

Integrating Pixel- and Polygon-Based Approaches to Wildfire Risk Assessment: Application to a High-Value Watershed on the Pike and San Isabel National Forests, Colorado, USA

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Abstract We develop a novel risk assessment approach that integrates complementary, yet distinct, spatial modeling approaches currently used in wildfire risk assessment. Motivation for this work stems largely from limitations of existing stochastic wildfire simulation systems, which can generate pixel-based outputs of fire behavior as well as polygon-based outputs of simulated final fire perimeters, but due to storage and processing limitations do not retain spatially resolved information on intensity within a given fire perimeter. Our approach surmounts this limitation by merging pixel- and polygon-based modeling results to portray a fuller picture of potential wildfire impacts to highly valued resources and assets (HVRAs). The approach is premised on using fire perimeters to calculate fire-level impacts while explicitly capturing spatial variation of wildfire intensity and HVRA susceptibility within the perimeter. Relative to earlier work that generated statistical expectations of risk, this new approach can better account for the range of possible fire-level or season-level outcomes, providing far more comprehensive information on wildfire risk. To illustrate the utility of this new approach, we focus on a municipal watershed on the Pike and San Isabel National Forests in Colorado, USA. We demonstrate a variety of useful modeling outputs, including exceedance probability charts, conditional distributions of watershed area burned and watershed impacts, and transmission of risk to the watershed based on ignition location. These types of results can provide more information than is otherwise available using existing

assessment frameworks, with significant implications for decision support in pre-fire planning, fuel treatment design, and wildfire incident response.

Keywords Burn probability · Water quality · Exceedance probability · Expected net value change · Wildfire hazard

1 Introduction

Spatial, risk-based information is increasingly being generated to inform wildfire planning and risk mitigation efforts around the globe [1–5]. Analyses vary in terms of the types of information generated and types of modeling approaches used. Probabilistic hazard analysis is perhaps the most fundamental step, intended to characterize the probability of wildfire occurrence as well as the potential fire behavior given fire occurs [6–8]. Information on possible wildfire activity alone, however, is insufficient to describe the possible consequences of wildfire [9]. A critical second step is therefore exposure analysis, which intersects fire likelihood and intensity metrics with locations of highly valued resources and assets (HVRAs) in order to characterize variation in HVRA exposure to wildfire [10, 11]. Going one step further, effects analysis characterizes the levels of HVRA loss or benefit that may result from varying levels of exposure [12].

Comprehensive wildfire risk assessment integrates these analyses, using the building blocks of wildfire likelihood, wildfire intensity, and HVRA susceptibility to wildfire [13]. In this framework, the susceptibility of an HVRA to wildfire is the relationship between fire intensity and fire effects (and possibly other environmental variables) and is quantified in terms of net value change (*NVC*). After incorporating probabilistic information on wildfire likelihood and intensity, risk

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can be quantified in terms of expected net value change (*eNVC*) [14].

There are two primary spatial methods of analysis for wildfire risk assessment—pixel-based and polygon-based—which stem from the format of stochastic wildfire simulation outputs [15]. Pixel-based outputs (also called gridded or raster outputs) aggregate results from thousands of simulated fires to quantify spatially resolved estimates of wildfire likelihood and intensity. To date, the use of pixel-based results has been more common, with myriad applications on federal land throughout the western USA at local, landscape, regional, and national scales [5, 10–14]. This approach is consistent with the format for many spatial fire modeling inputs and is appealing for its ability to capture spatial variation in factors influencing fire behavior as well as factors influencing fire effects. Pixel-based results can characterize the mean annual exposure of an HVRA to wildfire or mean annual wildfire effect on an HVRA but fail to provide information on variability about the mean. For example, a pixel-based exposure analysis can determine the mean annual area burned, but it provides no information on the likelihood that a large area will burn in a single, potentially catastrophic event.

With polygon-based analyses, by contrast, the fundamental unit of analysis is the individual fire perimeter itself (or the cumulative footprint of perimeters simulated in a given fire season). Principally, polygon-based approaches involve overlaying fire perimeter footprints with spatial HVRA data or other polygons of interest. The results of that overlay can be used to summarize information about potential fire impacts in a variety of ways. Using fire perimeters can provide useful information on the conditional distribution of HVRA area burned, as illustrated in an analysis looking at municipal watershed area burned [16]. Perimeter-based analyses can also tie back to ignition locations to explore spatial patterns in the transmission of wildfire risk across landscapes. For instance, by identifying the locations of all ignitions associated with fire perimeters ultimately reaching an identified critical wildlife habitat polygon, it is possible to delineate a “firedshed” as the area within which a wildfire could ignite and impact the habitat [16]. Related applications have examined the potential for ignitions to reach the wildland-urban interface and to impact human populations and to tie these potential impacts back to ignition location to differentiate areas of high potential for risk transmission [10, 17, 18].

A notable limitation of the polygon-based approach is that measures of fire intensity are not retained for each simulated fire, due to current storage and processing limitations. Thus, there are clear tradeoffs associated with both the pixel- and polygon-based modeling approaches. While the pixel-based approach provides critical information on fire likelihood and intensity and HVRA susceptibility at any given location, results can only be summarized in terms of statistical expectations; they do not provide information about the range of

impacts associated with individual fires and their intersection with HVRAs. Conversely, the polygon-based approach can better generate distributions of potential fire-HVRA interactions, but with only a limited ability to characterize potential fire effects.

In this paper, we develop a technique for integrating these complementary approaches to spatial wildfire risk assessment. This work leverages both pixel-based modeling outputs, which capture local variation in fire intensity and HVRA susceptibility, with polygon-based modeling outputs, that capture landscape potential to support large fire spread, distributions of HVRA area burned, and transmission of risk based on ignition location. Relative to earlier pixel-only work, this new approach better accounts for the range of possible fire-level or season-level outcomes. Relative to earlier polygon-only work, this new approach allows for estimation of the spatial extent to which fire-HVRA interactions occur in areas of high hazard and/or HVRA susceptibility, and thus allows for an improved ability to estimate fire-level or season-level fire effects.

To demonstrate this concept, we assessed wildfire risk to a high-value watershed located in the Pike and San Isabel National Forests in Colorado, USA. Large wildfires have resulted in significant concerns over post-fire sedimentation and resultant rehabilitation and water treatment costs, and protection of municipal watersheds from wildfire remains a highly salient issue in Colorado and elsewhere [19, 20]. Watersheds are a particularly relevant HVRA for demonstration of the new risk modeling technique, since capturing watershed area burned is a critical variable for predicting fire effects [21].

Our objectives for this work are to

1. Demonstrate the utility of merging pixel-based and polygon-based approaches for spatial wildfire risk assessment
2. Examine various approaches to integrating fire intensity metrics and characterizing conditional net value change (*eNVC*) within this framework
3. Illustrate application of the new risk modeling technique on National Forest System lands in the US Forest Service’s Rocky Mountain Region
4. Identify a range of potential applications for this new risk modeling technique to support and inform risk-based wildfire management

2 Risk Assessment Framework

In the following subsections, we describe the types of wildfire simulations available to support a landscape-scale wildfire risk assessment, review calculations of wildfire risk, and introduce our approach to integrate current pixel- and polygon-based methods for conducting exposure and effects analyses.

2.1 Wildfire Simulation

A fundamental component of this wildfire risk assessment framework is the use of wildfire simulation to estimate wildfire likelihood and intensity as it varies across a landscape. Two types of wildfire simulation can be used in hazard and risk assessments: (1) deterministic simulations of potential wildfire behavior and (2) stochastic simulations of wildfire occurrence, growth, and behavior. In the USA, the FlamMap5 software [22] is often used for estimating potential wildfire behavior characteristics for a given weather condition, with calculations made independently for each pixel across the landscape. A lesser-used feature of FlamMap5 can also be used to model fire spread in order to estimate spatial variability in wildfire likelihood, but results are conditional on a fire ignition and do not capture the underlying likelihood of fire occurrence in a given fire season. For this reason, the FSim large fire simulation system [15], which additionally captures the probability of a large fire occurrence using logistic regression coefficients derived from fire history records, is used to generate unconditional, annualized estimates of wildfire likelihood.

There are two critical differences between the deterministic potential fire behavior simulations of FlamMap5 and the stochastic simulations with FSim. First, the potential fire behavior simulations with FlamMap5 are for a single weather scenario that is typically defined to be on the more severe end of the weather spectrum (for example, the 97th percentile condition). In contrast, FSim simulations of fire intensity incorporate the whole range of possible weather scenarios, including scenarios that result in relatively benign behavior. Second, FSim inherently incorporates the effects of nonheading spread into its simulation of fire intensity, whereas FlamMap5, even though it can be used to make calculations in a nonheading direction, is typically used to simulate behavior at the head of a fire. That is, with FSim, the fire may have backed or flanked through the pixel during many of the iterations in which it burned, with greatly reduced fire intensity levels. Because measures of HVRA susceptibility are linked to fire intensity, the choice of fire behavior model can have potentially significant implications for estimates of fire effects.

For our purposes, our primary focus is FSim [15], a Monte Carlo style wildfire simulation system that simulates stochastic fire occurrence, growth, and suppression processes over many thousands of iterations (fire seasons). Each simulated fire season captures variability surrounding fire weather inputs and provides probabilistic information on the range of potential realizations of a fire season. FSim consists of three fire simulation modules: fire occurrence, fire growth, and fire containment. These modules are built on the foundation of a fourth module of weather generation. The weather generation module simulates daily values of the Energy Release Component (ERC) of the National Fire Danger Rating System using

time series analysis. The occurrence module simulates the daily likelihood that a fire will escape initial attack and become a large fire. This likelihood is calculated as a function of ERC-G for each day of a simulation. The fire growth module [23] simulates the daily growth of a newly ignited or ongoing fire, through both spotting and flame front spread, as a function of fuel, weather, and topography. The required inputs to simulate potential fire behavior include fuel characteristics (fuel model, canopy base height, and canopy bulk density), vegetation characteristics (forest canopy cover and height), and topography (slope, aspect and elevation), as described in a fire modeling landscape file (LCP). Flame front spread is simulated for surface fires using the Rothermel model [24] and for passive and active crown fires using a combination of surface and crown fire spread and transition models [24–27] as described in Finney [28]. The containment module simulates the daily likelihood that a simulated fire will be contained, and therefore no longer grow on subsequent days [29].

FSim produces spatial results in two formats: (1) gridded outputs representing measures of wildfire likelihood and intensity and (2) polygons representing the final fire perimeter of each simulated wildfire. A grid is a raster data layer consisting of an array of regularly spaced cells, or pixels. Gridded outputs include annual burn probability (*BP*) and conditional flame length probability (*FLP*). *BP* is calculated as the fraction of simulation iterations that resulted in each pixel burning. Conditional *FLP* is calculated at each pixel as the relative frequency of different flame length classes (Table 1), considering only the iterations in which the pixel burned. The flame length that occurs each time a pixel burns is influenced by the fuel, weather, and topographic conditions at the time of burning, as well as the relative spread direction as the fire passed the pixel. To generate the unconditional BP_i values required for Eq. 1, the conditional *FLP* values are multiplied by *BP*, across all six flame length classes. The *FLPs* at a pixel can also be used to estimate the conditional flame length (*CFL*), a probability-weighted average flame length value.

The polygon-format output of FSim is an ESRI shapefile containing the final perimeter of every simulated wildfire. An

Table 1 Flame length classification used in FSim based on fire intensity level (FIL) definitions

Flame length class (<i>i</i>)	Flame length range
Fire intensity level	Feet
FIL1	0–2
FIL2	2–4
FIL3	4–6
FIL4	6–8
FIL5	8–12
FIL6	12+

attribute table specifying certain characteristics of each simulated wildfire—the iteration during which it occurred, and its start location and date, duration, final size, and other characteristics—is included with the shapefile. However, the fire intensity (flame length class) that occurred at each pixel during each individual wildfire is not recorded; the only fire intensity information available from FSim is the *FLP* grids and the resulting *CFL* grid produced from them; *CFL* does not represent an individual fire, but instead integrates the results of all fires that burned a pixel. Fires occurring during the same fire season can be identified through attributes assigned to each fire, so that the cumulative area burned during an entire fire season can be output as well.

2.2 Quantifying Risk

Our approach to quantifying risk is consistent with long-standing frameworks for ecological risk assessment [30], as well as with emerging applications of wildfire risk assessment across planning scales and across geographic areas [13, 14]. It is important to note that the assessment framework explicitly adopts a resource- and asset-focused perspective [31, 32], contemplating not only wildfire occurrence and behavior but also the potential consequences of wildfire in terms of impacts to HVRAs. Finney [33] formalized the main framework for a pixel-based assessment of wildfire risk across a landscape, defining risk as expected net value change (*eNVC*)

$$eNVC = \sum_i^6 BP_i * RF_i \quad (1)$$

where BP_i is the annual probability of flame length class i occurring, and RF_i is a response function value representing the balance of benefits and losses to an HVRa when burned at flame length class i (using the flame length classes/fire intensity levels from Table 1). The use of response functions provides a flexible yet consistent platform for evaluating potential fire effects, and readily allows for the integration of other environmental variables (e.g., erosion potential) influencing fire effects.

An alternative but mathematically equivalent calculation of *eNVC* at a pixel is

$$eNVC = BP * cNVC \quad (2)$$

where *cNVC* is the conditional *NVC* given that the pixel burns

$$cNVC = \sum_i^6 FLP_i * RF_i \quad (3)$$

This alternative formulation that first calculates *cNVC* is necessary for the integration of pixel- and polygon-based approaches, as will be shown in the following section.

2.3 Integrating Pixel- and Polygon-Based Risk Results

Our approach for integrating pixel- and polygon-based results calculates the whole-fire *NVC* (NVC_{fire}) as the sum of pixel-based *cNVC* results for each pixel (k) that fell within each simulated fire perimeter (polygon), as shown in Eq. 4.

$$NVC_{fire} = \sum_k cNVC_k \quad (4)$$

where $cNVC_k$ is the conditional *NVC* at pixel k (the fire-caused *NVC* given that pixel k burns). *cNVC* is typically estimated as a function of fire intensity (and other variables), but as described, earlier information about fire intensity is not available for each simulated fire perimeter from FSim or any currently available stochastic wildfire simulation system. We therefore implemented three options (response scenarios) for producing a *cNVC* grid for use in Eq. 4. The options differ in how fire intensity is estimated for use in the response functions defining HVRA susceptibility.

1. Use the FSim-generated *FLPs* to calculate a weighted mean *cNVC*

$$cNVC_{FSim} = \sum_i^6 FLP_i * RF_i \quad (5)$$

where i represents the same six standard fire intensity levels (FILs) in Table 1. This FSim-based approach is functionally equivalent to the more common pixel-based risk calculations described earlier.

2. Use the potential heading fire flame length for the 97th percentile fuel moisture and wind speed condition with the response functions. This approach is based on FlamMap5 fire modeling outputs. At each pixel, *cNVC* is the response function value corresponding to the estimated 97th percentile flame length as classified into FILs.

$$cNVC_{FM97} = RF_i \quad (6)$$

3. For comparison, we calculate a third option where fire intensity is assumed to be the worst case any time a wildfire occurs— $cNVC_{worst}$. Though not universally true, the worst case (greatest loss) is often associated with the highest flame lengths (FIL6). This worst case scenario is applied to all burnable pixels, even where fuel, weather, and topographic conditions are not expected to produce intensities as high as FIL6.

$$cNVC_{worst} = RF_{FIL6} \quad (7)$$

In addition to the fire-level results calculated with Eq. 4, we also generated season-level results ($cNVC_{season}$) by summing

$cNVC_{fire}$ across all fires occurring in each simulated fire season. Further, by linking fire-level results back to ignition locations, we are able to more richly quantify potential for risk transmission, identify areas where ignitions could lead to unacceptable HVRA loss, and inform mitigation planning. To do so, we used a 3-km grid to smooth ignition points; selection of the window size is a balance between avoiding “holes” left by too fine a grid size and obscuring important spatial variability in landscape patterns from too large a grid size. Results could alternatively be summarized by watershed unit boundaries to examine patterns across very large landscapes, although that approach is not appropriate for a small landscape like our study area.

Figure 1 illustrates the main steps in the workflow of the integrated pixel-polygon risk calculation process. Pixel-based information stems from HVRA characterization, which provides location and response functions (the arrow indicates that the HVRA location can influence HVRA susceptibility), and from wildfire simulation, which provides FLPs. The integration of this information yields a grid or raster of $cNVC$ at each pixel. Simulated fire polygons are then overlaid onto the $cNVC$ raster to generate fire-level $cNVC$ (Eq. 4). To summarize, our new methods allow for the calculation of NVC_{fire} that incorporates spatial variation in localized fire intensity and HVRA susceptibility, while also accounting for the size, shape, and location of simulated fires.

3 Case Study

To demonstrate the integration of pixel- and polygon-based wildfire risk assessment results, we assessed wildfire risk to

the Cheesman Reservoir watershed on the Pike and San Isabel National Forests in Colorado, USA (Fig. 2). We defined the watershed area as the sub-basin portion of the 5th level hydrologic unit that drains to the Cheesman Reservoir, confirmed by the 1:100,000 National Hydrography Dataset Flowline Medium Resolution data layer. This current study was an offshoot of a broader multiyear science-management partnership between the Rocky Mountain Research Station and the Rocky Mountain Region to assess wildfire risks to multiple HVRAs. As part of that effort, the Rocky Mountain Region identified municipal watersheds as a high-priority HVRA, leading to related assessment efforts focused on wildfire risks to watersheds throughout the Region [34]. Here, we narrow our focus to the Cheesman Reservoir in part to highlight the methodological advances, but also because the watershed makes for an interesting case study location—it is impounded by a dam managed by Denver Water where post-fire sedimentation could lead to treatment costs, is identified as an important watershed for surface drinking water by the US Forest Service’s Forest-to-Faucets project, and is part of the watershed burned in the highly destructive Hayman Fire (2002).

3.1 Wildfire Simulation

We obtained fuel, vegetation, and topography layers from the LANDFIRE project (version 1.1; LANDFIRE 2010) at the native pixel size of 30 m in the best-fit UTM zone projection (NAD83 UTM Zone 13 N). To keep computational demands of fire simulation tractable, we resampled these layers to a 90-m pixel size and generated a fire modeling landscape file (LCP), but made no other adjustments to the layers. We used weather data for the period 1987–2010 from the CHEESMAN

Fig. 1 Flowchart illustrating the main steps in modeling approach merging pixel-based and polygon-based inputs to characterize wildfire risk

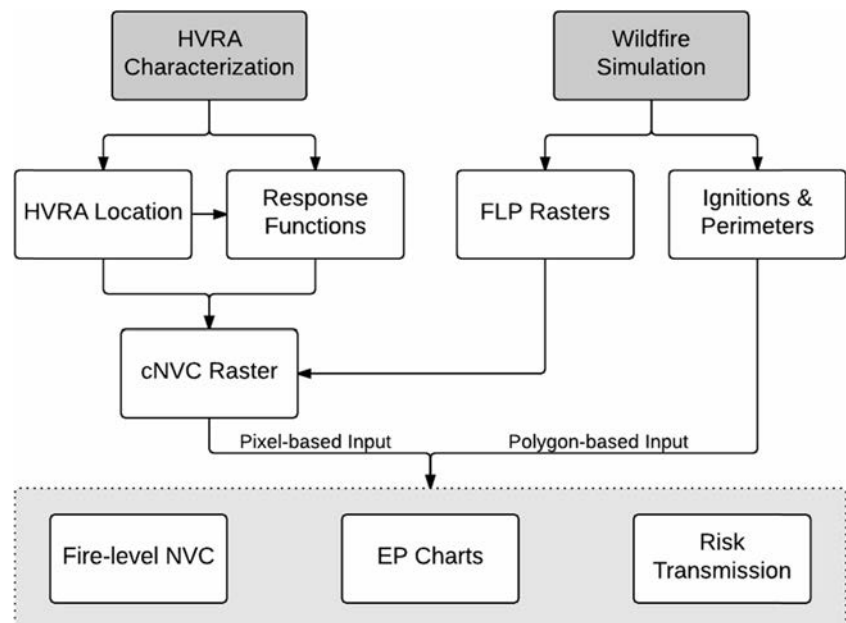
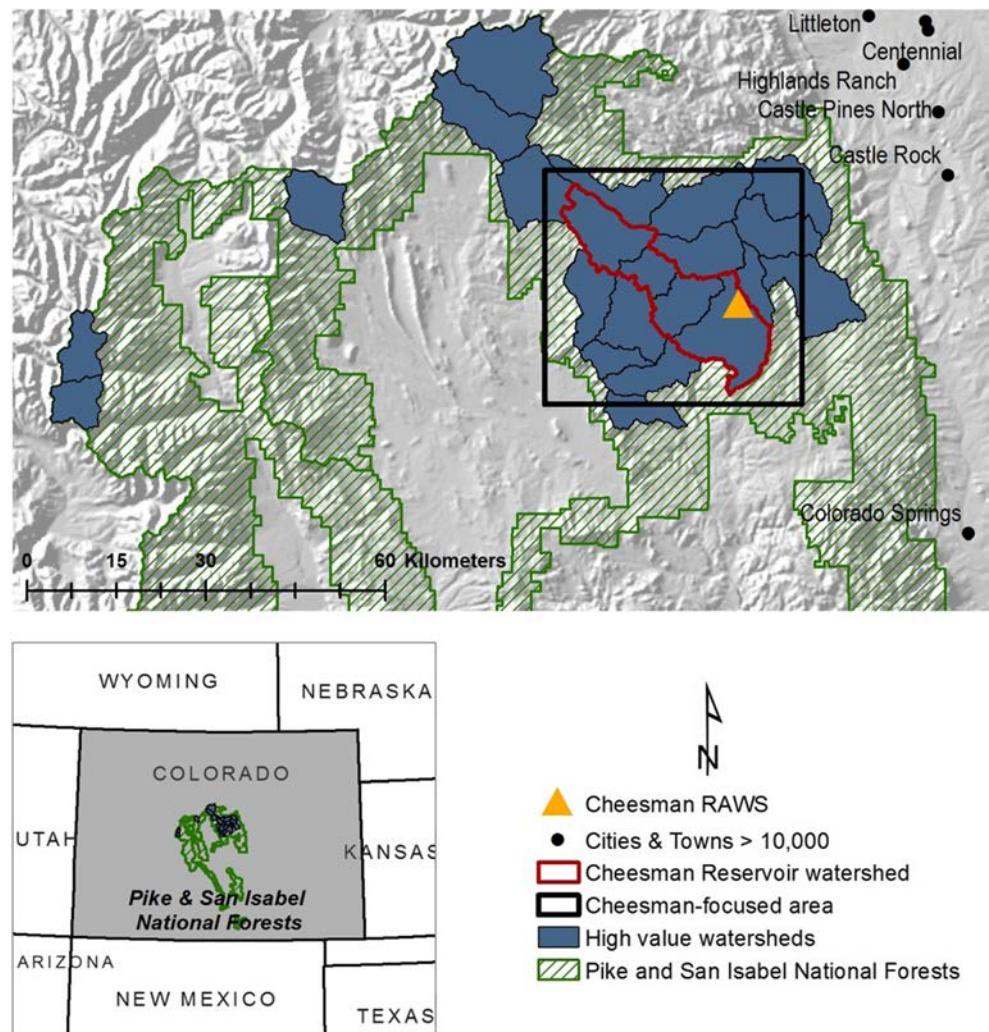


Fig. 2 Location of the Cheesman Reservoir watershed within the Pike and San Isabel National Forests, Colorado, USA. The four sub-watersheds (6th level hydrologic units) that comprise the watershed are outlined in red



RAWS (Fig. 2) to generate monthly wind speed and direction distributions, after converting the 10-min average wind speed to the probable maximum 1-min average wind speed [35].

We used FSim to generate fire perimeters (polygons) and pixel-based estimates of wildfire likelihood and intensity, across a rectangular 7.4 million ha study area that includes the National Forest boundary plus a 25-km buffer around it. Using historical fire occurrence data for the landscape area (1992–2010), we generated the required logistic regression coefficients for predicting large-fire occurrence probability and determined the historical distribution of the number of large fires per large-fire day [36]. We used a coarse spatial ignition probability grid constructed with the same method as that described in the reference [11]. We then used FSim to simulate 20,000 fire season iterations at a resolution of 90 m. The simulations were set to start at the beginning of the historical fire season (April 1), had a maximum fire size limit of 162,000 ha, and the FSim suppression module was enabled. The rate of spread for fuel models GR2 and GS2 was adjusted by a factor of 0.4; GS1 by 0.5; and GR1, GR3, GR4, and SH1

by 0.7. We did not adjust the spread rates for any other fuel models. The FSim simulation produced an ERSI shapefile containing the final perimeter of all simulated wildfires, and grids of BP and FLP_i ; from the FLP_i grids we calculated CFL .

For the deterministic fire behavior modeling with FlamMap5, we used the same LCP developed for FSim. We used wind and fuel moisture inputs consistent with the 97th percentile wind speed and fuel moisture condition at the Cheesman RAWS. Wind direction was uphill. A heading fire was assumed to occur at all pixels. We generated a flame-length grid representing the potential heading-fire flame length across the landscape.

3.2 Watershed Susceptibility

To characterize the susceptibility of the Cheesman Reservoir watershed to fire-caused damage, we applied the same expert-defined response functions that were used to assess wildfire risk to surface drinking water across the entire Rocky Mountain Region [34]. The response functions developed for that

assessment express $cNVC$ as percentage change in value from the pre-fire condition (Table 2). Forest Service resource specialists identified erosion potential as an important environmental variable influencing watershed susceptibility to post-fire sedimentation and water quality degradation. Erosion potential is categorized by soil type and slope steepness (US Department of Agriculture Natural Resources Conservation Service).

Table 2 generally indicates greater potential for detrimental impacts as flame lengths and erosion potential increase. The values in this table directly feed into $cNVC$ estimates for the various response scenarios described earlier. For example, where erosion potential is moderate and 97th percentile flame length is 5 feet (FIL3), $cNVC_{FM97}$ is -20 . The worst-case response function value ($cNVC_{worst}$) occurs at FIL6, with values of -30 for low erosion potential, -50 for moderate erosion potential, and -80 for high erosion potential. In this case, adding an additional best-case $cNVC$ scenario provides no information because, according to the response functions in Table 2, the best-case $cNVC$ is 0, or no change in value, regardless of erosion potential class.

3.3 Integrated Risk Calculations

We first generated grids representing each of the $cNVC$ scenarios by implementing Eqs. 5–7 using standard ArcGIS tools including Raster Calculator and Spatial Analyst reclassification tools. Next, calculation of potential fire-level impacts required first identifying the set of individual simulated fires whose perimeters reached any portion of the Cheesman Reservoir watershed. Based on these intersections, we calculated the area burned within the Cheesman Reservoir to generate fire-level and season-level conditional distributions of watershed area burned. Next, we used season-level watershed area burned results to generate exceedance probability (EP) charts that indicate the probability of exceeding a given level of watershed area burned during a single season. These charts allow for an enhanced probabilistic exploration of potential fire outcomes, for instance asking the probability of burning more than 25 % of the watershed in a given event, or of seeing an event as large as or larger than the Hayman Fire within the

fire modeling landscape. Each simulated fire season has a known probability of occurrence— $1/N$, where N is the total number of simulated fire seasons—so the probability of exceeding is simply the proportion of simulated fires that exceed some predefined value. An EP chart plots EP against the whole range of possible fire outcomes.

We then integrated the $cNVC$ grids with the fire perimeter polygons using the zonal statistics tool of the RMRS Raster Utility Tool [37]. Specifically, we calculated the sum of $cNVC$ values for all pixels within each fire perimeter. The RMRS Raster Utility Tool provided the ability to stack all three $cNVC$ grids in a composite grid and then run a zonal statistics function that treated each of the overlapping fire perimeter polygons as a zone. Without use of this custom tool, this analysis is exponentially more time consuming, involving iterating through every fire record, and counting or summing the pixels each perimeter overlays, in each of the response scenarios. As with area burned, we summarized both fire-level (NVC_{fire}) and season-level (NVC_{season}) impacts for all response scenarios.

We then joined the zonal statistics table with the original attribute table FSim produced for the fire perimeters, which includes fields indicating the start location. We used this joined table to produce a point feature layer consisting of the start location of each simulated fire, along with an attribute table that includes the sum of $cNVC$ values for each perimeter. Last, we used ArcGIS Spatial Analyst ‘Point Statistics’ tool with a 3-km rectangular window to produce a map indicating the mean NVC_{fire} for fires originating within each 3-km grid cell across the landscape.

4 Results

FSim results were generated for the entire Pike and San Isabel National Forest area; however, here, we summarize results for the area relative to the Cheesman Reservoir watershed, defined by a 5-km buffer around the outer boundary of ignitions that reach the watershed or “fireshed.” Out of 20,000 simulated fire seasons, 5156 ignitions occurred in the buffered fireshed. These ignitions burned 211.6 ha annually with an average fire size of 820.7 ha. Out of 4233 fire seasons, 59 %

Table 2 Expert-defined response functions for fire effects to watersheds and surface drinking water quality

Erosion potential category	Flame length class (fire intensity level)					
	1 0–2 feet	2 2–4 feet	3 4–6 feet	4 6–8 feet	5 8–12 feet	6 12+ feet
Low	0	0	–10	–20	–30	–30
Moderate	0	–10	–20	–30	–40	–50
High	0	–20	–40	–60	–80	–80

Response function values represent the percentage change in value from the pre-fire condition; negative numbers indicate a loss of value

did not have a large fire of 121 ha or more. On average, 37.5 % of all fires in this landscape become large fires.

Figure 3 presents an empirical cumulative distribution function for individual fire sizes as well as annual area burned (season-level results) for the Cheesman Reservoir landscape. The two curves are quite similar, reflecting the relative rarity of multiple large fires per season on this landscape. Results generally indicate a higher probability of relatively little area burned, but with potential for rare, very large wildfire events. Fire size distribution patterns shown in Fig. 3 are similar to findings by other authors [15, 38].

A total of 1122 fires (22 %) and 1055 fire seasons (25 %) that occurred within the buffered fireshed reached some portion of the Cheesman Reservoir watershed. The majority of fires that burned the watershed (over 80 %) burned 10 % or less of the watershed. The largest watershed area burned by any individual simulated fire was 12,789 ha, resulting in an annual probability of exceeding this fire size of less than 0.0001 (Fig. 4). These results are consistent with the local fire history, likely influenced by high-elevation fuel types that do not tend to produce large fires along with nonburnable lands (water, bare ground, snow, and ice) that can serve as barriers to fire growth.

Erosion potential is fairly high within the Cheesman Reservoir watershed, particularly in the southeast portion (Fig. 5a). Only 1 % of the watershed is classified as nonburnable and 17 % as low erosion potential. The watershed is predominantly in the moderate (41.5 %) and high (40.5 %) erosion potential classes. Burn probability within the watershed varies more than an order of magnitude, ranging from 0.0001 to 0.00135 (Fig. 5b). The areas of lowest *BP* are generally in the northwestern and southeastern portions, with the highest values in the middle subwatersheds. It is important to note that, in contrast to the pixel-based risk calculations presented earlier (Eq. 1), *BP* values are not used in our integrated risk modeling approach, which instead generates conditional fire-level and season-level impacts. However, as *BP* values are generated from the fire perimeters, the map is helpful to identify areas where more fire perimeters are likely to have burned. This information can be cross-referenced against flame length and erosion potential maps to see whether areas of high loss

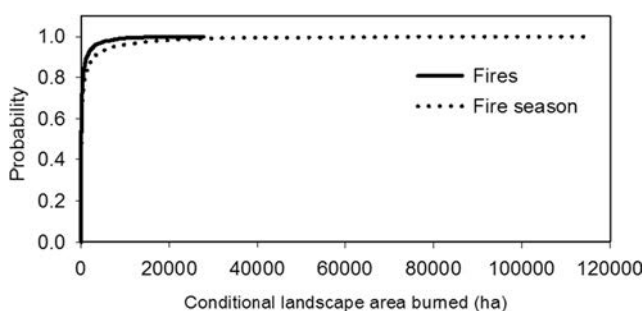


Fig. 3 Empirical cumulative fire-size distribution of simulated large wildfires and fire seasons using FSim

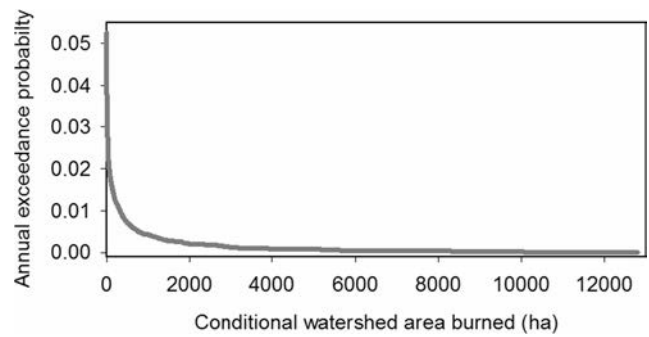


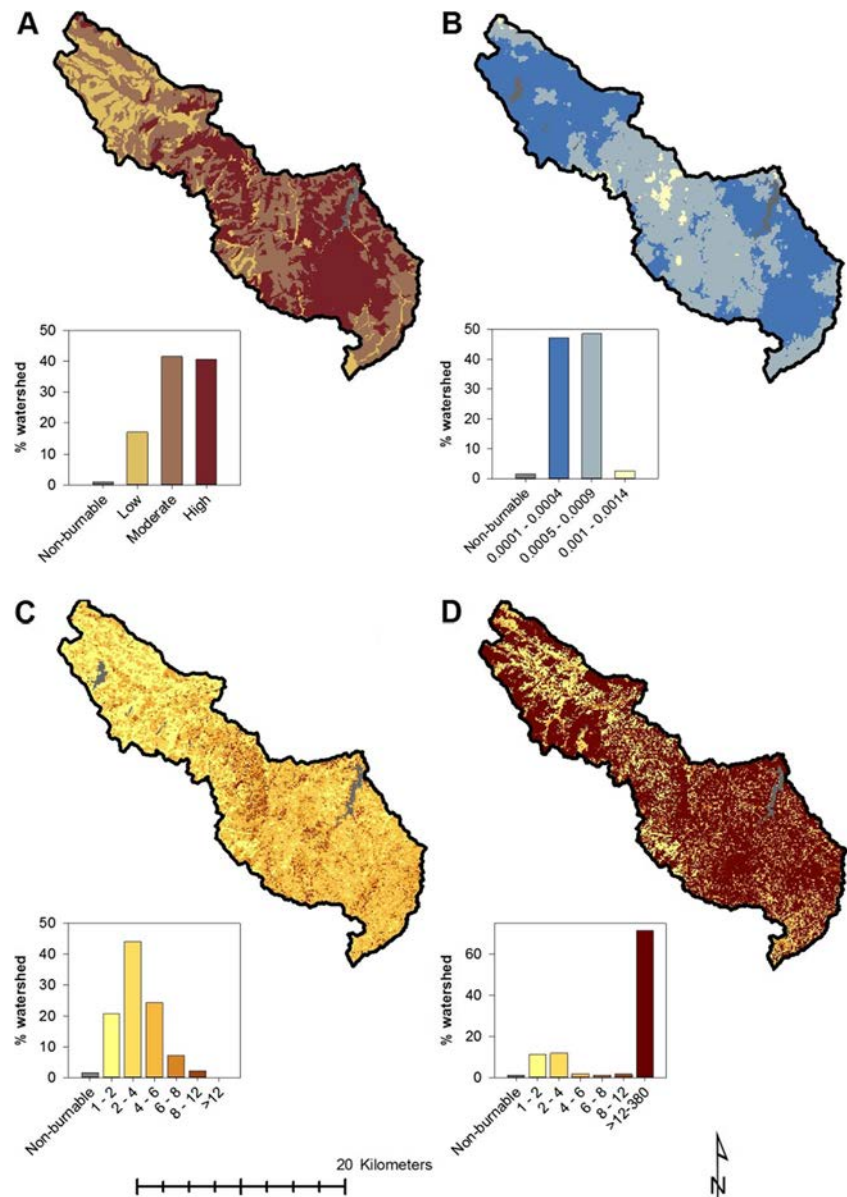
Fig. 4 Annual probability of exceeding given amounts of watershed area burned

potential are also areas more likely to be burned in fire events. Panels (C) and (D) illustrate spatial variation in *CFL* outputs from FSim and deterministic flame length outputs from FlamMap5 (FM97), respectively. The modal fire intensity class for *CFL* as calculated from FSim is FIL2, representing a mean flame length between 2 and 4 feet (Fig. 5c). Potential flame length (Fig. 5d) exhibits a similar spatial pattern, but the distribution of flame length classes is very different, as indicated by the histograms beneath each map for panels C and D. *CFL* values vary from 0.99 to 12 feet across the watershed, with *CFL* less than 4 feet in the majority of the watershed and some small areas where *CFL* is 4–6 feet throughout. Flame lengths from the static FlamMap5 (FM97) simulation based on the 97th percentile fire weather condition vary from 1.5 to 380 feet, considerably higher than *CFL* as simulated by FSim, with most flame lengths in the >12 foot category.

Figure 6 presents resultant *cNVC* values for each response scenario based upon the FlamMap5 flame lengths, FSim *FLPs*, erosion potential, and response functions. These figures illustrate the pixel-level *cNVC* if a fire were to occur in the given pixel. Panels (A), (B), and (C) provide *cNVC* results for the FSim, FM97, and worst-case scenarios, respectively. For panels (A) and (B), spatial variation in flame length, along with spatial variation in erosion potential, jointly determine *cNVC*. By design, spatial patterns of potential loss in panel (C) mirror the spatial patterns of erosion potential alone, since FIL6 is assumed on every pixel (Eq. 7). Panels (A)–(C) illustrate some similarities, for instance lower losses in the northwest corner of the watershed where erosion potential values tend to be lower. In addition to predicting overall lower levels of loss, the FSim fire intensity scenario (panel A) provides the highest degree of spatial variation in potential effects, due to the distribution of heading, backing, and flanking fires over thousands of iterations that produce highly variable flame lengths and associated responses (Fig. 5; panel C).

Figure 7 displays results of the merged pixel-polygon season-level analysis, i.e., where simulated fire perimeters are overlaid with pixel-level *cNVC* to determine fire-level and season-level impacts. In this figure, we summarize, for each *cNVC_{fire}* scenario, the range of possible season-level

Fig. 5 Erosion potential (a), FSim BP (b), FSim CFL (c), and FlamMap5 potential 97th percentile flame length (d) within the Cheesman Reservoir watershed



outcomes using boxplots. The $cNVC_{FSim}$ method consistently predict lower NVC than the FlamMap or worst-case methods, a function of the modeled FSim flame length probability distributions tending toward lower intensities (Fig. 5; panel C) as well as the low levels of loss at such low intensities (Table 2). By contrast, the $cNVC_{FM97}$ and $cNVC_{worst}$ scenarios are similar to each other in terms of mean values and range of variation.

Figure 8 displays scatterplots of annual watershed area burned and $cNVC$ for each response scenario. The left figures present the sum, or total, $cNVC$ for a given season, whereas the right figures present mean $cNVC$ values, i.e., watershed response is averaged across all burned pixels. The concentration of dots near 0 % watershed area burned confirms the results from Figs. 2 and 3 where significant levels of

watershed area burned are unlikely in any given fire season. Conditional loss (i.e., negative $cNVC$) increases with the amount of watershed burned by each fire season, and the slope of the lines across response scenarios (FSim, FM97, worst-case) reflects the underlying distribution of intensities and associated potential for losses. Evaluating the mean conditional loss can instead show the tendency toward relatively high or low levels of loss, which is not dictated by area burned per se but instead the location of fires with respect to areas of high fire intensity and/or high erosion potential. That is, spatial variation in erosion potential and likely fire intensity, as well as the spatial footprint of individual fires with respect to these factors, may be major drivers of post-fire watershed response. As annual watershed area burned increases, mean conditional loss results across all scenarios exhibit a central tendency,

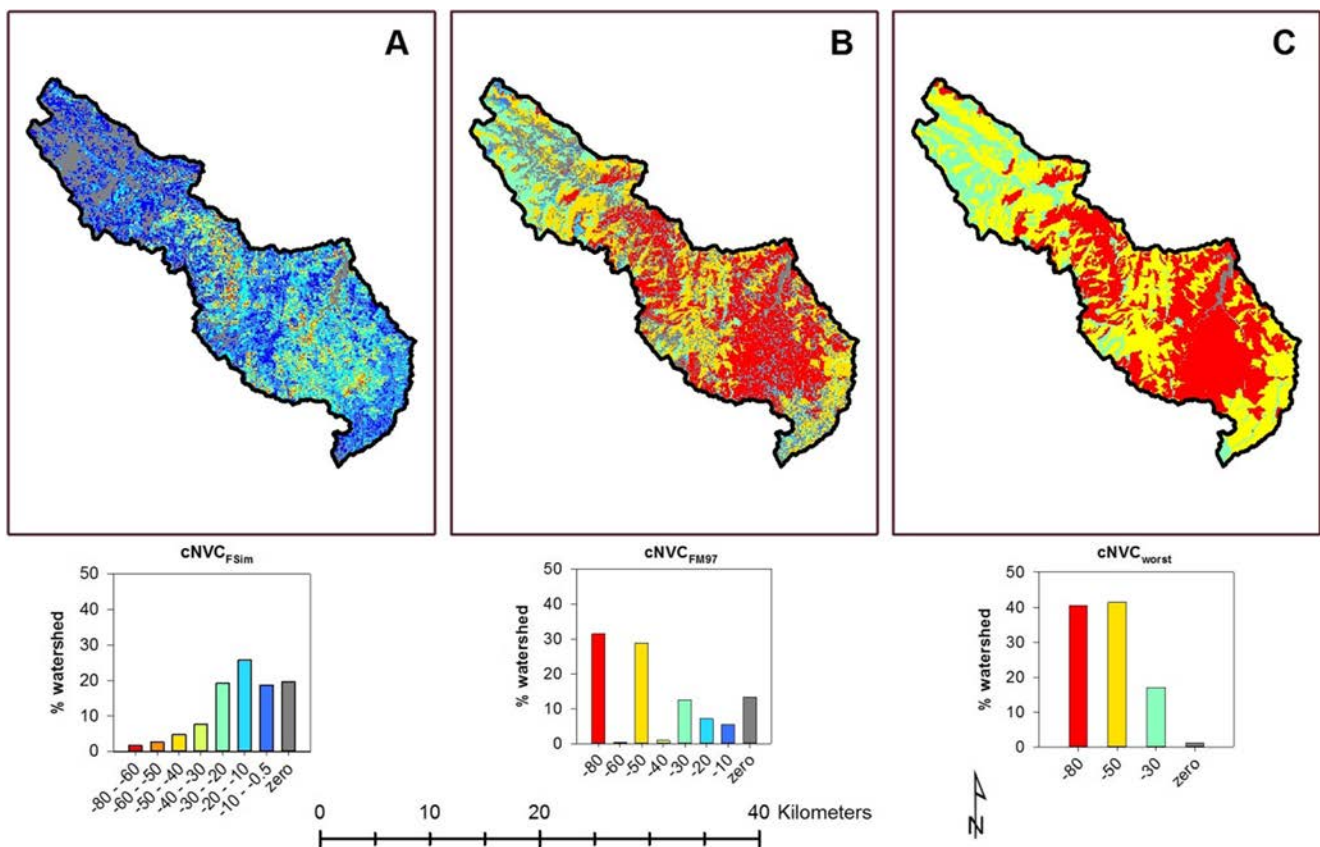
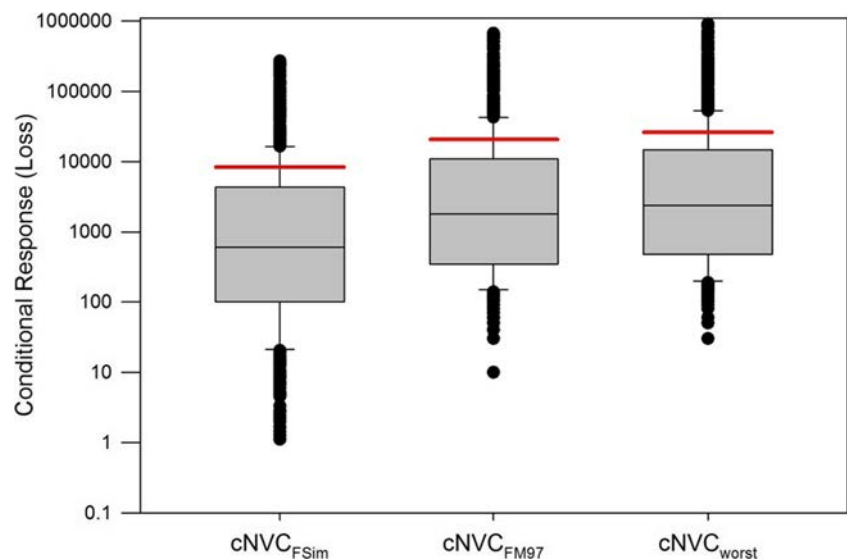


Fig. 6 Pixel-based estimates of cNVC, across the response scenarios

likely reflecting that as area burned increases, so too does the proportion of area burned at lower intensities or lower erosion potential. These results cement the importance of merging the pixel- and polygon-based results – capturing both distributions of HVRA area burned as well as localized variation in wildfire hazard and HVRA susceptibility.

Last, Fig. 9 presents results summarizing risk transmission potential across the fire modeling landscape. Panel (A) first identifies the “fired” as the area within which ignitions can reach the Cheesman Reservoir watershed, delineated using a 5-km buffered convex hull from the outermost selected ignition points. Ignitions are symbolized and colored according to

Fig. 7 Boxplots of fire-season level cNVC for three methods of estimating cNVC. Mean response values are indicated by the red lines. Note the y-axis is on a log scale



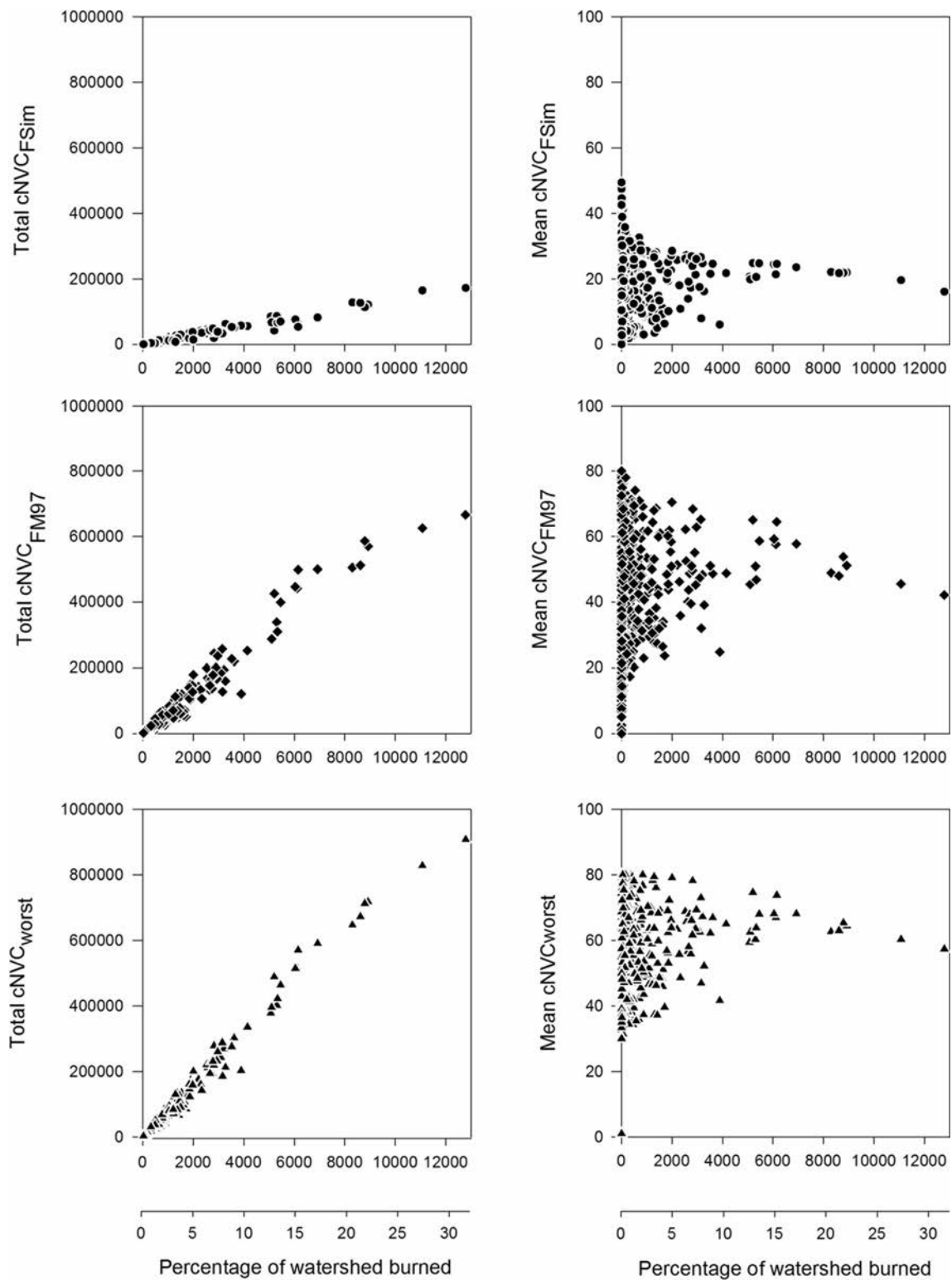
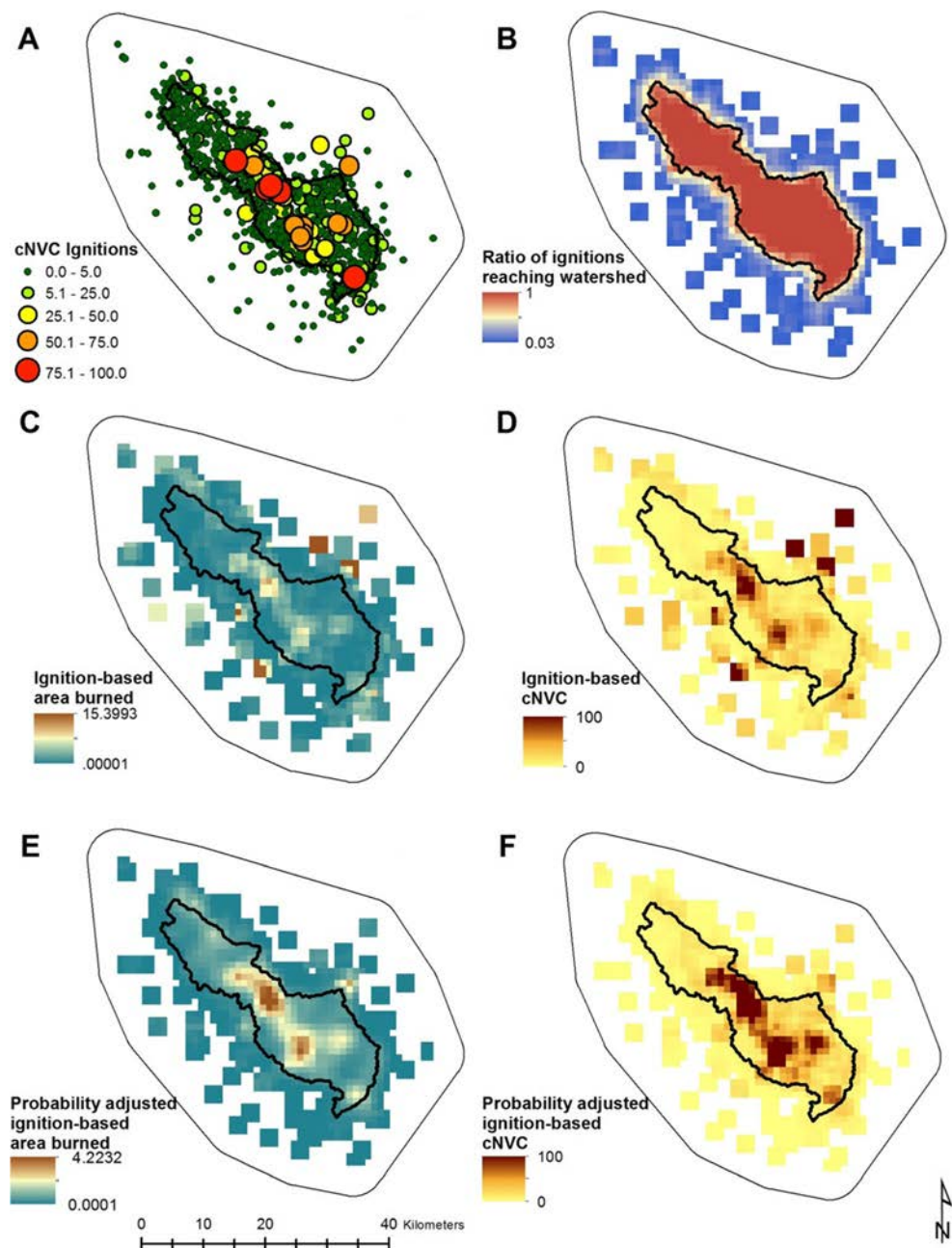


Fig. 8 Scatterplots of total fire-season cNVC vs watershed-area burned (*left panels*) and fire-season-mean cNVC vs watershed-area burned for the Cheesman Reservoir watershed

their total $cNVC_{FSim}$ value. Panel (B) similarly presents the same fireshed but displays a smoothed probability surface, to identify areas where ignitions are more/less likely to reach

the watershed. Panels (C) and (D) instead focus on the potential impacts associated with these ignitions reaching the watershed. Panel (C) indicates the percentage of the watershed

Fig. 9 Ignition location and percentage of total fire-level *NVC* of 1122 simulated wildfires that reached any portion of the Cheesman Reservoir watershed (a), probability ratio of an ignition reaching the watershed (b), ignition-based percent of watershed area burned (c), smoothed ignition-based mean fire-level *NVC* (d), probability adjusted ignition-based area burned (e), and probability adjusted ignition-based fire-level *NVC* across the landscape where the Cheesman Reservoir watershed occurs. Results for *NVC* have been scaled such that the pixel of maximum net loss (most negative *NVC*) is assigned a value of 100 and all other pixels are scaled in proportion to that



burned (see also Fig. 3), which tends to be rather low (<15.5 %). Not surprisingly, ignitions occurring within the watershed itself tend to burn more watershed area, especially the middle of the watershed where high burn probabilities (Fig. 5; panel B) suggest potential to support large fire growth; however, in the smoothing process, some of these values are obscured. Additionally, there are a few hotspots of potentially problematic ignitions generally located to the northeast and southwest of the watershed. Panel (D) presents conditional loss results attributed to ignition locations, using the *cNVC-FSim* scenario. Patterns of conditional loss in panel (D) largely

mirror those of area burned in panel (C), albeit with some exceptions. Panels (E) and (F) display probability adjusted results of (C) and (D) to better capture the rarity of high loss/area burned events relative to all ignitions in the area. Figure 9e shows the greatest watershed area burned can be attributed to ignitions within, and to the northeast of the watershed. Likewise, in Fig. 9f, ignitions occurring within the watershed are responsible for the greatest loss, relative to all ignitions on the landscape. As with Fig. 8, the nature of these results confirms the value of merging pixel- and polygon-based results by identifying locations where ignitions may

be more/less of a concern in terms of consequences to the Cheesman Reservoir.

5 Discussion and Conclusions

The integration of pixel- and polygon-based approaches to assessment of wildfire risk we demonstrated here expands the foundation for exposure and effects analyses, the primary components of risk assessment [9, 13, 30]. We illustrated application of the technique on National Forest System lands in the US Forest Service's Rocky Mountain Region, where protection of municipal water supplies from wildfire is a high priority. Our modeling results generated distributions of HVRA exposure and effects, explored how anticipated wildfire impacts vary as a function of modeled fire intensities and watershed response within the simulated fire perimeter, and examined spatial patterns of risk transmission across the broader landscape containing the Cheesman Reservoir watershed.

Integrating the pixel- and polygon-based modeling approaches provides a fuller picture of potential wildfire impacts to HVRAs. The major advancement entails the analysis of individual fire-level impacts and the generation of the annual distribution of potential wildfire impacts to an HVRA, rather than just averages or statistical expectations. The assessment framework is premised on the calculation of fire-level *NVC* conditional on the occurrence of a specific simulated fire, and the approach is explicitly designed to capture spatial variation of wildfire intensity and HVRA susceptibility across area burned within the perimeter. This new approach can begin to better capture variation in the following: environmental factors influencing fire occurrence, spread, and behavior; environmental factors influencing HVRA susceptibility; fire intensity influences on fire effects; HVRA area burned influences on fire effects; and environmental factors influencing the distribution of HVRA area burned within areas of high/low loss potential.

The method we employ here surmounts a limitation of current stochastic simulations systems—that raster data regarding fire intensity is not available for each simulated wildfire. If future wildfire simulation systems are capable of storing fire-level information regarding fire intensity, then further improvements in estimating fire-level effects to HVRAs will be possible, although possibly at great expense in terms of data storage and processing requirements. The polygon-based calculations can also increase computational demands, particularly as the size of the analysis landscape and the number of simulated fire increases. For very large landscapes or regional analysis, the perimeter files may need to be broken into manageable chunks rather than one merged perimeter file for the entire simulation area. However, the time needed to perform these calculations is still a fraction of the time

required for the wildfire simulation itself. Therefore, it is likely that if sufficient time and resources are available to run FSim at the appropriate scale (see [34] for a discussion of FSim calibration at larger scales), then they are also available to perform the necessary polygon-based analysis.

As with other fire models, application of FSim requires careful critique of terrain, fuel, and vegetation characteristics, historical weather data, and information on historical fire occurrence [11, 14, 17]. In support of this type of analysis, continued calibration efforts focused on not only fire behavior metrics but also fire perimeter footprints will be helpful [39]. So too will continued research refining linkages between fire behavior models and post-fire erosion models [40, 41].

A number of analytical opportunities are made available from merging the pixel- and polygon-based approaches, as well as leveraging the strengths of the individual approaches. We demonstrated how exceedance probability charts can be used to estimate potential impacts, and future applications could compare not just HVRA area burned but HVRA *cNVC*, for instance to identify the likelihood of experiencing unacceptable loss levels, or comparing loss potential across HVRAs. The approach provides information not only on the range of possible fire-level or season-level outcomes, but can also help identify areas likely to transmit risk. Pre-season fire planning could use this type of assessment framework to demarcate areas of planned response on the basis of likely fire outcomes, and could refine strategic suppression objectives accordingly. Fuel treatment planning could similarly benefit from identification of likely high loss areas for reducing local fire intensities, or for identifying areas transmitting risk and seek to interrupt fire spread pathways. Planned future research is focused on integrating these new techniques into decision support systems [42], expanding the response function framework to potentially directly include watershed area burned, linking fire simulation models with other fire effects prediction models, better understanding transmission of risk associated with ignition locations, and more directly incorporating risk results into incident response decision support.

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