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RESEARCH ARTICLE

# Can we manage a future with more fire? Effectiveness of defensible space treatment depends on housing amount and configuration

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**Abstract**
*Context* Fire in forested wildland urban interface (WUI) landscapes is increasing throughout the western United States. Spatial patterns of fuels treatments affect fire behavior, but it is unclear how fire risk and fuel treatment effectiveness will change under future conditions.
*Objectives* (1) How do area burned, forest and fuel characteristics, and fire risk change over time under twenty-first-century climate? (2) When defensible space fuels treatments are applied around all houses, which scenarios of WUI housing amount and configuration minimize fire risk?
*Methods* In generic 10,000-ha US Northern Rocky Mountain subalpine forest landscapes, we simulated 21 scenarios differing in fuels treatment, housing amount and configuration (neutral landscape models), and projected future climate using the process-based model iLand. We compared fire risk at three scales: 1-ha home ignition zone (HIZ), 9-ha safe suppression zone (SSZ), and landscape.
*Results* Under warm-dry climate, annual area burned increased, but area burned at high fire intensity peaked in the 2060s and then declined sharply; fire risk followed similar trends. Defensible space treatments maintained low flame lengths in HIZs. Clustered housing was more effective at reducing SSZ risk compared to dispersed housing. At landscape scales, treating more of the landscape reduced fire risk but configuration was unimportant.
*Conclusions* The most effective strategy for reducing fire risk depends on the scale at which risk is assessed. Clustering WUI developments and treating between 10 and 30% of the landscape every 10 years can reduce fire risk across multiple scales.

**Electronic supplementary material** The online version of this article (https://doi.org/10.1007/s10980-020-01162-x) contains supplementary material, which is available to authorized users.

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## Introduction

Human communities in increasingly fire-prone landscapes need to understand and adapt to expected changes in wildfire activity (Moritz et al. 2014; Schoennagel et al. 2017). Defined as the area where

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structures meet or intermingle with wildland vegetation (USDA and USDI 2001; Radeloff et al. 2005), the wildland urban interface (WUI) comprises 10% of the area, one third of the houses, and one third of the population of the conterminous United States (Martinuzzi et al. 2015). However, 69% of the buildings destroyed by wildfire are in the WUI (Kramer et al. 2018). Wildfire in WUI communities in western US forests is increasing due to climate change (Westerling et al. 2006; Abatzoglou and Williams 2016; Westerling 2016), human ignitions (Balch et al. 2017), rapid WUI growth (Radeloff et al. 2018), and, in some forest types, fuel accumulation due to past fire exclusion (Dodge 1972; Graham et al. 2004). Moderate to large increases in fire probability are expected in nearly 40% of existing western US WUI over the next two decades (Schoennagel et al. 2017). It is uncertain whether and how WUI communities can effectively mitigate increases in wildfire risk.

Managing fire-prone WUI communities entails minimizing fire risk to structures (hereafter, "fire risk"), often by removing fuels in the area immediately surrounding a structure (30–60 m radius; NFPA 2018). Maintaining this so-called "defensible space" is considered one of the most effective strategies for preventing structure ignition and subsequent loss (Cohen 2000; Bhandary and Muller 2009; Syphard et al. 2014). Structures can be ignited by direct flame contact, by radiant heat from nearby burning vegetation, or by firebrands, which can travel long distances from high-intensity fire (Cohen 2000; Calkin et al. 2014; Caton et al. 2017). Fuels reduction treatments in the WUI entail removing surface and canopy fuels, which decreases fire intensity (i.e., the energy output of the fire) and spread, and increasing canopy base height, which lowers the likelihood of crown fire initiation (Graham et al. 2004; Agee and Skinner 2005; Reinhardt et al. 2008; Caton et al. 2017). Removing fuels in defensible space therefore reduces the likelihood of structure ignition due to direct flame contact or radiant heat, whereas removing fuels within and near WUI communities reduces firebrand production by reducing fire intensity and size. The effectiveness of fuels reduction in altering fire behavior both locally and within the larger landscape depends on forest type and fire weather (Schoennagel et al. 2004).

Maintaining acceptable levels of fire risk may or may not be possible as climate conditions and fire activity change (Schoennagel et al. 2017). Effects of fuels treatment on fire in forested and WUI landscapes under current conditions are well studied (e.g., Finney et al. 2007; Schmidt et al. 2008; Sturtevant et al. 2009; Ager et al. 2010b; Dicus and Osborne 2015; Barros et al. 2017), but feedbacks among climate, recurring fires, and forest regrowth may alter treatment efficacy in the future. Warmer, drier springs and summers, including prolonged heat waves or drought, deplete fuel moisture over large areas and may lead to increasing fire spread and intensity (Byram 1959; Bessie and Johnson 1995; McKenzie et al. 2004; Littell et al. 2009; Abatzoglou and Williams 2016; Westerling 2016), amplifying fire risk. Alternatively, drier growing season conditions may diminish biomass productivity and reduce fuel loads in some ecosystems (Westerling and Bryant 2008; Moritz et al. 2012). Furthermore, an increase in area burned may consume fuels and thus dampen subsequent fire activity (Stephens et al. 2013; Parks et al. 2015; Romme and Turner 2015). Process-based forest landscape and disturbance simulation models enable exploration of emergent spatiotemporal dynamics among forests, fuels treatments, and fire under novel climate drivers and over decadal time scales (Korzukhin et al. 1996; Seidl et al. 2011; Gustafson 2013; Scholes 2017).

Strategic design and placement of fuels treatments can disrupt fire spread, reduce intensity, and facilitate fire suppression within a landscape (Agee et al. 2000; Finney 2001; Finney et al. 2007). Above a threshold proportion of a landscape (i.e., critical percolation probability; Gardner et al. 1987), randomly placed fuels treatments can form a continuous fire break (Bevers et al. 2004). Previous studies have used relatively simple models to identify spatially optimal fuel treatments for disrupting fire spread given assumptions about fuel treatment effectiveness (e.g., Finney 2007; Wei et al. 2008). These models often examine single fire events under a suite of potential fire start locations and fire weather conditions. However, effects of spatial patterns of fuel treatments on fire behavior remain incompletely understood across multiple fire seasons under simultaneously changing climate and fuel conditions.

Fuel treatments in the WUI need to account for the locations of structures, which may not coincide with the locations of spatially optimal fuel treatments (Bar Massada et al. 2011). The amount and configuration of structures can also affect WUI fire risk (Ager et al.

2010b; Syphard et al. 2012; Alexandre et al. 2016). Lower-density and isolated houses may have a higher probability of being damaged or destroyed by wildfire because houses are embedded within contiguous vegetation and difficult for suppression crews to access (Syphard et al. 2012, 2014, 2019). State and local governments across the western US are seeking land use planning solutions to minimize fire risk in current and future WUI developments (Rasker and Barrett 2016; Steelman 2016).

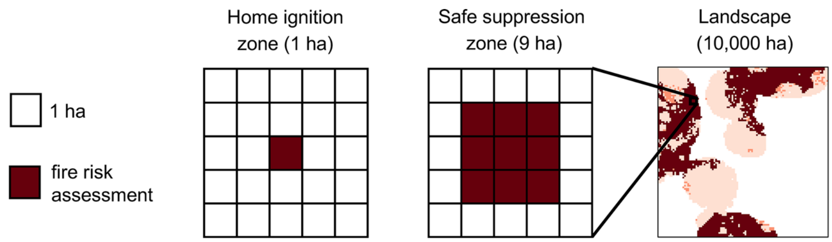
In our study, we used neutral landscape models (NLMs) to evaluate hypothetical scenarios of WUI development. We applied defensible space treatments in the 1-ha area around each home in our simulations, and thus the amount and configuration of WUI housing corresponded to the amount and configuration of fuels treatments. By using NLMs to vary amount and configuration independently, we were able to quantify relationships between landscape pattern of structures (assuming defensible space fuels treatments) and resulting fire processes (Gardner et al. 1987; Turner et al. 1989; Gardner and Urban 2007).

We then explored the influence of changing climate and the spatial pattern of houses with defensible space fuels treatments on fire risk in US Northern Rocky Mountain subalpine forests over the twenty-first century (Table 1). We focused on mesic subalpine forests because they make up a large proportion of Northern Rocky Mountain forests (Baker 2009) and the effects of fuels reductions on lowering fire risk are less well-studied compared to dry forest types (Hudak et al. 2011). We used NLMs, the forest simulation model iLand (Seidl et al. 2012), and widely applied fire behavior modeling equations for estimating fire intensity (sensu Nelson et al. 2017) to evaluate fire risk to WUI structures at three spatial scales. We quantified fire intensity in the 1-ha defensible space immediately surrounding a structure (home ignition zone, HIZ), in the 9-ha safe suppression zone (SSZ) in which intensity must be low for firefighters to work safely (Scott 2003), and at the landscape scale at which high intensity fire patches produce firebrands (Fig. 1). Although fire risk was assessed at three scales, fuels were only treated within each home's 1-ha defensible space. We asked: (1) How do area burned, forest and fuel characteristics, and fire risk change over time under twenty-first-century climate? (2) When defensible space treatments are applied around all houses, which scenarios of WUI housing amount and configuration minimize fire risk at each spatial scale? We hypothesized that fire risk to structures would increase at all scales over the twenty-first century with warmer and drier climate, decrease at SSZ and landscape scales with greater housing amount due to greater area treated, and decrease at SSZ scale with clustered rather than dispersed housing configurations (Table 2). However, we expected that fire risk quantified at the landscape scale would be higher in clustered rather than dispersed scenarios due to larger areas of contiguous forest.

**Table 1** Factors and levels for 21 simulation scenarios, 18 with treatment (3 amounts × 2 configurations × 3 GCMs) and 3 without (3 GCMs)

| Factor | Levels |
|---|---|
| Fuels treatment | 1. Aggressive fuels reduction in 1-ha defensible space around each structure (NFPA 2016, 2018) every 10 years |
| | 2. No treatment (not multiplied by full factorial) |
| Housing amount (i.e., amount of landscape treated) | 1. Amount = 10% |
| | 2. Amount = 30% |
| | 3. Amount = 50% |
| Housing configuration | 1. Dispersed (random percolation neutral landscape models) |
| | 2. Clustered (random rectangular neutral landscape models) |
| General Circulation Model (GCM), all forced with Representative Concentration Pathway 8.5 | 1. CanESM2 |
| | 2. HadGEM2-CC |
| | 3. HadGEM2-ES |

Each scenario was run for $n = 20$ neutral landscapes, for a total of 420 simulation runs




| | | | |
|---|---|---|---|
| **Primary mechanism(s) of structure ignition** | Direct flame contact or radiant heat | Radiant heat or firebrands (embers) | Firebrands (embers) |
| **Fire risk measurement(s)** | Fire intensity in home ignition zone (HIZ), quantified by flame length (m) | Percentage of houses exposed to at least one ha of high intensity fire in the safe suppression zone (SSZ) | Percentage of landscape burned at high intensity (PLAND)<br>High intensity fire largest patch index (LPI)<br>High intensity fire area-weighted mean patch size (AREA_AM) |

**Fig. 1** Three spatial scales at which fire risk is measured. In the home ignition zone, which corresponds with the 1-ha defensible space around a structure, higher fire intensity implies increased fire risk. Fire risk is assessed at the safe suppression zone scale as the percentage of houses exposed to at least 1 ha of adjacent high intensity fire (8-neighbor rule). In the entire landscape, class-level metrics for high intensity fire are calculated to assess fire risk; lighter pink colors represent areas of low to moderate fire intensity

## Methods

### Study area

The US Northern Rocky Mountains encompass over 30 million ha from central Wyoming to the US–Canada border and are dominated by conifer forests (Baker 2009). Subalpine forests occupy $\sim$ 45% of the forested area (Rollins and Frame 2006; Harvey et al. 2016). Lodgepole pine (*Pinus contorta* var. *latifolia*) often dominates the lower subalpine zone, Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*) tend to dominate the upper subalpine zone, and whitebark pine (*Pinus albicaulis*) is common near upper tree line (Baker 2009). These high-elevation, cool, mesic forests have continuous, abundant canopy fuels and are adapted to infrequent (100–300 year return interval) stand-replacing fire regimes (Romme and Despain 1989; Schoennagel et al. 2004; Whitlock et al. 2008; Higuera et al. 2011). Fire activity in the Northern Rocky Mountains is strongly linked to climatic drivers that lower fuel moisture during the fire season (Littell et al. 2009), and high-intensity and -severity crown fires in subalpine forests are driven by rare combinations of drought and high wind (Romme 1982; Renkin and Despain 1992; Bessie and Johnson 1995). As climate has changed in recent decades, this region has experienced some of the greatest increases in number of large fires and area burned among western US forests (Westerling et al. 2006; Westerling 2016), and the proportion of area burned as stand-replacing fire has also increased (Harvey et al. 2016). Although the US Northern Rocky Mountains are characterized by extensive areas of public land, WUI development has rapidly expanded in recent decades (Radeloff et al. 2018), and by some estimates $> 80\%$ of potential WUI remains undeveloped and available for future growth (Gude et al. 2008).

### Simulation model

We used the process-based forest landscape and disturbance model iLand, which simulates growth, mortality, and competition at the level of individual trees and cohorts of saplings and seedlings; considers species-specific responses to environmental drivers; and incorporates spatially explicit processes such as seed dispersal and fire spread (Seidl et al. 2012, 2014; Seidl and Rammer 2020). Trees $> 4$ m in height are individually modeled and spatially explicit, and trees compete with their neighbors for light, nutrients, and water. Processes are simulated at multiple temporal

**Table 2** Hypotheses for the effects of fuel treatment, housing amount, housing configuration, and twenty-first-century climate on fire risk to structures at three spatial scales

| Hypothesis description | Expectations and rationale | Hypothesized effects | | |
|---|---|---|---|---|
| | | Fire risk in HIZ | Fire risk in SSZ | Landscape fire risk |
| *Fuels treatment* | | | | |
| Effect of fuels treatment in defensible space, compared to no treatment | Fuels removal will reduce fire intensity and therefore risk at all scales | – | – | – |
| *Housing amount* | | | | |
| Effect of increased amount of landscape treated | As more of the landscape is treated, treated areas will be more likely to intersect with SSZs of adjacent structures or with high intensity fire patches, therefore reducing fire risk | 0 | – | – |
| *Housing configuration* | | | | |
| Effect of clustered rather than dispersed housing configuration | SSZ fire risk will be lower in clustered scenarios because structures and therefore treated areas will be more likely to be adjacent to one another. However, landscape scale fire risk may increase because there may be larger patches of contiguous forest in clustered scenarios | 0 | – | + |
| *Climate* | | | | |
| Effect of later compared to earlier twenty-first-century climate | Future climate will lead to increased fire risk due to both increased frequency of drought and increased area burned; however, negative feedbacks from fuels consumed by fire or decreased productivity during the course of this simulation may mitigate this increased risk, so this expectation is uncertain | + | + | + |

Effect of fire risk is summarized as increased (+), decreased (–), or no change (0)

and spatial scales. For example, daily climate drivers, including minimum and maximum temperature, precipitation, radiation, and vapor pressure deficit affect canopy carbon uptake, which is further modified by species-specific tolerances for temperature extremes, drought stress, shading, and nutrient availability. Available light is calculated at $2 \times 2$ m horizontal resolution based on shortwave radiation and shading due to tree crowns. Other environmental conditions, such as soil water and nutrients are calculated at the resolution of 1-ha stands. Trees die due to intrinsic reasons, with increasing mortality probability as trees approach their maximum age or size. Environmental stressors that lead to carbon starvation and disturbances such as fire also cause tree mortality in the model. Seed masting, production, quantity, and dispersal distances vary by species, and seedling establishment occurs when specific environmental thresholds for winter chilling, growing degree days, and soil water potential are met (Nitschke and Innes 2008; Hansen et al. 2018). Stems $< 4$ m in height (seedlings and saplings) are modeled as cohorts at 2-m resolution until they reach 4 m in height. iLand has been parameterized and evaluated for five widespread trees species in the US Northern Rocky Mountains and generates realistic stand structures, variability among stands, forest composition, and fire-induced regeneration of serotinous lodgepole pine (Braziunas et al. 2018; Hansen et al. 2018, 2020).

Fire behavior in iLand responds dynamically to fire-year weather (fuel moisture), fuels, and topography (Seidl et al. 2014; Seidl and Rammer 2020). Dead surface fuels are tracked in two pools, forest floor (1-h and 10-h fuels) and downed woody debris (100-h and 1000-h fuels). In this study, we extended iLand to quantify live woody surface fuels as well as canopy fuel metrics including canopy fuel load, canopy bulk density, and canopy base height at 1-ha resolution (Online Resource Appendix A). Fuel moisture is estimated from the Keetch–Byram Drought Index

(KBDI), an index for predicting fire potential based on soil moisture depletion in response to cumulative precipitation and evapotranspiration (Keetch and Byram 1968). KBDI—originally ranging from 0 to 800—is standardized on a scale of 0 (wettest) to 1 (driest) and computed annually in iLand, which enables the index to capture changes in fire season length in addition to extremely hot and dry years. KBDI serves as a proxy for fuel moisture in calculating fuel loads in iLand, and additionally modifies fire ignition probabilities and fire sizes. Fire size is sampled from a negative exponential distribution, and threshold KBDI values are used to constrain fire sizes in cool-wet years or establish a minimum fire size in hot-dry years. Wind speed is randomly selected from a user-specified range and held constant during a fire event. Fire is modeled at 20-m resolution and spreads via a cellular automaton model in eight possible directions, influenced by topography, wind speed, and wind direction. Fire spread is constrained by a minimum fuel load required for spread and a maximum potential fire size, along with a fire extinction probability that is applied to each burning pixel. Fire severity and resulting tree mortality are calculated from fuel loads, fuel moisture, and species- and size-specific fire resistance. Hansen et al. (2020) parameterized and evaluated the iLand fire module for this region, and Turner et al. (in prep) updated fire severity parameters based on additional analyses. We here specified a baseline fire return interval of 160 years, representing lodgepole pine forests at the lower end of their elevation range (Schoennagel et al. 2003).

## Simulation landscapes and initial conditions

To focus on effects of climate and spatial pattern of fuels reduction treatments, we minimized variability in other factors by creating a generic 10,000-ha simulation landscape (1-ha resolution) that was flat with spatially homogeneous soil and climate conditions representative of lodgepole pine-dominated forest near the WUI community West Yellowstone, MT (Turner et al. 2016). We extracted soil texture and effective depth from CONUS-SOIL (Miller and White 1998) and daily climate drivers from 1950 to 2005 for the CanESM2 general circulation model (4-km resolution; climate projections described below). We assigned a soil fertility value assuming underlying rhyolitic parent material (Despain 1990; Braziunas et al. 2018).

Initial forest composition and stand structures were generated from a 300-year model spinup under historical climate following Hansen et al. (2020). We first identified forest inventory and analysis (FIA) plots in northwest Wyoming (FIADB 2019) that were representative of dense lodgepole-pine dominated subalpine forest (1900–2400 m elevation; Schoennagel et al. 2003). We selected plots dominated by lodgepole pine based on importance value (IV) $\geq$ 1.5 (IV = species proportion of stand density + species proportion of basal area). We used these plots ($n$ = 106 plots) to initialize lodgepole pine and four other species, which were present in minor proportions: Douglas-fir (*Pseudotsuga menziesii* var. *glauca*), subalpine fir, Engelmann spruce, and quaking aspen (*Populus tremuloides*). Serotinous and non-serotinous lodgepole pine are simulated separately in iLand, and we assumed that 25% of initial lodgepole pine trees were serotinous based on field observations of high-serotiny stands (Schoennagel et al. 2003). For year 0 of the spinup, we varied initial stand structure and species composition derived from FIA plots at 10-m resolution across the landscape.

We then simulated forest development under historical climate conditions and fire activity over a 300-year period. Each year, climate was randomly drawn with replacement from 1950 to 2005 under CanESM2. We included a 2.5-km buffer around the edge of the study landscape to ensure the landscape edges had an equal probability of burning (total simulated landscape size = 22,500 ha). Following spinup, most of the landscape was lodgepole pine-dominated with a mix of stand ages and structures consistent with the regional landscape (Online Resource Appendix B, Fig. B1). Stands (1-ha resolution) were considered forested when there were $\geq$ 50 trees ha$^{-1}$ (Hansen et al. 2018) based on stems $\geq$ 2 m in height, which comprise the canopy fuel layer (Keane 2015).

## Simulation experiment

### *Overview*

For this 10,000-ha subalpine forest landscape, we conducted a simulation experiment in which we estimated fire risk for 21 scenarios that differed in projected future climate, whether or not fuels were treated, and housing amount and configuration (Table 1 and described below). We simulated 20 replicates of each scenario in iLand for 120 years (1980–2099), resulting in 420 simulation runs (360 with fuels treatments and 60 without).

*Climate projections*

We used three general circulation models (GCMs) to represent a range of potential future climates (Fig. B2). Projected temperature is similar among models, but some models project increased precipitation (CanESM2; Chylek et al. 2011) whereas others have distinct periods of drought varying in timing and intensity (HadGEM2-CC and HadGEM2-ES; Collins et al. 2011). All GCMs were forced with representative concentration pathway (RCP) 8.5, which is a higher emissions pathway that most closely tracks current and expected $CO_2$ emissions through midcentury (Schwalm et al. 2020). We focused on variability among GCMs (emphasizing differences in precipitation) rather than RCPs (3° versus 5 °C warming) because of the strong effects of aridity on fire activity (Abatzoglou and Williams 2016; Higuera and Abatzoglou 2020) and drought on postfire tree regeneration (Stevens-Rumann and Morgan 2019). We extracted daily climate drivers through 2099 for each GCM from MACAv2-METDATA, which uses the Multivariate Adaptive Constructed Analogs approach and METDATA observational dataset to statistically downscale climate drivers to 4-km resolution (Abatzoglou and Brown 2012; Abatzoglou 2013).

*Defensible space fuels treatments*

In treatment scenarios, we simulated defensible space management in the 1-ha area surrounding each hypothetical house based on National Fire Protection Association (NFPA) standards (NFPA 2018). We followed the most aggressive fuel reduction prescriptions in the NFPA standard because our goal was to reduce fire risk as much as possible within defensible space. For the surface fuel layer, we removed dead and downed (100-h and 1000-h) fuels and all live vegetation less than 4 m in height (tree seedlings and saplings). For the canopy fuel layer, we used species-specific maximum crown radius equations (Purves et al. 2007) to approximate an average crown radius based on stand quadratic mean diameter (QMD). Following guidelines for recommended crown spacing of 5.5 m between crowns (NFPA 2018), we then derived maximum stocking densities for each tree species based on stand QMD (Fig. B3). For each 1-ha grid cell in which defensible space treatment was applied, the species with the maximum IV was used to set maximum stocking targets, and smaller trees were preferentially removed (i.e., thinning from below, which simultaneously increases canopy base height while reducing canopy fuels; Graham et al. 1999). Defensible space treatment was implemented during the first simulation year (1980) and repeated every 10 years based on a conservative estimate of treatment duration effectiveness (Kalies and Yocom Kent 2016; Schoennagel et al. 2017).

*Amount and configuration of houses and fuels treatments*

We used neutral landscape models to generate replicate maps that varied in the amount and configuration of housing, and therefore fuels treatments, within the simulation landscape. We assumed that only one house would be built within a given 1-ha grid cell. The surrounding hectare constituted that structure's defensible space and was classified as developed area. We selected levels of housing amount consistent with the definition of intermix WUI ($>$ 6.17 houses km$^{-2}$ and at least 50% wildland vegetation; USDA and USDI 2001; Radeloff et al. 2005). We simulated three levels of housing amount (10, 30, or 50 houses km$^{-2}$), corresponding to 10%, 30%, or 50% of the landscape classified as developed area rather than wildland vegetation. Housing configuration was then either randomly dispersed, in which single houses are intermixed with wildland vegetation consistent with scattered sprawl, or clustered next to areas of large, contiguous open space, consistent with conservation development (Pejchar et al. 2007).

We generated 20 neutral landscapes for each combination of the three housing amounts and two configurations using the NLMR R package (Fig. 2; Sciaini et al. 2018). Randomly dispersed housing was generated from simple random percolation models (Gardner et al. 1987). Clustered housing was implemented using random rectangular neutral landscape models, in which overlapping rectangular patches are randomly distributed until the landscape is filled, with

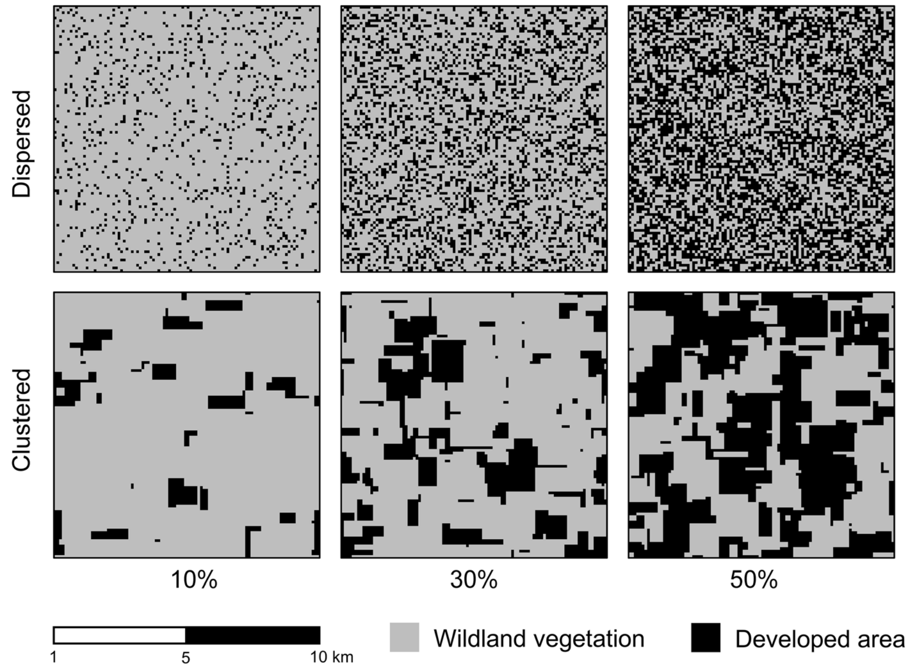



**Fig. 2** Example neutral landscapes generated for three housing amounts (amount of defensible space in the landscape = 10%, 30%, or 50%) and two housing configurations (randomly dispersed or clustered) with the NLMR R package. We assumed only one structure was built within each 1-ha developed area, which constituted that structure's defensible space. Simulations were conducted on 20 distinct neutral landscapes for each scenario

the user specifying the range of patch sizes and the total amount of area in each class (Gustafson and Parker 1992). We set minimum and maximum patch size based on the size of developed areas in conservation development subdivisions for mountainous counties in Colorado (Sarah E. Reed and Liba Pejchar 2019, unpublished data). Patches were defined using the 8-neighbor rule. In our landscapes, mean development patch sizes were 33, 76, and 285 ha for 10%, 30%, and 50% developed area, respectively, and were within the range of Colorado conservation development data (Fig. B4). Consistent with conservation development principles, landscapes with clustered housing were characterized by large areas of contiguous wildland vegetation even when half of the landscape was developed (Fig. 2).

## Fire intensity and risk calculations

To quantify fire risk to structures, we first used established fire behavior modeling methods to estimate fire intensity at the resolution of a 1-ha grid cell based on fire weather and fuels characteristics derived from iLand outputs (see Online Appendix A for details on quantification of fuels and fire intensity). By estimating fire intensity as a dynamic response to changes in forest conditions and environmental drivers, we thereby capitalized on the strengths of using the process-based forest simulation model iLand to characterize future conditions. Canopy fuel characteristics, surface fire behavior fuel model classification, fire spread rates and intensities, and crown fire occurrence were similar to comparison data and responded appropriately to variation in fuel loads, fuel moisture, and wind speed (Online Appendix A). We also used fire intensity (flame length, m) to assign fire intensity class (low, moderate, or high). High intensity fire corresponds with flame lengths $\geq$ 2.4 m, at which point fire control is unlikely to be effective and, as flame lengths increase, extreme fire behavior is likely (Roussopoulos and Johnson 1975; Rothermel 1983).

We then assessed fire risk to structures at each of our three spatial scales (Fig. 1). Home ignition zone risk was quantified as fire intensity within the 1-ha treated area of defensible space around each structure, with higher fire intensities implying increased risk. Safe suppression zone fire risk was quantified as the percentage of structures exposed to high intensity fire in at least one of the eight neighboring grid cells in a given year. Fire risk in the HIZ and SSZ were averaged across areas classified as developed and containing structures in the simulation each year, an approach that assumes houses are rebuilt after fire. Fire risk for the entire landscape was quantified by using three class-level landscape metrics calculated for high intensity area burned: percentage of landscape burned at high intensity (PLAND), largest patch index (LPI), and area-weighted mean patch size (AREA_AM).

### Analysis

We first calculated annual area burned, fire risk, and mean forest and fuel characteristics across the entire landscape for each replicate of each scenario. To evaluate temporal trends in area burned and fire risk (question 1), which are dominated by discrete events, we fit a loess smooth local regression line to each response variable. We chose a smoothing span of 100 years based on the lower bound of the historical fire return interval for lodgepole pine forest. For all other temporal trends, we evaluated changes in mean values over time.

To compare scenarios of housing amount and configuration (question 2), we calculated the average annual fire risk at HIZ, SSZ, and landscape scales over the 120-year duration of the simulation experiment for each replicate ($n$ = 20 per scenario). For each no treatment replicate, we quantified HIZ and SSZ fire risk assuming houses were present by randomly selecting a map from one of the housing amount and configuration scenarios. We performed two complementary analyses. First, we compared mean fire risk between no treatment and treatment scenarios, focusing on the magnitude of change rather than statistical tests of significance. Mean values reported in the text are scenario means $\pm$ 1 standard error, and figures show 95% confidence intervals. Second, we fit linear mixed effects models to treatment scenarios only, omitting no treatment scenarios, to disentangle the effect of amount versus configuration of housing. We included amount, configuration, and their interaction as fixed effects and GCM as a random effect. We calculated variance explained by fixed effects (marginal $R^2_{LMM(m)}$) and by the full model (conditional $R^2_{LMM(c)}$; Nakagawa and Schielzeth 2013), and we evaluated the significance of GCM as a random effect with a likelihood ratio test of the full versus reduced model. We applied a square root transformation to SSZ and landscape fire risk response variables to meet assumptions of normality and equal variance. We determined that assumptions were adequately met based on quantile–quantile plots (normality) and residual plots (equal variance) for each model. Analyses were conducted in R version 3.6.1 (R Core Team 2019), primarily using the car (Fox and Weisberg 2019), landscapemetrics (Hesselbarth et al. 2019), lme4 (Bates et al. 2015), lmerTest (Kuznetsova et al. 2017), MuMIn (Barton 2019), plotrix (Lemon 2006), raster (Hijmans 2019), RSQLite (Muller et al. 2019), stats, and tidyverse (Wickham et al. 2019) packages.

## Results

### Changes in forests and fire over time (question 1)

#### *Area burned, forest and fuel characteristics (no treatment scenarios)*

Annual area burned increased during the twenty-first century under all GCMs (Fig. 3). Under the two warm-dry climate models (HadGEM2-CC and HadGEM2-ES), the latter half of the century was characterized by many large fire years. Over this 50-year period, there were 10 years in which annual area burned exceeded one quarter of the landscape area (mean across $n$ = 20 replicates), and cumulative area burned increased exponentially starting in 2050 (Figs. 4, B6). However, the amount of area that burned at high fire intensity did not follow this same trajectory. Rather, high intensity area burned peaked in 2065 (HadGEM2-ES) or 2066 (HadGEM2-CC) and then sharply declined (Fig. 3b, c). Under warm-wet CanESM2 climate projections, in which area burned increased more slowly, high intensity area burned continued to increase through the end of the twenty-first century (Fig. 3a).

Forested area ($\geq$ 50 trees ha$^{-1}$ based on stems $\geq$ 2 m in height) and mean canopy fuel loads exhibited punctuated declines over time (Figs. 4, B7). Abrupt declines in forest area coincided with large fire years in combination with harsh environmental conditions inhibiting the establishment of trees after fire. Similarly, canopy fuel loads and bulk densities exhibited abrupt declines following large fire years but recovered in some cases to pre-fire levels given sufficient

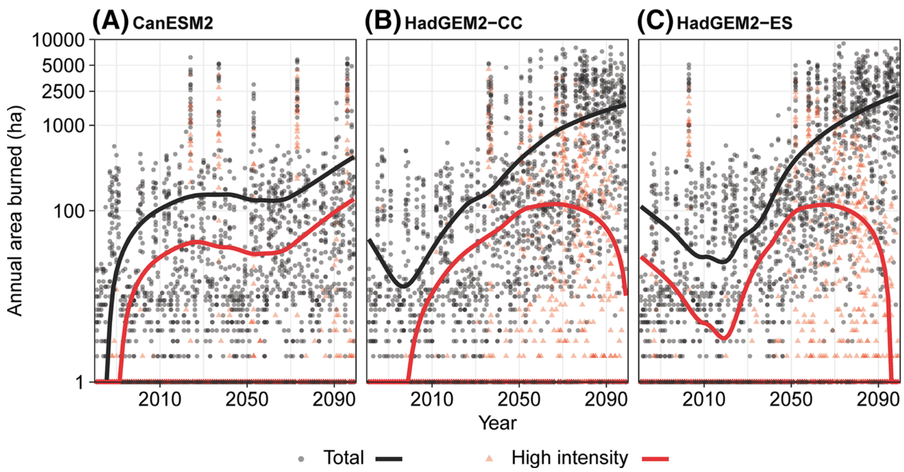



**Fig. 3** Total (black circles and line) and high intensity (red triangles and line) area burned over time in no treatment scenarios and under three general circulation models: **a** CanESM2, **b** HadGEM2-CC, and **c** HadGEM2-ES. Points give annual values for each replicate ($n$ = 20) and each year. Solid lines are a loess smooth local regression with span of 100 years. The y-axis is plotted on a log10 scale and + 1 ha has been added to all values to enable plotting on a log axis

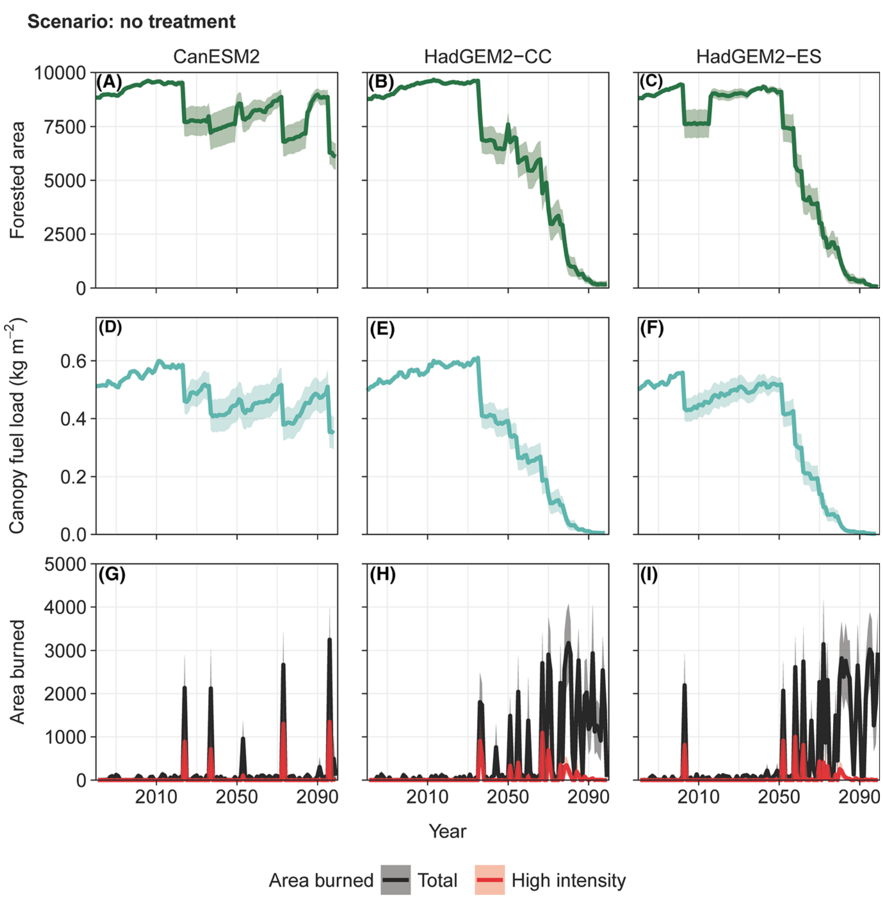



**Fig. 4** **a–c** Total forested area, **d–f** canopy fuel load, and **g–i** total and high intensity annual area burned in no treatment scenarios under all three GCMs. Area was considered forested if there were $\geq$ 50 trees ha$^{-1}$ of $\geq$ 2 m in height. Solid lines are mean values and ribbons show a 95% confidence interval

time between large fires (e.g., in the CanESM2 and HadGEM2-ES climate models). More than 50% of forest cover was maintained under warm-wet climate, whereas nearly all forest was lost under warm-dry climate projections.

Mean surface fuel load trajectories differed from canopy fuels (Fig. B8). Forest floor biomass (1-h and 10-h fuels) declined more gradually than canopy fuels, and declines were non-linear in warm-dry climate projections. Downed woody debris (100-h and 1000-h fuels) initially increased and then declined later in the twenty-first century, but average fuel loads remained > 90 Mg biomass $ha^{-1}$ in 2099. Seedling and sapling biomass increased in warm-wet climate and also exhibited local maxima. Consistent with these trends, forested area in younger age classes (stand ages < 40 and 40–100 years) experienced periods of intermittent or ongoing expansion (Fig. B5g–i).

#### *Area burned, forest and fuel characteristics (treatment scenarios)*

Treating as much as half of the landscape resulted in lower total and high intensity area burned compared to no treatment scenarios but did not alter overarching trends (Fig. B10). Average fuel loads in untreated wildland followed similar trends regardless of treatment scenario (Figs. 5, B8). In treated areas (i.e., defensible space), fuel loads were consistently lower and canopy base height was consistently higher relative to untreated areas.

#### *Fire risk (no treatment versus treatment scenarios)*

Fire risk at all scales followed similar trends as high intensity area burned (Fig. 6). For example, under no treatment HadGEM2-CC and HadGEM2-ES scenarios, fire risk peaked near or after the middle of the twenty-first century and subsequently declined. Although defensible space treatments maintained consistently low flame lengths in the home ignition zone (Fig. 6a–c), treating large amounts of the landscape could only dampen, but not eliminate, fire risk at safe suppression zone and landscape scales (Fig. 6d–i). Similarly to total and high intensity area burned, fire risk was dominated by discrete events. In addition to dampening mean fire risk, treatment could also decrease maximum fire risk during large fire years (Table B1). For example, under HadGEM2-CC the maximum percentage of houses exposed to high intensity fire in a single year declined from 51.12% (no treatment) to 16.20% when half of the landscape was treated and houses were clustered.

### Effect of housing amount and configuration scenarios on fire risk (question 2)

#### *Home ignition zone*

Flame length in the home ignition zone did not differ with housing amount or configuration scenarios (Table 3) but was reduced by more than 70% relative to no treatment (Fig. 7, Table B1). For example, defensible space treatments reduced flame lengths from 2.05 ± 0.10 m (no treatment) to ≤ 0.55 ± 0.00 m (all treatment scenarios) under warm-dry HadGEM2-CC (Fig. 8a). With no fuels treatments, mean flame lengths were close to or exceeded the threshold for high intensity fire of ≥ 2.4 m under all GCMs.

#### *Safe suppression zone*

Housing amount and configuration both influenced fire risk in the safe suppression zone, and clustered housing was much more effective than dispersed housing at reducing fire risk (Table 3). For example, under HadGEM2-CC clustered housing with defensible space treatments on 10% of the landscape reduced the average annual percentage of houses exposed to high intensity fire at this scale from 0.78 ± 0.04% $year^{-1}$ to 0.40 ± 0.02% $year^{-1}$ (a 48% reduction in fire risk; Fig. 8b). Across all GCMs, clustered housing on 10%, 30%, and 50% of the landscape decreased fire risk by 53 ± 5%, 63 ± 5%, and 76 ± 5%, respectively (Fig. 7). In contrast, dispersed housing scenarios reduced fire risk by < 25% even when half the landscape was treated, and most dispersed treatment scenarios resulted in minimal reductions or increases in fire risk relative to no treatment (Table B1).

#### *Landscape scale*

At the landscape scale, housing amount affected fire risk, but configuration did not (Tables 3, B2). Across all GCMs, treating 10%, 30%, and 50% of the landscape reduced largest high intensity patch size by 10–18%, 41%, and 66–70%, respectively (Fig. 7). However,

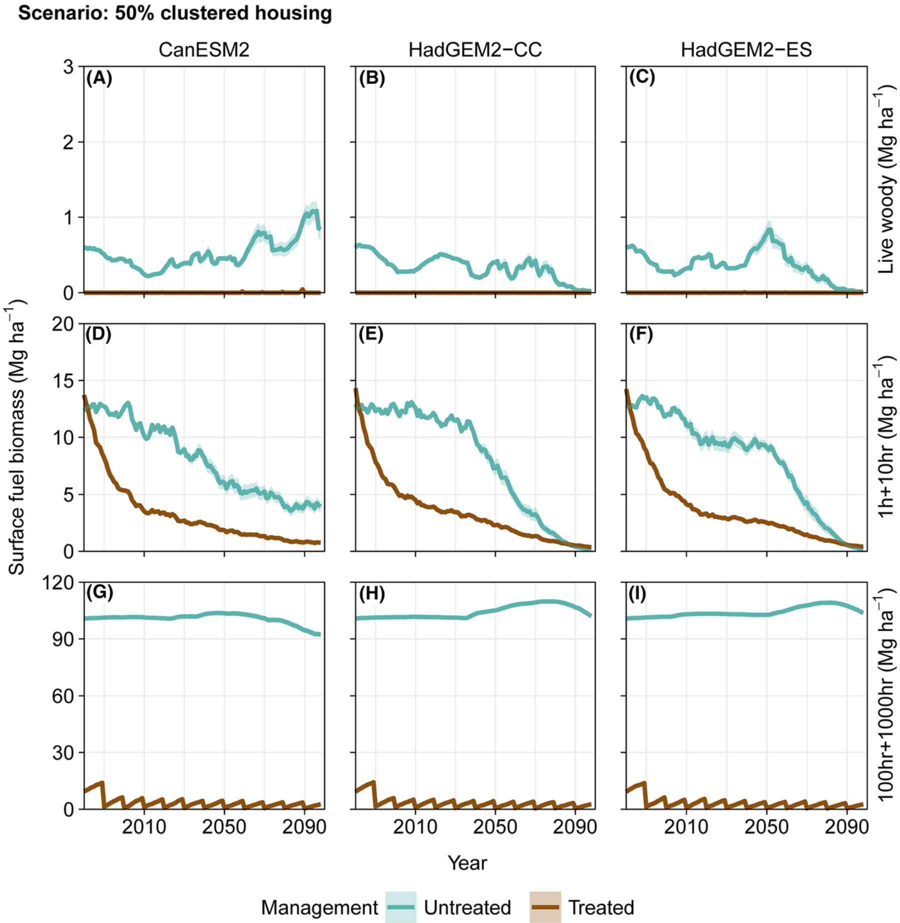



**Fig. 5** Surface fuel biomass in 50% clustered housing with defensible space treatment scenarios under all three GCMs. **a**–**c** Seedling and sapling (live woody) biomass, **d**–**f** forest floor biomass (1-h and 10-h fuels), and **g**–**i** downed woody biomass (100-h and 1000-h fuels). Solid lines are mean values and ribbons show a 95% confidence interval. Average values are shown for untreated (teal) and treated (brown) forest

treating 10% of the landscape did not always decrease the maximum fire risk experienced during the twenty-first century (Table B1). For example, maximum largest high intensity patch size increased in four out of six scenarios when only 10% of the landscape was treated, whereas treating 30% of the landscape consistently reduced maximum landscape fire risk. The effect of housing amount and configuration on fire risk at landscape scales was generally consistent among landscape metrics and GCMs.

*Random effects*

For all linear mixed effects models of fire risk metrics, the random effect of GCM was significant and increased variance explained (Table 3).

## Discussion

Our results suggest that the most effective strategy for reducing fire risk depends on the scale at which risk is assessed. The spatial configuration of houses with defensible space treatments was particularly important at neighborhood safe suppression zone scales, while the amount of area treated was most important at landscape scales; however, neither was important at home ignition zone scales. Structures can be ignited in different ways, even if they are not exposed to high intensity fire in the home ignition zone (Fig. 1). Accounting for fire risk at neighborhood and landscape scales is critical because direct or indirect firebrand ignitions can be responsible for the majority of structure loss (Mell et al. 2010; Maranghides et al.

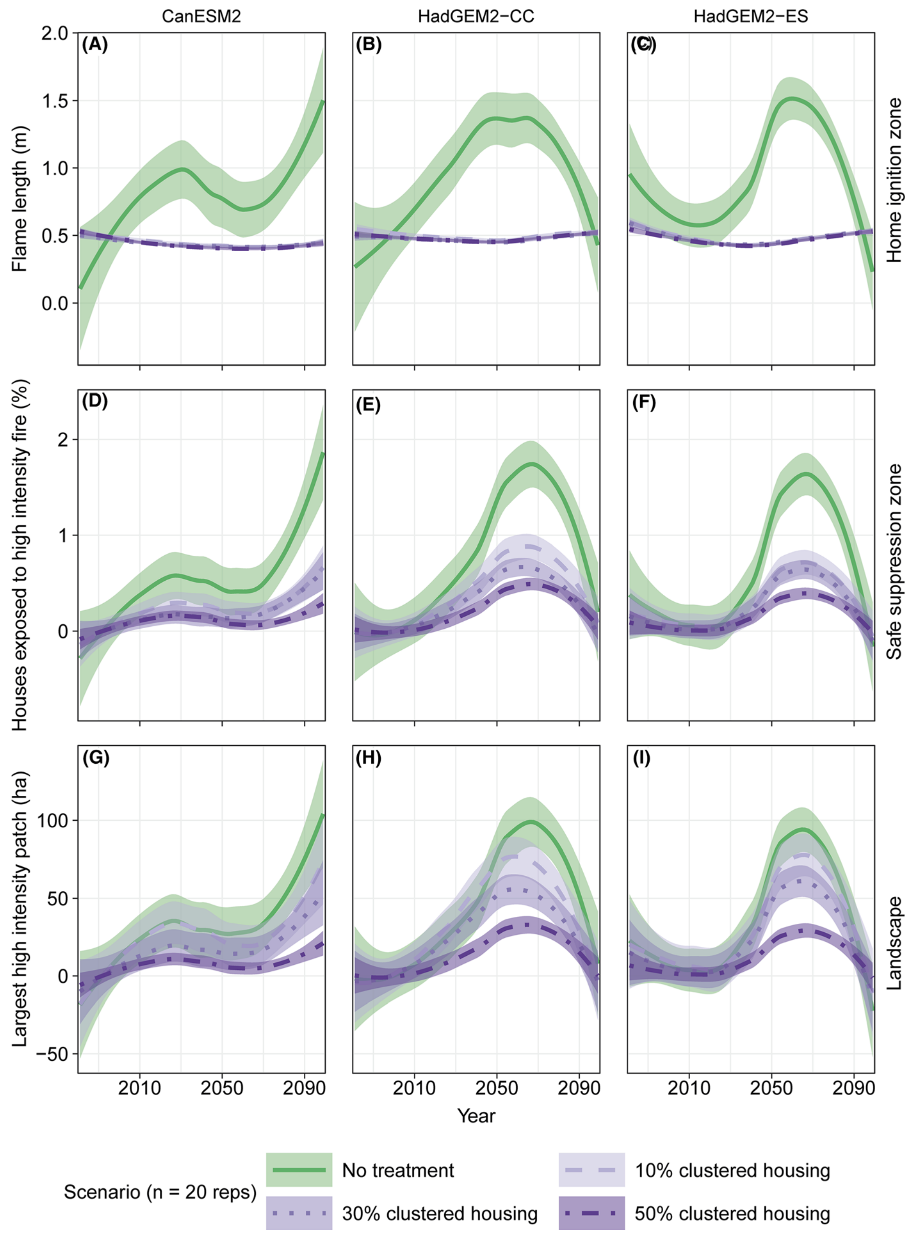



**Fig. 6** Fire risk over time at three scales: **a**–**c** Home ignition zone, quantified as average flame length (m) in HIZ areas that burned, **d**–**f** safe suppression zone, quantified as the percentage of houses exposed to high intensity fire in the SSZ, and **g**–**i** landscape scale, quantified as the largest high intensity patch index (LPI, ha). Fire risk is compared among no treatment (green, solid lines) and clustered treatment (shades of purple, dotted and dashed lines) scenarios ($n = 20$ replicates per scenario). Lines are a loess smooth local regression with span of 100 years and ribbons give a 95% confidence interval

2013). Our results can help guide WUI development planning and the spatial targeting of fuels management. At a minimum, clustering development and treating defensible space on between 10 and 30% of the landscape every 10 years can meaningfully reduce fire risk across multiple scales. In current WUI communities where < 30% of the area is developed and homes are not clustered, treating defensible space only may be insufficient to reduce risk. Homeowners in these communities should consider treating more than the immediate 1-ha area around their homes, which may require collaboration with neighboring

**Table 3** Results of linear mixed effects models for fire risk metrics at three spatial scales

| Fire risk scale | Fire risk metric | $R^2_{LMM(m)}$ | $R^2_{LMM(c)}$ | Fixed effects | Estimate | t value | p | Random effect | Standard deviation | $\chi^2$ | p |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Home ignition zone (HIZ) | Fire intensity in HIZ, quantified by flame length [m] | 0.01 | 0.23 | Intercept | 0.5288 | 56.28 | < 0.001 | General circulation model (GCM) | 0.0145 | 80.37 | < 0.001 |
| | | | | Amount | 0.0002 | 1.49 | 0.14 | | | | |
| | | | | Configuration (clustered) | – 0.0025 | – 0.42 | 0.68 | | | | |
| | | | | Amount × Configuration (clustered) | – 0.0001 | – 0.33 | 0.74 | | | | |
| Safe suppression zone (SSZ) | Percentage of houses exposed to at least one ha of high intensity fire in the SSZ [% $year^{-1}$] | 0.55 | 0.71 | Intercept | 0.8380 | 16.13 | < 0.001 | General circulation model (GCM) | 0.0849 | 152.93 | < 0.001 |
| | | | | Amount | – 0.0026 | – 5.20 | < 0.001 | | | | |
| | | | | Configuration (clustered) | – 0.2489 | – 10.17 | < 0.001 | | | | |
| | | | | Amount × Configuration (clustered) | – 0.0013 | – 1.76 | 0.08 | | | | |
| Landscape | High intensity fire largest patch index (LPI) [ha $year^{-1}$] | 0.43 | 0.55 | Intercept | 6.3291 | 20.35 | < 0.001 | General circulation model (GCM) | 0.4758 | 72.43 | < 0.001 |
| | | | | Amount | – 0.0566 | – 13.26 | < 0.001 | | | | |
| | | | | Configuration (clustered) | – 0.2453 | – 1.19 | 0.24 | | | | |
| | | | | Amount × Configuration (clustered) | 0.0022 | 0.37 | 0.71 | | | | |

To meet assumptions, we applied a square root transformation to SSZ and landscape fire risk metrics. Variance explained is reported for fixed effects only (marginal $R^2_{LMM(m)}$) and for the full model (conditional $R^2_{LMM(c)}$). The configuration estimate shows the effect of clustered relative to dispersed configurations on fire risk. We performed likelihood ratio tests on the full versus reduced linear model to test the significance of general circulation model as a random effect

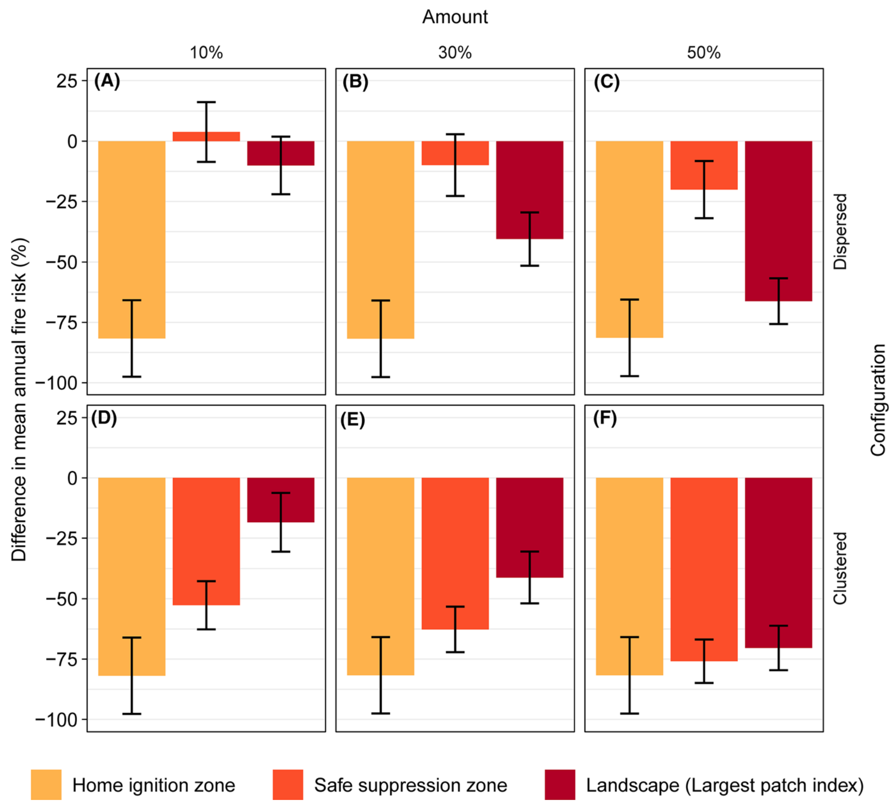



**Fig. 7** Difference in mean annual fire risk (%) under defensible space treatment scenarios varying in amount (columns) and configuration (rows), relative to no management. Differences are calculated across all three GCMs ($n = 60$ observations per each amount $\times$ configuration scenario). Effect of amount and configuration on fire risk is quantified at three spatial scales: Home ignition zone (yellow), safe suppression zone (orange), and landscape based on largest high intensity patch size (red). Error bars show $\pm$ 95% approximate confidence interval using Welch's formula for unequal variances

public and private landowners. In addition, we found that fire risk in wildland urban interface landscapes changed over time due to feedbacks among climate, recurring large fires, and changing fuel characteristics. Coupling fire behavior assessments with a process-based and spatially explicit forest simulation model allowed us to paint a more comprehensive picture of changing fire risk and fuels treatment effectiveness in WUI landscapes over the course of the twenty-first century.

### Feedbacks among climate, fire, and fuels dictate trends in fire risk over time

Area burned increased over time as climate warmed, especially when projected climate was punctuated by extreme droughts (i.e., HadGEM2-CC and HadGEM2-ES). However, although high intensity area burned initially tracked increases in total area burned, these trends decoupled in warm-dry scenarios as fuel loads decreased, and the landscape supported little to no high intensity fire by the end of the century. When fuels could recover sufficiently between fires (e.g., canopy fuels in CanESM2), forest fires continued to burn forests at high intensities. These diverging trends are consistent with expectations that increasing fire frequency can decrease fire intensity in forest ecosystems (Ager et al. 2017) and that feedbacks between fire and vegetation may trigger shifts in long-term fire regimes with climate warming (Prichard et al. 2017). Fire risk at safe suppression zone and landscape scales mirrored trajectories of high intensity area burned. In general, these findings support our hypothesis that warmer and drier future climate would increase fire risk, but that negative feedbacks from fuels consumed by fire could eventually mitigate increases in risk.

Differences among general circulation models resulted in qualitatively different trends in forest extent, fuels, fire behavior, and fire risk throughout the twenty-first century. Despite similar increases in temperature, higher amounts of precipitation in warm-wet CanESM2 led to fewer extremely dry, large fire years relative to the warm-dry climate projections. However, climate models may differ only in the timing of important milestones such as forest loss and peak fire risk. For example, even though

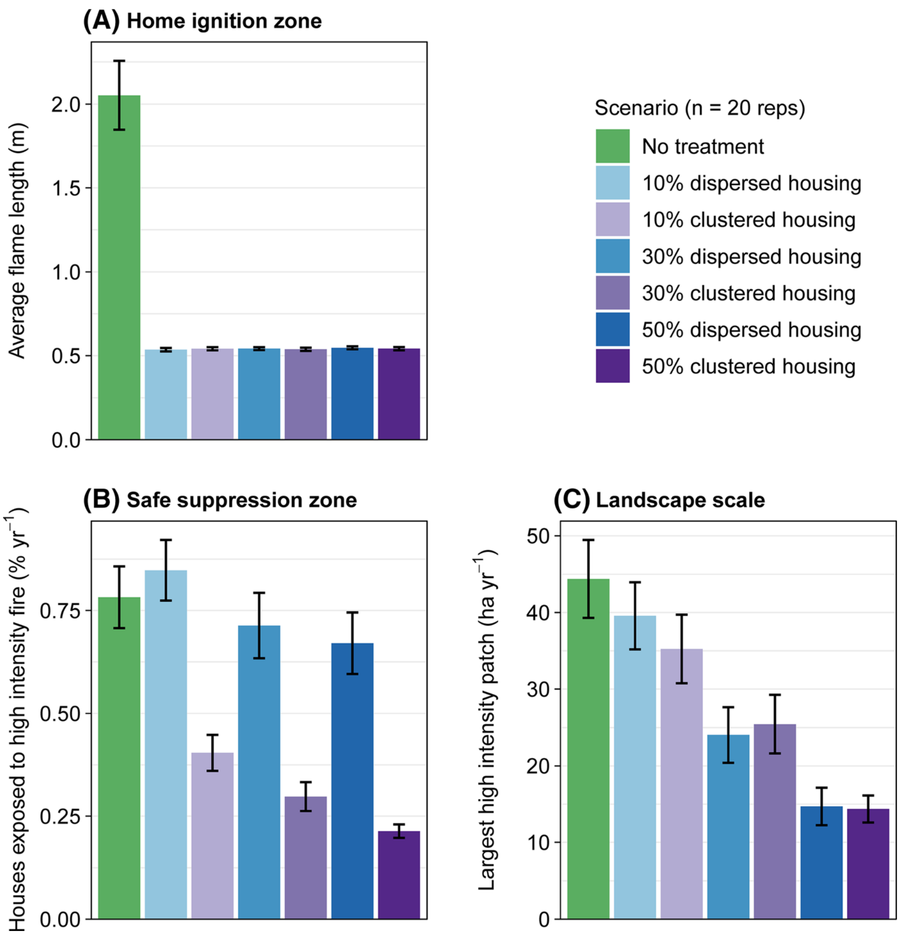



**Fig. 8** Fire risk over the duration of the simulation under HadGEM2-CC at three spatial scales: **a** Home ignition zone, quantified as average flame length (m) in HIZ areas that burned, **b** safe suppression zone, quantified as the average annual percentage of houses exposed to high intensity fire in the SSZ (% year$^{-1}$), and **c** landscape scale, quantified as the average annual largest high intensity patch index (ha year$^{-1}$). Fire risk is compared across all treatment scenarios ($n$ = 20 replicates per scenario), including no treatment (green), dispersed housing (shades of blue, with darker shades corresponding to increasing amount of the landscape treated), and clustered housing (shades of purple, darker shades for increasing amount). Error bars show ± 95% confidence interval

forest extent is largely maintained throughout the century under CanESM2, declining canopy and forest floor fuel loads would likely result in declining forested area if the simulation continued beyond 2099. Making long-term climate projections at regional scales is a complex process, and one GCM is not necessarily more likely than another (Taylor et al. 2012). To anticipate forest change and fire risk at management-relevant scales, climate projections should be continually assessed and refined with improved understanding of global and regional climate drivers.

## Effect of housing amount and configuration depends on the scale at which fire risk is assessed

Defensible space fuels treatments consistently reduced fire risk in the home ignition zone, but contrary to our hypothesis, some treatment scenarios did not reduce fire risk at broader scales. In addition to dampening mean fire risk, some scenarios substantially decreased maximum annual fire risk, indicating that fuels reductions were particularly important for mitigating risk during extreme fire years. We only simulated one level of treatment intensity in our study, aggressive defensible space treatment around all houses based on

NFPA standards and repeated every 10 years. This is currently unrealistic for most WUI communities, in which local policies and organizations, social norms, practical skills, and financial resources all affect private property owner fuels treatment decisions and capabilities (Stidham et al. 2014; Abrams et al. 2015; Carroll and Paveglio 2016). Therefore, our results represent a "best-case" scenario for the potential benefits of defensible space fuels treatments. However, if fuel treatments are regularly applied in the same area, subsequent treatments will likely be less labor intensive and less costly.

Increasing treatment amount generally decreased fire risk at safe suppression zone and landscape scales. The importance of treatment amount was most evident at landscape scales, where treating between 10 and 30% of the landscape every 10 years was necessary to reduce maximum fire risk and treating 30% reduced mean risk by > 25% for all GCM and landscape metric combinations. Our findings are consistent with previous studies that assessed fire behavior at landscape scales and found optimal reductions in spread rates and burn probabilities when 20% of the landscape was treated per decade (Finney et al. 2007; Ager et al. 2010b). In contrast to our results, these studies also found diminishing returns at higher treatment amounts, although neither incorporated long-term changes in climate and fire return interval. When more of the landscape is treated, there are also trade-offs between reducing fire risk and maintaining desired forest conditions or ecosystem services such as carbon storage, timber production, and wildlife habitat (Ager et al. 2010a, b; Spies et al. 2017).

As expected, clustered housing with defensible space treatments was much more effective at reducing fire risk in the safe suppression zone than dispersed housing. We also hypothesized that clustered relative to dispersed configurations would increase fire risk at landscape scales, but this was not the case. We modeled our clustered configurations after conservation development subdivisions, which prioritize maintaining large, contiguous undeveloped areas for multiple benefits such as biodiversity, flood control, and scenic beauty (Pejchar et al. 2007). Our findings suggest that, assuming homeowners implement defensible space treatments, adhering to conservation development principles facilitates neighborhood-scale reductions in fire risk relative to randomly dispersed sprawl. When treatments and houses were randomly dispersed, between 30 and 50% of the landscape had to be treated every 10 years in order to consistently reduce SSZ fire risk. This brackets the critical percolation threshold for random maps ($p_{crit}$ = 41%, 8-neighbor rule; Plotnick and Gardner 1993; Turner and Gardner 2015), at which point all houses will have at least one neighbor implementing defensible space treatments. Clustering may have additional fire protection benefits relative to dispersed housing, such as more efficient access for firefighting crews (Syphard et al. 2012).

## Assumptions and limitations

We aimed to understand the roles of changing climate, fire, and spatial pattern of treatments in affecting fire risk in WUI landscapes, and we made some simplifying assumptions to isolate the importance of these driving factors. We assumed that underlying environmental and climate conditions were spatially homogeneous, that topography was flat and wind speed was constant during a fire event, that aggressive defensible space treatments were perfectly implemented, that only one structure was present in a 1-ha grid cell, that all structures were rebuilt after fire, and that all structures were equally susceptible to high intensity fire. In real WUI landscapes, individual structures differ in their vulnerability to direct flame contact, radiant heat, and firebrands due to differences in construction materials and building components (Hakes et al. 2017). In addition, our study focused on long-term trends in climate-driven fire risk, rather than near-term seasonal and daily changes in fire weather and behavior.

An important limitation of our study is that we only considered forest fuel loads, excluding grasses and shrubs. However, by counting saplings and seedlings as live woody surface fuels, we derived estimates for surface fuel loads comparable to a shrub layer. Landscaping, vehicles, infrastructure, fuel tanks, and other structures also contribute to fire spread, fire intensity, and firebrand production in the WUI (Murphy et al. 2007; Cohen and Stratton 2008; Suzuki et al. 2012). Wildfires have caused extensive damage in developed areas with little wildland vegetation, highlighting the importance of considering these non-wildland fuel loads (Kramer et al. 2019). Our results are therefore most applicable to landscapes in which wildland vegetation is the dominant fuel, and to this end, we designed our housing density and development amount scenarios based on the definition of intermix WUI (USDA and USDI 2001; Radeloff et al. 2005).

## Implications

In forested WUI landscapes, fire risk to structures is expected to increase in the coming decades, and some exposure to high intensity fire is likely unavoidable even when defensible space is treated. Even when 50% of the landscape was treated every 10 years, large fire years exposed > 15% of the houses to high intensity fire in the safe suppression zone, and contiguous high intensity patch sizes exceeded 850 ha. During these extreme fire years, wildland fire suppression is also less effective (Keane et al. 2008; Ingalsbee 2017) and firefighting resources may already be limited if fire is widespread at regional and national scales (WFEC 2014). Managing and adapting to a future with more fire will require multiple approaches, including hardening homes against fire based on WUI building codes (Hakes et al. 2017, ICC 2017), incorporating fire risk into planning and regulation of WUI developments (Spyratos et al. 2007; Bihari et al. 2012; Syphard et al. 2012; Haas et al. 2013; Keeley and Syphard 2019), developing community wildfire protection plans to coordinate efforts in multi-jurisdictional landscapes (WFEC 2014; Rasker and Barrett 2016), and accepting an inevitable level of risk in fire-prone forests where fire activity is expected to increase (Moritz et al. 2014; Schoennagel et al. 2017). Although previous studies have found that local, neighborhood, and landscape scale factors predict building loss due to wildfire (Syphard et al. 2014; Alexandre et al. 2016), WUI fire risk assessments often characterize risk to structures only based on local scale burn probability and fire intensity. Our study offers a template for assessing fire risk to structures at multiple scales to better incorporate different mechanisms of structure ignition due to wildfire.

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**Data availability** Data, code, and software used for model simulations and analyses in this manuscript are publicly available in the Environmental Data Initiative repository, https://doi.org/10.6073/pasta/696e59acecd0bd289dae1afe3316c09c.

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