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Assessing the Expected Effects of Wildfire on Vegetation Condition on the Bridger-Teton National Forest, Wyoming, USA

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Abstract

Characterizing wildfire risk to a fire-adapted ecosystem presents particular challenges due to its broad spatial extent, inherent complexity, and the difficulty in defining wildfire-induced losses and benefits. Our approach couples stochastic wildfire simulation with a vegetation condition assessment framework to estimate the conditional and expected response of vegetation condition to wildfire. We illustrate application of this framework for the Bridger-Teton National Forest (BTNF) in western Wyoming, USA. Results illustrate generally positive net effects of wildfire on vegetation condition across the major forested biophysical settings on the Forest, supporting the notion that wildfire can play a role in restoring or enhancing the ecological integrity of landscapes affected by fire exclusion. These results carry significant implications for future management of wildfire on the BTNF, and highlight temporal relationships between short-term incident response and long-term ecological integrity.

Keywords: *departure analysis; fire effects; LANDFIRE; ecological integrity*

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Introduction

An understanding of wildfire risk—the likelihood and magnitude of wildfire-induced loss or benefit to highly valued resources and assets (HVRAs)—is fundamental to effective wildland fire management. Risk-based information supports planning efforts aimed at minimizing wildfire-related losses and maximizing wildfire-related benefits. The primary modeling components of wildfire risk assessment include exposure analysis and effects analysis (Thompson and Calkin 2011). Assessment of HVRA exposure to wildfire—the likelihood and intensity of wildfire where an HVRA exists—is increasingly used to inform fire management planning and fuel treatment prioritization across the wildland fire management spectrum, including pre-wildfire planning (Scott and others 2012a,b), fuel treatment design (Ager and others 2010), and wildfire incident response (Calkin and others 2011b). Further, assessing the potential effects of fire on HVRAs under varying levels of exposure can provide a more comprehensive basis for evaluating the potential consequences of wildfire (Thompson and others 2013a).

Although the term “risk” is typically associated with the notion of loss—indeed, most efforts to estimate wildfire risk limit their focus to adverse fire effects—wildfires can also result in substantial ecological benefits. A comprehensive assessment of wildfire risk should therefore consider the beneficial ecological effects of wildfire (Thompson and Calkin 2011; Thompson and others 2013a). This recognition is consistent with Federal wildland fire policy that (1) establishes risk management as the basis for wildland fire management, and (2) allows for flexibility when responding to incidents to account for beneficial effects (National Interagency Fire Center 2009). Furthermore, accounting for ecological considerations in wildland fire management planning is consistent with the USDA Forest Service 2012 planning rule’s emphasis on the restoration and maintenance of resilient ecosystems (Federal Register 77 No. 68) as well as the management policies of many national parks and protected areas. Managers of Federal lands face the difficult task of protecting resources and assets susceptible to wildfire-induced loss while simultaneously allowing fire to play its natural role in sustaining ecosystems.

Many recent wildfire risk assessment efforts have had direct ties to resource objectives and the beneficial role of fire, for instance, evaluating dry forest restoration and impacts to fire-dependent wildlife habitat.

However, the consideration of broader ecological objectives regarding ecosystem condition has been limited. While early national-scale efforts did include fire-adapted ecosystems as an HVRA (Calkin and others 2010; Thompson and others 2011a,b), the analyses used only coarse scale information on fire regime group and did not integrate spatial information related to the extent, complexity, and/or variability of ecosystem components. A more refined, and more intensive, approach could instead consider fire-adapted ecosystems on the basis of variables like biophysical setting and the geographic distribution of successional states. Our primary objective for this paper is to describe how we addressed the challenges of assessing risk to fire-adapted ecosystems by integrating vegetation condition and wildfire risk assessment frameworks. Further, we illustrate a landscape-scale application of this integrated framework to assess the expected effects of wildfire on vegetation condition, and discuss how assessment results can inform wildland fire management decisions.

The biological elements (e.g., vegetation, wildlife) and ecological processes (e.g., nutrient cycling, soil development, hydrologic function) of fire-adapted ecosystems have evolved with recurring wildfire, and wildfire plays a critical role in their sustainability (Keane and others 2002). Wildfire is a driving force behind the composition, structure, and function of fire-adapted ecosystems (Agee 1998). However, the fire regime characteristics—primarily the frequency, severity, and size of fires—vary widely among individual ecosystems (Agee 1998; Noss and others 2006). Thus, an assessment of the effects of wildfire on fire-adapted ecosystems begins with classification of individual ecosystem types based on the characteristic fire regime of the system. Vegetation classifications based on biophysical site characteristics (e.g., soil, climate, topography) and disturbance regimes are readily available for delineating broad ecosystem types across a landscape (e.g., Rollins 2009).

Spatial and temporal variability in fire regime characteristics also exist within individual ecosystem types due to heterogeneity in fuel, temporal fuel dynamics, weather, topography, and ignitions (Ehle and Baker 2003; Noss and others 2006; Turner and Romme 1994). For example, an ecosystem associated with a "low severity" fire regime may occasionally experience moderate- and high-severity fires in particular locations and under particular conditions. This variability leads to a dynamic mix of ecosystem states, within any individual ecosystem type, characterized by compositional, structural, and functional components. The spatial characterization of fire-adapted ecosystems, therefore, should account for the interdependence and dynamic nature of disturbance and vegetation on the condition of the system as a whole.

An assessment of current vegetation condition—current proportional distribution of successional states relative to a reference distribution—serves as a measure of ecosystem resiliency and ecological integrity. The USDA Forest Service 2012 planning rule directives define ecological integrity as "the quality or condition of an ecosystem when its dominant ecological characteristics… occur within the natural range of variation and can withstand and recover from most perturbations imposed by natural environmental dynamics or human influence" (Proposed FSH 1909.12 Chapter 10.5). The Interagency Fire Regime Condition Class (FRCC) Guidebook standard landscape mapping methodology (Barrett and others 2010) provides a foundation for such a vegetation condition assessment (VCA). Our primary assumptions in using this VCA approach are: (1) vegetation composition and structure are dominant characteristics of fire-adapted ecosystems and serve as indicators for other functional characteristics, and (2) historical conditions provide an acceptable reference for assessing current vegetation condition and ecological integrity based on the concept that the conditions with which biologic and other ecosystem components have evolved are likely to sustain them in the future (Landres and others 1999; Keane and others 2009; Swetnam and others 1999).

Wildfire Simulation

Spatial wildfire simulation is the backbone of quantitative risk assessment (Finney 2005; Miller and Ager 2012; Scott and others 2013b). FSim, the large-fire simulator (Finney and others 2011), is a comprehensive, stochastic wildfire occurrence, growth, and suppression simulation system that pairs a wildfire growth model (Finney 1998, 2002) and a model of ignition probability with simulated weather streams in order to simulate wildfire ignition and growth for tens of thousands of fire seasons. The results of these simulations are used to estimate, in raster format, the annual burn probability (BP) and conditional flame-length probability (FLP_i) across the landscape. FSim BP is the annual probability of burning; it is estimated by dividing the number of simulated fire seasons that burned each pixel by the total number of simulated fire seasons. FLP_i is the conditional probability of wildfire burning in the i^{th} flame-length category, given that a wildfire occurs at all. At a given pixel, FLP_i values across the range of flame-length categories sum to one. FSim results have been used for spatial risk analyses in a number of contexts (Calkin and others 2010; Scott and others 2012a,b; Thompson and others 2011, 2013a,b).

Simulation of daily values of Energy Release Component (*ERC*) of the National Fire Danger Rating System is the foundation of FSim's operation. *ERC* is calculated from historical weather data (Cohen and Deeming 1985). The simulated *ERC* is used in two ways: first, to determine the probability of a wildfire start for each day, and second, to determine which of three fuel moisture scenarios to use for the day. The three scenarios correspond to *ERC* classes with breaks at the 80th, 90th, and 97th percentile *ERC* values. *ERC* is simulated for each day of each simulated fire season based on the historical seasonal trend in mean and standard deviation of *ERC* using temporal autocorrelation (Finney and others 2011). Wildfire growth occurs only on days for which the simulated *ERC* exceeds the 80th percentile. Simulated wildfire growth for each day of each fire is also a function of wind speed and direction. Wind characteristics for each day are determined by a random draw from the historical monthly joint frequency distribution of wind speed and direction. This draw is independent of *ERC*, and each day's draw is independent of the others.

A wildfire in FSim grows until it is either contained or self-extinguishes. FSim includes a suppression module based on a containment probability model (Finney and others 2009) that relates the likelihood of wildfire containment on a given day to current and previous fire growth. Containment success is simulated stochastically based on comparison of a random draw with the modeled containment success probability. Self-extinguishment occurs when *ERC* remains below the 80th percentile value for several days in a row, if the entire perimeter reaches non-burnable land cover, or if the simulation reaches the last calendar day of the year.

Vegetation Condition Assessment

The VCA methodology uses biophysical settings (BpSs) as the primary environmental descriptor (Barrett and others 2010). BpSs are mapped using characteristics of the biophysical environment and named and described based on approximation of the historical disturbance regime, thus providing a suitable characterization of a fire-adapted ecosystem. Multiple successional states may compose an individual BpS at any one time. The LANDFIRE data (Rollins 2009) used in this case study apply the classification developed by Hann (2003) that is also applied in the FRCC Guidebook (Barrett and others 2010). This classification allows up to five natural successional states, referred to as S-Classes and labeled A through E, to be represented in an individual BpS. Additional S-Classes identify current vegetation conditions that are uncharacteristic of the reference condition. These include native vegetation with composition or structure components outside the range of variation estimated for the reference period (uncharacteristic native; UN) and introduced exotic vegetation (uncharacteristic exotic; UE). The majority of S-Classes for each BpS are mapped based on rules describing specific thresholds for lifeform, cover, and height data as documented in BpS model descriptions (LANDFIRE 2007). In some cases, the cover and height rules are specific to an existing vegetation type or group of types.

For each BpS, the VCA methodology compares the current amount of mapped S-Classes for each BpS within a stratification, such as a watershed, to a modeled reference distribution. The reference amount represents the mean proportion of each stage's class as estimated by simulation of historical disturbance probabilities and vegetative succession in the Vegetation Dynamics Development Tool (ESSA Technologies Ltd. 2007) over multiple simulations.

A stratification, or assessment unit, must be identified for each BpS prior to conducting the VCA. An assessment unit is the contiguous land area within which the current distribution of S-Classes is compared to the reference distribution. The appropriate assessment unit size for a BpS is related to its dominant disturbance regime (Barrett and others 2010). If the assessment unit is too small relative to the historical size of disturbances, a single disturbance event, even one within the natural range of variation, could result in one successional stage dominating the landscape, indicating departure from the reference condition. Conversely, if the assessment unit is too large, then even an abnormally large disturbance event may not change the current distribution of S-Classes, failing to show a departure from the reference condition.

For each assessment unit where a BpS occurs, S-Class departure from the reference condition is quantified as the S-Class percent difference (Barrett and others 2010)

$$SClass\ percent\ difference = \frac{CP - RP}{max(RP, CP)} * 100 \qquad (1)$$

where *CP* is the current proportion and *RP* is the reference proportion for the S-Class. Positive values of this measure indicate that the current proportion of the S-Class exceeds the reference proportion; negative values indicate that the current is less than the reference proportion. If the current proportion is twice the reference proportion, the S-Class percent difference is +50 percent; if the current proportion is half of the reference, then percent difference is -50 percent.

Risk Assessment Framework

A spatially explicit, quantitative wildfire risk assessment framework has been recommended for use to inform a variety of land and fire management decisions across a range of planning scales (Calkin and others 2011a). The fundamental components of this risk framework are wildfire likelihood, intensity, and effects (Finney 2005; Miller and Ager 2012; Scott 2006; Scott and others 2013b). The term "effects analysis" is often used to describe a comprehensive risk assessment that addresses all three fundamental components. The three primary data requirements to assess the expected response of HVRAs to wildfire include: (1) geospatial data of burn probability and wildfire intensity generated from a stochastic wildfire simulation, (2) geospatially identified HVRAs, and (3) response functions that describe the effects of fire on each HVRA across a range of fire intensity levels. Typically, the response functions describe fire effects as the net change in value (*NVC*) of the HVRA should it experience a fire of a given intensity. A response function value of –100 indicates the greatest possible reduction of value, or loss, whereas +100 indicates the greatest possible increase in value, or benefit. Pairing components 1 and 2 alone provides important information regarding where on the landscape HVRAs will likely interact with wildfire of different intensity levels (also known as exposure analysis). The addition of component 3 further characterizes the effects on HVRAs of this interaction with fire, which can lead to very different prioritization strategies than those based on exposure alone (Thompson and others 2013a).

The risk framework quantifies risk, for each pixel on a landscape, as the expected value of net value change, which is often simply called expected net value change, written as E(*NVC*). This calculation combines an estimate of *NVC* for a given fire intensity level (NVC_i) with FLP_i. Calculating E(*NVC*) is a two step process. First, the conditional *NVC,* or C(*NVC*), is calculated as the sum-product of FLP_i and NVC_i over a range of flame length classes

$$\mathrm{C}(NVC) = \sum FLP_i * NVC_i \qquad (2)$$

where C(*NVC*) is the conditional response of the HVRA to wildfire, given that one occurs. The expected value of *NVC* is

$$\mathrm{E}(NVC) = \mathrm{C}(NVC) * BP \qquad (3)$$

Because the term “risk” is often associated solely with adverse wildfire effects, we will hereafter use the terms “expected response” and “expected effects” in place of “risk,” and “effects analysis” in place of “risk assessment” when using this framework to quantify wildfire effects on vegetation condition. Expected response can be positive or negative.

Where empirical data and integrated modeling tools are lacking, structured protocols for eliciting and encapsulating expert judgment are available to characterize broad scale fire effects to HVRAs. In fact, a cornerstone of our overall modeling approach was reliance on local knowledge and expertise. We thereby outline a risk-based approach to quantitatively assess expected wildfire effects to the ecological integrity of fire-adapted ecosystems. Our intent is to demonstrate application of a novel approach to quantifying expected fire response in an ecological context, considering the amount of S-Classes across a BpS within an assessment unit, as a measure of the ecological integrity of fire-adapted ecosystems.

Methods

Our overall analytical approach was to first quantify the current vegetation condition—the current proportion of area represented by individual S-Classes relative to a reference proportion—for each biophysical setting, and then to apply a standard quantitative risk assessment framework based upon its results. This approach couples an assessment of vegetation condition with a stochastic wildfire simulation and a risk assessment framework to estimate the conditional and expected response of vegetation condition to wildfire.

Study Area

The case study we present originated from a broader assessment of wildfire risk to HVRAs within Grand Teton National Park and the Bridger-Teton National Forest (BTNF) in western Wyoming, USA (Scott and others 2013a). In that assessment, each agency first identified a suite of HVRAs to be analyzed, and then characterized the susceptibility and relative importance of those HVRAs according to the assessment process outlined by Thompson and others (2013a). In this paper, we specifically focus only on the quantification of the effects of wildfire on vegetation condition within the BTNF, using VCA as a foundation.

A wide range of biophysical settings and vegetation types occur within the 3.5 million acre BTNF (figure 1). The valley-bottoms, at roughly 2,000 m elevation, are covered by grasslands and grass mixed with sagebrush (*Artemisia tridentata*). The highest peaks in the study area exceed 3,600 m; the terrain above 3,000 m typically does not support wildfire spread due to the prevalence of rock and persistent snow. The slopes between the valley-bottoms and the peaks are covered by coniferous forests, montane meadows, and stands dominated by quaking aspen (*Populous tremuloides*).

Wildfire Simulation

A prerequisite to spatial wildfire simulation is the development of a fire modeling landscape file (LCP)—a suite of geospatial data layers characterizing vegetation, fuel, and topography. The vegetation and fuel layers for the LCP were derived from geospatial data describing BpS and existing vegetation characteristics. We used LANDFIRE version 1.0.5 (also referred to as "Refresh 2001") of these data (Rollins 2009) for an extent that includes a minimum buffer of 10 miles around the BTNF. This buffer allows for the simulation of wildfire spread onto the study area from adjacent land without introducing an artificial edge effect. To generate the most up-to-date and locally relevant LCP possible we consulted with local resource specialists to (1) critique and update vegetation characteristics and surface fire behavior fuel model mapping rules, and (2) to get updates for recent disturbances not accounted for in the LANDFIRE version 1.0.5 data. We acquired geospatial data on wildfire severity for the time period of 2000 through 2010 from the Teton-Interagency fire ecologist, and geospatial data on overstory canopy loss due to insects and disease for the time period of 2000 through 2008 from the USDA Forest Service Remote Sensing Applications Center (Goetz and others 2009). Surface fire behavior fuel mapping rules were adjusted based on local resource specialist expertise such that simulated fire behavior qualitatively agreed with expected fire behavior.

We used FSim to quantify overall *BP* and *FLP* across six fire intensity levels (FILs) at each point across the landscape. FSim uses the standard classification of FIL developed for the Fire Program Analysis project (table 1). Fire intensity in FSim incorporates the effects of relative spread direction (heading, flanking, and backing) as well as variability in wind speed, wind direction, and fuel moisture. An unpublished report on file at the BTNF (Scott and others 2013a) provides additional detail on our wildfire simulation modeling, including our analysis of local wildfire and weather history for input into FSim.

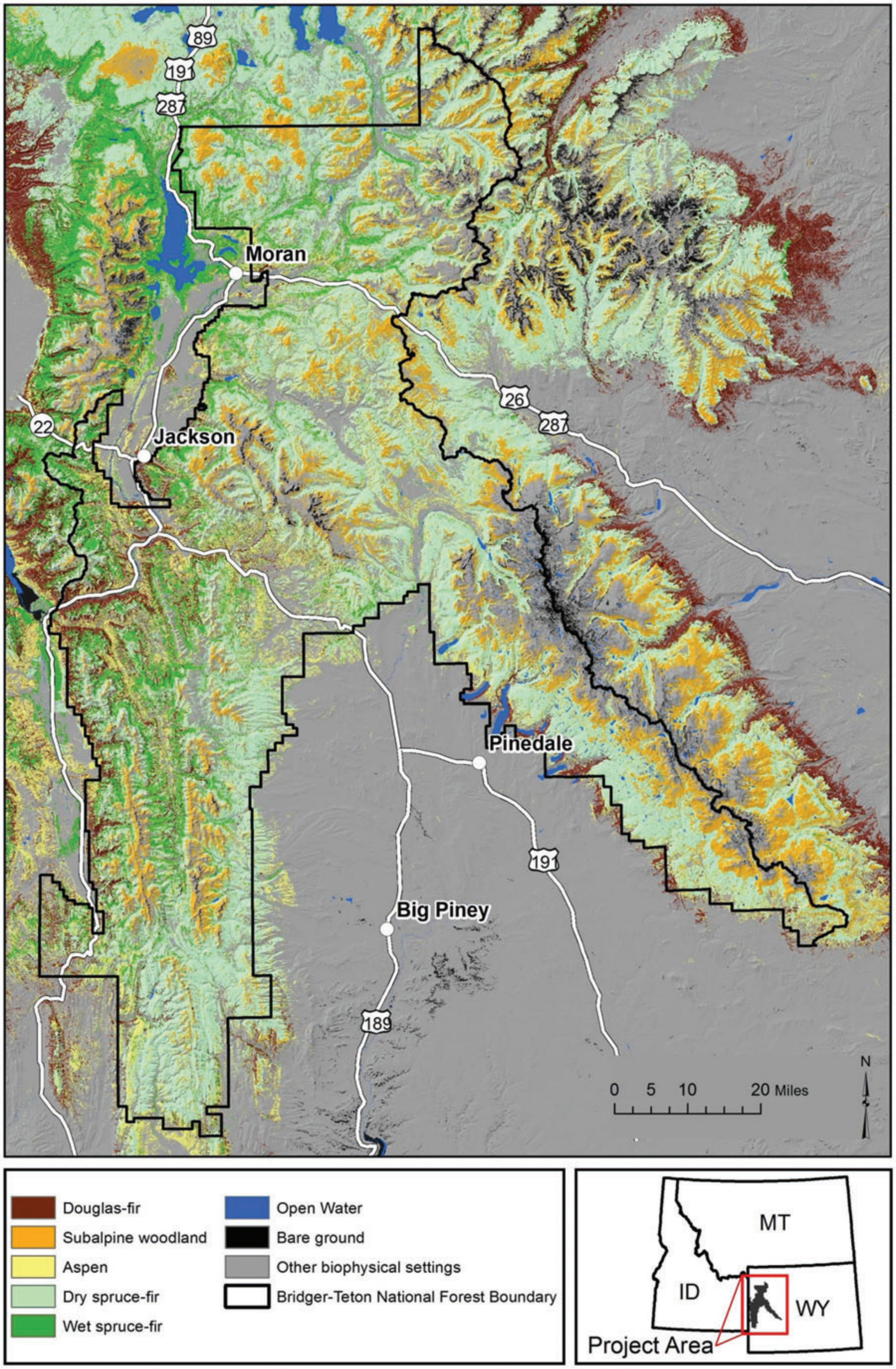

Figure 1. Spatial distribution of the five primary LANDFIRE biophysical settings assessed on the Bridger-Teton National Forest and surrounding area.

Table 1—Flame length range associated with six Fire Intensity Levels (FILs) as used in the FSim large-fire simulator.

Fire Intensity Level (FIL)	**Flame length** range (feet)
FIL1	0-2
FIL2	2-4
FIL3	4-6
FIL4	6-8
FIL5	8-12
FIL6	12+

We supplied FSim with weather data for the period of 1990-2010 from the Raspberry Remote Automated Weather Station (RAWS), located centrally in the landscape. We gathered fire occurrence data (start location and date, cause, and final size) for all jurisdictions in the analysis area during the period of 1990-2009, and critiqued the data to identify and remove duplicate and erroneous values. We used FireFamilyPlus software to generate logistic regression coefficients for estimating the probability of fire occurrence as a function of *ERC*. Because multiple fires can start on the same day, we also provided a table to FSim indicating the historical distribution of the number of fires per fire-day. FSim uses these historical fire occurrence parameters to simulate the ignition of wildfires as a function of simulated *ERC*.

FSim can optionally use information regarding the spatial density of ignitions across the landscape. We used an ignition density grid that was generated for a companion study on the same landscape (Scott and others 2012a) using a statistical modeling approach similar to that of Syphard and others (2008). Using FSim, we simulated 20,000 fire-season iterations at a 90-m raster resolution (2 ac per pixel).

Vegetation Condition Assessment

We used the Interagency Fire Regime Condition Class (FRCC) Guidebook standard landscape mapping methodology (Hann and others 2008) to determine, for each BpS, the percent difference of each S-Class relative to the reference condition (Equation 1). The same LANDFIRE version 1.0.5 BpS and existing vegetation data layers used for creating the LCP were also used to generate an S-Class data layer. There are 29 LANDFIRE BpS classes (Rollins 2009) mapped within the BTNF (excluding the bare ground, open water, and perennial ice and snow classes). We ultimately identified five BpSs that represent the predominant fire-adapted forest ecosystems of the BTNF, accounting for 71 percent of the land area (figure 1).

Resource specialists critiqued the LANDFIRE S-Class mapping rules for errors and local applicability. Adjustments were made to fix issues with rule overlap and local applicability of uncharacteristic native conditions. The adjusted rules were applied using GIS software. Next, resource specialists developed S-Class transition rules in order to update the ca. 2001 geospatial data for wildfire and insect and disease disturbance not accounted for in the LANDFIRE version 1.0.5 data as discussed above.

Per guidance from the Interagency FRCC Guidebook (Barrett and others 2010), we delineated assessment units based on the dominant historical fire regime of each BpS. We ultimately delineated two landscape levels for the assessment (figure 2). The larger level uses major rivers and hydrologic unit boundaries to delineate major mountain ranges of the BTNF. This level is applied to the three BpSs associated with fire regime groups IV and V (table 2). Sub-basins (that is, 4th level hydrologic unit code) within the larger landscapes represent the second landscape level, which we applied to the two BpSs associated with fire regime group III.

We used version 2.2.0 of the FRCC Mapping Tool to conduct the assessment. The tool calculates the S-Class percent difference (Equation 1) for each combination of BpS, S-Class and assessment unit. We then classified the S-Class percent difference values into three categories representing the status of the S-Class: deficit, similar, or surplus (table 3). This metric is especially informative because it indicates whether a particular S-Class needs to be reduced, maintained, or recruited to move a BpS towards the reference condition within a particular assessment unit.

Effects Analysis

The effects analysis integrates the VCA and wildfire simulation results (figure 3). To characterize the effects of wildfire on VCA we held a workshop at which resource specialists from the BTNF defined a response function for each unique combination of BpS, S-Class and status present within the BTNF. Response functions quantify net value change, expressed as a relative percentage loss or benefit, as a function of fire intensity and other landscape characteristics (Thompson and others 2011, 2013a). A positive value in a response function indicates a benefit of wildfire at that intensity level; a negative response function value indicates a loss, or decrease in value. Response function values may range from –100 (greatest possible loss of resource value) to +100 (greatest increase in value). In the design and implementation of the workshop we adhered to guidance for expert judgment elicitation (Kohl and others 2010; Kuhnert and others 2010).

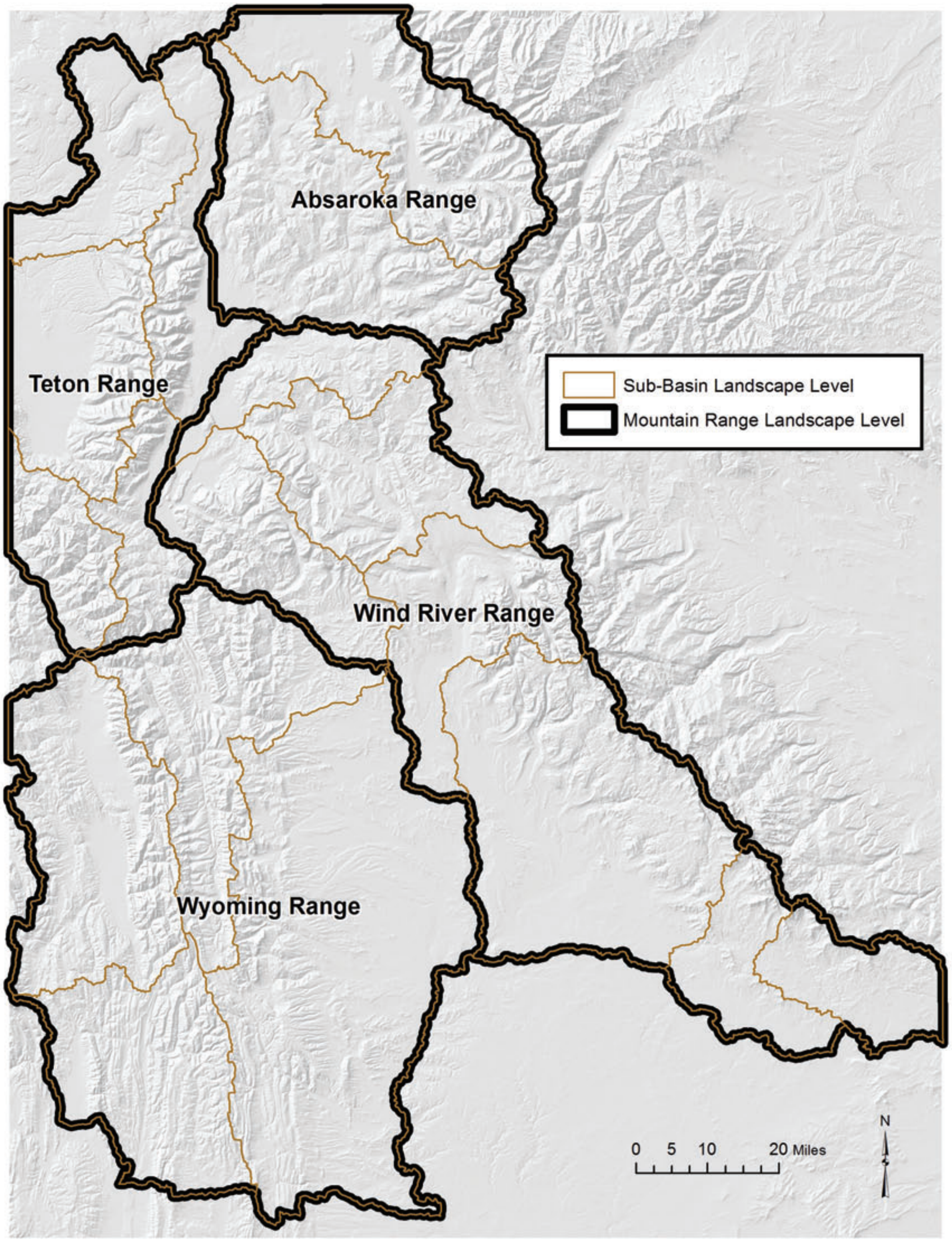

Figure 2. Assessment unit delineations for the mountain range landscape level (four assessment units; used for the two biophysical settings in Fire Regime Group IV and V) and the sub-basin landscape level (12 assessment units; used for the four biophysical settings in Fire Regime Group III (table 2)).

Table 2—Landscape level and associated fire regime group for each biophysical setting (BpS) assessed on the Bridger-Teton National Forest. Assessment units are delineated in Figure 2.

Landscape level	Number of assessment units	Fire regime			Associated biophysical settings (BpSs)	
		Group	Frequency	Severity	Complete name and model number	Short name
Sub-Basin	12	III	35 – 200 years	Low – Mixed	Northern Rocky Mountain Subalpine Woodland and Parkland - 2110460	Subalpine woodland
					Middle Rocky Mountain Montane Douglas-fir Forest and Woodland - 2111660	Douglas-fir
Mountain Range	4	IV	35 – 200 years	Replacement	Rocky Mountain Aspen Forest and Woodland - 2010110	Aspen
		V	200+ years	Replacement - Any	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland - 2110550	Dry spruce-fir
					Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland - 2110560	Wet spruce-fir

Table 3—Thresholds used by the FRCC Mapping Tool ver. 2.2.0 to calculate S-Class status.

S-Class Status	Absolute difference between current S-Class proportion and reference proportion[a]
Deficit	-100% and < -33%
Similar	≥ -33% and ≤ 33%
Surplus	>33% and 100%

[a] This assessment was conducted using the Interagency FRCC Guidebook version 1.3.0 (Hann and others 2008) methodology and version 2.2.0 of the FRCC Mapping Tool. Version 3.0 of the Guidebook (Barrett and others 2010) and version 3.1.0 of the FRCC Mapping Tool use different thresholds.

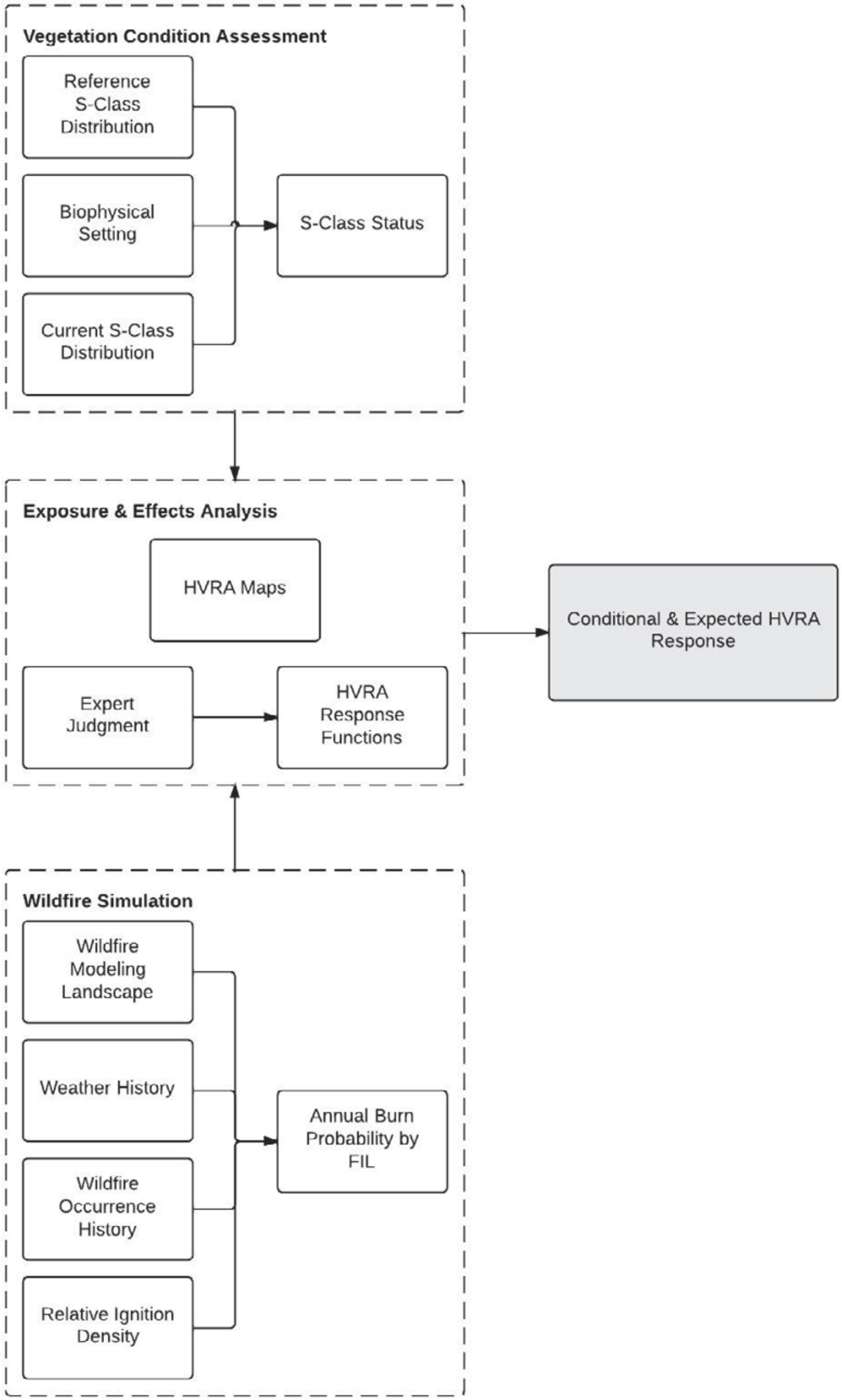

Figure 3. Calculating conditional and expected response of vegetation condition to wildfire is a function of three modeling processes: vegetation condition assessment, exposure and effects analysis, and wildfire simulation.

In developing a response function for a combination of BpS, S-Class and status, we asked the resource specialists to consider how a wildfire occurring at each of six different fire intensity levels would affect the vegetation type, cover, and height, and therefore S-Class. Then we asked them to consider how that change in S-Class would affect the overall proportion of S-Classes within each BpS. That is, we asked the specialists to consider not only direct wildfire impacts to S-Class, but also how those impacts would lead to desirable or undesirable shifts in S-Class proportion at the stratum level (i.e., BpS). For instance, a wildfire-related transition from an S-Class with a surplus of acres to an S-Class with a deficit of acres can be considered ecologically beneficial—wildfire is expected to move the proportion of both S-Classes towards the reference proportion thus improving the ecological integrity of the stratum as a whole.

For each pixel on the landscape, we used a GIS to first calculate the conditional response to wildfire (*CR*) as

$$CR = \sum FLP_i * RF_i \tag{4}$$

Conditional response is an estimate of the likely response, given that a fire occurs. Next, we calculated the expected value of the response to wildfire (*ER*) as

$$ER = CR * BP \tag{5}$$

Expected response incorporates the likelihood of occurrence. Finally, we computed the mean values of *BP*, *CR* and *ER* for the unique combinations of BpS, S-Class and status. By coupling the land area associated with each of those combinations with the mean BP, we also estimated the expected annual area burned.

Results

Wildfire Simulation

The wildfire simulation resulted in an annual mean of 5.9 fires exceeding 250 ac, with a mean size of 6,108 ac. This corresponds to a mean annual area burned of 36,508 ac/yr compared to the historical 20-year mean of 30,001 ac/yr. More importantly, FSim estimates how those acres burned are distributed across the landscape as burn probability (figure 4). The spatial pattern of *BP* is a function of ignition density and spread rate potential within an area of the landscape.

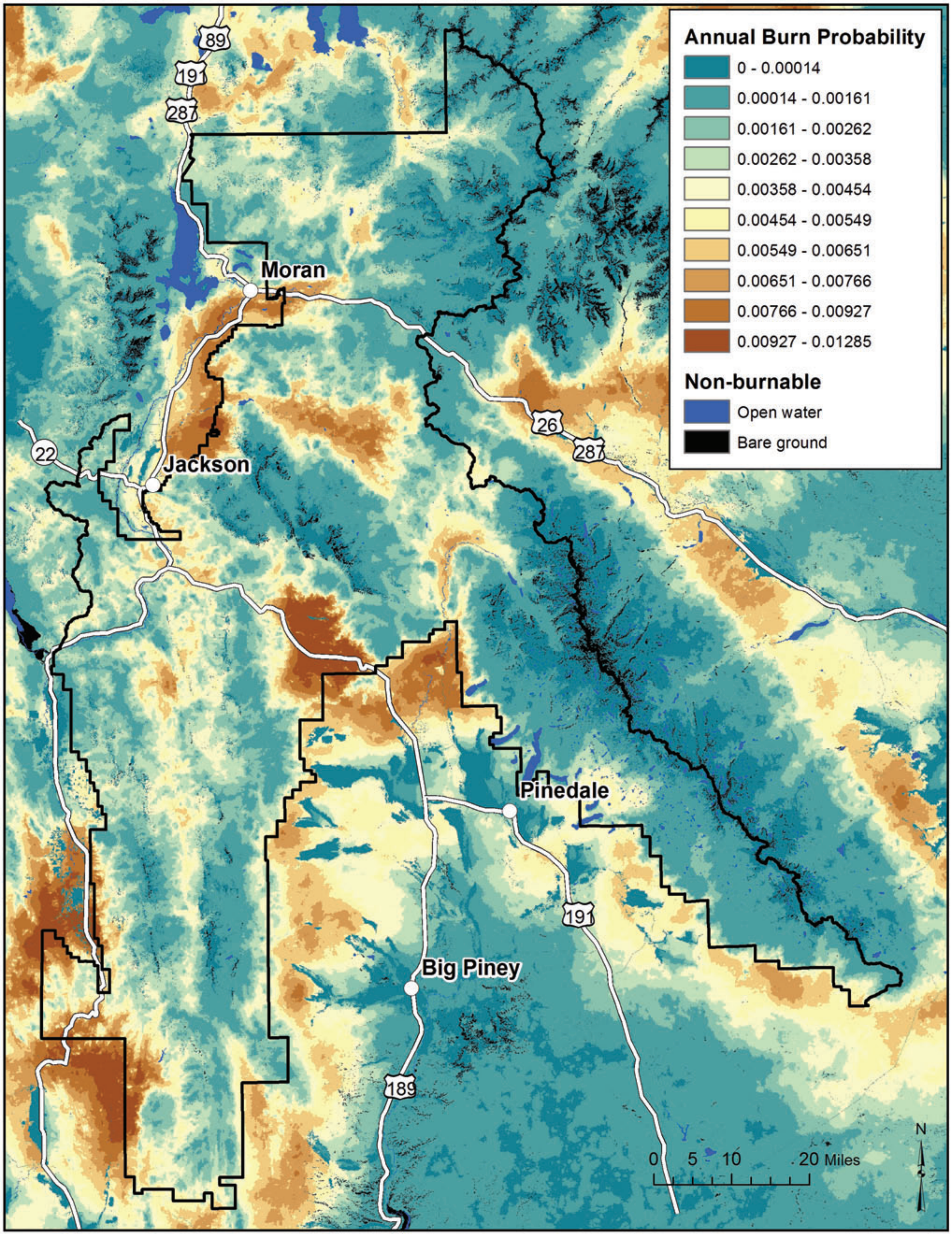

Figure 4. Simulated annual burn probability across the fire modeling landscape. Areas in brown have the highest burn probabilities; areas in blue the lowest.

The south-central portion of the landscape has both low ignition potential and low spread rate potential (fuel is predominantly sparse grass), so that portion has some of the lowest burn probabilities. The highest *BP* values occur in the moderate grass and grass-shrub fuelbeds (fuel models GR2, GR4 and GS2; Scott and Burgan 2005) because these fuel models exhibit relatively high spread rates.

The simulation of fire intensity in FSim inherently incorporates the effects of relative spread direction (heading, flanking, and backing) and variability in wind speed, wind direction, and fuel moisture. These factors, coupled with a heterogeneous mix of fuel and topography, result in a spatially variable distribution of burn probability both within and among FILs (figure 5). Conditional probabilities are generally lower for greater fire intensities, with very low probabilities for FIL 6 (flame length >12 feet). Some of the highest conditional burn probabilities are for FIL 2, which corresponds to 2- to 4-foot flame lengths.

Vegetation Condition Assessment

Each of the five BpSs assessed has one or more S-Classes in deficit or surplus status, suggesting varying but widespread departure of the current vegetation condition from the reference condition (table 4). A combination of BpS and S-Class showing more than one status indicates a variation in status among assessment units. Small amounts of S-Class U were found in several BpSs, primarily due to the mapping of riparian existing vegetation types (EVTs) to the non-riparian BpSs. This discrepancy results from differences in the LANDFIRE BpS and EVT mapping methodologies. BpS is "coarser" in concept than EVT because it is mapped using biophysical gradient modeling, without the integration of remotely sensed imagery that is used for mapping EVT (Rollins 2009). Therefore, EVT data may reflect subtleties gleaned from the remotely sensed vegetation that are missed by the BpS mapping process, possibly resulting in an invalid characterization of the UN S-Class where EVT and BpS seem to conflict. Because this potential problem does not cover a significant area, we have chosen to exclude results for S-Class U from the analysis.

In all four mountain range assessment units, the dry spruce-fir BpS (covering 37 percent of the BTNF) showed a deficit of the mid-development S-Class (B) and a surplus of early-development and spruce-fir dominated late-development S-Classes (A and D). The status of lodgepole-dominated late-development S-Class C was similar to the reference condition (table 4). For the subalpine woodland BpS (11 percent), there is a deficit of mid-development/closed-structure S-Class B and a surplus of late-development/open-structure S-Class D.

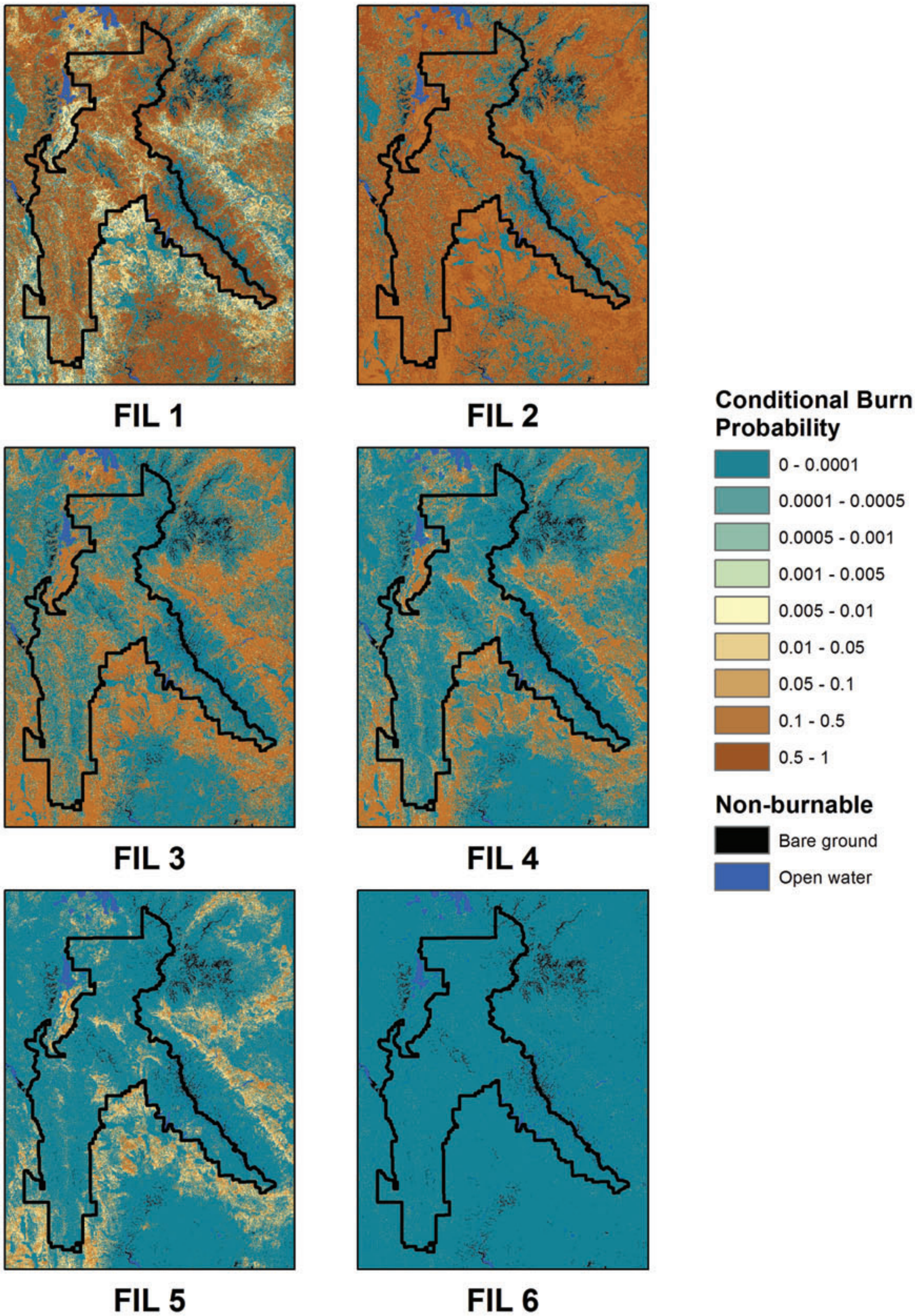

Figure 5. Conditional flame-length probability (FLP) by fire intensity level (FIL). These probability values are conditional on wildfire occurrence and are thus quantified on the scale of 0-1. For burnable pixels, the sum of FLP values across all six FILs is exactly 1. Fire intensity levels are classified by simulated flame length. FIL1 = 0-2 ft; FIL2 = 2-4 ft; FIL3 = 4-6 ft; FIL4 = 6-8 ft; FIL5 = 8-12 ft; FIL6 = 12+ ft.

Table 4. S-Class status results and reference proportion.

Biophysical setting	S-Class: Development stage/structure	Status			Reference proportion (%)
		Deficit	Similar	Surplus	
Dry spruce-fir	A: Early/All			X	5
	B: Mid/All	X			30
	C: Late/All[a]		X		50
	D: Late/All[b]			X	15
Subalpine woodland	A: Early/All		X	X	25
	B: Mid/Closed	X			35
	C: Mid/Open	X	X		10
	D: Late/Open			X	5
	E: Late/Closed	X	X		25
Wet spruce-fir	A: Early/All		X	X	10
	B: Mid/Closed[c]	X			20
	C: Mid/Open	X			10
	D: Late/Open			X	40
	E: Late/Closed	X			20
Aspen	A: Early/All	X	X		15
	B: Mid/All	X			20
	C: Late/Closed[d]	X	X		25
	D: Late/Open			X	25
	E: Late/Closed[e]	X	X		15
Douglas-fir	A: Early/All		X	X	10
	B: Mid/Closed	X			10
	C: Mid/Open	X	X		10
	D: Late/Open		X		50
	E: Late/Closed		X	X	20

[a] Lodgepole dominant.
[b] Spruce-fir dominant.
[c] S-Class B is in such a deficit that it does not exist on the current landscape.
[d] Aspen dominant.
[e] Conifers dominant or co-dominant.

The early-development, mid-development/open structure, and late-development/closed-structure S-Classes (A, C and E) each fall into two status classes due to variation across assessment units. In the wet spruce-fir BpS (9 percent), the status of the early-development S-Class (A) was split between similar and surplus; the remaining S-Classes were either in deficit or surplus status, but not similar. In the aspen BpS (9 percent), the status of each S-Class is deficit or surplus in at least one assessment unit, indicating widespread departure from the reference condition. However, the status was similar for at least some assessment units for the early development (A), aspen-dominated late-development/closed-structure (C), and conifer-dominated late-development/closed-structure (E) S-Classes. In the Douglas-fir BpS (5 percent), the mid-development/closed-structure S-Class (B) is in deficit in all assessment units, but the status of the other S-Classes was similar to the reference condition in at least one all assessment units.

Effects Analysis

The response functions produced by the workshop participants indicate a range of both positive and negative effects of fire (table 5). Many of the response functions have strong positive values, reaching as high as +100 percent where late-development/open-structure in the aspen BpS (S-Class D) is in surplus, indicating an expectation for substantial ecological benefits due to wildfire. Such benefits were largely assigned where a given S-Class is in surplus, in some cases even for very high fire intensities, especially if fire is expected to transition the surplus S-Class to an S-Class currently in deficit. Benefits are also associated with maintenance of an S-Class that is already in similar or deficit status, though these benefits were generally not as great. Lastly, the distribution of fire-related benefits and losses varies according to S-Class status and FIL, indicating the added value of assessing vegetation departure at the S-Class level, rather than merely indicating whether a given BpS is departed.

Differences in mean annual burn probability among BpSs are driven by ignition density and spread rate potential within and adjacent to the BpS. Wildfire simulation results show a wide range in BpS exposure to wildfire, with the aspen and Douglas-fir BpSs roughly three times as likely to experience wildfire as the subalpine woodland (figure 6). The mean conditional response for all BpS classes is positive, indicating that, on average, wildfire is expected to have a net beneficial effect on vegetation condition, moving the current distribution of successional stages towards the reference distribution in each of the BpSs (figure 6). Mean conditional response integrates information from tabular response functions and conditional flame-length probabilities across FILs, summarized across all combinations of BpS, S-Class, and status.

Table 5. Response functions for each combination of biophysical setting (BpS), S-Class and status present within the Bridger-Teton National Forest. The response function value indicates the relative percentage change in value after burning at the given fire intensity level (FIL) (measured in flame length classes). Highlighted cells indicate a non-negative response to wildfire. This table only presents combinations that actually exist on the landscape, and is not an exhaustive listing of all possible combinations of BpS, S-Class and status.

Biophysical setting	S-Class: Development stage/structure	Status	FIL1	FIL2	FIL3	FIL4	FIL5	FIL6
Dry spruce-fir	A: Early/All	Surplus	40	40	-20	-30	-30	-30
	B: Mid/All	Deficit	30	15	-10	-50	-70	-80
	C: Late/All	Similar	30	30	15	0	-60	-70
	D: Late/All	Surplus	10	20	40	40	20	10
Subalpine woodland	A: Early/All	surplus	30	30		-20	-20	-20
	A: Early/All	similar	30	30	-10	-20	-20	-20
	B: Mid/closed	Deficit	30	40	0	-70	-80	-80
	C: Mid/Open	Similar	20	30	0	-60	-70	-70
	C: Mid/Open	deficit	30	40	0	-70	-80	-80
	D: Late/Open	Surplus	10	20	40	60	20	0
	E: Late/Closed	similar	30	20	0	-60	-90	-90
	E: Late/Closed	deficit	40	30	-10	-70	-100	-100
Wet spruce-fir	A: Early/All	Surplus	30	30	-20	-30	-30	-30
	A: Early/All	similar	30	30	-20	-30	-30	-30
	C: Mid/Open	deficit	30	40	0	-70	-80	-80
	D: Late/Open	Surplus	10	20	40	60	20	0
	E: Late/Closed	deficit	40	30	-10	-70	-100	-100
Aspen	A: Early/All	similar	0	0	-10	-30	-50	-70
	A: Early/All	Deficit	0	0	-20	-40	-60	-80
	B: Mid/All	deficit	-10	-10	-20	-40	-60	-80
	C: Late/Closed	similar	20	20	0	-20	-40	-60
	C: Late/Closed	Deficit	10	10	-10	-30	-50	-70
	D: Late/Open	Surplus	10	20	40	100	100	100
	E: Late/Closed	similar	10	10	10	10	10	10
	E: Late/Closed	deficit	0	0	0	0	0	0
Douglas-fir	A: Early/All	Surplus	30	30	-20	-30	-30	-30
	A: Early/All	similar	30	30	-20	-30	-30	-30
	B: Mid/closed	Deficit	40	40	20	-50	-50	-50
	C: Mid/Open	Similar	50	60	60	0	-50	-50
	C: Mid/Open	Deficit	60	70	70	0	-60	-60
	D: Late/Open	similar	50	60	60	20	-40	-50
	E: Late/Closed	surplus	0	20	70	70	-40	-50
	E: Late/Closed	similar	70	70	70	70	-40	-50

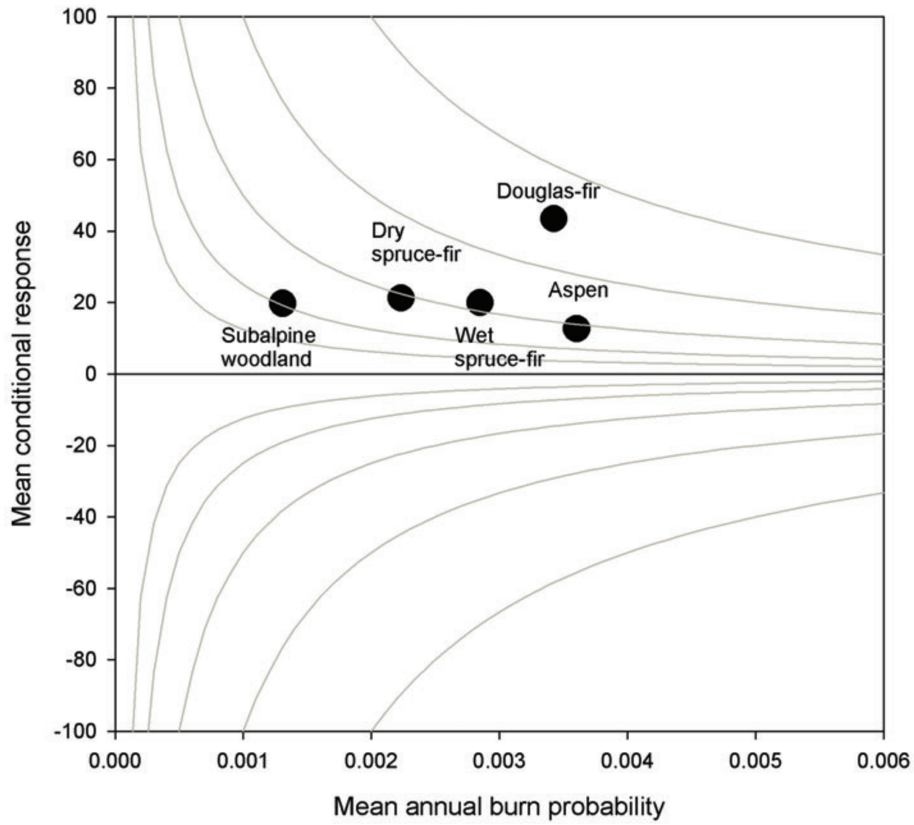

Figure 6. Mean annual burn probability and mean conditional response to wildfire for each of five biophysical settings assessed on the Bridger-Teton National Forest. Light gray reference lines indicate equal expected response.

The strongest positive response is in the Douglas-fir BpS. The product of annual burn probability and conditional response yields expected response. Thus, although they vary in both burn probability and conditional response, the overall expected responses for the dry spruce-fir, wet spruce fir, and aspen BpSs are roughly equal (figure 6).

Variation in *BP* and *CR* exists among S-Classes of a BpS (figure 7). Particularly noteworthy is the range of conditional responses to wildfire, especially for the aspen BpS, which shows a slightly negative response to wildfire where the early-development S-Class is similar or in deficit to the reference proportion and where the mid-development S-Class (B) is in deficit. By cross-referencing these results with the response functions, the causes of the negative response become apparent—the response function indicates strong adverse effects of fire in the middle and higher FILs for all three of those combinations of S-Class and status.

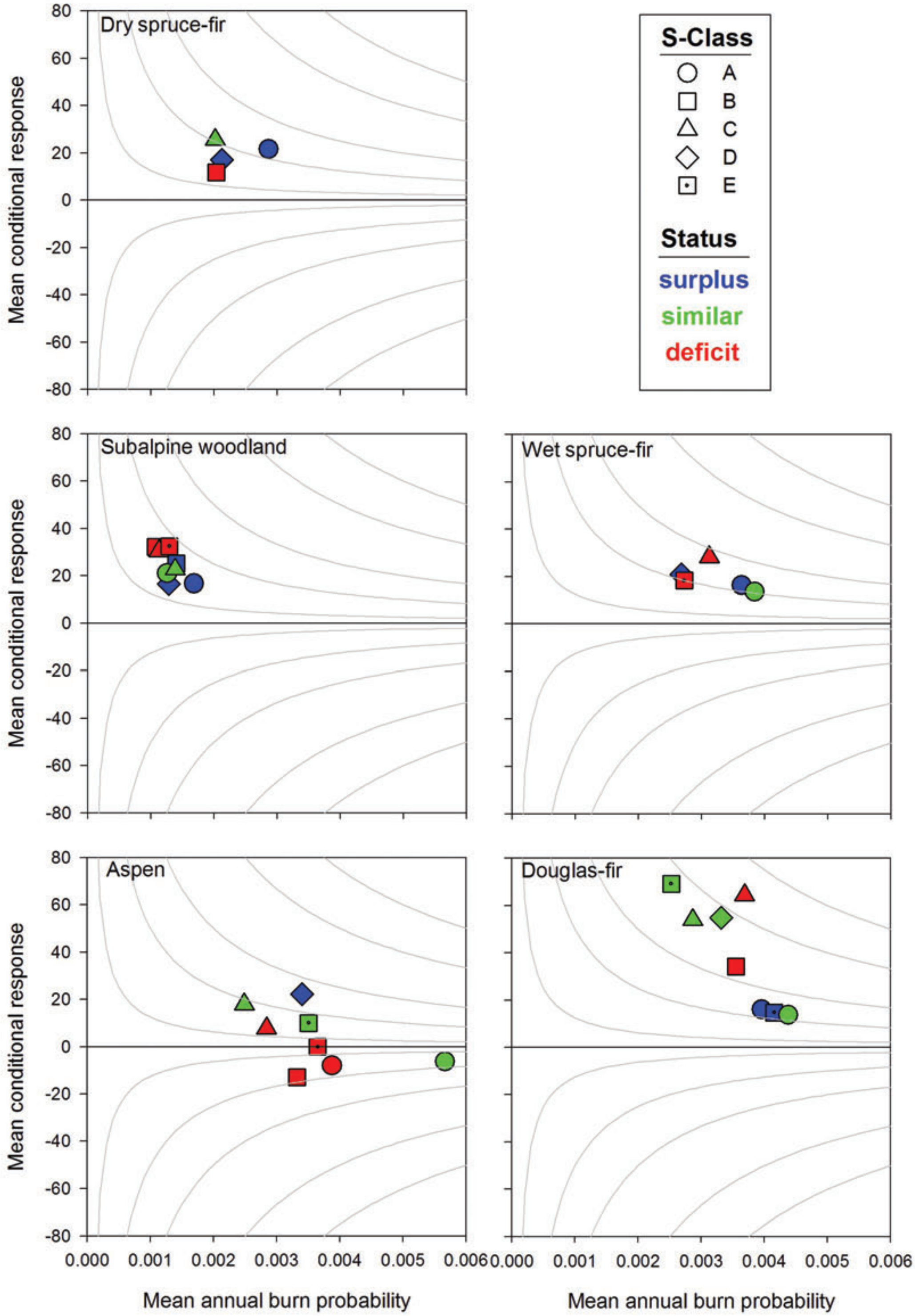

Figure 7. Mean annual burn probability and mean conditional response to wildfire of succession class (S-Class) and status combinations for each of five biophysical settings on the Bridger-Teton National Forest. Light gray reference lines indicate equal expected response (see table 6 for details).

The land area of each BpS and S-Class status combination multiplied by the mean annual burn probability yields an expectation for annual area burned (table 6). The dry spruce-fir BpS has the highest expected annual area burned, due in part to its large land area. Expected response is presented as a percentage of the maximum expected response occurring in any combination of BpS, S-Class and status. In this analysis, the maximum expected response occurs where the mid-development/open-structure S-Class of the Douglas-fir BpS (C) is in deficit. This S-Class also has the second-highest conditional response (behind where the late-development/closed-structure S-Class (E) is similar to the reference proportion, which exhibits the third-highest expected response. In other words, taken as a whole, the Douglas-fir BpS exhibits the most beneficial effects of wildfire, both conditional and expected. Within the Douglas-fir BpS, all combinations of S-Class and status show a positive mean response to wildfire. The greatest conditional benefits occur where the late-development/closed-structure S-Class (E) is similar to the reference proportion. Interestingly, in assessment units where that S-Class is in surplus is among the three S-Classes with the least wildfire benefit. The reason for this divergence of conditional response within a single S-Class can be seen in the response functions. Where this S-Class is similar to the reference condition, the response function values are strongly positive for low-intensity fire, indicating the benefit of low-intensity fire in maintaining the S-Class through under-burning. The response functions reflect that low-intensity fire is less beneficial where late-development/closed-structure is in surplus. The aspen BpS is the only BpS where an S-Class exhibits a negative mean conditional response. The mean conditional response of the early and mid-development aspen S-Classes are all slightly negative, regardless of status.

Even though most S-Classes exhibit a positive mean condition response, individual grid cells within an S-Class can still have a negative conditional response (figure 8) if response functions include negative values. In the Aspen BpS, for which some S-Classes had a negative mean conditional response, 14 percent of land area exhibits a negative response. In the Douglas-fir BpS, which had the most positive conditional response, only 2 percent of the BpS had a negative net response, owing to negative response function values at higher FILs.

Table 6. Summary of land area, mean burn probability, expected area burned and mean expected and conditional response to wildfire of five BpSs on the Bridger-Teton National Forest. Mean expected response (per pixel) is expressed as a percentage of the maximum response. Mean conditional response is expressed on the response-function scale (-100 to +100). A BpS and S-Class combination can have more than one status if vegetation condition varies among assessment landscapes.

						Mean response per pixel	
Bio-physical setting	S-Class: Development stage/status	Status	Land area (ac)	Mean annual burn probability (fraction)	Expected annual area burned (ac)	Expected response (percent of max)	Conditional response
Dry spruce-fir	A: Early/All	Surplus	253,779	0.002864	726	26	21.6
	B: Mid/All	Deficit	18,973	0.002042	40	10	11.8
	C: Late/All	Similar	497,850	0.002023	1,006	22	23.6
	D: Late/All	Surplus	492,179	0.002127	1,048	15	17.1
Subalpine woodland	A: Early/All	Surplus	30,839	0.001684	52	12	16.7
	A: Early/All	Similar	94,873	0.001259	119	11	21.0
	B: Mid/closed	Deficit	381	0.001074	0	15	32.2
	C: Mid/Open	Similar	1,712	0.001384	2	13	22.8
	C: Mid/Open	Deficit	14,802	0.001124	17	14	30.4
	D: Late/Open	Surplus	204,215	0.001287	262	9	16.6
	E: Late/Closed	Similar	3,773	0.001406	5	15	25.3
	E: Late/Closed	Deficit	35,240	0.001293	44	18	32.5
Wet spruce-fir	A: Early/All	Surplus	34,096	0.003630	124	25	16.4
	A: Early/All	Similar	12,916	0.003837	49	22	13.5
	C: Mid/Open	Deficit	12,276	0.003121	40	37	28.3
	D: Late/Open	Surplus	229,435	0.002678	615	24	20.9
	E: Late/Closed	Deficit	27,636	0.002722	74	21	18.3
Aspen	A: Early/All	Similar	37,355	0.005669	213	-15	-6.3
	A: Early/All	Deficit	2,459	0.003877	10	-13	-8.0
	B: Mid/All	Deficit	16,109	0.003323	54	-18	-12.8
	C: Late/Closed	Similar	4,460	0.002487	10	19	18.0
	C: Late/Closed	Deficit	33,325	0.002838	94	9	7.8
	D: Late/Open	Surplus	204,922	0.003402	697	32	22.2
	E: Late/Closed	Similar	20,917	0.003505	74	15	10.0
	E: Late/Closed	Deficit	5,733	0.003648	20	0	0.0
Douglas-fir	A: Early/All	Surplus	11,649	0.003960	47	27	16.1
	A: Early/All	Similar	11,673	0.004379	52	25	13.7
	B: Mid/closed	Deficit	15	0.003550	0	51	34.2
	C: Mid/Open	Similar	2,773	0.002865	7	65	53.9
	C: Mid/Open	Deficit	6,133	0.003684	22	100	64.4
	D: Late/Open	Similar	87,663	0.003318	292	77	54.7
	E: Late/Closed	Surplus	24,777	0.004155	104	26	14.8
	E: Late/Closed	Similar	28,652	0.002521	72	73	69.2

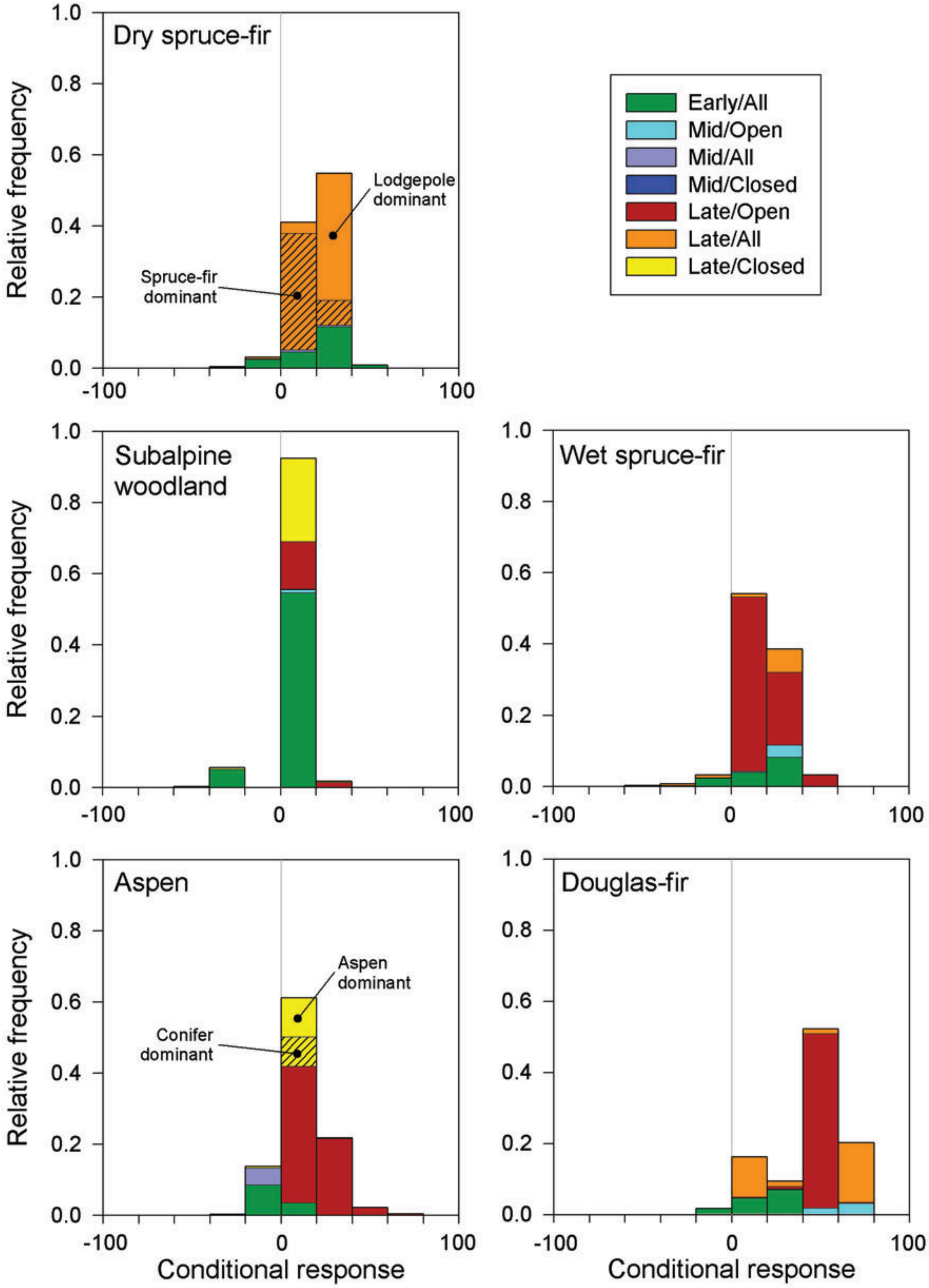

Figure 8. Histograms of the conditional response to wildfire of individual succession classes (S-Classes) within five biophysical settings (BpSs) on the Bridger-Teton National Forest. Stacked bars reflect that different S-Classes can produce the same effect, depending on their response functions and exposure to fire intensity. Likewise, a particular combination of BpS and S-Class can be found in multiple conditional response bars, indicating variability in fire intensity or S-Class status across the landscape (see table 6 for S-Class descriptions within each BpS).

In addition to the tabular and graphical summaries reported above, the effects analysis produces a map of conditional and expected response of vegetation condition to wildfire (figure 9). As also seen in figure 8, very little land area resulted in negative conditional or expected response. A small amount of the landscape exhibited a neutral response, bracketing zero. The majority of the landscape exhibits varying degrees of net benefit. Expected response is the product of condition response and *BP*, so the small differences in the two maps are due to variation in *BP* across the landscape.

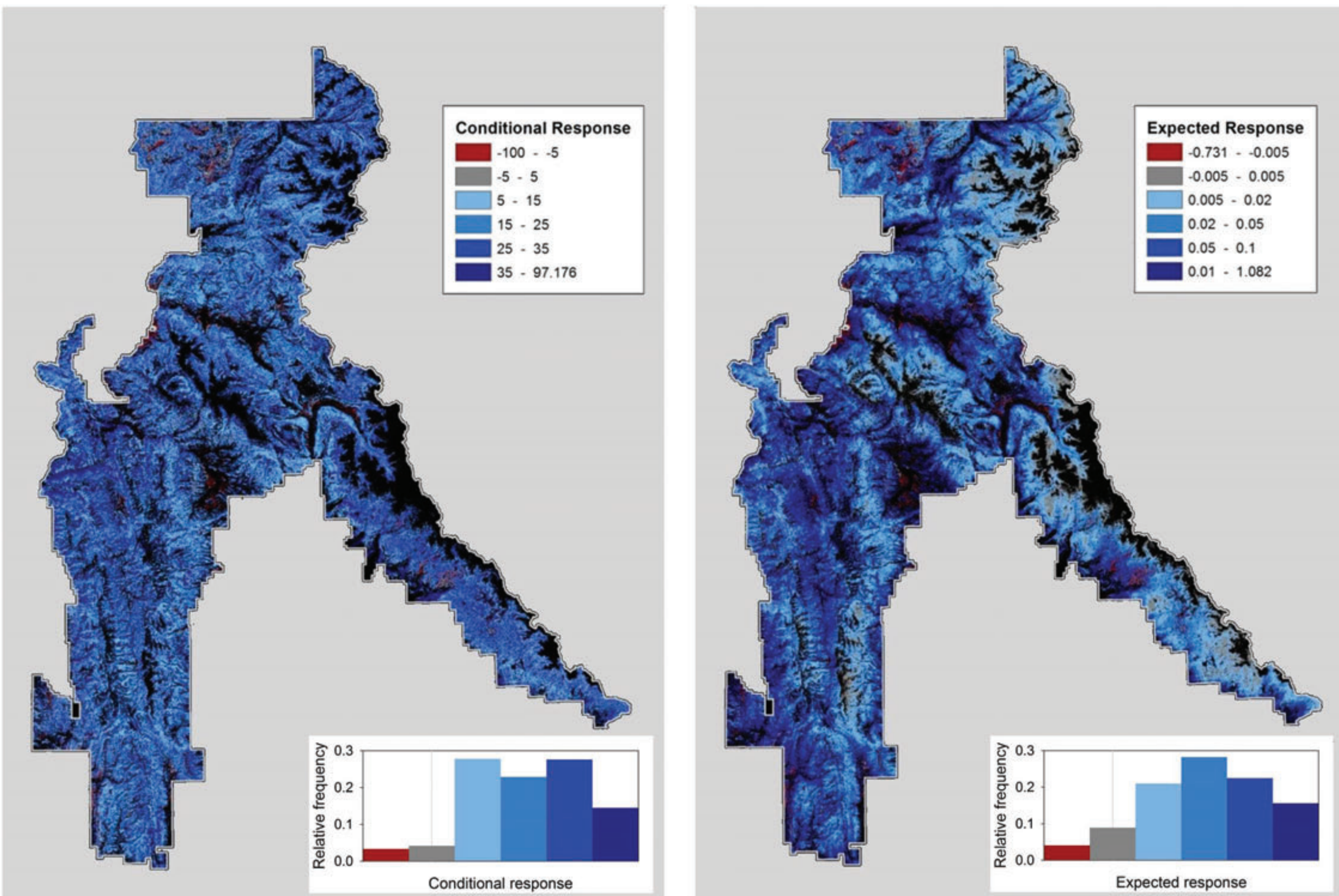

Figure 9. Conditional response (left) and expected response (right) of vegetation condition to wildfire. Expected response is the product of conditional response and annual burn probability (figure 4). The X-axes of the histograms correspond to the classes indicated in the legends. Neutral response is depicted in gray.

Discussion

Our results illustrate generally positive net effects of wildfire on vegetation condition across the major forested BpSs on the BTNF, supporting the notion that wildfire can play a role in restoring or enhancing the ecological integrity of landscapes affected by fire exclusion. Our results further support the assertions that incorporating information regarding expected response to wildfire can be much more informative than analysis of wildfire characteristics in and of themselves. Partitioning response functions according to indicators of vegetation condition, or ecological integrity, such as S-Class status, can lead to risk-informed restoration decision processes. These results carry significant implications for future management of wildfire on the Forest, and highlight temporal relationships between short-term incident response and long-term ecological integrity. Granted, our results provide but a snapshot of a dynamic system, but the analyses demonstrated here can be periodically performed over time to monitor trends in ecological integrity and associated wildfire risks.

At least three opportunities stem directly from this integrated assessment of vegetation condition and wildfire effects. First, restoration needs could be prioritized on the basis of S-Class status. That is, areas of high vegetation condition departure could be targeted for intentional vegetation manipulation to move towards desired conditions. Second, prescribed fire planning could build off analysis of restoration needs, targeting specific fire intensities in specific locations to achieve restoration objectives. These planning efforts could tie directly to expert-defined response functions, which neatly encapsulate information required regarding desired intensities. Third, land management units could seek to refine their land and fire management plans to account for the spatial distribution of wildfire effects on vegetation condition across the landscape. For instance, in areas of expected net benefit, wildfire response objectives could be spatially delineated to promote the management of fire for resource benefits (Thompson and others 2013c). This type of analysis would dovetail nicely with a trend of increased use of geospatial information and risk assessment results to support wildfire incident response planning.

Any comprehensive analysis of wildfire risk will need to consider the full suite of HVRAs, including socioeconomic HVRAs. Whereas our use of the VCA approach and focus on an ecological HVRA allowed beneficial effects of wildfire to be shown, in many contexts and locations it will be difficult to promote wildland fire (both planned and unplanned ignitions) as a management or restoration tool due to high potential for loss. In the broader Teton Interagency Risk Assessment (Scott and others 2013a) we found wildfire threats were highest primarily in locations near highly important and highly susceptible HVRAs, including the wildland urban interface, high-value BTNF investments, and critical wildlife habitat. These threats tended to be spatially concentrated. That is, the majority of the risk on a landscape may be housed in a relatively small spatial extent. Explicit evaluation of potential fire-related benefits may engender support for additional use of wildland fire as a management tool, or enable less aggressive suppression where it does not directly threaten resources and assets more susceptible to loss.

Another caveat relates to our use of multiple models to analyze vegetation departure (VCA), to simulate wildfire (FSim), and to characterize fire effects (response functions), and the associated potential for errors and uncertainties. A particular concern relates to the potential for under-prediction of crown fire behavior, which could affect estimates of flame lengths and patterns of burn probability in forested areas. However, the 20-year historical mean annual area burned corresponded well with the simulated mean annual area burned, suggesting reasonable validity of the burn probability results. We'd further note that we undertook great effort to work with local experts to calibrate vegetation and fuel input layers and to examine simulation assumptions and results. Reliance on local practitioner and resource specialist judgment was a common thread throughout our entire analytical process.

In terms of recommendations for future analyses, a critical component is up-front investment to set the stage for success. Both the vegetation condition and wildfire effects assessments require intensive geospatial data management and expertise in natural resources management and modeling. Appropriate resources and expertise should be identified early in the process. Following the principles of expert judgment elicitation, it is recommended to distribute information to resource specialists prior to holding the response function workshops, and to invest time in clearly articulating assessment objectives. This early engagement is important not only to familiarize experts with the process and to start thinking though potential fire effects, but also to help identify additional geospatial information to incorporate into response functions for characterizing fire effects. Time is always a constraint in such efforts, but where possible, scheduling a pre-workshop to discuss and critique conceptual models of post-fire S-Class transitions could be helpful for defining response functions.

FSim was designed to be used by specialized analysts to assess national fire program management alternatives (Finney and others 2011). Although it has subsequently been used a number of times at finer scales, FSim remains a system in continued development and is available to a relatively small set of users. Fortunately, alternatives exist. FlamMap5—the most-recent version of the FlamMap software (Finney 2006)—has the ability to generate the gridded burn probability and flame-length probability information needed for this assessment method. Unlike FSim, the results from FlamMap5 do not correspond to a year or fire season. Instead, FlamMap5 results relate to a relatively short duration "problem-fire" scenario—a specified wind speed, wind direction, fire duration, and set of fuel moisture contents. The primary stochastic element of FlamMap5 is ignition location. Depending on how the user defines the problem-fire scenario, the relative frequency of different flame-length classes could be quite different from FSim. FSim simulates fire intensity in all weather scenarios, whereas FlamMap5 is used to simulate problematic scenarios. Because of this difference, FlamMap5 is likely to generate higher conditional flame lengths than FSim; that, in turn, affects conditional wildfire response. Nonetheless, the use of FlamMap5 could be a useful first step in the assessment of the expected effects of wildfire on vegetation condition.

Graphically depicting the results as the combination of *BP* and conditional net response enables exploration of implications for fire management (figure 10). While stylized, this framework provides a useful model for thinking through the implications of HVRA exposure and effects and how various management strategies may target different risk factors. Wildfire risk mitigation activities (fire prevention, preparedness, suppression, hazard reduction and susceptibility reduction) are indicated anywhere conditional wildfire response is negative. Areas of the landscape where expected response is most negative (high *BP* and strongly negative conditional response) may be explored as higher priority treatment areas relative to areas where conditional response is less negative and *BP* is low. Treatments in such areas could be strategically placed to lower *BP* values across the landscape and/or to reduce localized fire intensities to reduce *CR*. Where conditional response is positive, a variety of wildland fire management practices are available. Where both *CR* and *BP* are high, managing wildfires (unplanned ignitions) may provide the greatest chance of success. Prescribed fire may be considered where the conditional effects of wildfire are positive, but not likely to occur without management intervention. Prescribed fire may also be effective even where *CR* is negative if there is some intensity level that is achievable with prescribed fire for which the response function value is positive.

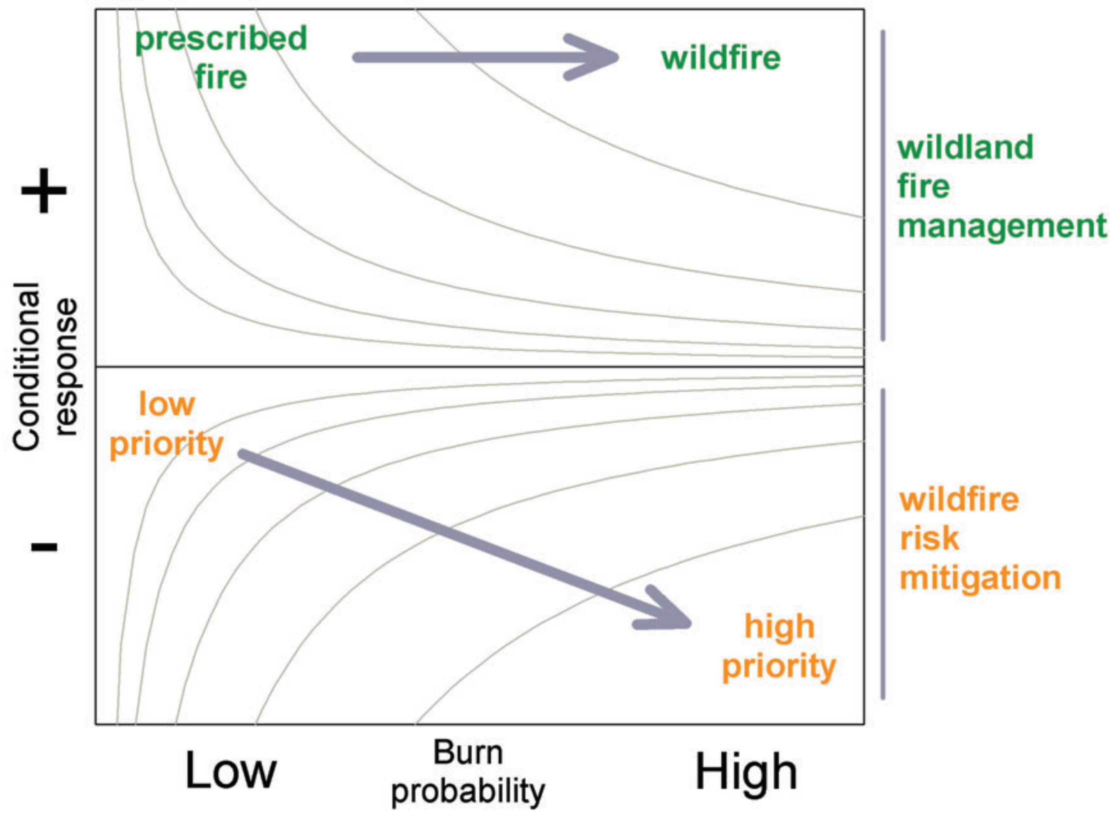

Figure 10. Implications of conditional response and burn probability on wildfire risk mitigation priorities and wildland fire management. Where conditional response is positive and burn probability (BP) is high, management of wildfire for these benefits is a good strategy. Where conditional response is high but BP is low, prescribed fire can be used to capture the benefits of wildland fire.

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