

Research paper

A national approach for integrating wildfire simulation modeling into Wildland Urban Interface risk assessments within the United States



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HIGHLIGHTS

- Employs a probabilistic exposure analysis to identify the likelihood of populated places interacting with wildfire.
- Classified at-risk areas according to a risk matrix comprised of population density and burn probability categories.
- Risk matrix allows planners and managers a quick way to identify where the risk is located spatial, and to qualify the driving factors of the risk (population or burn probability or both).
- Suggests a number of ways that managers and planners can use this information for decision-making, fuels modifications and residential planning.

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ABSTRACT

Ongoing human development into fire-prone areas contributes to increasing wildfire risk to human life. It is critically important, therefore, to have the ability to characterize wildfire risk to populated places, and to identify geographic areas with relatively high risk. A fundamental component of wildfire risk analysis is establishing the likelihood of wildfire occurrence and interaction with social and ecological values. A variety of fire modeling systems exist that can provide spatially resolved estimates of wildfire likelihood, which when coupled with maps of values-at-risk enable probabilistic exposure analysis. With this study we demonstrate the feasibility and utility of pairing burn probabilities with geospatially identified populated places in order to inform the development of next-generation, risk-based Wildland-Urban Interface (WUI) maps. Specifically, we integrate a newly developed Residentially Developed Populated Areas dataset with a stochastic, spatially-explicit wildfire spread simulation model. We classify residential population densities and burn probabilities into three categories (low, medium, high) to create a risk matrix and summarize wildfire risk to populated places at the county-level throughout the continental United States. Our methods provide a new framework for producing consistent national maps which spatially identifies the magnitude and the driving factors behind the wildland fire risk to populated places. This framework advances probabilistic exposure analysis for decision support in emergency management, rural and urban community planning efforts, and more broadly wildfire management and policy-making.

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1. Introduction

Human development and public safety are threatened when wildfires burn in proximity to populated communities. Many fires in the United States over the last decade have caused significant residential property loss, most recently the Waldo Canyon (2012) and Black Forest (2013) fires proximal to Colorado Springs, CO which resulted in 507 and 346 primary residences destroyed respectively.

Wildfires can further, in tragic circumstances, lead to fatalities, for instance 14 deaths were associated with the 2007 Southern California fires. Fatalities and property loss from wildfire are certainly not isolated to the US, for instance the 2009 Black Saturday bushfire events in Australia resulted in 173 fatalities, 414 injuries and over 2000 homes destroyed. Given the potential for highly adverse consequences, it is critical for planners and managers to have the ability to characterize wildfire risk to populated places, and to identify geographic areas with relatively high risk (Murnane, 2006). Identifying high risk communities can help prioritize areas for risk mitigation efforts to reduce the likelihood of residential disasters. Reducing wildfire risk can in turn translate to reduced risk to the public and to firefighters, whose safety is the highest priority guiding federal wildfire management and incident response.

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Table 1
Federal Register WUI Community Definition.

Urban wildland interface community definition			
Category	Structures per acre	Population density: people per square mile	Description
Interface	"usually" ≥ 3 (with shared municipal services)	≥ 250	<ol style="list-style-type: none"> 1. Where structures directly abut wildland fuels 2. There is a clear line of demarcation between structures and wildland fuels; wildland fuels do not generally continue into the developed area. 3. Fire protection is generally provided by a local government fire department with the responsibility to protect the structure from both an interior fire and an advancing wildland fire.
Intermix	$\geq 1/40$ acres (from 1 per 40 acres to "very close together")	28–250	<ol style="list-style-type: none"> 1. Where structures are scattered throughout a wildland area 2. No clear line of demarcation; wildland fuels are continuous outside of and within the developed area. 3. Fire protection districts funded by taxing authorities normally provided life and property fire protection and may also have wildland fire protection responsibilities.
Occluded	The development density for an occluded community is usually similar to those found in the interface community, but the occluded area is usually less than 1000 acres in size	<ol style="list-style-type: none"> 1. Where structures abut an island of wildland fuels, often within a city (park or open space). 2. There is a clear line of demarcation between structures and wildland fuels. 3. Fire protection is normally provided by local government fire departments. 	

Adapted from Mell et al. (2010).

The wildland urban interface (WUI) is defined as "the area where structures and other human developments meet or intermingle with undeveloped wildlands" (USDA & USDI, 2001). This definition has been further divided into subcategories based on structure and/or population density and their location within or proximate to wildland fuels (Table 1). Even though the Federal Register defines a community to be at risk to wildland fire if it resides within the WUI, there is no criteria for a measure of exposure or fire likelihood (Mell, Manzello, Maranghides, Dutry, & Rehm, 2010), a key component in a risk assessment.

Wildfire risk can be characterized as a composite function of fire likelihood, fire intensity, and fire effects (Finney, 2005). That is, a wildfire risk assessment considers both the probability and magnitude of wildfire-related impacts. This definition is consistent with classical economic theory (Knight, 1921) as well as with contemporary ecological risk assessment frameworks (Thompson & Calkin, 2011). In broad terms the primary analytical components of wildfire risk are exposure analysis and effects analysis. Wildfire exposure analysis is premised on the integration of maps of resources and assets (in this case human communities) with wildfire modeling outputs (Ager, Buonopane, Reger, & Finney, 2013; Salis et al., 2012; Scott, Helmbrecht, Thompson, Calkin, & Marcille, 2012a). Exposure is often quantified in terms of burn probability (BP), where BP represents the likelihood of a given location experiencing wildfire during a defined period of time. Our focus in this manuscript is incorporating risk-based information into WUI mapping products, thereby advancing probabilistic exposure analysis for decision support in emergency management, rural and urban community planning efforts, and more broadly wildfire management and policy-making.

1.1. Delineating populated places

Historically, WUI mapping has taken a geospatial approach to identify where people or structures come in contact with potential

fuels and has focused on interacting census-based housing or population data with vegetation mapping (Radeloff et al., 2005; Theobald & Romme, 2007; Wilmer & Aplet, 2005). One of the significant limitations identified with the census-based approach occurs where public lands are included within a census block resulting in large, sparsely settled areas where the housing density may be too low to be considered WUI, even when a small cluster of homes is surrounded by uninhabited public lands (Stewart et al., 2009). Bar Massada, Radeloff, Stewart and Hawbaker (2009) addressed the problem of large census blocks resulting in coarse resolution of housing data in rural, northern Wisconsin by manually digitizing individually built structures from aerial photographs for their study area. However, mapping structures at a national level through the use of aerial photography would be very time-intensive and can lead to large inaccuracies, especially in areas of dense canopy coverage, and therefore to date no such dataset exists nationally. Dasymetric mapping, a technique in which population data that is organized by a large or arbitrary area unit (e.g. census block) can be more accurately distributed within that unit through the use of overlays of other geographic boundaries, has been demonstrated to address these issues (Theobald & Romme, 2007). The overlay boundaries exclude, restrict, or confine the population to the most appropriate locations and commonly consist of uninhabitable data layers, including water bodies, steep slopes and protected areas such as National Parks.

LandScan USATM (Bhaduri, Bright, Coleman, & Urban, 2007) is a nationally consistent population dataset which employs dasymetric mapping to further locate populations within a census block. This dataset utilizes information on various geographic layers, including structure locations where available, to map people in their nighttime residential locations at a 90 meter scale nationwide, and is further discussed in the methods section. We utilize this dataset as our population layer due to its national coverage, fine scale resolution, and its ability to match populations with their residential homes.

1.2. Incorporating risk-based information into WUI mapping

WUI maps present a geospatial delineation of where vegetation is coincident with human development, which is a clear baseline for informing wildland fire and fuels management to protect human life and property. Although some may have used WUI maps as a proxy for hazard or risk, this use is not consistent with their intended purpose and such use is limited by the fact that vegetation presence confers little information on the propensity for fire ignition, spread, or intensity. The need for information on topological fire spread across landscapes is especially important because the spread of large fires, rather than localized ignitions, account for the majority of area burned within the United States, and therefore contribute the most to burn probabilities (Calkin, Gebert, Jones, & Neilson, 2005; Short, 2013; Strauss, Bednar, & Mees, 1989).

In the absence of nationally consistent burn probability datasets, many authors have relied on various proxies to assess wildland fire risk to human populations at local to regional scales. These early efforts focused on creating a link between land cover types and historical fire regimes (Haight, Cleland, Hammer, Radeloff, & Rupp, 2004; Menakis, Cohen, & Bradshaw, 2003; Theobald & Romme, 2007). However, these methods did not account for variations in topography, fire spread rates, or fire likelihood. Gaither, Poudyal, Goodrick, Bowker, Malone and Gan (2011) and Poudyal, Johnson-Gaither, Goodrick, Bowker and Gan (2012) relied on a raster-based index of wildfire potential that does incorporate some of this information, but the index is not truly probabilistic and is not based on explicit representation of topographic fire spread.

Other efforts however have generated spatially resolved estimates of wildfire likelihood (Ager, Valliant, & Finney, 2010; Atkinson, Chladil, Janssen, & Lucieer, 2010; Bar Massada et al., 2009). These studies used alternative methods to interact fine scale data representing human development with simulated likelihood of wildfire to develop risk-based WUI maps. Although these approaches provide improved understanding of WUI exposure compared with vegetation-based mapping, the data needs are such that the methods have not yet been able to provide the detail and consistency necessary for national scale exposure and risk assessments. Similarly, the Wildland Fire Decision Support System (WFDSS) overlays wildfire spread probability contours with structure location data derived from cadastral data (data that spatially delineates the ownership, value and extent of lands for taxation purposes), thereby providing rapid probabilistic exposure analysis for ongoing incidents (Calkin, Thompson, Finney, & Hyde, 2011). Although WFDSS is a nationally supported model, a unified national cadaster does not exist (approximately 70 percent of the cadastral data for the Western US is maintained within WFDSS).

Recent advancements in computational power and wildfire modeling efficiency using the Minimum Travel Time (MTT; Finney, 2002) algorithm, as well as investment in the nationally consistent fuels LANDFIRE dataset (Rollins & Frame, 2006), enable probabilistic wildfire behavior models that can represent the likelihood and expected intensity of wildfires at fine resolution across broad scales. The large fire modeling system FSim, enables prospective assessment of wildfire likelihood and behavior (Finney, McHugh, Grenfell, & Riley, 2011a), with increasing applications for a variety of purposes and across a variety of planning scales (Scott et al., 2012a; Scott, Helmbrecht, Parks, & Miller, 2012b; Thompson, Scott, Helmbrecht, & Calkin, 2012; Thompson, Valliant, Haas, Gebert, & Stockmann, 2012). FSim utilizes LANDFIRE fuels and the MTT algorithm to spatially simulate large fire growth across a landscape. This model captures the spatial and temporal variability in weather, fire ignitions, and fuels to generate burn probabilities and fireline intensities for the contiguous land area of the United States, by simulating tens of thousands of fire seasons. This model is similar to the “randig” model implemented by Ager et al. (2010). While

Table 2

A list of commonly used acronyms.

Acronym	Definition
BP	Burn Probability as output from FSim
FPU	Fire Planning Unit
FSim	Large fire simulator model
PAD	Protected Areas Dataset
RDPA	Residentially Developed Populated Areas
RPP	Risk to Populated Places
SILVIS WUI(3)	WUI datasets developed by the SILVIS lab in Wisconsin
WUI	Wildland Urban Interface

both FSim and randig use the same random ignition process and MTT algorithm for fire growth, randig only simulates a single burn period, typically 8 hours, with constant weather, while FSim simulates multiple burn periods over days or weeks and changing weather scenarios obtained from historical weather records. This enables the simulation of fire growth from ignition to containment, and captures the variability in burning conditions.

FSim outputs are calibrated to historical data on the basis of mean annual burn probability and fire size-frequency distributions, and enable the first consistent dataset of fire likelihood needed for a national-scale exposure risk assessment. Thompson, Calkin, Gilbertson-Day and Ager (2011) demonstrated a proof-of-concept risk assessment that considered risk to several human and ecological values, utilizing the outputs from FSim. The authors integrated LandScan USA 2006 population data with the FSim burn probabilities to assess the risk to population from wildland fires. We further these efforts by refining the methods and including population density information to locate and quantify wildland fire exposure to populated areas.

Within this paper we propose and implement new methods to conduct standardized national assessment and characterization of Wildfire Risk to Populated Places (RPP) within the continental United States. We recognize that this map is not truly a quantification of “risk” since the effects of wildfire are not estimated (e.g. many structures within wildfire perimeters are not destroyed), but rather integrates and characterizes spatially explicit risk-based information. Specifically we employ probabilistic exposure analysis to identify the likelihood of populated places interacting with wildfire, and classify at-risk areas according to a risk matrix comprised of population density and burn probability categories. To do so we geospatially overlay a modification of the LandScan 2009™ USA dataset with simulated burn probabilities from the large fire simulator, FSim. The coupling of burn probability modeling with population mapping can form the basis for next generation WUI products, which could inform and facilitate fuels reduction prioritization and planning efforts. We present national-scale results, drill-down to a few selected areas to compare and contrast our results with existing methods, and present recommendations for implementation and future refinement. In particular we stress the importance of moving beyond the use of flammable vegetation as a proxy for wildfire hazard, highlight the potential benefits of incorporating spatially resolved data on wildfire likelihood and behavior, and more accurately reflect the highest priorities of federal wildfire management. Given the large number of acronyms used throughout the paper, we provide a list of the most commonly used acronyms and their definition in Table 2.

2. Methods

2.1. Geospatial identification of populated areas

We used the 2009 LandScan USA™ 3 arc-second (~90 m²) nighttime residential population distribution dataset (Oak Ridge National Laboratory, 2008) as our population layer. The nucleus

of this dataset is the census block population data. However, as already discussed, the population within a census block polygon is likely to be clustered rather than evenly distributed, particularly in rural areas. Therefore, LandScan USA™ (here in known as LandScan) uses “Intelligent” dasymetric modeling to further refine the distribution of the population for each polygon (Bhaduri et al., 2007). Rather than evenly distributing the population throughout the census block, the LandScan algorithm divides each polygon into a 1 arc-second grid and distributes the total block population to the grid cells according to weights proportional to the calculated likelihood of being populated. The likelihood of being populated is based on proximity to landmarks and geographic features such as roads and water bodies, as well as geologic features such as slope. Where available, structure location data was also incorporated into this methodology for the release of the LandScan dataset (Dr. Budhendra Bhaduri (ORNL), personal communication, April 2010). These statistical models are further improved through analyst intervention to validate input data and parameters. The sum of the population of all cells within a census block is constrained to equal that of the census block in order to maintain the integrity of the census data. After the calculations are performed, the 1 arc-second grids are aggregated up to the 3 arc-seconds product. This product is in a geographic projection which is not appropriate for density calculations since the area of these latitudinal and longitudinal cells will vary depending on distance from the equator. In order to maintain the population of the dataset, we converted the center of each cell to a point attributed with the corresponding population counts. We then projected these points to Alber's equal area projection, and created a grid which represented the summed population of all points falling within an equal area cell. The resulting 90 m² dataset (~3 arc-seconds) is appropriate for population density calculations, since each cell represents the same area of land.

We used a smoothing filter to distribute the population in all directions to conservatively identify the lands that are most likely to have people and residential structures located on them. We used a Gaussian filter, which allows the center pixel of a moving window filter to contribute the most weight to the new output value, while the pixels farthest away contribute the least. The Gaussian filter takes the following form:

$$f(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

where x is the distance from the center pixel in the horizontal axis and y is the distance from the focal pixel in the vertical axis, and σ is the standard deviation of the Gaussian distribution. Theoretically, the Gaussian filter requires an infinite window size; however, the function decays rapidly toward zero, allowing a simple rectangular filter to approximate the function. For this study we used a 2070 meter (23 pixels) by 2070 meter square filter which equates to approximately a 1 km radius from the central pixel. This gradient takes advantage of the resolution and spatial configuration of the LandScan population dataset while creating a conservative buffer to account for dispersed populations and residential structures.

Finally, we used the population sum within each 270 m pixel to aggregate the 90 m smoothed dataset up to match the resolution of the national LANDFIRE fuels dataset used in the fire behavior modeling as described below. This method maintains the overall population of the contiguous US, within rounding. We termed this smoothed population density dataset “Residentially Developed Populated Areas” (RDPA) with units being people per 7.29 ha, the areal unit corresponding to one pixel.

Using similar population density ranges to the Federal Register WUI categorization (Table 1), we divided the RDPA into three categories population categories:

Low: 0.01–0.8 people per 7.29 ha
 Medium: 0.8–7.0 people per 7.29 ha (Same as Intermix)
 High: >7.0 people per 7.29 ha (Same as Interface).

The federal register places the lower limit of WUI to be 28 people per square mile (2.6 km² or 0.8 people per 270 m pixel). We retained a lower category in addition to the federal registrar definitions to account for isolated islands of RDPA which may fall below the density criterion due to the filtering process outlined above.

Recognizing that a complete pixel by pixel validation of a national map is difficult, if not impossible (if there were an error-free national map of populated places against which to compare, there would not be a need for this undertaking), it is still informative to investigate the fidelity and utility of our RDPA dataset at more local scales. Therefore we review a case study that compares and contrasts our RDPA dataset with one of the most commonly used WUI maps, the SILVIS WUI product (Radeloff et al., 2005). The SILVIS WUI product overlays census block housing densities with vegetation data from the National Land Cover Dataset (NLCD) to delineate the various WUI categories. Using dasymetric mapping, SILVIS recently updated their WUI maps to a new product called SILVIS WUI3 (http://silvis.forest.wisc.edu/maps/wui3/wui3_sample_metadata.xml). This product integrates a single predictor of where population is likely to reside within a census block: the Protected Area Database (PAD) (DellaSala, Staus, Strittholt, Hackman, & Lacobelli 2001). They used the PAD information to exclude the population from being located within a census block where development is prohibited by land designation, and delineate these areas as non-WUI. Additionally, this product excludes census blocks with a very low population density from the final WUI classification. This differs from LandScan method which uses multiple overlays in the dasymetric process.

In order to be able to perform a direct comparison of the three datasets (RDPA, SILVIS WUI and SILVIS WUI3), we integrated the RDPA dataset the flammable fuels categories from the LANDFIRE (Rollins & Frame, 2006) Fire Behavior Fuel Model 40 (FBFM40) layer to spatially delineate the WUI. We used the LANDFIRE fuel model layer, rather than the NLCD vegetation layer, because the LANDFIRE fuel model layer is the basis for the FSim modeling, described below. This fuels layer follows descriptions of surface fuels as delineated by Scott and Burgan (2005). All fuel classes are considered flammable fuels except the Non-burnable fuels category described in the LANDFIRE FBFM40 layer metadata. We mapped a pixel as WUI when it met both of the following criteria:

- 1) RDPA above 0.01 people per 7.29 ha and
- 2) Presence of a flammable fuel category

Two of the FBFM40 fuel categories were not mapped as WUI due to being un-inhabitable: water and snow/ice, and were therefore masked out of the RDPA creation. The urban, agricultural and barren fuel categories are considered non-burnable fuel models due to the lack of vegetation or presence of irrigation.

2.2. Wildfire simulation and burn probability modeling

Burn probabilities are the spatially explicit likelihood of fire (Parisien, Miller, Ager, & Finney, 2010), which we obtained from the fire simulation model FSim (Finney, Grenfell, et al., 2011b). Finney, McHugh, et al. (2011a) simulated fire ignition and growth for 10,000–50,000 annual weather scenarios for each of 134 separate land areas (Fire Planning Units or FPU) of the US. Aggregating these simulation results leads to spatially resolved estimates of burn probability for the entire United States. As a brief summary of the simulation process, four modules of the FSim program are used to simulate burn probabilities: weather, fire occurrence, fire

growth and fire suppression. The simulation begins with analysis of weather station data from each FPU to produce an autoregressive model of daily and seasonal fuel moisture variation as expressed by a fire danger rating index. In addition to fuel moisture variation, the weather analysis tabulates wind speed and direction probabilities by month for each FPU in the United States from National Fire Danger Rating System (NFDRS) Remote Automated Weather Stations (RAWS) (Zachariasson, Zeller, Nikolov, & McClelland, 2003; <http://www.fs.fed.us/raws>). The autoregressive fuel moisture model generates the thousands of years of artificial time-series of fuel moisture variation that capture the statistical characteristics of fuel moisture trends. This index is highly predictive of fire occurrence (Andrews, Loftsgaarden, & Bradshaw, 2003), and historical fire records are used to produce a logistic model of daily large fire occurrence probability in each FPU using the index as the independent variable. The historical fire occurrence data is also used to create ignition density grids that indicate the relative probability of a wildfire occurring across the fire modeling landscape. Thus, where historical ignition patterns reflect anthropogenic influences, this will be captured in the ignition density grid. For each simulated day, FSim first estimates the number of large fire ignitions according to a logistic regression model, and then ignitions are probabilistically located according to the ignition density grid. Fire growth and containment are then simulated through time, driven by the landscape characteristics and the simulated weather conditions.

We established a lower limit for burn probabilities to account for probabilities that were not statistically different from zero due to the nature of the FSim model. The lower confidence interval ($z = 1.96$) for a given sample of 10,000 fire years is not statistically significantly different from zero until you reach a burn probability of 0.0004 (4 fires in 10,000 years). Even at this probability, the lower confidence interval is only marginally higher than zero. Therefore, we selected a burn probability of 0.0005 (5 fires in 10,000 years) as our lowest acceptable burn probability.

We classified burn probability by fire return interval into three classes: Low (1 fire/2000 yrs – 1 fire/100yrs.), Medium (1 fire/100 yrs – 1 fire/50 yrs) and High (greater than 1 fire/50 yrs). This resulted in a burn probability classification scheme of:

0.0005	≤	BP _{low}	≤	0.01
0.01	<	BP _{medium}	≤	0.02
0.02	<	BP _{high}		

2.3. Probabilistic exposure analysis and integration with RDPA

The interaction of the aforementioned Residentially Developed Populated Areas classes and the burn probability classes yields a 10 class risk matrix which can be used to summarize wildland fire risk to populated places (Fig. 1). For further classification we define “elevated risk” to comprise the four risk categories with Medium to High RDPA and Medium to High BP. The tenth class corresponds to no risk due to unpopulated areas, unburnable fuels, or both. Through the use of our risk matrix, we are able to determine not only the areas of high risk, but also the underlying factors that are driving risk (population densities and burn probabilities).

3. Results

We examined the geospatial delineation of the WUI in Oregon, where there are a large number of communities in fire prone areas. The census block based SILVIS WUI delineates 554,419 ha of WUI (Fig. 2) in Grant County Oregon, while Deschutes County contains 237,247 ha. Using this SILVIS product, managers would find that Grant County has approximately two times as many hectares of WUI than Deschutes County. Conversely, when the census blocks

RPP	Low RDPA	Medium RDPA	High RDPA	Un-populated
Low tBP				NO RISK
Medium tBP				
High tBP				
Unburnable	NO RISK			

Fig. 1. 10 Class Risk Matrix. Green, yellow and red distinguish across low, medium and high population density levels, respectively. (Colors presented for viewing with Fig. 3). Within a population density level, color intensity increases as total burn probability (tBP) increases.

are refined to better reflect where the population resides within the block, a different picture emerges. Using the SILVIS WUI3 dataset had the effect of reducing the total hectares of WUI to 66,681 ha in Deschutes Co and to 4186 ha in Grant County, resulting in Deschutes County containing almost 15 times more hectares of WUI than Grant County. In this new dataset, large census blocks which contain a residential population may fall out of the WUI classification due to being very sparsely populated, especially in census blocks with no protected area. We maintained a low density RDPA classification to capture the sparsely populated areas, including the populations associated with the large census blocks. Using the RDPA method, Deschutes County contains only twice as many hectares of WUI than Grant County (113,761 ha and 50,163 ha respectively). All three datasets produced similar spatial configuration of WUI, however, the dasymmetrically delineated WUI products (RDPA and SILVIS WUI3) produce opposite results in terms of the relative ratios of the hectares in comparison to the standard census block approach (SILVIS WUI). This is mainly due to the large census blocks of Grant County relative to Deschutes County. By retaining the lower population density category, the RDPA still produced a more conservative delineation of WUI acres when compared to SILVIS WUI, however, unlike SILVIS WUI3, RDPA allows for sparsely populated areas to be included.

3.1. Spatial distribution of risk to populated places for the continental US

LandScan USA bases total US population on projections from the 2000 Census results (305,012,899 people). Of this population, we found 13% (39,981,060 people) of the population to be at risk to wildland fire. Table 3 shows the number of people and the relative percentage of the at-risk population, sorted by each risk category. The majority of the at-risk population lies within the low BP, high RDPA category (60%). Isolating burn probability (BP), 78.9% of the at-risk population resides in areas of low BP, 12.4% within medium BP, and 8.7% within high BP. With regards to total at-risk population (RDPA), 3.9% lies within low RDPA, 19.8% within medium RDPA, and 76.4% within high RDPA. 20.2% of the at-risk population lies within our defined category of elevated risk.

Table 4 presents area of mapped Risk to Populated Places (RPP), similarly sorted according to risk category. In total we identified 84.8 million hectares of Wildfire Risk to Populated Places. Of that area, the largest share, 47.8%, lies in the low BP, low RDPA category, while only 7.7% of the total area of RPP lies in elevated risk category. Looking at BP, 76.6% of the area is mapped as low BP, 15.5% as medium BP, and 7.8% as high BP. 63.5% of the mapped area occurs

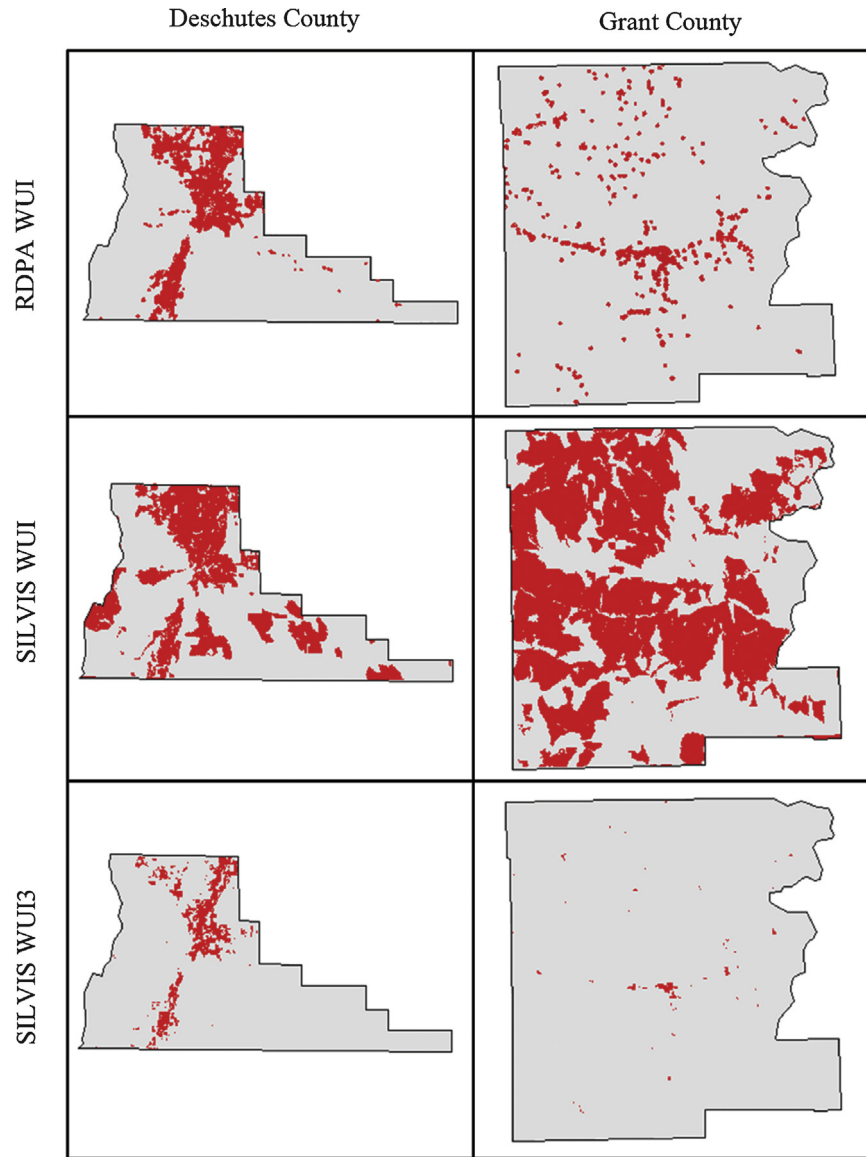


Fig. 2. Comparison of acres of mapped WUI (in dark red) using SILVIS and RDPA/LANDFIRE approaches for Grant and Deschutes Counties, Oregon.

Table 3
Population count by risk category, and relative percentage of total at-risk population.

Population at risk	Low RDPA		Medium RDPA		High RDPA	
	Count	%	Count	%	Count	%
Low BP	1,173,000	2.9%	6,245,700	15.6%	24,126,000	60.3%
Medium BP	244,710	0.6%	1,034,500	2.6%	3,698,400	9.3%
High BP	116,390	0.3%	643,960	1.6%	2,698,400	6.8%

RDPA: Residentially Developed Populated Area; tBP: total Burn Probability.

Table 4
Hectares by risk category, and relative percentage of total area of risk to populated places.

Hectares of risk	Low RDPA		Medium RDPA		High RDPA	
	Ha	% Area	Ha	% Area	Ha	% Area
Low BP	40,532,828	47.8%	18,446,523	21.8%	5,981,202	7.1%
Medium BP	9,123,325	10.8%	3,142,528	3.7%	921,760	1.1%
High BP	4,195,702	4.9%	1,842,427	2.2%	610,986	0.7%

RDPA: Residentially Developed Populated Area; tBP: total Burn Probability.

within low RDPA, 27.6% within medium RDPA, and 8.9% within high RDPA.

By looking at the spatial distribution of RPP (Fig. 3), we found that Southern California, Central California, Central Appalachia and Florida have the highest concentration of elevated risk interaction classes, with isolated pockets of the high interaction classes found throughout the west. The Southern Plains have broad areas of medium to high BP, however the RDPA density is generally low in these areas, and conversely, with the exception of Florida and the eastern seaboard, the southeast has high population densities coupled with low burn probabilities.

We tabulated risk to populated places by county for the continental US. The total percent of a county with risk to populated places varied dramatically across the U.S. from less than 0.01% to 88%, with a mean of 14% and a standard deviation of 19%. Using the Risk Matrix, we can rank counties according to total area of risk, and additionally according to area of elevated risk. Table 5 presents a ranking of the top 25 counties by area at risk, and by area of elevated risk. San Diego, San Bernadino, Riverside, and Los Angeles counties in California, and Pima and Maricopa counties in Arizona, in particular stand out. Four counties in Oklahoma have substantial at-risk area, yet none of these appear in the top 25 list for levels of elevated risk. Conversely, some counties that do not appear in the top 25 list for overall area at risk do show up for elevated risk, for instance Pike county in Kentucky and Parker county in Texas.

Distinguishing on the basis of risk categories and our aggregated class of elevated risk, we further teased out distinctions in relative risk across the nation. For example, while Los Angeles County, CA only has 34% of its total area in a risk category, 14% of its total area lies within elevated risk classes. Conversely, while 71% of Cleveland County, OK area is in a risk category, only 1.5% lies in the elevated risk categories (Table 5). Depending on the needs of policy makers and land managers, the utilization of the risk matrix can identify areas of high concern for wildfire risk to populated places.

4. Discussion

Mapping wildfire risk to human life and development is an integral component of emergency management, wildfire prevention, and preparedness planning. As described in the introduction, existing WUI maps have been used by many in the fire management community to prioritize investments in prevention and mitigation. Often prioritization is based upon simple measures such as acres of mapped WUI. We showed that depending on the population dataset used, the number of acres of mapped WUI can dramatically change. Using daysmetrically delineated population layers greatly reduces the problem of overestimation of WUI acres due to the clustered populations found in otherwise largely un-inhabited large census blocks. However, care must be taken to avoid underestimation of WUI due to actual sparsely populated blocks. Using multiple overlays in the daysmetric mapping process, as employed by LandScan, resulted in a more conservative estimate of WUI acres in areas with large census blocks, without dropping the sparsely populated areas out of the delineation. Future improvements in population mapping will continue to resolve these issues.

Another issue with using acres of WUI as a simple measure for prioritization is that doing so effectively assumes that a) flammable vegetation is a suitable proxy for wildfire hazard, and b) every acre with flammable vegetation is equally likely to burn. We described a proposed methodological improvement to existing methods for risk-based WUI mapping: the use of wildfire simulation models to generate estimates of likely fire occurrence proximal to and/or within populated areas.

Our integration of simulation modeling outputs attempts to account for the variable likelihood of burning, which can greatly

affect estimates of fire risk. In comparison to standard WUI maps that ignore variable probability, our RPP map shows not only where human development and wildland fuels co-occur, but also quantifies the probability of exposure in populated places. The RPP assessment allows managers to simultaneously identify areas of WUI, and prioritize risk reduction programs based on their individual needs. This product also can help avoid the prioritization of areas with broader populated areas but low likelihood of fire over areas where fire is quite likely to reach human development. Through the use of our new risk matrix, we were able to determine not only the areas of high risk, but also what was driving that high risk: high population density, or high burn probability, or both.

This methodological change allows for a nationally consistent dataset of wildfire risk to populated places that is more consistent with existing federal wildland fire policy. Our methodology creates a risk matrix to define wildfire risk to populated places in such a way as to inform federal budgetary allocations and allow planners to prioritize areas for fire risk reduction projects, such as ignition prevention planning, hazardous fuels reduction, prepositioning of firefighting resources, and increased access for firefighting equipment (truck turnarounds, fire hydrants, etc.).

A wide array of rural and urban community planning applications could benefit from the risk matrix and RPP map. Zoning for future housing development could avoid areas of particularly high burn probability, and requirements for homeowners to obtain fire insurance could be instituted. The RPP results could also help target high-risk areas for revising building codes, or for programs to engage and educate homeowners on managing their home ignition zone. A fruitful next step could be to identify communities with particularly high levels of exposure that do not yet have Firewise or similar community programs already implemented.

The methods presented in this article can be scaled down to improve fire planning at the regional, community and local levels. Community Wildfire Protection Plans could greatly be enhanced through the use of this risk-based WUI mapping. Local communities are more likely to have better access to actual structure location data, which can be combined with the population to provide additional information for local planners. Likewise regional planning offices may be able to improve existing fuels layers based upon local knowledge and updated disturbance mapping (Stratton, 2009). Refined information on the causes and spatial patterns of ignitions could similarly help refine fire modeling inputs. Lastly, more detailed analyses could also identify evacuation triggers (Dennison, Cova, & Mortiz, 2007) and potential safety concerns associated with limited egress routes (Cova, Theobald, Norman, & Siebeneck, 2013). Under these circumstances, the methods developed in this article could be employed using the local datasets to refine the Risk to Populated Places maps and subsequently prioritize mitigation activities in accordance with these finer scale maps.

As with any semi-empirical model, fire behavior models, including FSim, come with assumptions and limitations that must be taken into consideration. These models make many simplifications to model fire spread, including the predictions for transitions to crown fires (Opperman, Gould, Finney, & Tymstra, 2006) as well as crown and surface fire rates of spread (Cruz & Alexander, 2010). Additionally, the models are sensitive to data inputs, and improvements in fuels and weather inputs should greatly increase the accuracy of these models, especially at local scales (Atkinson et al., 2010). The use of more process based physical models could improve fire behavior models (Stewart, Radeloff, & Hammer, 2003), however, there is still a need in the research community to improve our understanding of basic physical and chemical properties of fire, such as the fire–fuel interactions of combustion and heat transfer processes (Finney, Cohen, McAllister, & Jolly, 2012). Recent critiques of existing fire modeling systems (Alexander and Cruz, 2011; Mell et al., 2010) all point

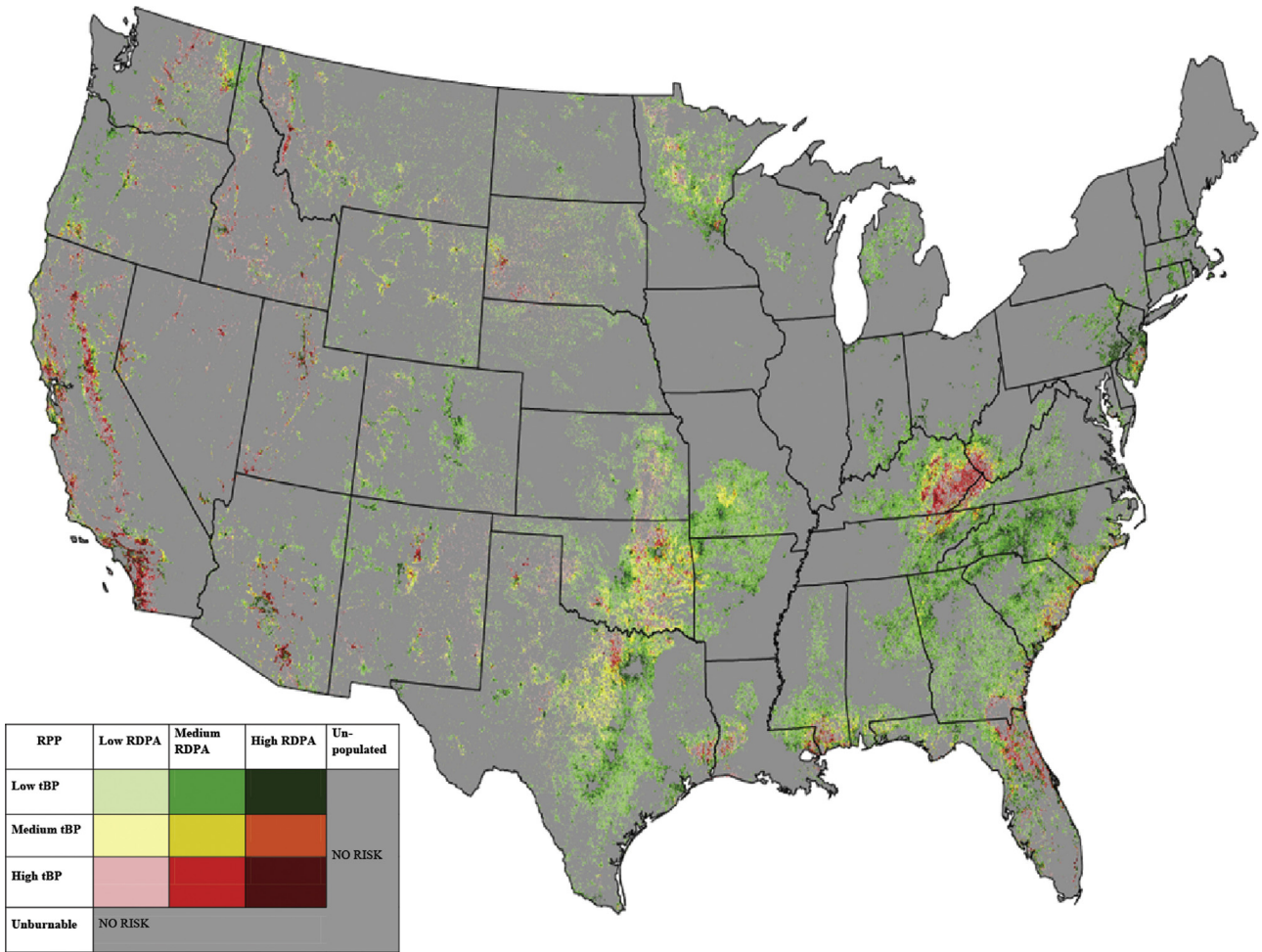


Fig. 3. National map of risk to populated places, sorted by color-coded risk matrix levels.

Table 5

The top 25 counties with the most hectares of RDPA at risk. The left table represents hectares from all risk categories, while the right table shows hectares from the high risk categories.

Overall risk			High risk		
County	State	Hectares risk	County	State	Hectares HIGH risk
San Diego	California	349,078	San Diego	California	201,364
San Bernardino	California	341,709	Riverside	California	173,595
Pima	Arizona	299,655	Pima	Arizona	121,767
Riverside	California	299,247	San Bernardino	California	106,549
Maricopa	Arizona	295,836	Los Angeles	California	97,657
Los Angeles	California	284,860	Maricopa	Arizona	89,538
St. Louis	Minnesota	271,515	Pike	Kentucky	83,787
Cochise	Arizona	255,371	Berkeley	South Carolina	68,117
Yavapai	Arizona	223,462	Parker	Texas	62,221
Mohave	Arizona	210,853	Shasta	California	61,747
El Paso	Colorado	205,766	Wise	Texas	59,823
Shasta	California	195,970	El Dorado	California	57,389
McCurtain	Oklahoma	193,966	San Luis Obispo	California	53,424
Okanogan	Washington	192,005	Laurel	Kentucky	50,691
Mendocino	California	191,772	Floyd	Kentucky	48,133
Osage	Oklahoma	191,729	Butte	California	47,404
Le Flore	Oklahoma	191,473	Pulaski	Kentucky	47,047
Lincoln	Oklahoma	189,520	Okanogan	Washington	44,306
Stevens	Washington	188,529	St. Tammany	Louisiana	43,679
Spokane	Washington	187,042	Charleston	South Carolina	42,572
Washington	Arkansas	184,979	Buchanan	Virginia	42,010
Coconino	Arizona	181,853	Sequoyah	Oklahoma	41,537
San Luis Obispo	California	180,621	Sonoma	California	41,435
Sonoma	California	179,185	Ravalli	Montana	41,281
Texas	Missouri	179,149	Santa Fe	New Mexico	40,698

to a collective need for improved laboratory testing, field study and verification, and incorporation of this information into model refinement and development. Although predicting fire spread is complex and subject to numerous uncertainties, we believe it is critical to account for this component in wildland fire models and risk assessments. This is especially true in the Wildland Urban Interface, where much of the fire risk comes from large fire spread rather than localized ignitions, particularly in the western U.S.

A critical component of any fire modeling effort is transparency in modeling assumptions and uncertainties, as well as justifying the choice of the specific fire behavior model. There is no particular method or modeling system suited for all tasks, and selection therefore depends on model strengths and weaknesses, cost, availability, and how well the model predicts the fire behavior of interest to the end user (Sullivan, 2009). Our aim in this effort was to generate a consistent, national-scale map of risk to populated places, and critical to this effort were spatially resolved estimates of burn probability derived from a model that explicitly simulates fire growth. We therefore opted to use outputs from the FSim simulation model, which provided the primary fire behavior outputs in which we were interested, at the appropriate nation-wide scale. FSim has undergone validation efforts (Finney et al., 2011a), and has been shown to successfully replicate historic patterns of fire occurrence, fire size distributions, and burn probabilities.

Additional research is needed on the effects of firebranding on home ignition to better represent the probability of remote fires igniting in populated areas where the primary fuel source may be residential structures and not wildland fuels. We are concerned primarily with the interaction of burn probabilities with human populations. FSim considers urban areas to be un-burnable; however, structures made of combustible fuels may be ignited by nearby wildland fires through firebrands. Wang (2011) showed that the homes within 300–500 m of the flaming front are most likely to assess damage due to burning firebrands landing on flammable home surfaces or in proximate residential fuels. The fuel type has a significant role in the firebranding potential, and modification of fire branding distances based on fuel type could result in improved model results. Also, studies have found that winds play an important role in home ignition from firebranding, however this study did not take into account a prevailing wind direction, rather it used a set distance to model firebranding. The FSim model is spatially explicit by nature, and the probability of one cell burning is highly correlated with its neighboring cells burning at the same time. Research into structure-to-structure ignition processes, which can play a key role in fire spread, is also recommended (Mell et al., 2010).

5. Conclusions

Developing and employing wildfire risk assessment models can aid management decision-making, and can facilitate prioritization of investments in mitigating losses and restoring landscapes. In order to assess the risk of wildland fire to the WUI, the likelihood of fire occurrence within and proximal to the WUI must be quantified. A major contention of this paper is that next-generation WUI maps incorporating spatial, probabilistic information on the exposure of high values to wildfire are more informative than simpler analyses identifying geographic areas where populated places may or may not interact with wildfire.

By intersecting a new spatially explicit wildfire simulation model with fine scale population data we have created a nationally consistent mapping product that enables the estimation of wildfire risk to populated places. We have demonstrated that this methodology allows for a more informed assessment of relative risk compared with existing national-scale WUI mapping products that do not account for fire likelihood or behavior. These

methods should allow governmental agencies at county, state, and national levels to better assess, prioritize and mitigate wildfire risk to populated places. This framework also provides the potential for future investigations into how factors influencing wildfire occurrence and intensity (e.g., insect and disease, climate change) and human development patterns could affect wildfire risk across geographic regions. Wise application of this framework has the potential to reduce wildfire management cost while improving public and firefighter safety.

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