# 4
# Uncertainty and Probability in Wildfire Management Decision Support: An Example from the United States

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## ABSTRACT

Wildfire risk assessment is increasingly being adopted to support federal wildfire management decisions in the United States. Existing decision support systems, specifically the Wildland Fire Decision Support System (WFDSS), provide a rich set of probabilistic and risk-based information to support the management of active wildfire incidents. WFDSS offers a wide range of decision-support components, including fire behavior modeling, fire weather information, air quality and smoke management, economics, organization assessment, and risk assessment. Here we focus on WFDSS's provision of probabilistic information and how it can facilitate strategic and tactical decision making. However, the management of active wildfire incidents can be highly complex and subject to multiple uncertainties, only some of which are addressed by WFDSS. We review remaining uncertainties, including identified issues in how fire managers interpret and apply probabilistic information, and conclude with observations and predictions for the future direction of risk-based wildfire decision support.

## 4.1. INTRODUCTION

Wildland fire activity around the globe is driven by complex interactions between natural and human processes [*Spies et al.*, 2014]. Wildland fire can result in significant ecological and socioeconomic loss, most notably the loss of human life. At the same time, wildland fire can be a powerful tool to achieve a wide range of purposes, including clearing vegetation for agroforestry and hunting objectives, reducing hazardous fuel loads, and restoring and maintaining habitat for fire-dependent species.

Figure 4.1 provides an overview of wildfire management illustrating the major drivers of wildfire risk as well as their respective management options, if applicable. (Note that whereas "wildland fire" is an all-encompassing term including unplanned and planned ignitions, our focus here is on unplanned ignitions, or "wildfires.") Given an ignition, weather, topography, fuel conditions, and suppression activities jointly determine the likelihood of fire reaching a given point on the landscape, as well as the intensity of wildfire. Prior to an ignition, risk mitigation options include investing in ignition prevention programs (e.g., campfire bans), reducing hazardous fuel loads (e.g., removing underbrush and reducing tree density), and investing in suppression response capacity (e.g., training and purchasing additional firefighting equipment). Factors related to the location and environment of highly valued resources and assets (HVRAs) can also be changed, by reducing HVRA exposure to fire (e.g., zoning regulations), and reducing HVRA susceptibility to fire (e.g., home construction practices).

Efficient management of wildfire activity is challenged by multiple sources of uncertainty [*Thompson and Calkin*, 2011]. First, variability surrounding weather conditions precludes deterministic prediction of fire growth and behavior, an uncertainty that is compounded by underlying knowledge gaps in fire-spread theory [*Finney et al.*, 2011a; *Finney et al.*, 2012]. Second, knowledge gaps surrounding the effects of fire preclude determination of impacts to vegetation, soil, and other ecosystem

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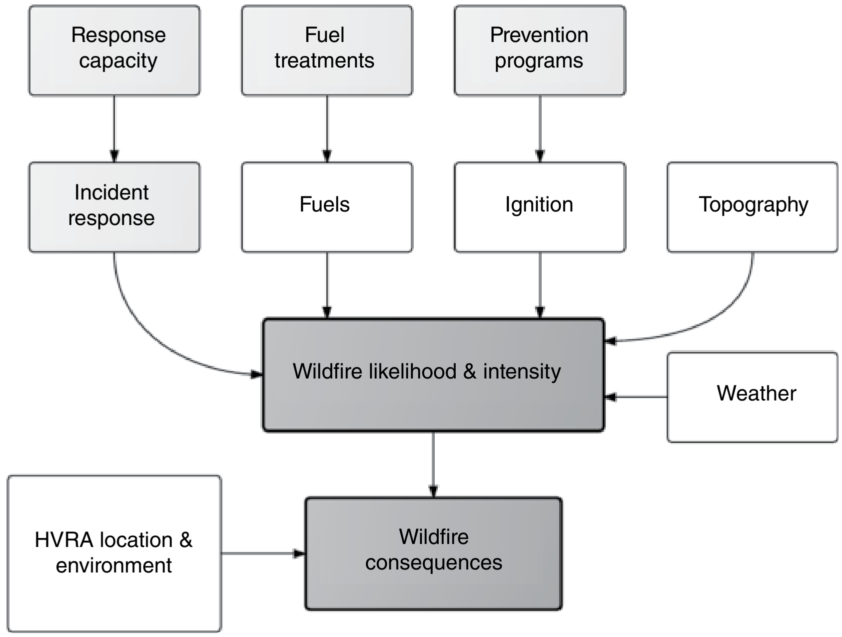


**Figure 4.1** Conceptual overview of major factors influencing wildfire risk management. Boxes in light grey represent primary management options, and boxes in dark grey represent the primary components of wildfire risk [modified from *Calkin et al.*, 2011b].

components, and in turn the monetization of these impacts for cost-benefit analysis [*Venn and Calkin*, 2011; *Hyde et al.*, 2012]. Third, partial control, human error, and limited understanding of the productivity and effectiveness of firefighting resources constrain the development and implementation of optimal suppression strategies [*Holmes and Calkin*, 2013; *Thompson*, 2013]. Last, fire manager decision processes can be subject to a number of suboptimal heuristics and biases in complex, uncertain environments [*Maguire and Albright,* 2005; *Thompson,* 2014].

A wide range of models and decision support systems exist to help support risk-informed wildfire decision making, many of which specifically target one or more of the aforementioned sources of uncertainty [*Ager et al.*, 2014; *Chuvieco et al.*, 2012; *Kaloudis et al.*, 2010; *Calkin et al.*, 2011a; *Noonan-Wright et al.*, 2011; *Petrovic and Carlson*, 2012; *Rodríguez y Silva and González-Cabán*, 2010; *Salis et al.*, 2012]. In a prefire planning environment, structured decision processes can systematically and deliberatively address uncertainties with a range of techniques [*Warmink et al.*, 2010; *Marcot et al.*, 2012; *Thompson et al.*, 2013a; *Skinner et al.*, 2014]. As an illustration, *Thompson et al.* [2015] detail how stochastic simulation, expert judgment elicitation, and multicriteria decision analysis could be used to address natural variability, knowledge gaps, and preference uncertainty, respectively.

Wildfire risk assessment is increasingly being adopted across landscapes and ownerships throughout the United

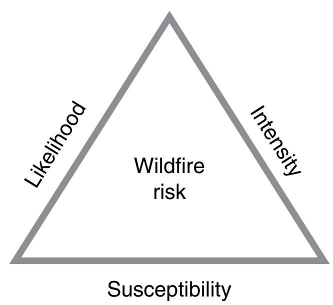


**Figure 4.2** Wildfire risk triangle, composed of the likelihood and intensity of wildfire along with the susceptibility of resources and assets to wildfire [*Scott et al.*, 2013].

States for decision support [*Calkin et al.*, 2011b; *Thompson et al.*, 2013b]. Assessment of wildfire risk follows a widely adopted ecological risk assessment paradigm, the two principal components of which are exposure analysis and effects analysis [*Fairbrother and Turnley,* 2005]. A generalized framework known as the "wildfire risk triangle" (Fig. 4.2) depicts risk as a function of the likelihood of fire, the intensity at which fire burns, and the susceptibility of resources and assets to loss-benefit from fire, which can be summarized to quantify risk in terms of expected net value change [*Finney,* 2005; *Scott et al.*, 2013]. This is a value-focused approach that considers not just the possibility of wildfire occurring but also its potential ecological and socioeconomic consequences, including benefits or net gains.

Wildfire risk has several important features that may influence mitigation planning relative to risks presented by other natural hazards. First, wildfire risk is inherently spatial: the likelihood and intensity of fire are driven by complex spatial interactions between ignition locations, fuel conditions, topography, and weather patterns. Furthermore, the location of resources and assets determines their respective exposure to wildfire as well as their susceptibility (e.g., watersheds with steeper slopes and more erodible soils may lead to greater postfire erosion and water quality concerns). Second, wildfire can lead to substantial benefits, in terms of restoring and maintaining ecological conditions, as well as reducing future wildfire hazard. Third, in contrast to phenomena such as earthquakes and hurricanes, the likelihood and intensity of the natural hazard itself can be reduced, either preventatively or throughout the course of an event (see Fig. 4.1).

Although valuable for prioritizing mitigation needs and planning incident response in a prefire decision environment, comprehensive and systematic risk assessment is often not possible in the dynamic and time-pressed active incident decision environment. Where risk assessments have already been performed, results can inform real-time evaluations of potential consequences, but fire managers must still be responsive to changing conditions and the specific characteristics of the wildfire incident as it unfolds. With that said, existing decision-support systems can still provide a rich set of probabilistic and risk-based information to support the management of active wildfire incidents.

In this chapter, we focus on the Wildland Fire Decision Support System (WFDSS), a web-based system developed and used within the United States. Per federal policy [*Fire Executive Council*, 2009], fire managers are directed to "use a decision support process to guide and document wildfire management decisions," and WFDSS is increasingly adopted as the system of decision support, particularly for large and complex wildfires. WFDSS was designed to be a single system to replace all previous processes, to integrate fire science and information technology, and to streamline and improve fire management decision making [*Zimmerman,* 2012]. Beyond decision documentation functionality, WFDSS provides a wide range of decision support components, including fire behavior modeling, fire weather information, air quality and smoke management, economics, organization assessment, and risk assessment [*Calkin et al.*, 2011a; *Noonan-Wright et al.*, 2011]. Notably, WFDSS provides support through not only informational and analytical *content*, but also through an iterative decision *process*; both are critical for effective decision support [*Thompson et al.*, 2013a].

In the subsequent sections, we expand upon decision support functionality within WFDSS, focusing on provision of probabilistic information and how it can facilitate strategic and tactical decision making. To begin, we provide a brief overview of wildfire management in the United States. We then illustrate the role of stochastic wildfire simulation and compare and contrast modeling efforts in prefire and during-fire contexts. We next review remaining uncertainties, including identified issues in how fire managers interpret and apply probabilistic information, and conclude with observations and predictions for the future direction of risk-based wildfire decision support.

## 4.2. WILDFIRE MANAGEMENT

In the United States and elsewhere around the globe, the dominant management response is to aggressively suppress wildfires to keep them as small as possible. Generally speaking this approach is highly successful; in the United States, typically 95%–98% of all ignitions are rapidly contained during "initial attack" operations [*Calkin et al.*, 2005]. However, those rare fires that escape initial containment efforts account for a disproportionate share of area burned, as high as 95% depending on the geographic extent [*Short,* 2013]. Escaped large wildfires are a particularly prominent issue in the western United States, where topography is steeper, wildland areas are larger, and public acceptance of frequent prescribed burning to reduce hazard isn't as high as in other regions like the southeastern United States

Federal policy provides substantial flexibility regarding the management of large wildfires [*Fire Executive Council*, 2009], so that ecological benefits and reduced future hazard can be recognized and integrated into strategy development. However, for a variety of reasons, many of which are more sociopolitical than technical in nature, fire managers tend to be averse to implementing strategies that promote fire on the landscape [*Thompson,* 2014]. Paradoxically, the result of aggressive suppression in some ecosystems is the accumulation of fuels that would otherwise have burned by periodic fire, so that, over time, fires become increasingly intense and resistant to control [*Arno and Brown*, 1991; *Calkin et al.*, 2014a].

These larger wildfires require a more coordinated response effort that can extend over the course of multiple days to weeks. Management of active wildfire events is dynamic and entails a series of recurrent, linked decisions made by multiple actors, beginning with identification of the appropriate scale and type of response organization. On federal lands in the United States, the management of escaped wildfires follows the National Incident Management System. Under this system, local land managers have shared responsibility with Incident Management Teams (IMTs) to determine appropriate strategies and tactics to achieve land and resource objectives, subject to constraints on firefighting resource availability and firefighter safety. The complexity of the wildfire incident determines the type of IMT; more complex incidents typically require IMTs with more training, experience, and organizational structure. Factors considered in the analysis of incident complexity include potential fire behavior, threatened HVRAs, land ownership and jurisdiction, and sociopolitical concerns.

IMTs next determine the amount and type of firefighting resources to order, including hand crews, engines, bulldozers, and aerial resources. If unavailable, IMTs may request alternative firefighting resources that could act as substitutes, or may be forced to reevaluate strategies and tactics. The third level of decision making entails deploying resource mixes to achieve specific missions, which generally include restriction of fire growth or localized protection of HVRAs. Last, periodic reassessment in response to changing conditions helps ensure the appropriateness of strategies, the type of response organization, and the amount and type of firefighting resources present.

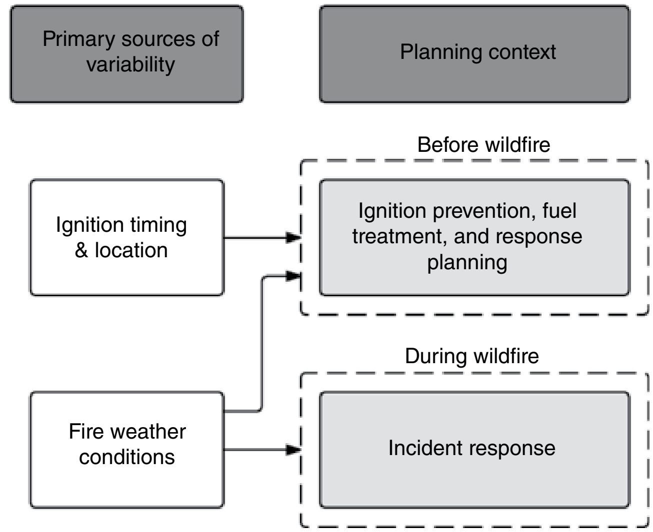


**Figure 4.3** Primary sources of variability in burn probability modeling and their relation to the planning context.

## 4.3. PROBABILISTIC INFORMATION AND RISK-BASED WILDFIRE DECISION SUPPORT

Stochastic wildfire simulation is a foundational element of wildfire risk assessment. The state of fire modeling has significantly advanced in the past decade or so, leveraging improved fire spread algorithms with expanded computational capacity to enable spatially explicit simulation of thousands of possible realizations of fire events [*Finney,* 2002; *Finney et al.*, 2011a; *Finney et al.*, 2011b]. Further, more comprehensive fire-history databases enable improved calibration and validation of model results [*Short,* 2013].

These models rely on rasterized, or pixelated, representations of fire growth and final fire perimeters, and the aggregation of thousands of simulation runs quantifies the probability of any given pixel burning. Because most area burned comes from rare large fires [*Short,* 2013], localized burn probabilities are often influenced more by the spread of fire from remote ignitions rather than local ignitions. It is therefore critical for these models to incorporate geospatial information on topography, fuel conditions, and weather patterns to model the spread of fire across the landscape.

Burn probability modeling is now common practice in the United States, with a growing array of applications across planning contexts and geographic areas. Figure 4.3 identifies the primary sources of variability addressed with burn probability modeling, and their relation to the planning context. In both contexts, fire weather is a key source of uncertainty; temperature, humidity, and, in particular, wind speed and direction are drivers of fire behavior. Before a wildfire occurs, the exact timing and location of the ignition are unknown, although predictive models may use historical spatiotemporal patterns of human- and lightning-caused fires. The timing of ignitions is important with respect to the length of the fire season; fires that ignite earlier in the season have a longer period in which weather conditions may drive growth, whereas fires that ignite near the end of the season have a shorter window. The location of ignitions is important with respect to landscape conditions that could support fire spread as well as resources and assets that could be impacted by fire. By contrast, after an ignition has been detected, fire weather remains the primary source of uncertainty, and reliance on short-term forecasts can improve model prediction.

Within WFDSS the Fire Spread Probability (FSPro) modeling system is the main source of probabilistic information provided to fire managers [*Calkin et al.*, 2011a; *Finney et al.*, 2011a]. FSPro ingests local weather forecasts as well as historical weather data and simulates thousands of possible realizations of fire spread given the current location and size of the fire. FSPro simulation results depict burn probability contours over a defined temporal horizon (e.g., 7 days). Localized burn probabilities are calculated as the proportion of runs that a given pixel burns by the simulated fire events. Probability contours sometimes appear similar in shape to concentric circles, but variation in topography, fuels, and wind conditions influence their exact shape.

The type of advanced analysis afforded by FSPro is not used for all incidents; use is instead typically restricted to the most complex incidents with potential to be long duration and/or large in size. However, on incidents where

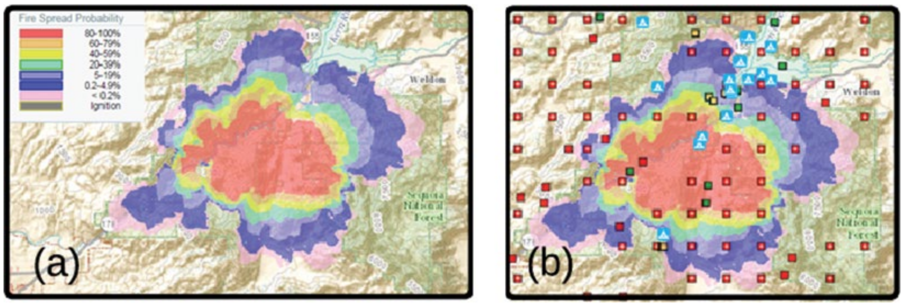


**Figure 4.4** Example FSPro burn (a) probability contours and (b) exposure of a select set of resources and assets.

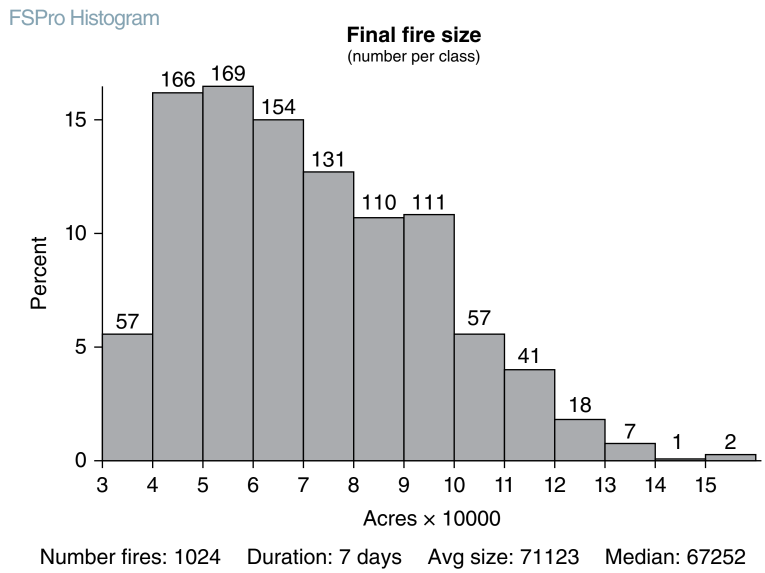


**Figure 4.5** Histogram of simulated final fire sizes output from FSPro.

FSPro is used, fire managers and analysts often perform multiple FSPro runs over the course of an event in response to changing fire and weather conditions. FSPro doesn't directly simulate suppression efforts, although users can manually update landscape inputs to account for barriers to spread such as fire lines constructed by hand crews or dozers.

Figure 4.4a illustrates burn probability contours generated for the SQF Canyon Fire, which occurred in 2010 on the Kern River Ranger District of the Sequoia National Forest in California. These particular results are for a 7 day run (i.e., fire spread is modeled over the course of 7 days), for 1000 simulated growth projections. Spatial patterns in the burn probability contours can help fire managers understand fire potential in the absence of suppression and the subsequent probability of resources or assets being impacted by fire.

In addition to fire spread probability, the potential exposure of resources and assets is a key driver of risk-informed incident management. WFDSS provides this functionality as well, leveraging multiple geospatial databases compiled by different agencies to display a range of infrastructure and natural and cultural resources (i.e., HVRAs). Figure 4.4b provides an example of exposure analysis within WFDSS, specifically highlighting the locations of private building clusters (red squares), federal buildings (green and tan squares), and campgrounds (blue squares). Additional layers representing communication and energy infrastructure, roads and trails, air-quality concern areas, critical wildlife habitat, and so on, are available but not displayed here for ease of presentation. The ability to determine where fire spread may result in negative consequences can be a major driver of firefighting strategy and tactics, including division of labor between suppression and localized protection of buildings and other assets.

WFDSS provides reports with a suite of additional information from FSPro analyses to understand model results and to support decision making. Figure 4.5 presents a histogram of simulated final fire sizes, reflecting the underlying distribution of fire events from which the burn probability contours were generated. In addition to

Values list

| Category | 80–100% | 60–79% | 40–59% | 20–39% | 5–19% | 0.2–4.9% | <0.2% | Expected value |
|---|---|---|---|---|---|---|---|---|
| BLM buildings | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.63 |
| Building clusters: Kern | 290 | 215 | 290 | 208 | 297 | 794 | 128 | 676 |
| Communication towers | 0 | 3 | 0 | 0 | 27 | 3 | 39 | 5.59 |
| County: Kern | 47,894 acres | 12,029 acres | 14,062 acres | 15,602 acres | 24,995 acres | 53,989 acres | 26,671 acres | 67,791 acres |
| Des areas: Greenhorn creek IRA | 9,323 acres | 3,854 acres | 3,003 acres | 1,702 acres | 2,701 acres | 3,690 acres | 1,974 acres | 13,536 acres |
| Des areas: Mill creek IRA | 11,596 acres | 1,551 acres | 1,960 acres | 1,319 acres | 2,236 acres | 5,408 acres | 2,205 acres | 13,320 acres |
| Des areas: Piute cypress ISA WSA | 2,499 acres | 1,003 acres | 1,183 acres | 424 acres | 0 acres | 0 acres | 0 acres | 3,670 acres |
| Des areas: Woolstaff IRA | 155 acres | 506 acres | 853 acres | 1,095 acres | 1,362 acres | 10,497 acres | 6,261 acres | 1,698 acres |
| Electric power plants | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0.25 |
| Electric sub stations | 1 | 0 | 0 | 0 | 5 | 0 | 0 | 1.53 |
| Electric transmission lines | 7.9 miles | 0.8 miles | 1.3 miles | 1.1 miles | 3.6 miles | 6.3 miles | 2.0 miles | 9.27 miles |
| Ozone non-attainment | 47,894 acres | 12,029 acres | 14,062 acres | 15,602 acres | 24,995 acres | 53,989 acres | 26,671 acres | 67,791 acres |
| Particulates non-attainment | 11,626 acres | 3,860 acres | 4,393 acres | 3,336 acres | 6,300 acres | 15,315 acres | 9,248 acres | 17,558 acres |
| Responsible agency: BLM | 8,647 acres | 2,690 acres | 3,750 acres | 4,969 acres | 9,604 acres | 7,565 acres | 3,247 acres | 14,431 acres |
| Responsible agency: CDF | 8,075 acres | 1,429 acres | 2,296 acres | 3,645 acres | 4,657 acres | 15,179 acres | 7,702 acres | 11,494 acres |
| Responsible agency: LOCAL | 0 acres | 0 acres | 25 acres | 123 acres | 144 acres | 0 acres | 0 acres | 67.4 acres |
| Responsible agency: USFS | 31,172 acres | 7,909 acres | 7,990 acres | 6,865 acres | 10,591 acres | 31,245 acres | 15,722 acres | 41,798 acres |
| Roads | 25.2 miles | 2.3 miles | 1.2 miles | 3.8 miles | 8.2 miles | 13.0 miles | 4.4 miles | 27.4 miles |
| Surface Mgmt agency: BLM | 8,341 acres | 2,661 acres | 3,689 acres | 4,910 acres | 9,556 acres | 7,472 acres | 2,794 acres | 14,079 acres |
| Surface Mgmt agency: DOD | 0 acres | 0 acres | 0 acres | 0 acres | 151 acres | 54 acres | 0 acres | 20.3 acres |
| Surface Mgmt agency: USFS | 30,458 acres | 7,748 acres | 7,435 acres | 6,372 acres | 9,538 acres | 29,525 acres | 14,365 acres | 40,439 acres |
| USFS buildings | 3 | 0 | 0 | 0 | 1 | 0 | 0 | 2.83 |

**Figure 4.6** Tabular exposure analysis results summarizing FSPro results intersected with spatial value layers; results are presented across burn probability zones as well as in terms of expected values.

supporting strategic evaluation of fire potential, WFDSS also provides additional fire modeling tools focusing on short- and near-term fire behavior to facilitate tactical and operational decisions.

Figure 4.6 provides tabular exposure analysis results, which overlay FSPro burn probability contours with spatial values-at-risk inventory layers and quantify expected values. As an example, the second row in the table shows the number of building clusters in Kern County broken down by burn probability zone, resulting in an expected value of 676 building clusters impacted by fire. In addition to HVRAs that may be impacted by fire, results also indicate whether the fire might spread onto land managed by other agencies, which can be critically important to prepare for as agencies may have different mandates and different fire management objectives.

## 4.4. FUTURE DIRECTIONS FOR WILDFIRE DECISION SUPPORT

Returning to sources of uncertainty enumerated earlier, WFDSS and specifically FSPro provide the decision support functionality to address uncertainty over possible fire spread directions and subsequent exposure of HVRAs. However, multiple other sources of uncertainty remain that fire managers must face. Below we identify opportunities for future directions of risk modeling and economic research to directly address these remaining uncertainties, ideally to improve risk-informed and cost-effective fire management.

### 4.4.1. Addressing the Consequences of Wildfire

Many contemporary landscape-scale wildfire risk assessments follow the exposure and effects analysis framework first identified by *Finney* [2005] and later formalized by *Scott et al.* [2013]. That framework quantifies wildfire risk for any discrete location on the landscape as the expected net change in value (*eNVC*) of all highly valued resources and assets (HVRAs) exposed to wildfire at that location. The calculation of *eNVC* incorporates the likelihood of burning and the conditional net value change (*cNVC*) given that a fire occurs.

$$eNVC_k = BP_k * cNVC_k$$

where $BP_k$ is the burn probability at pixel $k$. BP is determined through stochastic simulation of wildfire occurrence and spread. The calculation of $cNVC_k$ incorporates intensity results of a deterministic or stochastic wildfire simulation, as well as the susceptibility of HVRAs to wildfire. Specifically,

$$cNVC_k = \sum_i \sum_j \left( FLP_{ik} * RF_{ij} * RI_j \right)$$

**Table 4.1** Response Functions and Relative Importance Weights for Two Stylized HVRAs

| | Response function value, by flame-length class (FLC) | | | | | | |
|---|---|---|---|---|---|---|---|
| HVRA | FLC 1 | FLC 2 | FLC 3 | FLC 4 | FLC 5 | FLC 6 | Relative importance weight |
| Critical infrastructure | –10 | –10 | –80 | –80 | –80 | –80 | 100 |
| Fire-dependent wildlife habitat | +50 | +40 | +30 | –10 | –30 | –60 | 80 |

*Source:* See *Thompson et al.* [2015].
*Note:* FLCs are presented in order of increasing flame length, and users can define the number of categories and their corresponding flame lengths depending upon the application. The response function for critical infrastructure illustrates minimal loss until a flame length threshold is crossed with significant loss, whereas the response function for the wildlife habitat illustrates beneficial effects at low to moderate intensity fire. Response functions can be nonlinear, and can be multivariate with additional HVRA-specific information

where $FLP_{ik}$ is the conditional probability burning in flame-length class $i$ at pixel $k$, and $RF_{ij}$ is a "response function" value that indicates the consequence to HVRA $j$ of a wildfire occurring in flame-length class $i$, and RI is the "relative importance" per unit area of HVRA $j$. Response function values for physical assets like residential structures and critical infrastructure are always negative, indicating a net loss of value when exposed to wildfire. Wildfire positively affects the value of some resources, such as wildlife habitat or fire-adapted ecosystems, so $RF$ values can also be positive. Response functions are designed by resource specialists who rely on their experience and the scientific literature. Relative importance weighting is necessary to put all coincident HVRAs into a common currency. Relative importance values are determined by the line officers ultimately responsible for managing the landscape. To illustrate, Table 4.1 presents example response functions and relative importance weights for two stylized HVRAs, where response values range from –100 to +100, and importance weights range from 0 to +100.

The quantitative framework described above is designed to support land, resource, and fuel-management planning, typically relying on more advanced fire modeling systems that simulate tens of thousands of fire seasons to generate burn probabilities and flame length distributions [*Finney et al.*, 2011b; *Thompson et al.*, 2013b]. However, its results can also support planning for the response to a wildfire before one has started and even for planning the management of a wildfire after it has escaped initial attack. For example, the $cNVC_k$ values can be summed within each simulated fire perimeter from a stochastic fire modeling system, resulting in an estimate of the overall $NVC$ for the fire. Because the simulated fire start location is known, this new NVC attribute can be used to identify the net "risk source" associated with each ignition. Net "risk source" maps that average the consequence of all simulated fires starting across different parts of a landscape, whether positive or negative, can then succinctly summarize consequences of ignitions in various locations. Such an analysis could help to create a spatial wildfire management response plan by identifying locations on the landscape where fires tend to result in positive net effects and where they tend to cause damage. Likewise, a similar analysis can be done using simulated fire perimeters generated by FSPro for an ongoing wildfire event. That analysis would not generate a risk-source map, but would instead quantify the likelihood of exceeding threshold quantities of net value change, a small improvement over the analysis currently available in WFDSS.

To demonstrate potential applications in the real-time incident decision environment, Figure 4.7 illustrates risk modeling results generated from FSPro outputs. Fire perimeters were simulated on a real incident on a landscape in the southern Sierras in California, and paired with a preexisting $cNVC$ grid that was generated following the risk assessment framework outlined above. While the scatterplot generally indicates increasing net loss as simulated fire size grows, variation in loss stems from the shape and location of the fire with respect to potential fire intensity, HVRA location, and HVRA susceptibility. Notably, the greatest losses do not come from the largest fires but rather tend to concentrate around 15,000–20,000 acres, and this result underscores the importance of the fire's shape and location in addition to its size. Some of the most consequential fires may have burned into a community, whereas the fires that grew the largest may have done so by virtue of growing into undeveloped wildlands with few susceptible HVRAs.

Figure 4.8 further summarizes simulated fire-level net loss using an exceedance probability chart. These results display the likelihood of experiencing a given level of net loss, which can be compared against prospective suppression expenditures to inform cost-effectiveness analysis. For example, there is approximately a 20%

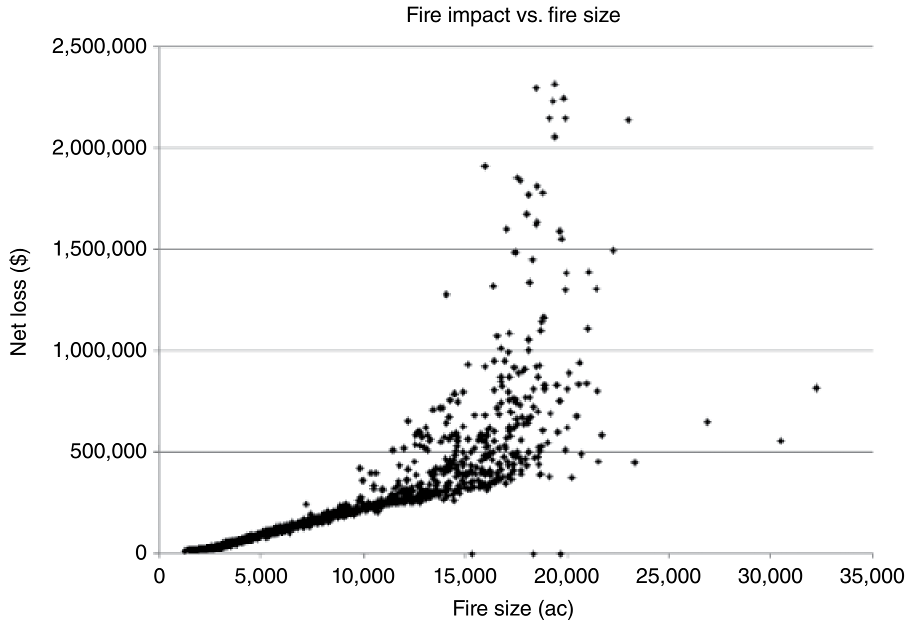


**Figure 4.7** Scatterplot of fire-level *cNVC* versus fire size.

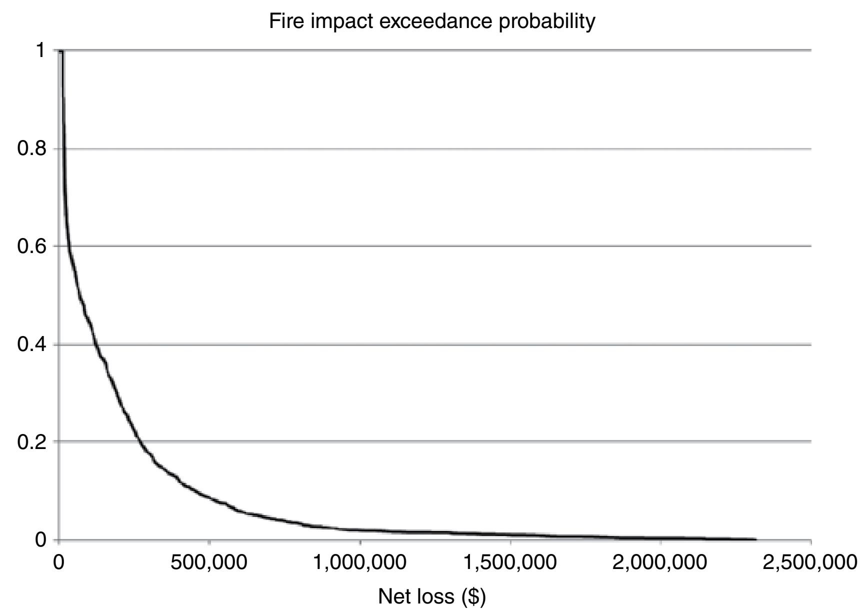


**Figure 4.8** Exceedance probability curve for fire-level *cNVC*, expressed in monetary units.

chance of exceeding $250,000 in losses. For illustration, results are presented in monetary terms, although operationally the quantification of all possible market and nonmarket impacts can be challenging [*Venn and Calkin*, 2011]. Extensions include modifying these exceedance probability curves in cases where response functions indicate potential for benefit, and probabilistically analyzing prefire risk mitigation investments in terms of avoided losses.

### 4.4.2. Suppression Effectiveness

Despite the scale of investment in large wildfire suppression, relatively little is understood about how suppression actions influence large wildfire spread and those conditions that ultimately lead to containment [*Finney et al.*, 2009]. Wildfire containment under initial attack (IA) has typically been modeled by evaluating the elliptical rate of spread of an ignition under identified fuel and weather conditions compared with the productive capacity and arrival time of IA resources [see for example *Fried and Fried*, 1996]. However, the large fire environment presents additional complexity and it has not been demonstrated if the IA containment approach is relevant to large wildfire suppression.

There is considerable uncertainty in managing large wildfires including the quality of weather forecasts, complex environmental conditions, variation in the type and quality of suppression resources, and whether or not requested suppression resources will be assigned [*Thompson and Calkin*, 2011]. Additionally, many resources are engaged in non-line-building activities such as point protection, contingency line development, and mop up. Further, given that the wildfire escaped IA, it is likely that the characteristics of wildfire growth are such that line-building efforts may not be feasible or effective.

Data necessary to understand suppression effectiveness within the United States can be difficult to obtain. Some recent studies have relied on primary reporting systems such as the Incident Status Summary (ICS-209) Situation report. However, these data do not provide spatial characteristics of the fire environment and rely on self-reporting by the incident team responsible for managing the events. In particular, some of the most relevant data for suppression modeling (specifically percentage of the wildfire contained, growth potential, and reported values at risk) are subjective and may not be accurately reported [*Holmes and Calkin*, 2013].

Despite these challenges, several authors have examined the ICS-209 data to model suppression effectiveness. *Finney et al.* [2009] modeled the probability that on a given day a large fire would be declared fully contained by examining wildfire suppression resource assignment, daily fire growth, fuel type, and other reported data within the 209 reports. The most significant factor in achieving wildfire containment was quiescent periods during the fire. That is, containment was most directly related to the number of low growth fire days and the number of previous intervals of low growth. Containment probability was negatively related to the presence of timber fuel types. No significant relationship was found between likelihood of containment and fire size or number of personnel assigned. *Holmes and Calkin* [2013] utilized similar data from the ICS-209 to examine the relative efficiency of suppression resources by comparing published resource line-building production rates published by *Broyles* [2011] with daily line built estimated from reported fire size and percentage containment. The results indicated that the actual production rates of suppression resources on a set of large wildland fires in 2009 were relatively low; 14% for engines, 18% for dozers, and 35% for hand crews compared to the reported standard production rates. Helicopters were the one exception with actual production rates estimated to be close to published rates (93%). Limited understanding of the objectives of resource assignments and the conditions of the suppression environment limit the ability of research efforts to characterize the conditions under which suppression activities are most effective.

In-flight GPS-based systems such as the Automated Flight Following and Operational Loads Monitoring systems allow for analysis of the spatial use patterns of wildfire aviation resources such as Large Air Tankers (LATs), large planes capable of dropping greater than 1800 gal of retardant or water. Understanding the cost effectiveness of LATs has been a particular emphasis area of the US Forest Service over the last several years as the existing fleet of Korean War vintage aircraft are replaced with newer ships. *Calkin et al.* [2014b] tied individual retardant drops from LATs to wildfire outcomes during the 2010 and 2011 wildfire seasons in the United States. The authors found that approximately half of all use of LATs occurred after the fire had escaped initial attack. On those incidents where LATs were used during initial attack, 75% escaped, compared to the 2%–4% annual escape rate on all wildfire ignitions. These results suggest that LAT usage on IA is typically restricted to only those fires with a very high escape rate. Information on the effectiveness of LATs in large fire support is currently limited due to missing data on the objectives and outcomes of retardant drops in supporting large fire strategies.

The practice of wildfire management is highly complex, and, currently, there are many challenges to understanding the effectiveness of wildfire suppression actions. Improved and expanded data collection systems and continued research efforts are critical to our understanding of the conditions that lead to effective suppression, informed trade-off analyses of alternative suppression strategies and organizations, and safer and more economically efficient outcomes.

### 4.4.3. Fire Managers' Use and Interpretation of Probabilities and Decision Making Under Uncertainty

Decision-support tools may be able to leverage how managers respond to risk information to mitigate some cognitive biases and decision heuristics. Common biases and decision heuristics have been linked to the wildfire management environment [Table 4.2; see also *Maguire and Albright*, 2005], and wildfire managers have exhibited several of these when choosing among strategies in hypothetical wildfire scenarios [*Wilson et al.*, 2011; *Wibbenmeyer et al.*, 2013]. In some cases, the informational content or way in which information is presented can affect decisions. Framing potential wildfire outcomes in certain ways can increase the salience of certain outcomes, and trigger an analytical response from decision makers.

**Table 4.2** Select Set of Identified Cognitive Biases That Influence How Fire Managers Perceive and Respond to Risk

| Cognitive biases | Impacts |
|---|---|
| Discounting bias | Tendency to overweight short-term risk over long-term risk |
| Loss aversion | Tendency to exhibit risk-averse behavior when outcomes are framed as gains and to exhibit risk-seeking behavior for outcomes framed as losses |
| Overconfidence bias | Tendency to be overconfident in the state of knowledge or accuracy of beliefs |
| Status quo bias | Tendency to disproportionately stick with the status quo alternative |
| Sunk cost bias | Tendency to continue with ineffectual strategy/tactics because significant resources have already been expended |

For example, presenting information about the duration of use of suppression resources as an accident or fatality rate may highlight for managers the risk to personnel of using those resources. Presenting fatality rates instead of usage rates has been shown to result in reduced exposure of personnel to risk in hypothetical fire scenarios [*Hand et al.*, 2015], although this may exacerbate other biases related to responses to outcome probabilities.

Biased responses to outcome probabilities [see *Tversky and Kahneman,* 1992; *Prelec,* 1998] may be less amenable to direct intervention through decision support tools. An option for addressing cognitive biases that may not respond well to different information framing may be to identify those managers who tend to exhibit responses to risk that are most closely aligned with agency preferences and facilitate training and knowledge transfers among managers. Heterogeneity in responses to risk (and probabilities in particular) is evident among managers, and a portion of managers appear to make decisions that minimize expected losses in a risk environment [*Hand et al.*, 2015]. Decision support could help by providing structured decision processes [*Maguire and Albright*, 2005] that mirror risk-based training efforts and knowledge transfer among managers.

## 4.5. CONCLUSION

Wildfire management is complex, dynamic, and uncertain, and a full investigation into wildfire risk assessment and mitigation planning is beyond the scope of a single chapter. Nevertheless, we highlighted salient uncertainties faced in the management of active large wildfire incidents, reviewed an existing decision-support system widely used in the United States (WFDSS), and illustrated how probabilistic information provided by WFDSS can inform risk-based decision making. Significant sources of uncertainty remain, which vary according to the degree of influence they may exert on decision processes as well as approaches to manage those uncertainties and improve decisions. A fundamental need for increased wildfire management efficiency is improved understanding of suppression effectiveness, requiring large-scale collection of operational data across incidents. We expect continued research into risk and decision analysis will play a role for years to come in wildfire management and risk mitigation, and that in particular advanced risk modeling techniques will be used to inform wildfire management decisions.

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