

Wildfire Risk Transmission in the Colorado Front Range, USA

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Wildfires are a global phenomenon that in some circumstances can result in human casualties, economic loss, and ecosystem service degradation. In this article we spatially identify wildfire risk transmission pathways and locate the areas of highest exposure of human populations to wildland fires under severe, but not uncommon, weather events. We quantify varying levels of exposure in terms of population potentially affected and tie the exposure back to the spatial source of the risk for the Front Range of Colorado, USA. We use probabilistic fire simulation modeling to address where fire ignitions are most likely to cause the highest impact to human communities, and to explore the role that various landowners play in that transmission of risk. Our results indicated that, given an ignition and the right fire weather conditions, large areas along the Front Range in Colorado could be exposed to wildfires with high potential to impact human populations, and that overall private ignitions have the potential to impact more people than federal ignitions. These results can be used to identify high-priority areas for wildfire risk mitigation using various mitigation tools.

KEY WORDS: Exposure analysis; human populated areas; Randig; risk transmission; wildfires

1. INTRODUCTION

Wildfires are a global phenomenon that in some circumstances can result in human casualties, economic loss, and ecosystem service degradation. Under certain conditions, human activities (i.e., suppression) can alter the course of the wildfire event. However, extreme events often overwhelm suppression and first responder capacity, leading to uncontrollable and potentially catastrophic consequences. High-loss events in the recent past include the 1997 Sumatra and Kalimantan fires of Indonesia (240 fatalities), the 2009 Black Saturday bushfires in Victoria, Australia (173 fatalities), and the 2007 forest fires in Greece (84 fatalities). A comprehensive list spans the globe and extends back in time. For example,

the 1910 fires in the interior northwest of the United States (86 fatalities) catalyzed federal wildfire policy changes and ushered in an era of aggressive suppression.

Increasingly, the wildfire management community is turning to risk assessment as a key input to the wildfire decision-making processes aimed at preventing loss, for both prefire mitigation activities as well as active incident management.^(1–4) The fundamental pieces involved in quantifying wildfire risk are spatially resolved estimates of wildfire likelihood and intensity, maps of highly valued resources and assets (HVRAs), and characterizations of HVRA susceptibility to fire.⁽⁵⁾ Analytically, the quantification of wildfire risk can be separated into exposure analysis, which explores the degree to which HVRAs will be exposed to risk factors (fire likelihood and intensity), and effects analysis, which explores the potential consequences (loss or benefit) to the HVRA at various exposure levels.⁽⁶⁾ In this article, we focus on a single HVRA, human populated areas, and

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describe a novel exposure analysis intended to facilitate efficient wildfire risk mitigation at the wildland-urban interface (WUI).

Wildfire risk to human populated areas is driven by environmental and anthropogenic factors that influence both the wildfire hazard itself, as well as the exposure to and effects on human communities. Past fire suppression has led to increased fuels accumulation, which can increase the magnitude and likelihood of environmental and human impacts. Land-use patterns can inflate risks by increasing human-caused ignitions (e.g., agricultural burning and increased human access to remote areas), altering fuel conditions (e.g., agricultural land abandonment, increased fuel accumulations), and increasing exposure to wildland fires (e.g., exurban residential development and recreation road access to remote areas allows for humans to occupy areas previously difficult to access). Changing climate is likely to further inflate risks by increasing wildfire activity in many areas around the globe.⁽⁷⁾ Given these potentially increasing risk factors, damaging wildfire events are likely to continue into the future.

Beyond the location of human development, the two critical factors that determine wildfire risk to human populated areas are the ignition location on the landscape, and the underlying potential for fire spread on the landscape. The locations of wildland fire ignitions vary across a landscape due to a number of factors, including human development, lightning-prone landforms (e.g., mountain ridges), recreation access, and proximity to roads.^(8–10) Where large fires occur over large landscapes, the influence of ignition patterns on wildfire likelihood (burn probabilities) is minimal,⁽¹¹⁾ especially under extreme fire weather events.⁽¹²⁾ However, ignition location patterns play a larger role in burn probabilities where fires are smaller in size.^(13,14) Population density and area burned from wildland fire ignitions are often inversely related,⁽¹⁵⁾ meaning that the higher the population density, the smaller the fires, given an ignition. This is often due to the increase in fire suppression efforts and the landscape fragmentation found in proximity to human development.^(12,16) In human-dominated, fragmented landscapes, the human-caused ignitions tend to be more clustered than lightning-caused ignitions.^(17–20) Even small fires in proximity to high-density populations can result in greater direct exposure to human populations than larger, remote fires.

Although ignitions are the source of the hazard, it is the spread of the ignition that ultimately

causes the greatest effects on human and natural resources. Frequently, damaging wildland fires burn the majority of their acreage during one or two burn periods, under severe weather events, through rapid fire spread.^(21,22) It is during these events that high winds and dry fuel conditions make suppression of wildland fires difficult and dangerous, even in urban settings where response times are shortest. Therefore, it is critical to understand where on the landscape a potential ignition, under severe weather events, could spread and cause the highest exposure to human populations. Recent and emerging improvements in wildfire risk assessment tools^(23–26) have greatly facilitated this task, allowing for the coupling of spatially explicit fire spread and burn probability modeling with geospatial representations of human development.^(4,27,28) Although these and related modeling approaches capture the spatial influences of ignition location and landscape fire spread potential, results are typically aggregated across simulated fires and summarized at the raster level, which provides limited information regarding sources of risk.⁽²⁾ The use of individual simulated fire perimeters as the unit of analysis provides important information masked by pixel-level analyses,^(3,29) such as risk transmission. Risk transmission is the transfer of risk originating in one place or landscape to a spatially or temporally separate landscape. Systematic examination of ignition locations and fire perimeters can identify risk transmission within and across landowners.⁽³⁰⁾

The issue of risk transmission into human populated areas is particularly salient for federal land management agencies, such as the U.S. Forest Service (USFS), that annually invest hundreds of millions of dollars into actions to mitigate wildfire risk. The National Fire Plan (NFP) developed in 2001 provided a substantial boost in funding to hazardous fuel reduction programs on forested lands in an effort to reduce the risk of wildland fires. A primary objective of the NFP and the Healthy Forest Restoration Act of 2003 (Public Law 108–148, section 103) is to reduce the risk from wildfires in the WUI. More recent efforts, such as the National Cohesive Wildland Fire Management Strategy, have focused on creating fire-resilient landscapes and fire-adapted communities to minimize losses. For fuel treatments on public lands to be effective at attaining these objectives and minimizing WUI risk, the treatments must be strategically located to interact with wildfire, and when tested by fire must reduce the likelihood and/or intensity of fire within the WUI. Often, private landowners control

large tracts of land in between public lands and the more densely populated WUI lands.⁽³¹⁾ Not only are these private lands potential sources of wildland fires, they can facilitate the spread of fires igniting in remote public lands, across a landscape, to more heavily populated lands.⁽²⁾ It is therefore an essential first step in WUI risk mitigation that transmission pathways be identified in order to locate areas where investments on public or private land may or may not be cost effective at measurably reducing WUI risk.

The objective of this study is to spatially identify WUI risk transmission pathways and locate the areas of highest exposure of human populations to wildland fires under severe, but not uncommon, weather events. We quantify varying levels of exposure in terms of population potentially affected by simulated fire perimeters, and tie the population affected back to the ignition location. The spread of a fire from an ignition point, through a populated area, identifies the risk transmission pathways, while the ignition point itself identifies the source of the risk. The amount of population affected by each fire perimeter is the level of exposure. We aim to determine if the land ownership designation of wildfire ignitions provides differential levels of exposure to human populations, and if there is a high level of risk transmission among and between land ownerships. We hypothesize that wildland fires ignited on private land will result in higher levels of exposure to human populations than federal ignitions, and that risk transmission levels will be greatest from private to private landowners. As a case study location we focus on the Front Range of Colorado, USA, a densely populated fire-prone region that has experienced recent high-loss wildfire events. We use probabilistic fire simulation modeling to address where fire ignitions spread and lead to exposure of human populations, and to quantify the role that federal lands play in that transmission of exposure. We do this by simulating potential wildfire perimeters under severe wildfire weather and intersecting these perimeters with maps of human population to determine the number of people who may be directly impacted by the simulated events, from both federal and nonfederal ignitions. Additionally, we generate a map of population affected by fire ignitions to identify geographic hotspots of potential activity. This type of analysis is necessary for promoting a realistic vision of shared responsibility across landowners and homeowners, and for identifying the most cost-effective suite of actions to reduce WUI loss.⁽³²⁾

2. METHODS

2.1. Study Area and Fire History

For this study, we investigate the likelihood that short-duration burn events under severe fire weather conditions will impact human populations. While the location and density of human structures may play a larger role in determining the value of infrastructure at risk and the suppression response, fire management priorities are first and foremost to protect human life and safety. Numerous federal and state-level risk assessments have used population data, such as Landscan USA,⁽³³⁾ since it balances the first priority of human life and safety with second priorities of property.^(4,34,35) Since more than 85% of Colorado's population lives in the Front Range Urban Corridor, we restricted our analysis to this area (Fig. 1). The Front Range in Colorado is the eastern-most mountain range of the Rocky Mountains, stretching from Pikes Peak to the Colorado/Wyoming state line. The Front Range urban corridor consists of 16 counties that span this mountain range and follows the I-25 corridor from Cheyenne, Wyoming in the north to Pueblo, Colorado in the south. We further restricted our study area to the 11 counties within this corridor that lie within the state of Colorado, and contain National Forest lands (National Grasslands administered by USFS are excluded). Five counties (Adams, Arapahoe, Denver, Ebert, and Weld) were excluded due to lack of National Forest lands, and two counties (El Paso and Pueblo) were truncated to only include the western portion of the counties that contain forested and mixed forest, shrub, and grass landscapes. A similar analysis for homogeneous grasslands would be informative for those landscapes; however, the vastly different fire behavior, as well as different suppression response and effectiveness, would make it difficult to compare the two landscapes side by side. The resulting study area comprises 3 million hectares of lands under various ownerships, including numerous federal agencies (1.2 million ha, 41%) as well as state (81,590 ha, 3%), county and municipal (56,119 ha, 2%), and private lands (1.6 million ha, 54%; Fig. 1). State, county, and municipal lands were grouped into the class state/local for this study. This mix of ownerships allowed us to investigate the relationship between fire ignition location and subsequent fire spread into populated areas.

The total population residing within the study area is 2.37 million people according to the Landscan

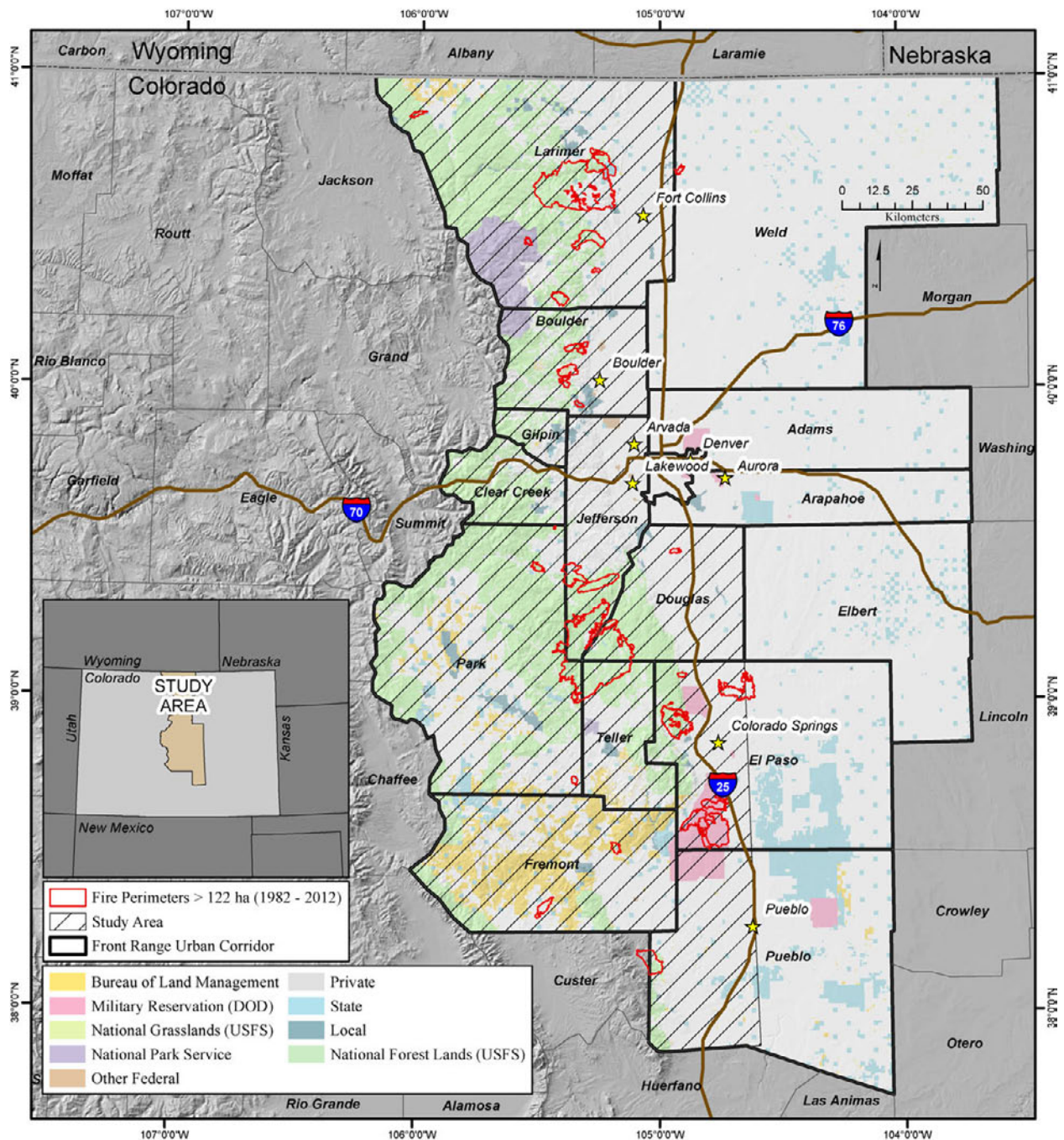


Fig. 1. The counties within the Front Range Urban Corridor, with land ownership, our truncated study area, and the recent large fire history within the study area.

2013 nighttime population data set. The population is clustered around the major urban centers of Colorado Springs, Pueblo, Boulder, and Fort Collins. The vast majority (98%) of human population within the study area resides on private lands and, therefore, the risk transmission we summarize here will pri-

marily be from federal or state/local lands to private lands or from private lands to private lands. The exception to this is with the residents of military bases on Department of Defense lands; this accounts for 1% of the population. In addition, private inholdings occur on lands administered by the Forest Service

and this population accounts for the remaining 1%. Private inholdings are common in Colorado, and are primarily due to old mining claims, as well as the railroad checkerboard inholdings found elsewhere in the western United States. These private inholdings are categorized as federally administered, but are actually privately owned in the study area. Therefore, results from private inholdings are included in the private ownership class, but also analyzed separately as a federally administered unit.

In the Front Range forests, the higher elevation lodgepole pine (*Pinus contorta*), Douglas fir (*Pseudo-tsuga menziesii*), and ponderosa pine (*Pinus ponderosa*) mixed forests have historically been characterized by mixed-severity fire regimes, and the lower elevation ponderosa pine dominant forests have historically been predominately low-severity fire regimes.⁽¹⁸⁾ Fire suppression in these areas has changed the historical fire regimes, especially in the lower elevation ponderosa pine forests, where fire exclusion has increased fuel loads, increasing the potential for higher severity fires.⁽³⁶⁾ In recent decades, the Front Range Mountains have experienced rapid growth in human development into the WUI, and this trend is likely to continue in the next 30 years.⁽³⁷⁾ Human development in and around fire-prone lands has created circumstances in which wildland fires increasingly result in adverse impacts on human lives and highly valued resources, as recently demonstrated by the series of highly damaging wildfire events in this area. The Hayman Fire of 2002 is the largest fire in Colorado's recorded history. It consumed over 55,850 ha of dry fuels northwest of Colorado Springs and destroyed 132 homes.⁽³⁶⁾ Five firefighters lost their lives in a vehicle accident and one smoke-related civilian death was attributed to the fire. The Fourmile Canyon Fire burned in 2010 outside of Boulder Colorado; 168 homes were lost and damages totaled over US\$220 million.⁽³⁸⁾ More recently in 2012, the Lower North Fork Fire claimed 16 homes and three lives. That same year, the High Park Fire outside of Fort Collins and the Waldo Canyon Fire adjacent to Colorado Springs burned 259 and 346 homes, respectively. Insurance claims for the Waldo Canyon totaled US\$352.6 million (<http://gazette.com/damage-assessment-grows-for-black-forest-fire/article/1503565>). The following year, and within eight miles of the Waldo Canyon Fire, the Black Forest Fire occurred destroying 464 homes, resulting in two civilian deaths and over US\$300 million in insurance claims to date.

While the specifics of each of these fires are slightly different, they all share some characteristics in terms of fire weather and fuel loadings. These fires all burned under dry and windy conditions, resulting in a few short-duration burn periods of rapid fire spread. For example, in 2002 while Colorado was in an extended drought, the Hayman Fire burned over 24,280 ha in one day during an extreme wind event involving gusts of up to 82 km/h.⁽³⁶⁾ The Fourmile Canyon Fire, similarly, burned the majority of its acres during the first day, when relative humidity and fuel moisture content were extremely low and winds were gusting to 64 km/h. Of the 168 homes lost in the Fourmile Canyon Fire, 162 were lost during this first 12-hour burn event.⁽³⁸⁾ High winds, accompanied by decreasing relative humidity, was the primary cause of Lower North Fork Fire escaping prescription and aggressive initial attack, leading to rapid fire spread and subsequent losses. The Waldo Canyon Fire also had an extreme burn period that lasted approximately 12 hours and burned the majority of the homes, with wind gusts of up to 105 km/h.

2.2. Wildfire Simulation

To simulate short-duration burn probabilities we utilized a command line form of FLAMMAP, called "Randig."⁽³⁹⁾ Randig works by placing a large number (>10,000) of random ignitions on a landscape. Each ignition grows in accordance with FLAMMAP fire spread logic as implemented by the minimum travel time algorithm,⁽⁴⁰⁾ using the Rothermel spread equations and the Scott and Reinhart crown fire initiation algorithm.⁽⁴¹⁾ The short-duration burn periods are simulated under constant weather conditions, assuming no suppression effect. This assumption is appropriate for modeling extreme wildfire spread events, especially in forested landscapes where fire weather and fire behavior can overwhelm suppression resources.⁽⁴²⁾

In order to investigate the fire spread potential for the short-duration fires typical of high-loss events on the Colorado Front Range, we used four representative severe weather scenarios. We developed scenarios typical of historically significant fire events based upon analysis of historical fire weather data obtained from Remote Automatic Weather Stations (RAWS), located in the Front Range. These scenarios are defined by a given windspeed, direction, burn period duration, and corresponding fire spotting probability (Fig. 2). The probability of each scenario being selected is based on the historically

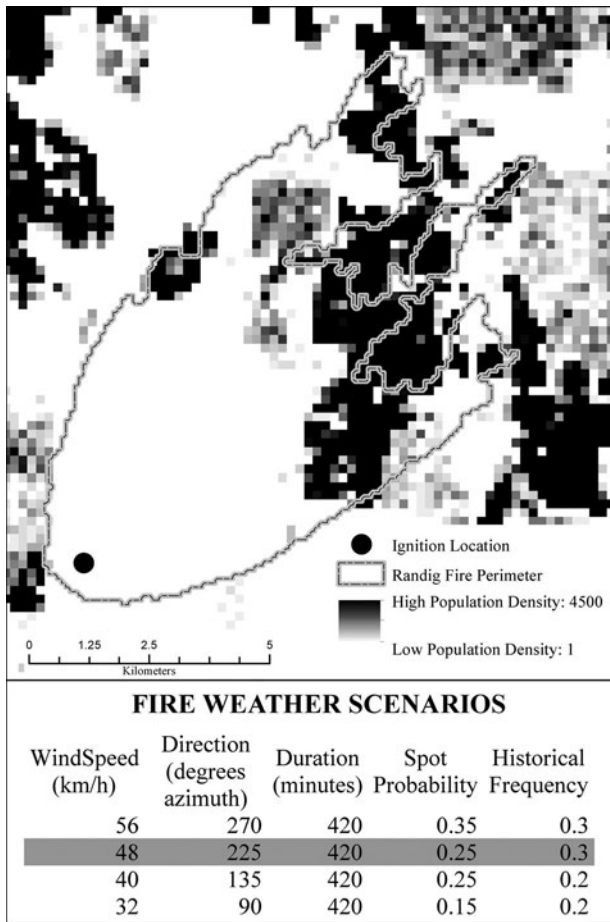


Fig. 2. Example Randig fire perimeter and ignition location overlaid with Landsat population. The possible fire weather scenarios are shown in the table, with the selected weather scenario corresponding to the perimeter shown.

observed windspeed and direction from the RAWS data. Windspeeds and directions more common in the historical record have a higher probability of being selected.

For our surface and canopy fuels and topographic landscape information, we resampled the LANDFIRE 2010 (LF 1.2.0) data set,⁽⁴³⁾ from its native resolution of 30 m up to the fire modeling resolution of 90 m, using the nearest neighbor technique. LANDFIRE data are commonly used in wildfire simulation modeling due to the fact that they are nationally available, standardized, and updated regularly to adjust for disturbances such as wildfires, fuel treatment, and urban development.⁽⁴⁴⁾ The data layers needed to create the required landscape file for Randig are elevation, slope, aspect, fuel model, canopy cover, canopy base height, canopy height,

and canopy bulk density. We clipped each resampled raster to a 10 km buffer around the study area. This buffer allows for fires burning on the edge of the study area to burn off the lands, thereby minimizing potential edge effect on simulated fire perimeters.

Wildland ignitions tend to follow patterns related to land-use, human access, and topographic features; therefore, we leveraged the historical fire occurrence database to determine historical density patterns of ignitions within the study area. We obtained fire occurrence history between 1992 and 2011 for the study area from the National Fire Occurrence Database,⁽⁴⁵⁾ a comprehensive database that includes ignition locations across ownership, regardless of final fire size. According to this database, a total of 5,194 ignitions burned 112,645 ha within the study area, from 1992 to 2011. Approximately half of these ignitions were located on federal lands (2,703), with the remaining located on private (2,346), local (54), or state (44) lands. We calculated an ignition density grid (IDG) based on the historical fire occurrence ignition patterns within a 10 km buffer of the study area, using kernel smoothing.⁽⁴⁶⁾ The left panel of Fig. 3 shows the IDG and the recent ignition locations within the study area. We simulated 50,000 ignitions located probabilistically according to the IDG. The outputs from the simulation model include individual fire ignition locations, fire perimeters, and an overall burn probability grid. The burn probability grid is simply the number of times a pixel burned divided by the number of simulations.

2.3. Identifying Wildfire Exposure Levels to Human Populations

We used the 2013 Landsat USATM 3 arc-second ($\sim 90 \text{ m}^2$) nighttime residential population distribution data set⁽³³⁾ as our population layer in order to assess the exposure from wildfire to human populations. The basis of this data set is the 2010 Census population counts by housing blocks—the smallest unit containing population information from the U.S. Census Bureau. The nighttime residential population layer attempts to locate people in their residences, and therefore is more applicable to fire risk to residential communities than the daytime population layer, which attempts to locate people at their place of employment. Landsat uses “intelligent” daysmetric mapping to locate the lands most likely to contain human populations as constrained by census housing blocks. Since large census blocks often have populations concentrated within a small area

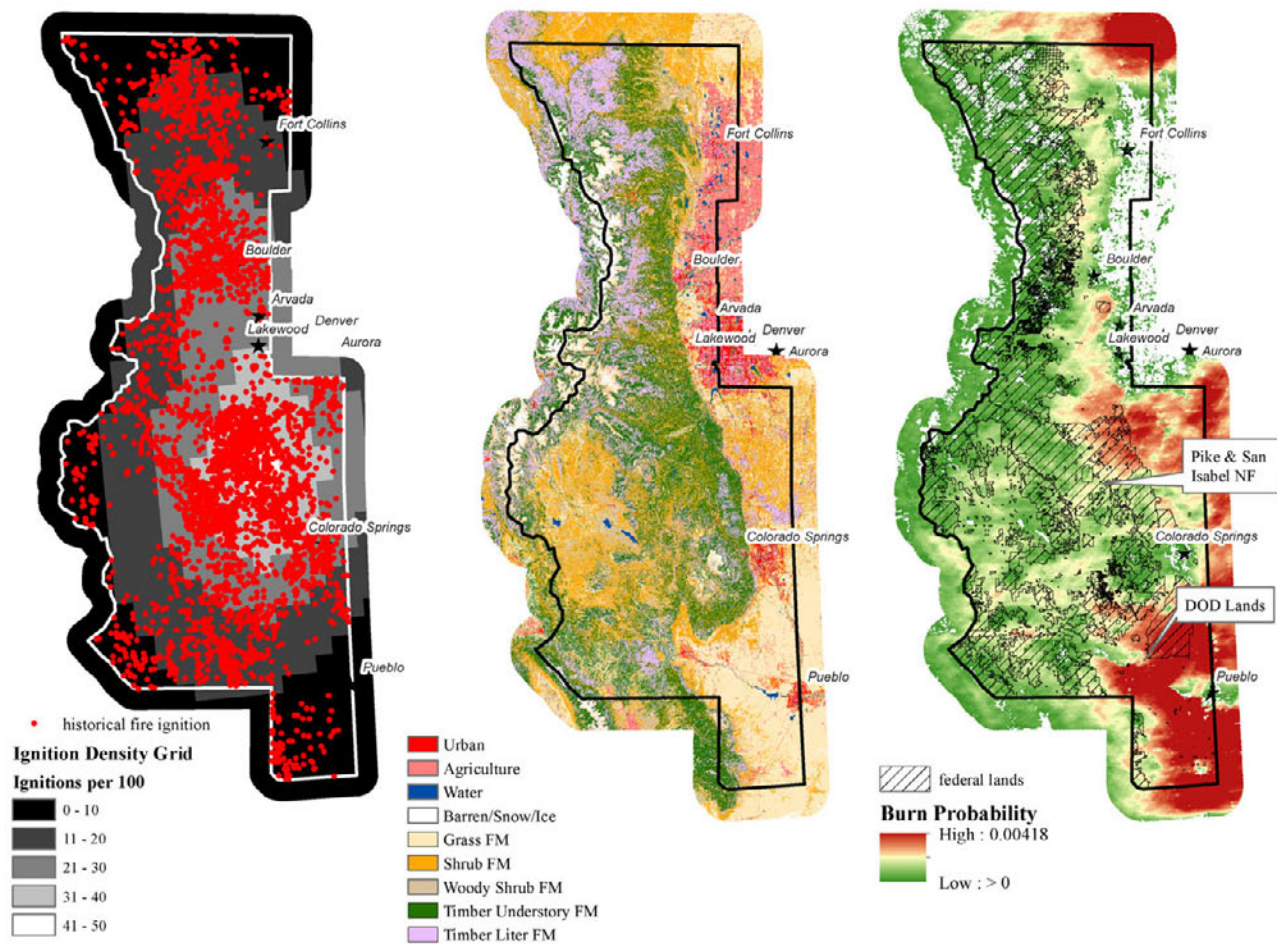


Fig. 3. A comparison of the study area's historical ignition patterns and ignition density grid (left), fuel model groups (center), and simulated burn probabilities from Randig (right)

within the block, assuming an even density of population is not appropriate.⁽⁴⁷⁾ The Landscan algorithm uses additional information, such as lights at night, roads, and topography, to identify the lands within the census block that are most likely to contain the population of the block. Since the raw Landscan data set is in a geographic projection where area units are not equal, population density counts are not feasible. Therefore, we converted the Landscan grid to points, projected these points to Albers equal area projection, and reconverted to a 90 m grid by summing up the population counts of the points in each pixel. This resulting grid is appropriate for population density counts since each pixel represents the same areal unit.

We overlaid Randig perimeter outputs with the Landscan population density grids to determine the level of exposure by calculating the total absolute

population (aPOP) directly exposed (i.e., residing in) by each fire perimeter (Fig. 2). Various factors can cause populations to be exposed indirectly from wild-land fires, such as through the spread of smoke or postfire impacts on drinking water quality. However, we focused only on direct exposure to human populations. For computational efficiency purposes, we performed these calculations using the RMRS Raster Utility's "zonal stats" function.⁽⁴⁸⁾ Each simulated fire was also attributed to the land ownership class and the county within which it ignited. Our hypothesis was that fires igniting on private lands would result in higher levels of exposure than ignitions on federal or state/local lands. The federal, state/local, and private land ownership classes were analyzed using a one-way ANOVA to determine if statistical differences in population exposure levels occur between the groups.

2.4. Spatially Identifying Sources of High-Risk Transmission

We define areas of high-risk transmission as those where ignitions under severe fire weather have a potential to rapidly spread onto lands that are occupied by people. We quantify varying levels of exposure in terms of population potentially exposed by simulated fire perimeters (aPOP), and tie the aPOP back to the ignition location. The spread of a fire from an ignition point, through a populated area, identifies the risk transmission pathways, while the ignition point itself identifies the source of the risk. We generate a map of risk transmission sources by exposure level, and calculate county-level totals of the aPOP by ownership class, as well as statistics on the factors that contribute to the total aPOP. These factors include total population, county size (hectares), propensity for fire spread (burn probability), and total fire load (number of ignitions). In addition, we summarize these data by federal administrative units. Finally, we visually compare our simulated results with recent high-loss wildland fire events on the Front Range.

3. RESULTS

3.1. Wildfire Simulation and Burn Probability

Using the Randig outputs, we found the mean burn probability for the study area to be 0.0012, with a minimum of 0.00002, a maximum of 0.00624, and a standard deviation of 0.0012. The burn probabilities tend to covary across the landscape with the fuel model groups (Fig. 3). In particular, areas of grass and shrub fuel models tend to have higher burn probabilities than timber fuel models. Grass and shrub areas tend to have larger simulated fire perimeters due to faster fire spread rates compared to timber fuel models and the fact that suppression efforts that are typically more effective in grass and shrub fuel models are not modeled in Randig. Notably, most of these grass fuel models and high burn probabilities are found on private lands, with the exception of the Department of Defense lands in the southeastern portion of the study area. Also, Forest Service lands of the Pike and San Isabel National Forests, south of Lakewood, CO, have high burn probabilities in comparison to other federal lands. This may be a function of not only fuel configuration, but also a higher density of ignitions as shown in the ignitions density grid (Fig. 3).

In addition to a burn probability surface, Randig also outputs information related to ignition location, fire size, and fire perimeter. Of the 50,000 simulated fires, 44,402 of the ignitions are within the study area, and the remaining ignitions are located in the 10 km buffer used to accommodate edge effects for the burn probabilities. Results throughout the remainder of the study only refer to the 44,402 ignitions located within the study area. The simulated fires ranged in size from 1.8 to 20,719 ha. The mean fire size was 3,919 ha, and the median was 2,853 ha. Approximately half of these fires ignited on private land (53%), 14% (7% of the total) of which ignited on private inholdings within federal administrative boundaries. Fires igniting on private lands were larger (mean 4,800 ha and median 3,804 ha) than those igniting on federal lands (mean 2,657 ha and median 1,487 ha). Similar to the burn probabilities, the increase in fire size on private lands can be attributed to the grass and shrub fuel models that are found in these areas. Even though wildfire suppression tends to have a higher success rate in the grass fuels than in timber fuels, the extreme weather conditions under which these ignitions were modeled would make suppressing these fires difficult and dangerous due to the rapid spread rates and increased spotting.

3.2. Identifying Wildfire Exposure Levels to Human Populations

Across all simulations, an average of 1,638 people were affected per fire, given an ignition anywhere on the landscape. The absolute population exposed (aPOP) from an individual fire perimeter ranged from 0 to 52,573, with a median of 109. Our hypothesis was that fires igniting on private lands would result in higher levels of exposure than ignitions on federal or state/local lands. We first calculated the correlation between fire size and aPOP to ensure that aPOP was not simply a function of simulated fire size. The Pearson's correlation coefficient was 0.28, indicating that aPOP was only weakly correlated with fire size. In addition, the fires with the highest aPOP are in the middle of the fire size distribution, with the largest fires having lower aPOP values, suggesting that landscape areas capable of supporting very large fire growth are geographically separate from areas of high population density. Not surprisingly, private ignitions accounted for higher levels of population exposed (mean 2,347, median 388) than federal ignitions (mean 856, median 18) or state/local ignitions

(mean 725, median 38) due, in part, to the proximity to populated areas. While there were no significant differences between federal and state/local levels of exposure (one-way ANOVA, $F = 1.5388$, $p = 0.22$), there were significantly higher levels of population exposure from private ignitions, versus federal (one-way ANOVA, $F = 1594.1$, $p < 0.001$), and state/local ignitions (one-way ANOVA, $F = 206.87$, $p < 0.001$), suggesting that ignitions on private lands do produce different levels of exposure to populations compared to federal and state/local.

3.3. Spatially Identifying Sources of High-Risk Transmission

A map that visualizes the spatial pattern of risk transmission sources by exposure level is necessary to identify hot spots of potential risk transmission. We created a raster where each pixel was assigned the aPOP from the ignition that resided within the pixel, by ownership (Fig. 4). Since we found no significant difference between federal and state/local ownership classes, we combined the classes for the remainder of the analysis into the federal class. If more than one ignition was located within a pixel, the ignition with the maximum value of aPOP was used for visualization of risk transmission sources. Areas in white contained no random ignition for that particular ownership class. The aPOP by ignition varies across the landscape, with the highest clusters surrounding the large urban areas of Colorado Springs, Pueblo, and south of Lakewood (Fig. 4). This is particularly true of private ignitions. Federal ignitions with the highest aPOP tend to occur in the area surrounding Colorado Springs.

At the county level, 35% of the total study area's aPOP comes from ignitions starting in El Paso County, 35% from Douglas County, 14% from Jefferson County, and 16% is distributed among the remaining eight counties. Fig. 5 displays the percentage that each county contributes to the total study area's aPOP, shown in shades of black. A total of 25% of the total study area's aPOP is from ignitions starting on federal lands while 75% is from ignitions starting on private land. The aPOP is broken down by ownership class in Fig. 5, where the black is federal lands and gray is private lands. El Paso County has the highest percentage of the total aPOP from fires igniting on federal lands—14% of the total—and Douglas County has the highest percentage of total aPOP from fires igniting on private lands (32%). In terms of the relative proportion of each county's to-

tal aPOP coming from fires igniting on federal lands, El Paso and Park counties have the highest with 41% and 38%, respectively.

Under a completely random process, we would expect that the proportion of each county's aPOP would be proportional to county-level population densities. However, there are many complex spatial interactions that influence the spatial pattern of aPOP. These factors include the interaction of total fire load (i.e., number of ignitions), the general propensity for fire spread (i.e., mean burn probability), and population density. In Fig. 5, we show that these factors contribute to the aPOP in different ways for each county. For example, while Park County contains the highest percentage of the total fire load, and one of the highest burn probabilities, the aPOP is one of the smallest, due to the low density of people in proximity to these flammable fuels. Douglas and El Paso counties account for the highest aPOP (35% each); however, in Douglas County this is driven by high burn probabilities, and in El Paso this is driven by high population. It is not simply the presence of high burn probability and high population anywhere within a county that results in a high aPOP, however. Rather it is the spatial proximity and/or overlap of the two. For example, Jefferson County contains the highest percentage of the population (25%), and a relatively high BP, however it only accounts for 12% of the aPOP. It is this complex spatial interaction of factors that requires the use of the spatial modeling methods we performed in this study, rather than a more simple statistical modeling approach.

There are 10 federal administrative units within the study area, including two National Forests, three military bases, two BLM districts, two National Parks/Monuments, and a National Wildlife Refuge. Private inholdings on the two National Forests are also considered units of federally administered lands, for a total of 12 units. Of the total aPOP from ignitions on federal lands or private inholdings, the Pike and San Isabel National Forests account for 51%, or 13% of the total aPOP for the entire study area (Table I). Collectively, the Department of Defense lands account for 27% of the aPOP from federal ignitions and 7% of the study area's total aPOP. Private inholdings account for 13% of the aPOP from federally administered lands, and 3% of the total study area's aPOP. On a per fire basis, fires igniting on the Department of Defense (DOD) Air Force Academy lands affect the largest amount of people, with an average of 10,122 people affected per fire, which is 10 times higher than the Pike and San Isabel National

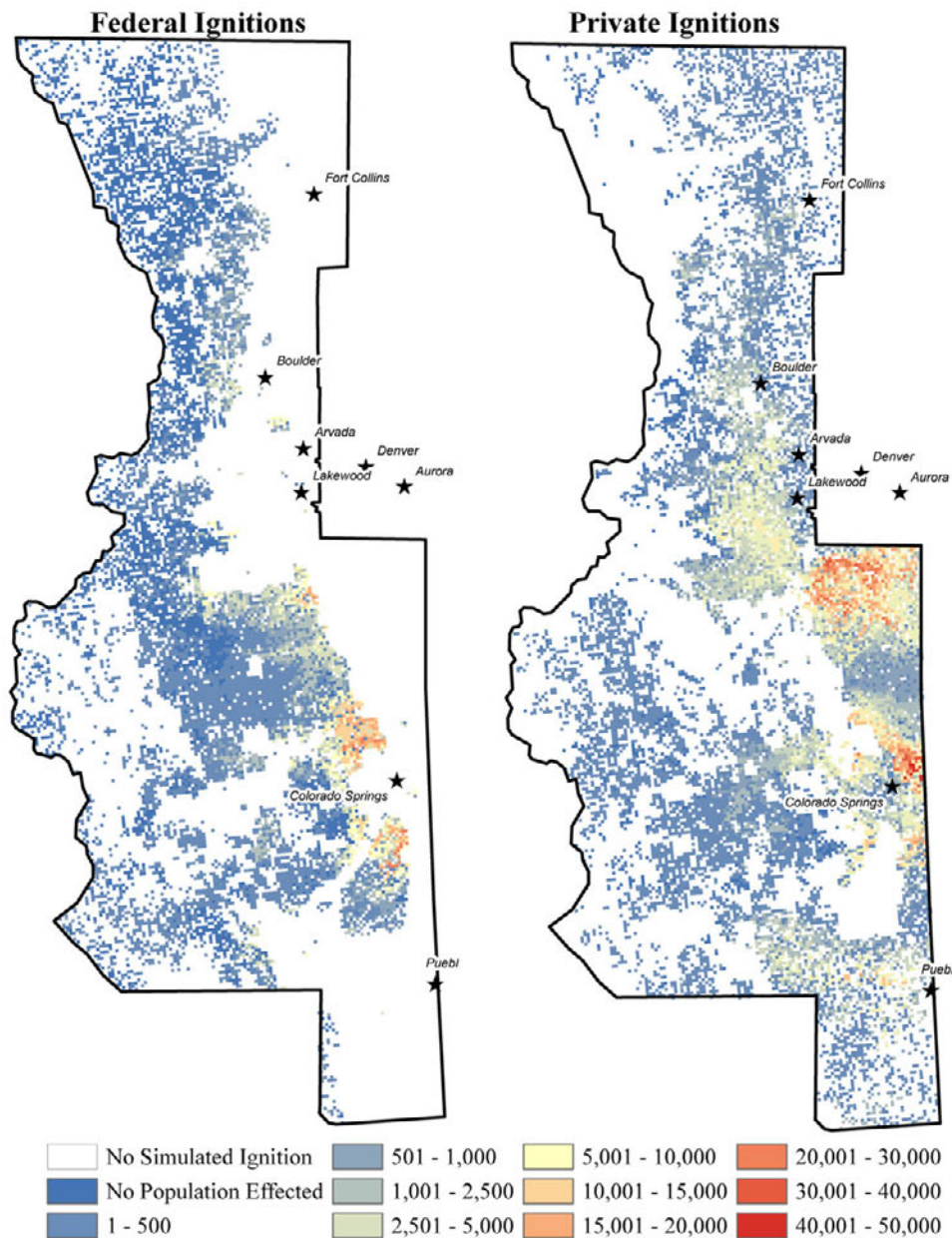


Fig. 4. Spatially identified sources of risk transmission by various exposure levels of aPOP, for federal (left) versus private (right) ignitions.

Forests. This is in part due to the fact that people reside on these DOD lands, and in part due to the high burn probabilities found on these lands (Fig. 3).

3.4. Comparison of Results with Recent Wildland Fires

We compared the simulated perimeters of high-impact fires to actual fire perimeters from the re-

cent past. Fig. 6 shows the location of four highly damaging fires within the past few years in the Colorado Front Range. These are the Black Forest, Waldo, Fourmile Canyon, and High Park fires. The Fourmile Canyon and High Park fires occurred in areas with relatively low aPOP affected from severe weather events. This figure highlights the fact that under similar weather conditions, an ignition in many other areas on the landscape had the potential

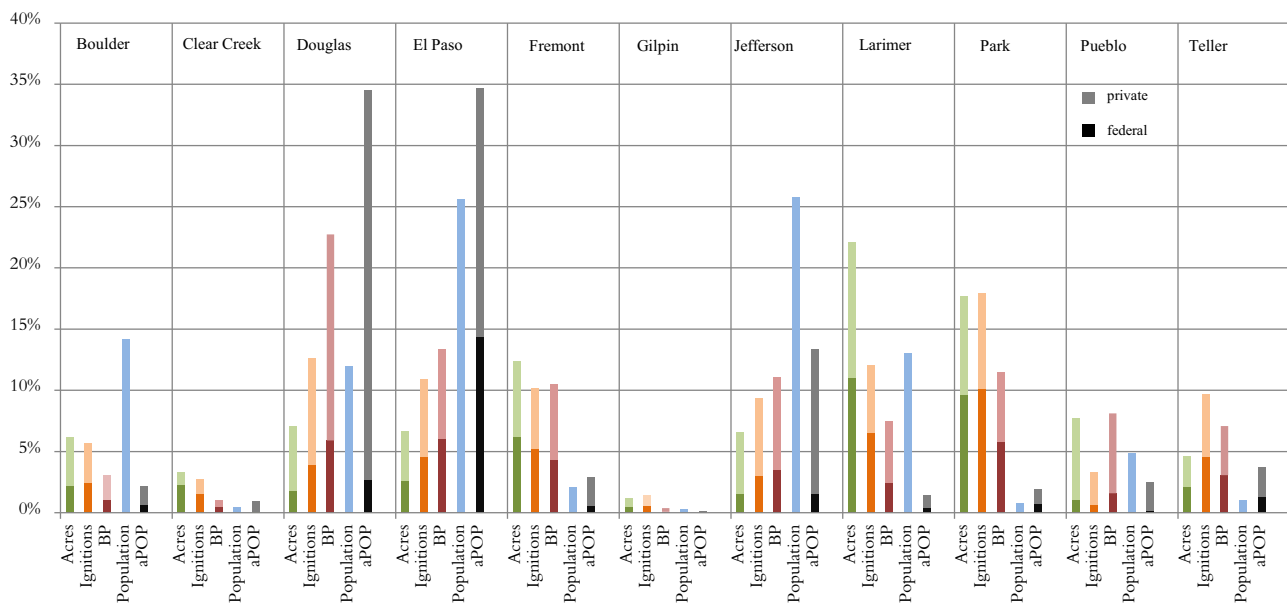


Fig. 5. This figure shows a comparison of county-level population exposed (aPOP), as a percentage of the total project area's aPOP, broken down by federal (black) versus private (grey) ownership. In addition, the proportion of factors contributing to the results (county size [acres], ignition loadings [ignitions], propensity for fire spread [BP]) are shown and broken down by federal (darker colors) versus private (lighter colors) ownership as well.

to expose more people than either of these two fires. The Waldo Canyon and Black Forest fires occurred in an area we identify as having high population exposure. We mapped the simulated perimeters of the three highest impact fires by ownership class (private, Forest Service, and other federal) in Fig. 6. These six fires are shown in more detail in the right-hand side of Fig. 6. The highest impact fire that ignited on private land was located approximately 2 km east of the Waldo Canyon Fire, just outside of Colorado Springs, and impacted over 52,000 people. The highest impact fire on federal lands occurred on Department of Defense lands just south of Colorado Springs, and affected 26,670 people. Interestingly, the highest impact Forest Service fire ignited within the Waldo Canyon Fire perimeter; however, the simulated fire primarily burned outside the Waldo Canyon Fire perimeter under a strong easterly wind (Fig. 6), and impacted over 23,000 people. Since the LANDFIRE fuels layers are from 2011, the LANDFIRE fuels were not yet altered to account for the fuel consumption from the Waldo Canyon Fire. Our analysis shows that this area is still highly susceptible to high impacts from wildfire. A future analysis incorporating burn severity and fuel changes could show the effects that the Waldo Canyon Fire might have on subsequent fire spread potential in the area.

4. DISCUSSION

This work illustrates the application of wildfire simulation modeling to quantify the exposure of residentially developed populated areas to short-duration wildland fires during severe fire weather conditions. These results can be useful for strategic planning efforts to address risk mitigation, especially when prioritization is necessary due to limited funds and available resources. For example, our results highlight areas on the Colorado Front Range, where if an ignition were to occur under severe fire weather, expedited measures should be taken to extinguish the fire before spread occurs or, if failing that, emergency evacuation and response may be warranted. This could be accomplished by prepositioning fire suppression resources during expected extreme fire weather.

The results can be useful in a PREFIRE season planning context as well, since they highlight areas by ownership that have an elevated potential for being the source of a highly damaging wildland fire event. Some mitigation actions that could be taken PREFIRE season are performing effective fuel treatments that will allow for increased initial attack success, and increasing fire prevention efforts in areas of elevated risk. Researchers have shown that

Table I. Summary of Federal Administrative Units' aPOP

Owner	Unit	% of Federal Hectares	% of Federal Ignitions	Mean aPOP/ Ignition	% of Total Federal aPOP	% of Total Project Area aPOP
Bureau of Land Management	Colorado-Front Range-Royal Gorge	6.09%	11.94%	213	3.02%	0.78%
Bureau of Land Management	Colorado- Northwest- Kremmling	0.35%	0.23%	2	< 0.00%	< 0.00%
Department of Defense	Air Force Academy	0.24%	0.99%	10,122	11.94%	3.09%
Department of Defense	Fort Carson	1.78%	4.25%	2,978	15.04%	3.89%
Department of Defense	Peterson AF Base	0.01%	0.04%	3,020	0.13%	0.03%
National Park Service	Florissant Fossil Beds National Monument	0.08%	0.40%	810	0.38%	0.10%
National Park Service	Rocky Mountain National Park	2.18%	2.97%	44	0.15%	0.04%
U.S. Fish & Wildlife Service	Rocky Flats National Wildlife Refuge	0.06%	0.18%	3,065	0.65%	0.17%
U.S. Forest Service	Arapaho & Roosevelt National Forests	32.04%	18.35%	203	4.42%	1.14%
Private Inholdings	Arapaho & Roosevelt National Forests	3.71%	7.06%	282	2.36%	0.61%
U.S. Forest Service	Pike & San Isabel National Forests	51.10%	46.37%	934	51.44%	13.31%
Private Inholdings	Pike & San Isabel National Forests	2.38%	7.23%	1,218	10.46%	2.71%

awareness of risk motivates landowners to mitigate their risk.^(49–51) Therefore, by quantitatively producing maps that identify the areas of highest risk transmission, landowners may be more motivated to mitigate the risk from their property if they can visually recognize their lands as a source of wildfire risk. In addition, development is likely to continue in this area. These results highlight areas that can benefit from fuels mitigation efforts pre-development and well-designed safety measures for homeowners and firefighters, such as increased egress options, fire hydrants, and building with fire resistant materials.

Since risk transmission is not just about the ignition source, but also about the subsequent spread onto adjacent lands, multiple landowners are likely to be exposed and, therefore, mitigation efforts must occur across boundaries. Simulation models suggest that random patterns of fuel treatments do not begin to restrict fire movement until 15–20% of the area is treated; however, if treatments are oriented

specifically to impede fire movement the effect is realized at a lower treatment area.⁽⁵²⁾ The first step in identifying where strategically located fuel treatments may be the most effective at reducing human exposure is to identify where on the broader landscape a high amount of exposure is present. Our results have done this for the Colorado Front Range; however, our methods can be extended to other landscapes to identify the areas with the highest sources of potential population exposure from wildland fires.

The next steps will necessarily involve a more detailed analysis at the local project level in areas of elevated exposure, to see how and if treatments could result in a reduction in exposure. The data need to conduct this research at local levels would ideally include better information on local fuels and ground cover, especially urban fuels surrounding homes and the location and type of fuel treatments performed on the ground. Information on actual housing location, as well as the number and associated

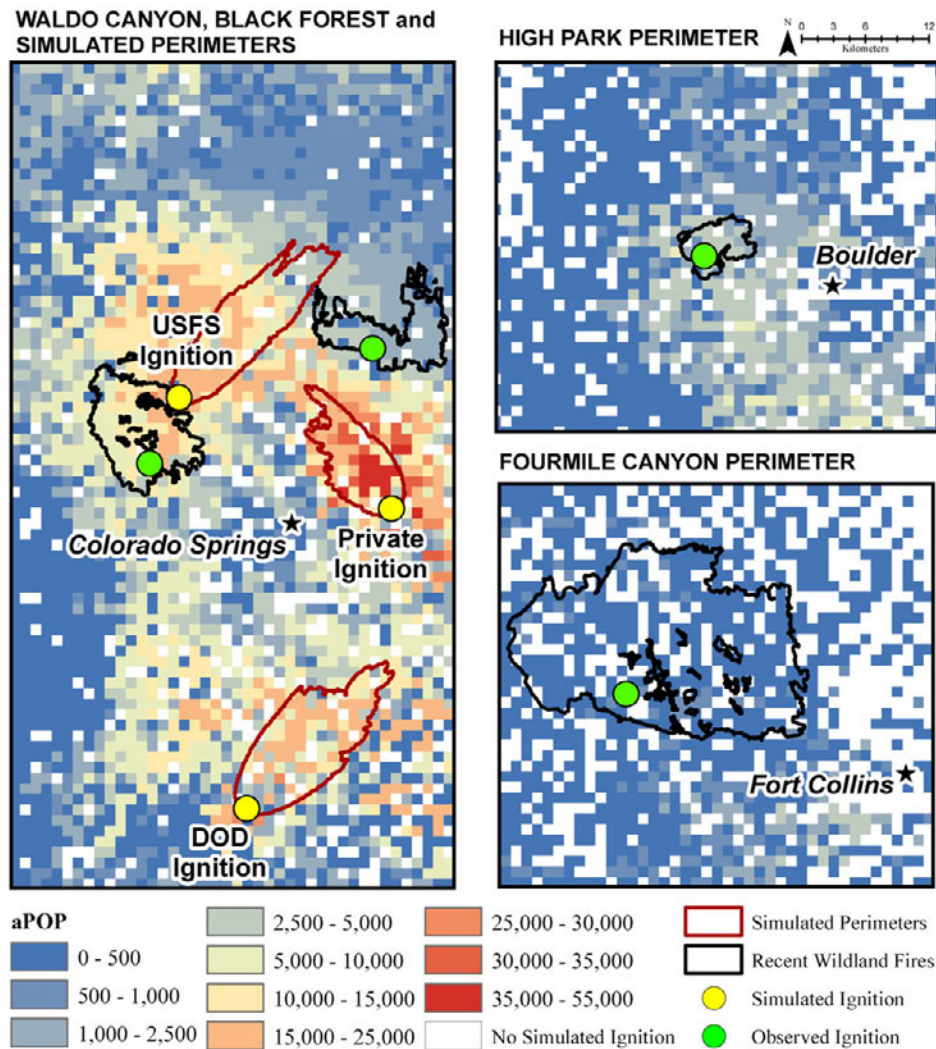


Fig. 6. Four historical and three simulated high-impact wildfire perimeters, overlaid with aPOP.

sociodemographic characteristics of people residing in each house, would also provide a more complete picture of the community impacts from potential wildland fires.

Future research could build upon this work by addressing modeling limitations and expanding the scope of analysis. Fire simulations could be rerun with fuel and vegetation conditions updated to reflect recent fire events not yet incorporated into the LANDFIRE data set, as well as to reflect alternative hypothetical fuel treatment scenarios. Modeling fire-to-home ignition, home-to-home ignition, and home destruction processes greatly increases modeling complexity and data demands, but could potentially improve estimates of likely wildfire-related

loss. Modeling the human life and safety impacts is potentially even more complex, although useful proxies could include assessing egress routes and relative evacuation difficulty. In addition, the effects of wildland fires on human populations extend beyond the direct impacts of home loss and population displacement. The impacts from smoke on human health can be far reaching; however, currently methods to use smoke dispersion models in a probabilistic, prefire context are not yet available since many of the models rely on real-time remotely sensed data of smoke and short-term forecasted winds.⁽⁵³⁾ Future research on postfire debris flows and sediment loadings on drinking water supplies would further round out the analysis of

effect to human populations. Continued attention to understanding the factors driving wildfire exposure and risk will ideally lead to improved and efficient design of wildfire risk mitigation strategies, across land managers and affected communities.

REFERENCES

- Noonan-Wright EK, Oppermann TS, Finney MA, Zimmerman GT, Seli RC, Elenz LM, Calkin DE, Fiedler JR. Developing the US wildland fire decision support system. *Journal of Combustion*, 2011; 2011:1–14.
- Ager AA, Vaillant NM, Finney MA, Preisler HK. Analyzing wildfire exposure and source-sink relationships on a fire prone forest landscape. *Forest Ecology and Management*, 2012; 267:271–283.
- Scott J, Helmbrecht D, Thompson MP, Calkin DE, Marcell K. Probabilistic assessment of wildfire hazard and municipal watershed exposure. *Natural Hazards*, 2012; 64(1):707–728.
- Haas JR, Calkin DE, Thompson MP. A national approach for integrating wildfire simulation modeling into wildland urban interface risk assessments within the United States. *Landscape and Urban Planning*, 2013; 119:44–53.
- Scott JH, Thompson MP, Calkin DE. A wildfire risk assessment framework for land and resource management. DoAF Service. Vol. RMRS-GTR-315, Series A wildfire risk assessment framework for land and resource management. Rocky Mountain Research Station, 2013.
- Thompson MP, Calkin DE. Uncertainty and risk in wildland fire management: A review. *Journal of Environmental Management*, 2011; 92(8):1895–1909.
- Flannigan MD, Krawchuk MA, de Groot WJ, Wotton BM, Gowman LM. Implications of changing climate for global wildland fire. *International Journal of Wildland Fire*, 2009; 18:483–507.
- Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB. Human influence on California fire regimes. *Ecological Applications*, 2007; 17(5):1388–1402.
- Keeley J, Fotheringham CJ. Impact of past, present, and future fire regimes on North American mediterranean shrublands. Pp. 218–262 in Veblen T, Baker W, Montenegro G, Swetnam TW (eds). *Fire and Climatic Change in Temperate Ecosystems of the Western Americas*. New York: Springer-Verlag, 2003.
- Stephens SL. Forest fire causes and extent on United States Forest Service lands. *International Journal of Wildland Fire*, 2005; 14(3):213–222.
- Parks SA, Parisien M-A, Miller C. Spatial bottom-up controls on fire likelihood vary across western North America. *Ecosphere*, 2012; 3(1):1–12.
- Bar Massada A, Syphard AD, Hawbaker TJ, Stewart SI, Radeloff VC. Effects of ignition location models on the burn patterns of simulated wildfires. *Environmental Modelling & Software*, 2011; 26(5):583–592.
- Yang J, He HS, Shifley SR. Spatial controls of occurrence and spread of wildfires in the Missouri Ozark highlands. *Ecological Applications*, 2008; 18(5):1212–1225.
- Carmel Y, Paz S, Jahashan F, Shoshany M. Assessing fire risk using Monte Carlo simulations of fire spread. *Forest Ecology and Management*, 2009; 257:370–377.
- Moreira F, Catry FX, Rego F, Bacao F. Size-dependent pattern of wildfire ignitions in Portugal: When do ignitions turn into big fires? *Landscape Ecology*, 2009; 2010(25):1405–1417.
- Sturtevant BR, Cleland DT. Human and biophysical factors influencing modern fire disturbance in northern Wisconsin. *International Journal of Wildland Fire*, 2007; 16(4):398–413.
- Krawchuk MA, Cumming SG, Flannigan MD, Wein RW. Biotic and abiotic regulation of lightning fire initiation in the mixedwood boreal forest. *Ecology*, 2006; 87(2):458–468.
- Veblen TT, Kitzberger T, Donnegan J. Climatic and human influences on fire regimes in ponderosa pine forests in the Colorado Front Range. *Ecological Applications*, 2000; 10(4):1178–1195.
- Syphard AD, Radeloff VC, Hawbaker TJ, Stewart SI. Conservation threats due to human-caused increases in fire frequency in mediterranean-climate ecosystems. *Conservation Biology*, 2009; 23(3):758–769.
- Cardille JA, Lambois M. From the redwood forest to the gulf stream waters: Human signature nearly ubiquitous in representative us landscapes. *Frontiers in Ecology and the Environment*, 2009; 8(3):130–134.
- Cohen J. The wildland-urban interface fire problem. *Fremon-tia*, 2010; 38(2,3):16–22.
- Menakis JP, Cohen J. Mapping wildland fire risk to flammable structures for the conterminous United States. In *Proceedings of Fire Conference 2000: The First National Congress on Fire Ecology, Prevention, and Management* Tallahassee, FL: Tall Timber Research Station, 2003.
- Carmel Y, Paz S, Jahashan F, Shoshany M. Assessing fire risk using Monte Carlo simulations of fire spread. *Forest Ecology and Management*, 2009; 257(1):370–377.
- Tymstra C, Bryce RW, Wotton BM, Taylor SW, Armitage OB. Development and Structure of Prometheus: The Canadian Wildland Fire Growth Simulation Model. Report No.: NOR-X-417. Edmonton, Alberta, Canada: Natural Resources Canada, 2010.
- Finney MA, McHugh CW, Grenfell IC, Riley KL. A simulation of probabilistic wildfire risk components for the continental United States. *Stochastic Environmental Research and Risk Assessment*, 2011; 25(7):973–1000.
- Finney M, Grenfell I, McHugh CW, Seli R, Trethewey D, Stratton R, Brittain S. A method for ensemble wildland fire simulation. *Environmental Modeling and Assessment*, 2011; 16(2):1–15.
- Calkin DE, Thompson MP, Finney MA, Hyde KD. A real-time risk-assessment tool supporting wildland fire decision-making. *Journal of Forestry*, 2011; 109(5):274–280.
- Atkinson D, Chladil M, Janssen V, Lucieer A. Implementation of quantitative bushfire analysis in a GIS environment. *International Journal of Wildland Fire*, 2010; 19:649–658.
- Thompson MP, Scott J, Kaiden JD, Gilbertson-Day JW. A polygon-based modeling approach to assess exposure of resources and assets to wildfire. *Natural Hazards*, 2013; 67(2):627–644.
- Ager AA, Buonopane M, Reger A, Finney MA. Wildfire exposure analysis on the national forests in the Pacific Northwest, USA. *Risk Analysis*, 2013; 33(6):1000–1020.
- Butler BJ. Family forest owners of the United States, 2006. USDA Forest Service. Series Family Forest Owners of the United States, 2006. Newtown Square, PA: Northern Research Station, 2008.
- Calkin DE, Cohen JD, Finney MA, Thompson MP. How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proceedings of the National Academy of Sciences*, 2014; 111(2):746–751.
- Landscan ORNL. 2008 High Resolution Population Distribution model. in L UT-Battelle (eds). Series Landscan 2008 High Resolution Population Distribution Model. Oak Ridge, TN: 2008.
- Calkin DE, Ager AA, Gilbertson-Day J. Wildfire Risk and Hazard: Procedures for the First Approximation. Report No.: RMRS-GTR-235. Fort Collins, CO: U.S. Department of Agriculture. Forest Service, Rocky Mountain Research Station, 2010.

35. Thompson MP, Calkin DE, Finney MA, Ager AA, Gilbertson-Day JW. Integrated national-scale assessment of wildfire risk to human and ecological values. *Stochastic Environmental Research and Risk Assessment*, 2011; 25:761–780.
36. Graham RT. Hayman Fire Case Study: Summary. US Department of Agriculture Forest Service. Series Hayman Fire Case Study: Summary. Fort Collins, CO: Rocky Mountain Research Station, 2003.
37. Theobald DM, Romme WH. Expansion of the US wildland–urban interface. *Landscape and Urban Planning*, 2007; 83(4):340–354.
38. Graham R, Finney M, McHugh C, Cohen J, Calkin D, Stratton R, Bradshaw L, Nikolov N. Fourmile Canyon Fire Findings. US Department of Agriculture Forest Service. Series Fourmile Canyon Fire Findings. Fort Collins, CO: Rocky Mountain Research Station, 2012.
39. Finney MA. An overview of FlamMap fire modeling capabilities. Pp. 213–220 in Andrews PL, Butler BW (eds). *Fuels Management—How to Measure Success: Conference Proceedings*. March 28–30, 2006, Portland, OR. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 2006.
40. Finney MA. Fire growth using minimum travel time methods. *Candian Journal of Forest Research*, 2002; 32(8):1420–1424.
41. Scott J, Reinhardt E. Assessing crown fire potential by linking models of surface and crown fire behavior. P. 59 in US Department of Agriculture Forest Service. Series *Assessing Crown Fire Potential by Linking Models of Surface and Crown Fire Behavior*. Fort Collins, CO: Rocky Mountain Research Station, 2001.
42. Finney M, Grenfell IC, McHugh CW. Modeling containment of large wildfires using generalized linear mixed-model analysis. *Forest Science*, 2009; 55(3):249–255.
43. Rollins MG, Frame CK. The landfire prototype project: Nationally consistent and locally relevant geospatial data for wildland fire management. US Department of Agriculture Forest Service. General Technical Report. Series *The Landfire Prototype Project: Nationally Consistent and Locally Relevant Geospatial Data for Wildland Fire Management*. Fort Collins: Rocky Mountain Research Station, 2006.
44. Ryan KC, Opperman TS. Landfire—A national vegetation/fuels data base for use in fuels treatment, restoration, and suppression planning. *Forest Ecology and Management*, 2013; 294:208–216.
45. Short K. Spatial wildfire occurrence data for the United States, 1992 – 2011 [fpa_fod.20130422]. in Rocky Mountain Research Station (ed). *Series Spatial Wildfire Occurrence Data for the United States, 1992–2011* [fpa_fod.20130422]. Fort Collins, CO: USDA Forest Service; 2013.
46. Berman M, Diggle P. Estimating weighted integrals of the second-order intensity of spatial point patterns. *Journal of the Royal Statistical Society*, 1989; 51(1):81–92.
47. Stewart SI, Wilmer B, Hammer RB, Aplet GH, Hawbaker TJ, Miller C, Radeloff VC. Wildland-urban interface maps vary with purpose and context. *Journal of Forestry*, 2009; 107:78–83.
48. Hogland JS, Anderson NM, Jones JG. Function modeling: Improved raster analysis through delayed reading and function raster datasets. In *Proceedings of the 36th Annual Meeting of the Council on Forest Engineering*, July 8–10, 2013 Missoula, MT: Council on Forest Engineering. Available at: http://web1.cnre.vt.edu/forestry/cofe/documents/2013/Hogland.Anderson_Jones.pdf.
49. Fischer AP, Kline JD, Ager AA, Charnley S, Olsen KA. Objective and perceived wildfire risk and its influence on private forest landowners' fuel reduction activities in Oregon's (USA) ponderosa pine ecoregion. *International Journal of Wildland Fire*, 2014; 23(1):143–153.
50. McCaffrey S, Stidham M, Toman E, Shindler B. Outreach programs, peer pressure, and common sense: What motivates homeowners to mitigate wildfire risk? *Environmental Management*, 2011; 48(3):475–488.
51. Rogers RW. Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation. Pp. 153–176 in Cacoppo J, Petty R (eds). *Social Psychophysiology: A Sourcebook*. New York: Guilford Press, 1983.
52. Finney MA. A computational method for optimising fuel treatment locations. *International Journal of Wildland Fire*, 2007; 16:702–711.
53. Yao J, Henderson SB. An empirical model to estimate daily forest fire smoke exposure over a large geographic area using air quality, meteorological, and remote sensing data. *Journal of Exposure Science & Environmental Epidemiology*, 2014; 24(3):328–335.