we also used stand height, lower canopy height, and canopy bulk density. We derived topographic parameters (i.e., elevation, slope, and aspect) from a 30-m digital elevation model. Canopy cover was based on a 30-m, satellite-derived geographic information system layer from 2001 (http://www.seamless.usgs.gov [Date accessed unknown]). Other vegetation attributes were directly or indirectly derived from a U.S. Forest Service Region 5 existing vegetation layer from the mid-1990s that provided compositional and coarse age structural data in polygons of variable size. Stand height was calculated by using the dominant tree species in the classified polygons and height equations used by the Forest Vegetation Simulator (FVS, Dixon 2002). Canopy bulk density was calculated using published information for individual trees and was then multiplied by percent canopy cover. Canopy base height includes ladder fuels that are typically low across the study area owing to fire suppression (Taylor and Skinner 2003). Canopy base heights were assigned a value of 0.5 m in mature conifer stands and 0.2 m in young conifer plantations with a 0.8 live crown ratio for hardwoods. Fuel models were assigned by recasting the original 13 fuel models used

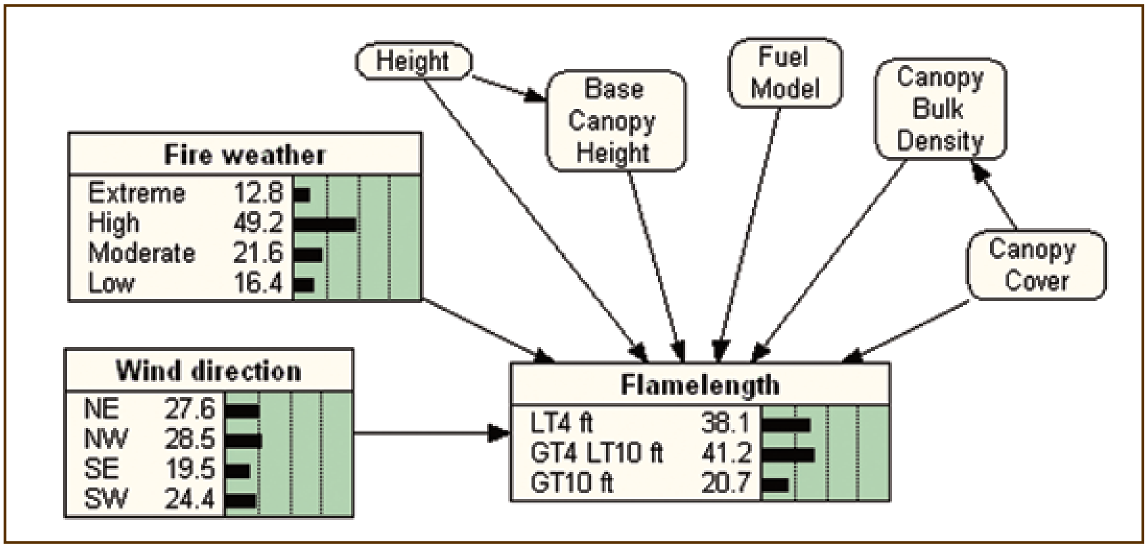

Figure 3—The probabilistic effects model used to characterize fire behavior (flamelength). For simplicity, only fire weather and wind direction were varied in this example. The probabilities for states of these two nodes were derived from retrospective analyses of the area burned during long-duration fires in northwest California, whereas the values in the node flamelength represent iterative calculations of the ancillary model, FlamMap.

in the Shasta-Trinity National Forest fire management plan for different vegetation types based on the new 40 fuel models (Scott and Burgan 2005). Although there are substantial uncertainties associated with most of these vegetation-related factors across the landscape, we fixed all of the foregoing parameters to focus on fire weather and wind.

Fire weather was modeled with four fuel moisture scenarios (i.e., 99^{th}, 95^{th}, 90^{th}, and 80^{th} percentiles) using two decades of fire weather collected at the Hayfork Ranger Station. Percentile conditions reflect the percentage of the time that weather conditions are likely to occur based on historical patterns. Data were manipulated using the software Fire Family Plus (Bradshaw and McCormick 2000). In FlamMap, fuel moistures were conditioned across topographic positions and aspects for 7 days using a daily range of temperature and humidity typical of the percentile conditions. Gridded windspeeds were paired with fuel moisture scenarios based on the speeds modeled on Hayfork Bally, the highest peak north of the weather station. Four fire weather scenarios were defined based on the fuel moisture conditions that characterized extreme, high, moderate, and low fire weather during the fire season (i.e., the 99^{th}, 95^{th}, 90^{th}, and 80^{th} percentile conditions). Gridded wind maps were assigned to these moisture conditions using mountain-top windspeeds of 32, 24, 12, and 6 miles per hour (mph), respectively.

Wind is an important driver of fire behavior in mountainous terrain, and our study area is no exception. Extensive fire runs have been observed during east-wind events that are typically associated with frontal systems. Topography can greatly reduce wind speed and direction, but locally, this effect is often contingent on the regional wind direction. To address the effect of regional wind direction, we generated estimates of local winds using a beta version of WindWizard (developed by the U.S. Forest Service, Rocky Mountain Research Station, by B. Butler and J. Forthorfer). Whereas downbursts, fire-generated winds, and winds related to land use and gravity are ignored in this model, gridded wind reduces windspeeds according to topographic position consistent with observations. Gridded wind from four synoptic directions (i.e., northwest [NE], southeast [SE], southwest [SW], and northwest [NW]) was used in FlamMap to provide a better estimate of local wind direction and speed than simply modeling a uniform speed and direction across all topographic positions.

Every node in a belief network has a probability table associated with it, but values are derived differently, depending on where the node sits in the network. Nodes that

Table 1—Conditional probabilities of low (< 1.2 m), moderate (1.2 to 3.1 m), and high (> 3.1 m) across combinations of four fire weather and four wind direction scenarios for the study area

Fire weather	Wind direction	High	Moderate	Low
Extreme	NE	0.397	0.320	0.281
Extreme	NW	0.381	0.328	0.291
Extreme	SE	0.384	0.354	0.262
Extreme	SW	0.362	0.368	0.270
High	NE	0.243	0.403	0.353
High	NW	0.224	0.413	0.363
High	SE	0.242	0.421	0.337
High	SW	0.226	0.424	0.349
Moderate	NE	0.135	0.444	0.421
Moderate	NW	0.127	0.449	0.422
Moderate	SE	0.135	0.448	0.417
Moderate	SW	0.129	0.443	0.428
Low	NE	0.090	0.418	0.492
Low	NW	0.089	0.411	0.498
Low	SE	0.089	0.416	0.495
Low	SW	0.088	0.410	0.502
Joint probabilities		0.207	0.412	0.381

Joint probabilities reflect the relative likelihoods of these different scenarios occurring based on the priors shown in Figure 3.

are influenced by other nodes have conditional probability tables that show how probabilities change in response to changes in the parent nodes. These relationships are often calculated using ancillary models. Nodes that vary independently of other nodes must have their probabilities (or priors) specified. In our belief network, the probability distributions for fire weather and wind direction were based on analyses of daily fire progression maps of two recent and nearby long-duration fires—the Biscuit Fire and the Big Bar Complex. Fuel moistures calculated in Fire Family Plus were associated with daily area burned using midday fire weather data, and the fire spread direction of a stratified sample of points was used to approximate wind direction in terms of area burned.

Results of Effects Modeling—
Retrospective analysis of fire weather during the Big Bar long-duration Fire indicates that nearly half of the area burned when Fire weather was high (defined as fuel moistures ranging from the 93th to 96th percentile conditions during the May 1 through October 31 fire season). Roughly 22 percent of the area burned when conditions were moderate (86th to 92th percentile), 16 percent burned when conditions were low (less than 86th percentile), and only 13 percent of the area burned when fuel moistures were extreme (97th to 100th percentile). These values were used as priors in the fire weather node of the belief network (Figure 3).

Analysis of fire spread during the Big Bar and Biscuit Fires showed that sites burned under a range of wind conditions, but winds from the NE and NW were associated with a greater area burned than were winds from the SE. An average of these two long-duration fires was used to define priors in the wind direction node of the belief network (Figure 3).

We calculated the conditional probabilities of fire behavior (i.e., flamelength) with multiple runs of FlamMap using different scenarios of fire weather and wind direction. For each scenario, we determined the area with modeled flamelengths less than 1.2 m (4 ft), 1.2 to 3.1 m (4 to 10 ft), and greater than 3.1 m (10 ft). These conditional probabilities are shown in Table 1. Wind direction has no appreciable effect on the overall pattern of expected flamelength as it varies by only a few percentages across wind scenarios.

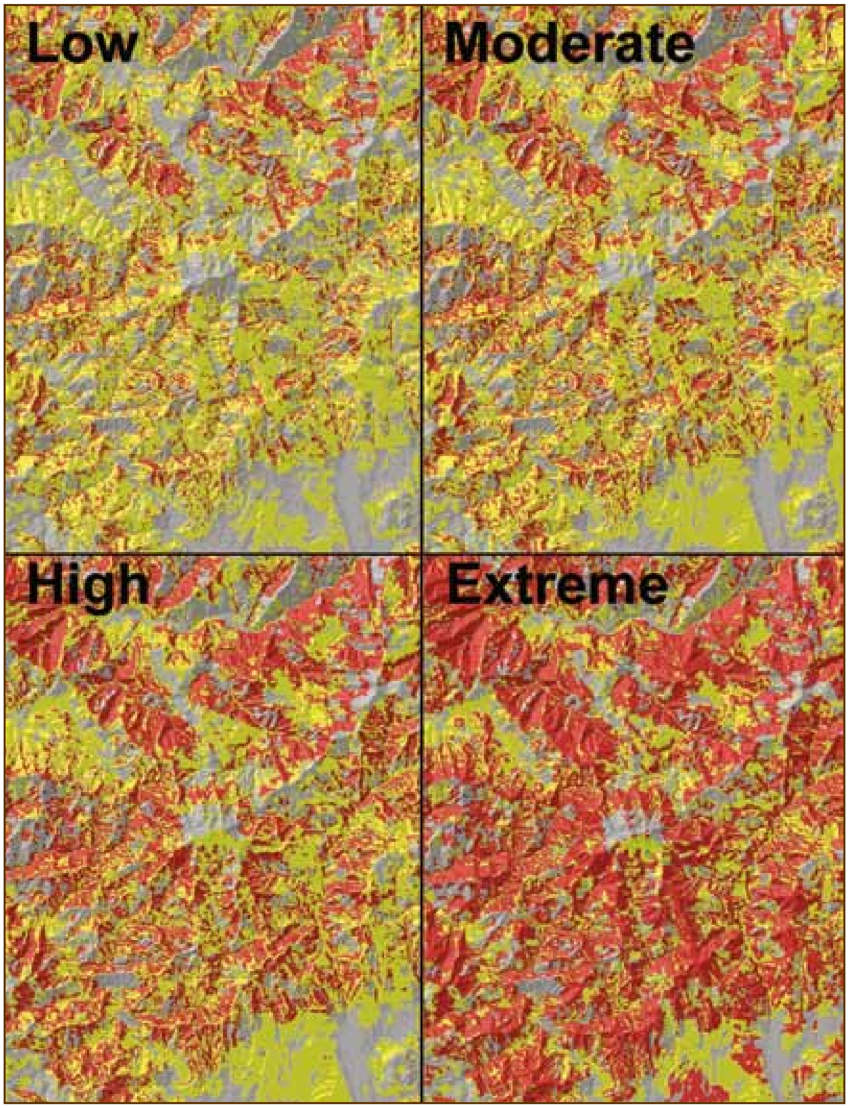

Figure 4—Maps showing conditional fire behavior (flamelength) according to four fire weather scenarios for an 18- by 23-km portion of the study area. Flamelengths were classified as low (shown in grey; less than 1.2 m), moderate (in yellow; 1.2 to 3.1 m), and high (in red; greater than 3.1 m). The values shown on each map were calculated with a weighted average of the four wind directions shown in Figure 2.

In contrast, fire weather has a substantive effect on flamelength (Figure 4). When fire weather is low, half the area is expected to have flamelengths that are low. These flamelengths are likely to result in minimal mortality to mature trees while reducing surface fuels and fuel ladders. During extreme conditions, high flamelengths dominate the landscape, and fires are likely to cause widespread mortality. Based on the joint probability distribution (Table 1), low- or moderate-severity flamelengths are likely to occur, presuming that future fire weather and winds are consistent with those of prior long-duration fire events. About 21 percent of the landscape can be expected to burn with flamelengths greater than 3.1 m during low to moderate fire weather compared to 38 percent that is likely during extreme fire weather.

We then compared the effects of fire weather and wind on the flamelengths of different portions of the study area. For example, the expected flamelengths in 43 northern

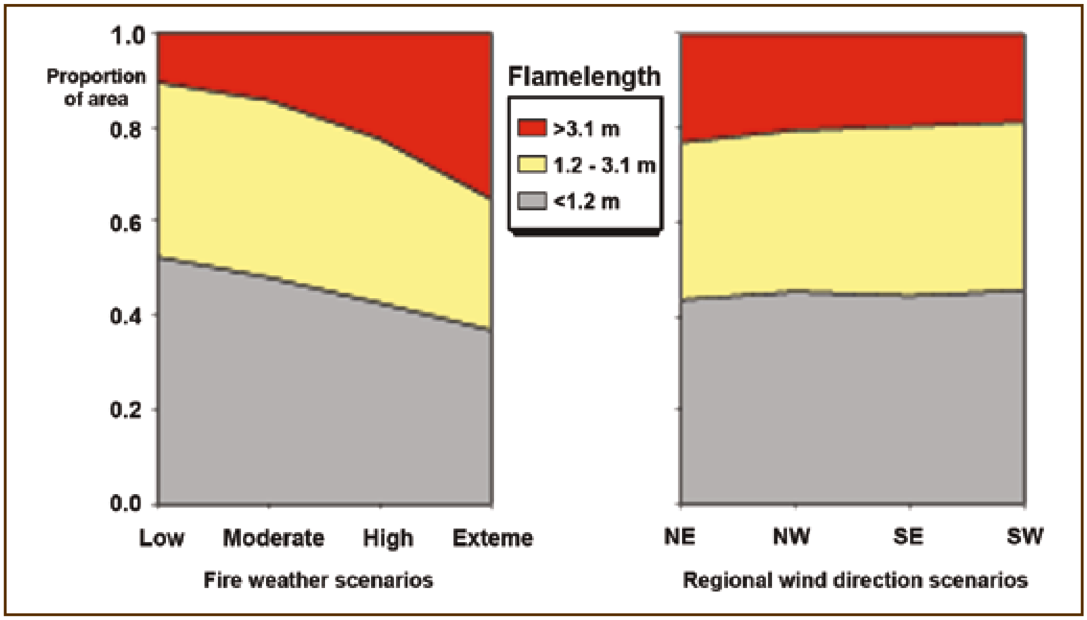

Figure 5—Change in fire risk for northern spotted owl habitat areas across fire weather and wind direction scenarios. High flamelengths shown in red are much more likely to be lethal to nesting trees than are low flamelengths. Note that under any modeled scenario, the habitat is likely to experience a range of flamelengths, as is typical of the region's mixed-severity fire regime.

spotted owl (*Strix occidentalis*) core areas is shown in Figure 5. Each core area is 60 ha (100 ac). Consistent with the overall pattern, the area expected to burn under different fire weather scenarios increases with the severity of fire weather, but flamelengths show little variability across the four modeled wind directions.

Summary

The simple-effects model shown here demonstrates how an important driver of forest outcomes—namely fire behavior—can be modeled in terms of conditional probability. This process transparently shows how assumptions of expected results may or may not matter. By varying vegetation and fuel inputs with proposed fuel treatment options, management outcomes can be considered within this same framework. Moreover, the uncertainties associated with the effects of different fire behaviors can be addressed with an expanded belief network.

The range of fire behavior that occurs during a single scenario in our model shows that the project area has a mixed-severity fire regime. This is consistent with retrospective analyses of past fires (Odion and others 2004, Taylor and Skinner 2003). Large fires burn under a range of fire weather and wind scenarios, and this leads to further variation in fire behavior. Owing to the combined influence of these spatial and temporal patterns, the fire regimes of the Klamath Mountains are truly complex. This complexity is likely to have contributed to the high biodiversity that characterizes the Klamaths, but it makes multiresource management decisions more challenging.

To be meaningful, comparative risk assessments must be capable of accommodating this ecological complexity. The CRAFT process allows managers to incorporate diverse objectives and sophisticated effects modeling to deal with these complexities and their associated uncertainties.

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