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ARTICLE

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Changes in wildfire occurrence and risk to homes from 1990 through 2019 in the Southern Rocky Mountains, USA

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Abstract

Wildfires and housing development have increased since the 1990s, presenting unique challenges for wildfire management. However, it is unclear how the relative influences of housing growth and changing wildfire occurrence have altered risk to homes, or the potential for wildfire to threaten homes. We used a random forests model to predict burn probability in relation to weather variables at 1-km resolution and monthly intervals from 1990 through 2019 in the Southern Rocky Mountains ecoregion. We quantified risk by combining the predicted burn probabilities with decadal housing density. We then compared the predicted burn probabilities and risk across the study area with observed values and quantified trends. Finally, we evaluated how housing growth and changes in burn probability influenced risk individually and combined. Fires burned 9055 km^2 and exposed more than 8500 homes from 1990 to 2019. Observed burned area increased 632% from the 1990s to the 2000s, which combined with housing growth, resulted in a 1342% increase in homes exposed. Increases continued in the 2010s but at lower rates; burned area by 65% and exposure by 32%. The random forests model had excellent fit and high correlation with observations (AUC $=$ 0.88 and $r = 0.9$). Observed values were within the 95% uncertainty interval for all years except 2016 (burned area) and 2000 (exposure). However, our model overpredicted in years with low observed burned area and underpredicted in years with high observed burned area. Overpredictions in risk resulted in lower rates of change in predicted risk compared with change in observed exposure. Increases in risk between the 1990s and 2000s were primarily due to warmer and drier weather conditions and secondarily because of housing growth. However, increases between the 2000s and 2010s were primarily due to housing growth. Our modeling approach identifies spatial and temporal patterns of wildfire potential and risk, which is critical information to guide decision-making. Because the drivers behind risk shift over time, strategies to mitigate risk may need to account for multiple drivers simultaneously.

KEYWORDS
exposure, hazard, machine learning, modeling, risk, wildland fire, wildland–urban interface

INTRODUCTION

Wildfires are a critical ecological process determining ecosystem structure and function, but pose serious risks to human lives, property, and ecosystem services (Bowman et al., 2009; Gill et al., 2013; He et al., 2019). The risk of wildfire to human life and property is increasing in many places because of climate change and shifts in land use (Abatzoglou et al., 2019; Bowman et al., 2017; Knorr et al., 2016), especially development (Gong et al., 2020; Güneralp et al., 2020). Development is now found close to wildlands in many parts of the world, expanding the wildland–urban interface (WUI) or where houses meet or intermingle with wildland vegetation (Johnston & Flannigan, 2018; Kaim et al., 2018; Lampin-Maillet et al., 2010). These trends are especially worrisome in areas where the WUI is extensive or growing and where wildfire risks to life and property are high (Radeloff et al., 2018).

Both WUI development and fire occurrence have increased in the United States, with substantial social, economic, and ecological impacts (Bowman et al., 2017; Chuvieco et al., 2014). From 1990 through 2010, the extent of the WUI increased from 581,000 to 770,000 km^2 (33% growth), and the number of homes in the WUI increased from 30.8 to 43.3 million (41% growth) (Radeloff et al., 2018). Concurrently, there have been large increases in wildfire ignitions and burned area (Hawbaker et al., 2020; Picotte et al., 2016), driven by shifts in climate and weather (Abatzoglou & Williams, 2016; Jolly et al., 2015; Westerling, 2016) and human activity expanding where ignitions occur in space and time (Balch et al., 2017; Syphard et al., 2017). Additionally, human activities have altered fuel loads by spreading invasive species, changing land use, and suppressing fires (Balch et al., 2013; Brooks et al., 2004; Hagmann et al., 2021; Parisien et al., 2016).

The combined effect of changes in development and wildfire occurrence has been an increase in the number of homes exposed to wildfires (Kramer et al., 2018; Radeloff et al., 2018; Strader, 2018). A recent estimate of the number of homes exposed by fires in the conterminous United States from 1992 through 2015 ranged from 2.2 to 2.8 million homes/year (Mietkiewicz et al., 2020), although the number of buildings destroyed is much lower, ranging from 245 in 2005 to 24,488 in 2018 (Headwaters Economics, 2021) or a little more than 10% of buildings exposed (Kramer et al., 2018). Accurately quantifying risk is therefore essential to mitigate risk to communities, critical infrastructure, water supplies, and other societal values. For example, the National Fire Plan (U.S. Departments of Agriculture and Interior, 2000), the Healthy Forests Restoration Act (U.S. Departments of Agriculture and Interior, 2003), and the Cohesive Fuels Treatment Strategy (U.S. Departments of Agriculture and Interior, 2006) all aim to reduce wildfire risk, as well as ensuring wildfire is allowed to occur where it has ecological benefits. Recognizing the dynamic nature of burn probabilities and risk over space and time and communicating how risk in one community compares to other communities may help increase awareness and prompt residents to act (Calkin et al., 2014; Champ & Brenkert-Smith, 2016; Kramer et al., 2021; Mockrin et al., 2018). Furthermore, recognizing the dynamics of risk in relation to changes in WUI development and wildfire occurrence will be critical for prioritizing risk mitigation actions while balancing contrasting priorities of reducing risk versus allowing fires to burn in the future (Liu et al., 2015; Liu & Wimberly, 2016; Radeloff et al., 2018).

Exposure and risk represent realized and potential effects of wildfires on WUI communities, respectively. Exposure has been defined as the combination of assets and observed fires (Ager et al., 2021; Argañaraz et al., 2017; Mietkiewicz et al., 2020; Radeloff et al., 2018) and also as the combination of assets and fire likelihood (Strader, 2018; Thompson et al., 2011) and fire intensity (Haas et al., 2013; Scott et al., 2013; Thompson et al., 2013). Thus, exposure represents the potential for loss without quantifying the effects on individual assets. In this study, we defined exposed homes as those contained within actual wildfire perimeters (Ager et al., 2021; Argañaraz et al., 2017; Mietkiewicz et al., 2020; Radeloff et al., 2018).

Definitions of risk combine probabilistic exposure with effects (Ludwig et al., 2018; Reisinger et al., 2020). Effects are typically assumed to include "adverse consequences on lives, livelihoods, health and well-being, economic, social and cultural assets and investments, infrastructure, services, ecosystems, and species" (Reisinger et al., 2020, p. 4), although others define risk to include both positive and negative effects on assets (Finney, 2005; Thompson et al., 2011). In practice, estimating the effects of wildfires on individual homes and structures in risk analyses is challenging because relationships between wildfire intensity and effects (response curves) are not well understood. Previous studies either assume all buildings are affected equally and incorporated flat response curves (Bar Massada et al., 2009; Thompson et al., 2011) or construct response curves from expert opinions (Scott et al., 2013;

Thompson et al., 2013). In reality, the effects of wildfires on homes can vary depending on landscape context, homeowner efforts to mitigate wildfire risk, vegetation immediately surrounding buildings, and building materials (Alexandre et al., 2016; Kramer et al., 2019; Meldrum et al., 2022; Papathoma-Köhle et al., 2022). Given the current state of knowledge and data available, incorporating response curves relating building damage to fire intensity in large-scale risk analyses likely underestimates the impacts on communities and adds more uncertainty than it resolves. In contrast to exposure, our definition of risk represents the potential for homes to be threatened by wildfires regardless of fire intensity or flame length, but still requires modeling to quantify (Bar Massada et al., 2009; Thompson et al., 2011). This definition follows existing literature but recognizes that we lack the methods and data needed to quantify the potential effects of wildfires on homes when estimating risk.

Estimating the probability of an area burning in a wildfire (burn probability) is essential when quantifying wildfire risk. However, there is no standard method to do so. A commonly used approach simulates fire spread and behavior based on stochastic ignition locations to generate burn probability maps (Finney et al., 2011). Burn probabilities are then combined with maps of assets (e.g., homes or critical watersheds), sometimes accounting for fire behavior and potential damage to assets (Haas et al., 2015; Scott et al., 2013; Thompson et al., 2013). This approach works well in areas where natural vegetation dominates, but not in the WUI where fuels differ greatly from wildlands (Caton et al., 2017; Elia et al., 2015; Hakes et al., 2017), and the fuel maps that the fire spread simulations rely on do not represent conditions in the WUI (Rollins, 2009). Accordingly, a national-scale analysis extrapolated simulated burn probabilities from wildlands into developed areas where there is no fuels information (Scott et al., 2020). Similarly, fire behavior models representing fire spread in WUI environments (e.g., home-to-home ignitions) are computationally demanding and not currently suitable for large-scale analyses (Linn et al., 2020; Rehm & Evans, 2013; Spyratos et al., 2007).

Statistical and machine learning methods offer an alternative to fire spread models to predict burn probabilities (Cicione et al., 2020; Scheller et al., 2019; Williams & Abatzoglou, 2016). Both statistical and machine learning models can be used to understand and predict various aspects of wildfire occurrence (e.g., probability of ignition and burning, fire size, and severity; Jain et al., 2020; Taylor et al., 2013; Xi et al., 2019), yet few studies use these methods to predict wildfire risk to homes. Among those that have, Bryant and Westerling (2014) generated spatially and temporally explicit risk projections in California for a suite of development and climate scenarios; however, they did not assess past changes in risk or the drivers of change. The work by Argañaraz et al. (2015) in the Sierras Chicas, Córdoba, Argentina, and by Syphard et al. (2019) in parts of California, USA both used machine learning models to produce spatially detailed risk estimates, but these assessments were for a single time period. Recent studies in the United States considered changes in exposure over time but did not use statistical or machine learning models to predict burn probability. Strader (2018) assessed changes in housing within wildfire likelihood zones based on 1992–2015 fire occurrence point densities and identified areas where both housing and fire occurrence increased. Radeloff et al. (2018) demonstrated that housing growth within 1990–2015 fire perimeters (62%) was greater than the national average (29%), indicating new development occurred in fire-prone areas. A third study combined fire footprints with the Zillow Transaction and Assessment Dataset (ZTRAX) database to evaluate how many homes were threatened by fires from 1992 to 2015 (Mietkiewicz et al., 2020). Finally, Haas et al. (2013) and Ager et al. (2021) quantified past building exposure in the United States and western United States using simulated fire spread but did not assess changes in exposure over time. None of these studies explicitly considered changes in risk though, whether through housing growth, increases in burn probability due to climate change, or their interactions. What remains missing are statistical and machine learning modeling approaches that can assess risk to homes, identify the drivers behind risk, and quantify how risk changes over time.

Many complex factors determine whether an area can burn, and identifying factors that contribute to changes in burn probability and risk is essential because merely identifying areas where homes were or were not exposed in the past does not account for this complexity. This is especially important given recent and projected increases in the extent of the WUI and burned area. Those increases raise important questions about how the spatial patterns of wildfire risk to homes have changed over time and why. Therefore, our goal was to assess the spatial and temporal patterns of wildfire exposure and to predict risk to homes within and outside the WUI in the 1990s, 2000s, and 2010s. Specifically, we asked: (1) How did observed burned area and exposure change over time? (2) What were the primary drivers of burn probability? And finally, (3) how did changes in housing growth and burn probability influence risk, individually or combined, in each decade? We focused our analysis on the Southern Rocky Mountains, USA (Southern Rockies), an ecoregion where both area burned and development in the WUI increased dramatically during the study period.

METHODS

Study area

The Southern Rockies ecoregion (Omernik & Griffith, 2014) (Figure 1) is 146,000 km^2, of which 139,000 km^2 or 97% was wildland vegetation in 2017 (58% forest, 29% shrubland, 11% grasslands, and 2% wetlands) (Brown et al., 2020; Figure 1). Forest composition varies with elevation, and dominant tree species include pinyon pine (*Pinus edulis*), juniper (*Juniperus scopulorum* and *Juniperus osteosperma*), ponderosa pine (*Pinus ponderosa*),

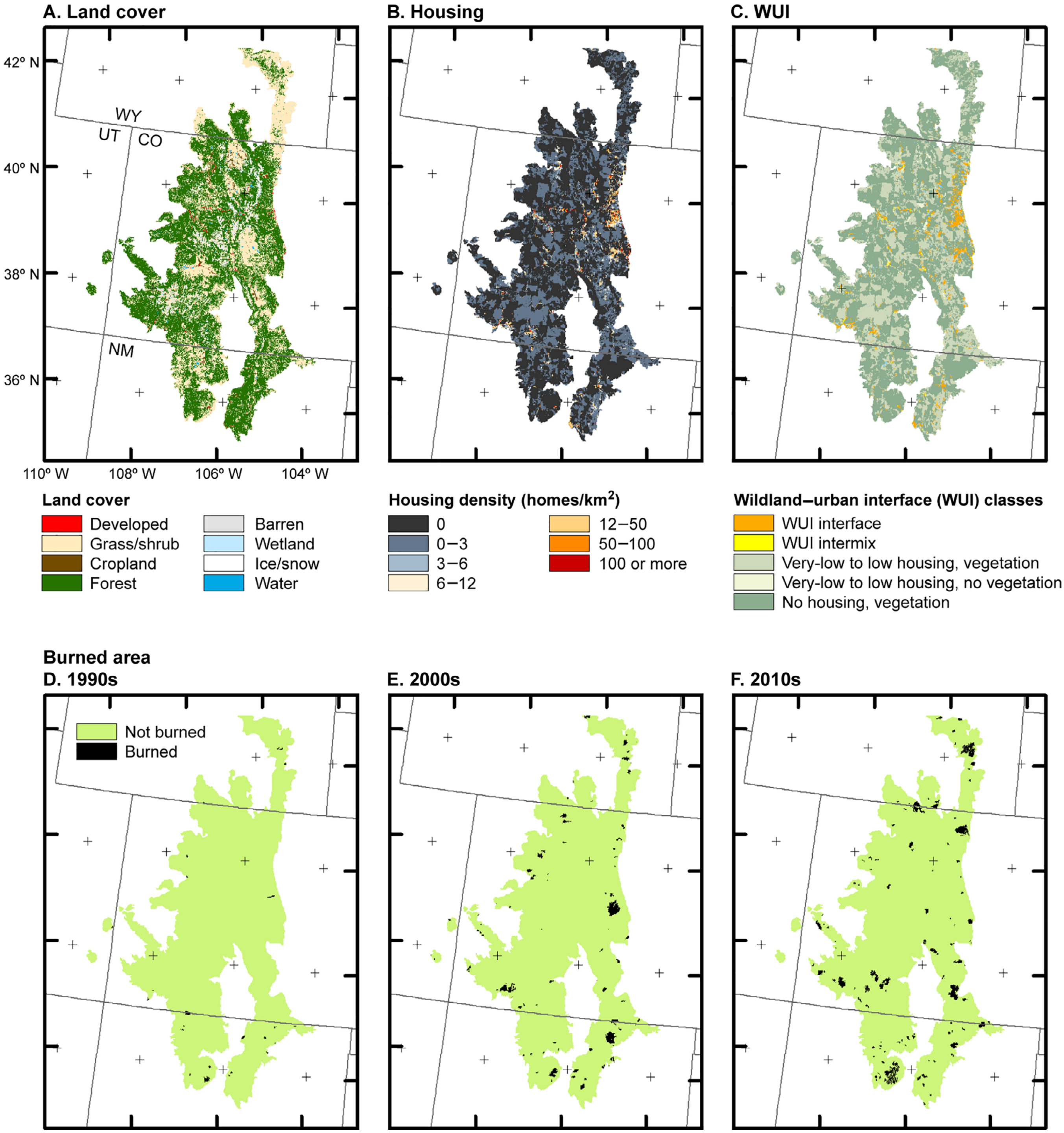

FIGURE 1 The extent of the Southern Rockies level III ecoregion, and our input data layers, including (A) 2017 Land Change Monitoring, Assessment, and Projection primary land cover, (B) 2010 housing density, (C) 2010 wildland–urban interface (WUI) classification, (D) 1990–1999 Monitoring Trends in Burn Severity (MTBS) burned area, (E) 2000–2009 MTBS burned area, and (F) 2010–2019 MTBS burned area. CO, Colorado; NM, New Mexico; UT, Utah; WY, Wyoming.

Douglas fir (*Pseudotsuga menziesii*), quaking aspen (*Populus tremuloides*), lodgepole pine (*Pinus contorta*), Engelmann spruce (*Picea engelmannii*), and subalpine fir (*Abies lasiocarpa*). Historical fire regimes varied greatly among vegetation types in the region (Baker, 2009; Sibold et al., 2006; Veblen et al., 2000). Like large parts of the western United States, the Southern Rockies ecoregion has experienced years with extensive fire activity. For example, the Monitoring Trends in Burn Severity (MTBS) data documented nearly 2000 km^2 burned in the 2002 and 2018 fire seasons, and the 2020 season burned 2700 km^2 (Eidenshink et al., 2007). However, contemporary burned area is likely much less than it was historically because of land management policies limiting fire occurrence, especially in low-elevation ponderosa pine forests (Parks, Miller, et al., 2015; Veblen et al., 2000). Ownership and housing development patterns are typical of the western United States; 98,000 km^2 (67%) is public land managed by state and federal agencies and 15,000 km^2 (10%) is designated wilderness (USGS Gap Analysis Project, 2018). The Southern Rockies ecoregion is close to but does not include neighboring cities like Denver and Colorado Springs, CO, Santa Fe, NM, and Cheyenne, WY. Although housing development within the ecoregion is relatively sparse, it has grown from 207,000 homes in 1990 to 326,000 homes in 2010, with 67% of the new homes in the WUI (Radeloff et al., 2018).

Assessing past patterns of burning and homes exposed to wildfires

We quantified observed annual area burned and exposure using the MTBS fire perimeters for 1990–2019 (Eidenshink et al., 2007) and block-level US Census housing data for 1990, 2000, and 2010 (Radeloff et al., 2018). The MTBS data include only large fires ($\geq$4 km^2); however, these fires account for the majority of burned area (Strauss et al., 1989) and have the most significant impacts on communities (Cohen, 2008; Kramer et al., 2018). While MTBS data products include burn severity rasters, we used the fire perimeters.

We calculated observed exposure in each year by counting the number of homes within wildfire perimeters, using housing data from the nearest previous census year (e.g., 1990 census housing data for 1990–1999 burned areas). We stratified burned area and exposure into four land use categories: (1) interface WUI where homes are next to wildland vegetation; (2) intermix WUI where homes are dispersed among wildland vegetation; (3) areas with very low housing density and wildland vegetation (less than 6.17 homes/km^2); and (4) nonvegetated/agriculture (Radeloff et al., 2018). The nonvegetated/agriculture WUI category included areas dominated by urban, agriculture, water, permanent snow/ice, and barren land cover types. We assessed historical patterns of burning and exposure by year and decade in each of the four WUI categories for the 1990–2019 period after resampling the data to 1-km resolution (Figure 1).

Modeling wildfire potential

We used a random forests model to predict burn probability. For the response variable, we used the MTBS perimeters as a binary indicator of burning in each month. Predictors represented weather conditions, land use and land cover, vegetation connectivity, past fire history, WUI classification, infrastructure, and topography. The predictor data layers, sampling strategy, and model fitting strategy, and model predictions are described in the following sections. All predictors considered are listed in Appendix S1: Table S1. Flowcharts of preprocessing steps completed for each variable are provided in Appendix S1: Figure S1 and preprocessing scripts are included in Hawbaker et al. (2022). To predict risk to homes, we combined the burn probability predictions with the decadal housing data.

Response and predictor data layers

We selected a suite of predictor variables to represent weather and landscape conditions that influence burn probability. We averaged weather-related predictors (mean daily precipitation, mean daily minimum and maximum relative humidity, mean daily minimum and maximum temperature, and mean and maximum daily wind speed) for each month from the GridMET data (Abatzoglou, 2013). We also calculated 1-, 3-, 6-, 9-, 12-, 18-, and 24-month lagged means of each monthly weather-related predictor except wind speed. Past studies have demonstrated that these monthly and lagged weather variables influence fire probability over the short term by affecting fire weather, fuel moisture and flammability, and long-term effects on fuel production and accumulation (Littell et al., 2016; Moritz et al., 2010; Riley et al., 2013).

Land cover and vegetation types also influence ignition rates and fire behavior (Keane, 2015; Parisien et al., 2016). Therefore, we included land cover from the Land Change Monitoring, Assessment, and Projection (LCMAP) primary land cover data for 1985–2019

(Brown et al., 2020). Because LCMAP data were not available for 1984, we used the 1985 LCMAP data for that year. We assigned values from the nearest Forest Inventory and Analysis forest type group raster (Ruefenacht et al., 2008) to pixels classified as forest in the LCMAP data to represent different forest types. We also simplified the LCMAP land cover data to an additional layer representing wildland vegetation (grass/shrub, forest, or wetland). To represent vegetation connectivity and the potential for large fire spread, we calculated the proportion of wildland vegetation pixels within 2-, 4-, 6-, 8-, 10-, and 12-km circular moving windows (Mansuy et al., 2019; Parisien et al., 2012). Furthermore, previously burned areas may limit the spread of future potential fires (Coop et al., 2016; Hurteau et al., 2019; Parks, Holsinger, et al., 2015). Thus, we included indicators of burning within the previous 5, 10, and 15 years using MTBS perimeters.

We included several variables to represent potential human influences on ignitions (Cardille et al., 2001; Hawbaker et al., 2013; Prestemon et al., 2013), including WUI category, distance to edges of protected, wilderness, and developed areas (negative inside and positive outside), and distance from powerlines, railroads, and roads (Brown et al., 2020; U.S. Department of Homeland Security, 2020; U.S. Geological Survey, 2018, 2020).

Other landscape predictors included topography (slope, aspect, and elevation) that affect vegetation, fuel moisture, and fire spread. For example, aspect and slope affect the rate at which fuels dry (Bradshaw et al., 1984), and slope influences fire spread (Rothermel, 1972). Additionally, topographic predictors may represent gradients in vegetation composition and productivity and fine-scale heterogeneity in temperature and moisture (Bassman et al., 2003; Peet, 1981).

We included month as a predictor to represent temporal patterns in human activities (e.g., ignitions caused by fireworks on the 4th of July) and weather conditions not captured by other predictors. We resampled all data to 1-km resolution using nearest neighbor resampling for categorical variables and bilinear interpolation for continuous variables. We derived predictors (e.g., slope) after the original data (e.g., elevation) were resampled to 1-km resolution. We excluded water, snow/ice, or barren land cover in the LCMAP primary land cover data (Brown et al., 2020) from all analyses. We standardized or scaled continuous nonweather variables to z-scores by subtracting their mean and dividing them by their standard deviation (SD). We scaled weather-related predictors to z-scores based on the mean and SD of each pixel's time series. We converted all categorical variables to binary indicators.

Sampling strategy

Developing models of rare events such as wildfires is difficult because of the limited number of observed events relative to the large number of nonevents (Dixon et al., 2005; Hosmer et al., 2013). Subsampling strategies, such as case–control sampling, can reduce data volume and improve model fitting efficiency (Hosmer et al., 2013). Here, we sampled 50% of the burned area and 0.5% of the not-burned area (Hawbaker et al., 2013), resulting in 4585 burned pixels and 311,083 not-burned pixels.

Random forests modeling strategy

We fit a random forests model (Breiman, 2001) using the sample of observed burned area from 1984 through 2019 as the response variable and the suite of predictors described above. Random forests utilize bagging to reduce variance and increase prediction accuracy (Breiman, 1996). When fitting and evaluating models, we applied cross-validation (CV) temporal blocking by randomly selecting 6 out of 36 years for each test group. This ensured that training and test samples would not be selected from the same fire or year, as this would violate the assumption that samples are independent (Roberts et al., 2017).

We removed correlated predictors before fitting the random forests model because correlated predictors can distort model estimation and prediction (Dormann et al., 2013) and introduce bias in predictor importance estimates (Strobl et al., 2007). For continuous predictors, we fit decision tree models to individual predictors using a maximum depth of three. We scored each predictor with the CV-test logistic loss and then ranked them from least to greatest CV-test loss. If any pair of predictors had a correlation >0.7, the predictor with the lower CV-test loss value was retained. We first selected the monthly weather-related predictors and then tested the lagged predictors of the selected monthly weather predictors. We applied the same CV-test loss and correlation tests to the remaining nonweather predictors. Finally, we selected indicator predictors using Pearson's χ^2 tests to determine whether observed frequencies of burned pixels matched expected frequencies for each class, retaining those with χ^2 p values ≤ 0.05.

We fit the random forests model using the initial set of selected predictors and tested all possible combinations of a set of hyperparameter values that control model structure: maximum tree depth (1, 2, 3, 5, and 7), column sampling rate (25%, 50%, 75%, and 100%), row sampling rate (50%, 75%, and 100%), and the number of estimators in the random forests model (100, 200, and 300). We selected the hyperparameter combination with the smallest logistic loss calculated with the CV-test samples. We report model fit using logistic loss and the area under a receiver operating characteristic curve (AUC) for the CV-train and CV-test samples (Hanley & McNeil, 1982).

To further reduce our set of predictor variables, we calculated each candidate predictor's permutated importance (Breiman, 2001) for each tree in the random forests model and summarized importance values for all features across all trees. Here, permutation importance was based on changes in AUC after the values of each individual predictor were randomly shuffled. We retained predictors that had minimum permutated importance values >0. Initial tests indicated that this approach was as effective as more computationally demanding forward sequential variable selection (Elith et al., 2008). After fitting the random forests model, we assessed variable importance and, for the three most important predictor variables, visualized partial dependence, or the relationship between predictions to a predictor variable, averaged over the values of the other predictors.

Finally, to determine whether there was spatial dependence unaccounted for by the selected predictors, we calculated semivariance values from the random forests residuals. We fit nugget-only and spherical semivariograms (Olea, 1999), tracking the semivariogram parameters and root mean squared error (RMSE) between the observed and predicted semivariance. We repeated this process 20 times using a 1% random sample of the residuals; fitting semivariograms to a larger sample size was not computationally feasible. We then used t tests of the semivariogram parameters and RMSE values to determine if the spherical variogram fits were significantly different than the nugget-only semivariograms, with p values >0.05 indicating that meaningful spatial dependence was not present in the random forests model residuals.

Predicting burn probability and burned area

Using the random forests model and selected predictor variables, we spatially predicted burn probability at 1-km resolution and monthly time steps from 1990 to 2019. Predictions were the mean of predictions across individual trees in the random forests model, but we also determined uncertainty by aggregating predictions from individual trees for a range of percentiles (minimum, 5%, 25%, 50%, 75%, 95%, and maximum; Mansuy et al., 2019; Meinshausen, 2006).

A convenient property of binary classifiers is that the sum of predicted probabilities equals the expected number of events as long as predicted probabilities are corrected for the sampling design (Hosmer et al., 2013). Using this property, we summed predicted burn probabilities to estimate the ecoregion predicted burned area and evaluated the performance of the random forests model by calculating the mean error as a measure of bias, RMSE as a measure of accuracy, and the Pearson correlation (r) as a measure of temporal agreement between the predicted and observed burned area. We calculated errors by comparing observed values to the random forests model predictions for the CV-test years, aggregated by month, year, decade, and WUI category.

Assessing wildfire risk to homes

To quantify predicted risk, we multiplied the predicted burn probability layers with housing counts from the 1990, 2000, and 2010 decadal census data (Radeloff et al., 2018) in the same manner we calculated exposure. Thus, based on the modeled burn probabilities, risk represented the expected number of homes exposed to fire in a given area and time period. We summarized risk predictions and calculated errors by month, year, and decade, and WUI categories as with the predictions of burned area.

Determining the relative influence of burn probability and housing growth on risk

Changes in risk occurred in response to the individual and combined effects of changes in housing density and predicted burn probability. The random forests model predictors and their importance only explained what drivers influenced increases in burn probability. Housing growth may also modify risk, independent of changes in those drivers and resulting burn probabilities. Therefore, we generated predictions for three scenarios with varying weather conditions (drivers of burn probability) and housing growth to disentangle the individual and combined effects of changes in burn probability and housing development on risk. The first scenario evaluated the combined effect, using both observed changes in weather to predict burn probability and observed housing density and provided a baseline scenario for comparisons. The additional scenarios evaluated the individual effects of changes in housing growth and burn probability. The "1990s stable housing" scenario held housing density constant at 1990s levels but predicted burn probabilities based on observed changes in weather, whereas the "1990s stable weather" scenario predicted burn probabilities using 1990s weather conditions but combined them with the observed change in housing density. We quantified the individual effects of changing burn probabilities and changing housing density on risk by comparing decadal changes in risk across the three scenarios. Greater rates of change in the "1990s stable weather" scenario relative to the "1990s stable housing" scenario would indicate that increases in housing density had a larger effect on risk than increases in burn probabilities.

RESULTS

Patterns of burning and homes exposed to wildfires

From 1990 to 2019, 237 fires burned 9055 km^2 in the Southern Rockies, approximately 6% of the ecoregion. Over 8500 housing units were exposed (within burned areas), accounting for more than 3% of all homes in the ecoregion in 2010. The majority of the burned area was outside the WUI; 97.2% was in very low housing density and wildland vegetation, and just under 3% was in the WUI (2.7% intermix and 0.1% interface). However, most homes exposed were in the WUI (62.7% in total, 61.7% in intermix WUI, and 1.0% in interface WUI). The exposed homes outside the WUI (36.4%) were in very low housing density and wildland vegetation. Because of the small amount of burned area and exposed homes in the interface WUI, we combined results for the interface and intermix WUI types in further analyses.

The observed burned area (Figure 2A) and the number of homes exposed (Figure 2B) varied substantially from year to year. Burned area averaged 301 km^2/year, and exposure averaged 286 homes/year. Several years had neither large fires nor exposed homes (1991, 1992, 1995, and 2007). Additionally, there was no exposure in 1990 and 1993, even though there were fires. In the remaining years, burned area ranged from 10 km^2 in 1990 to 2020 km^2 in 2002. Homes exposed ranged from 1 in 1997, 2007, and 2015 to 3085 in 2002.

Observed burned area increased by 632% from the 1990s to the 2000s, and exposure increased by 1342%. Burned area increased again between the 2000s and 2010s (65% increase), and exposure increased by 32%. These rates of change were much greater than the rate of housing growth in the Southern Rockies: 23% from 1990s to 2000s, and 18% from 2000s to 2010s. The most dramatic changes were observed in the WUI. Between the 1990s and 2000s, burned area in the WUI increased by 3467% and exposure increased by 13,523% (Table 1). However, rates of change in the WUI from the 2000s to the 2010s were substantially lower: 27% for burned area and 27% increase for exposure. Correlation between

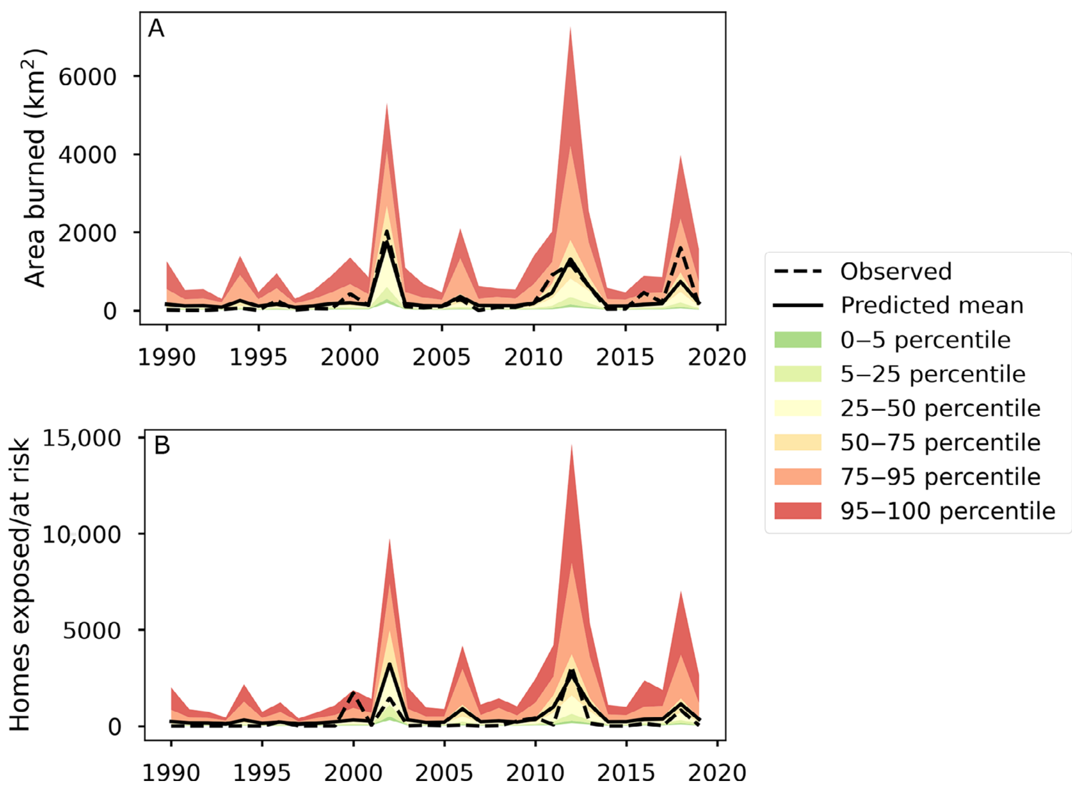

FIGURE 2 Annual trends in (A) observed and predicted burned area and (B) observed exposure and predicted risk to homes from 1990 to 2019. Predictions include the random forests mean and percentiles across individual models within the random forests.

burned area and homes exposed from 1990 to 2019 was high ($r = 0.66$), but the correlation between burned area and exposure varied considerably among decades ($r = 0.97$ in the 1990s, 0.71 in the 2000s, and 0.59 in the 2010s) and was significant ($p < 0.05$) for all decades except the 2010s ($p = 0.07$).

Modeling wildfire potential

Fire occurrence models

The best fit random forests model used 3 for maximum depth, 50% for row sampling, 100% for column sampling, and 100 individual models. AUC indicated good model fit (0.922 ± 0.004 for CV train and 0.880 ± 0.004 for CV test) and overlap between the train and test CV-fold logistic loss values indicated overfitting was unlikely (0.0454 ± 0.0018 for CV train and 0.0511 ± 0.0085 for CV test). Semivariograms indicated a lack of spatial dependence in the random forests model residuals; RMSE of the spherical semivariogram was not significantly different than RMSE values for nugget-only semivariograms (t test $p = 0.9967$; Appendix S1: Table S2 and Figure S2).

The initial predictor selection routine selected 53 out of 101 of the predictors considered (Appendix S1: Table S1). The remaining 53 predictors were further reduced to eight during the random forests model fitting. The indicator for June had the highest mean importance among all the predictors; however, importance varied considerably among the individual trees within the random forests (Figure 3). Other selected predictors were primarily related to weather conditions, including monthly average of daily maximum temperature, minimum humidity, and precipitation, and 1-, 3-, 9-, and 24-month lagged precipitation.

TABLE 1 Observed burned area (in square kilometers) and number of exposed homes by decade.

	Burned area (km^2)			Number of exposed homes		
Land use category	**1990s**	**2000s**	**2010s**	**1990s**	**2000s**	**2010s**
All	444	3250 (−632%)	5350 (−65%)	249	3592 (−1342%)	4739 (−32%)
No vegetation	0	7	2 (−71%)	0	75	1 (−99%)
Wildland–urban interface	3	107 (3467%)	136 (27%)	18	2470 (13,523%)	2892 (17%)
Very-low-density housing and vegetation	441	3136 (611%)	5212 (66%)	231	1048 (354%)	1846 (76%)

Note: Increases from the previous decade are shown in parentheses.

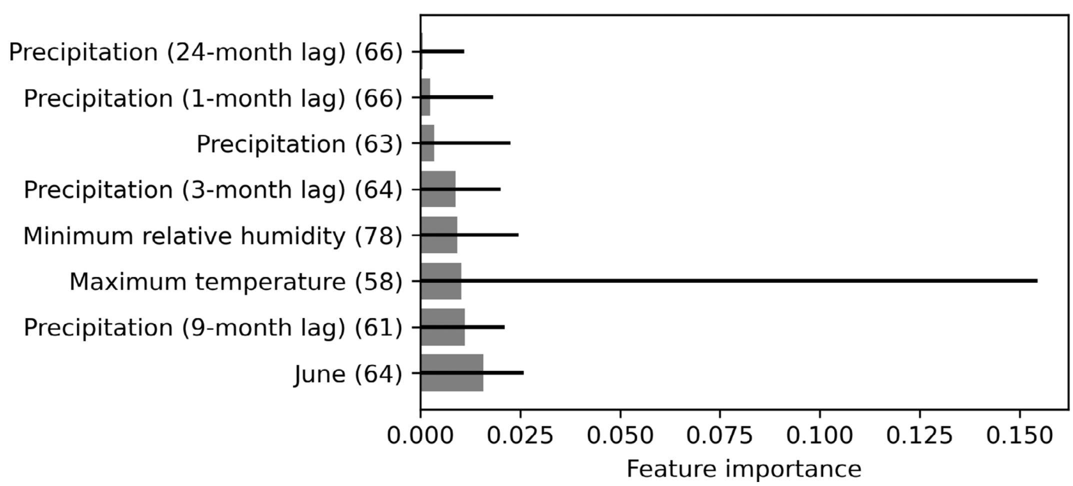

FIGURE 3 Permutation importance of the selected predictors. Gray bars show the mean permutation importance across test samples. Black lines show the range of permutation importance. Values in parentheses indicate the number of individual decision trees within the random forests models that selected the variable.

Partial dependence plots showed that burn probability was greater in June, had a negative relationship with 9-month lagged precipitation, and had a mostly positive relationship with monthly maximum temperature (Figure 4). However, there was substantial variability in partial dependence among individual trees in the random forests model, and the variability tended to be greatest at the edges of the distributions where observations were few. The mean partial dependence calculated using the random forests predicted mean tracked the observed data well for all three predictors, but as with the individual trees, diverged at the edges of predictor distributions.

Temporal trends and spatial patterns of predicted burned area and risk

To capture the range of temporal variability among model predictions, we summed the mean and percentiles of the random forests predictions for burned area and risk by year across the study area by month and aggregated by year and decade. Error metrics for burned area and risk generally improved with the length of time step (Table 2). Burned area RMSE was 230% of the observed mean burned area for months, 70% for years, and 30% for decades. Risk RMSE was slightly higher at 560% observed exposure for months, 191% for years, and 86% for decades. Similarly, correlations between observed burned area and predictions increased from 0.9 for months and years to 1.0 for decades. Correlations tended to be lower for risk but followed a similar pattern, increasing from months (0.7) to years (0.8) to decades (1.0). Burned area was underpredicted primarily in years with above-average observed burned area and overpredicted in years with below-average observed burned area, resulting in negative mean error values (Figure 2; Table 2). Risk followed similar patterns, but the overpredictions were larger than underpredictions, resulting in positive mean error values (Figure 2; Table 2).

To capture the range of temporal variability among model predictions, we also summed the percentiles of the predictions for burned area and risk by year across the study area (Figure 2). The prediction percentiles had high variability but tracked year-to-year variations in the observed burned area; correlations between observed and predicted burned area exceeded 0.9 for the 50th and larger percentiles (Table 2). Furthermore, the range of predictions overlapped the observed burned area and exposure in all years. For example, the 95th prediction percentile was greater than the observed in all years except burned area in 2016 and risk in 2000.

TABLE 2 Cross-validation test-fold error metrics and correlation comparing observed and predicted values of burned area (in square kilometers) and risk (homes) by time step (month, year, or decade).

Time step	Metric	Burned area	Risk
Month	ME	−1.41	19.90
	RMSE	57.72	133.40
	r	0.93	0.72
Year	ME	−16.95	238.82
	RMSE	213.22	547.03
	r	0.91	0.74
Decade	ME	−169.51	2388.17
	RMSE	917.59	2463.54
	r	0.99	1.00

Abbreviations: ME, mean error; *r*, correlation; RMSE, root mean squared error.

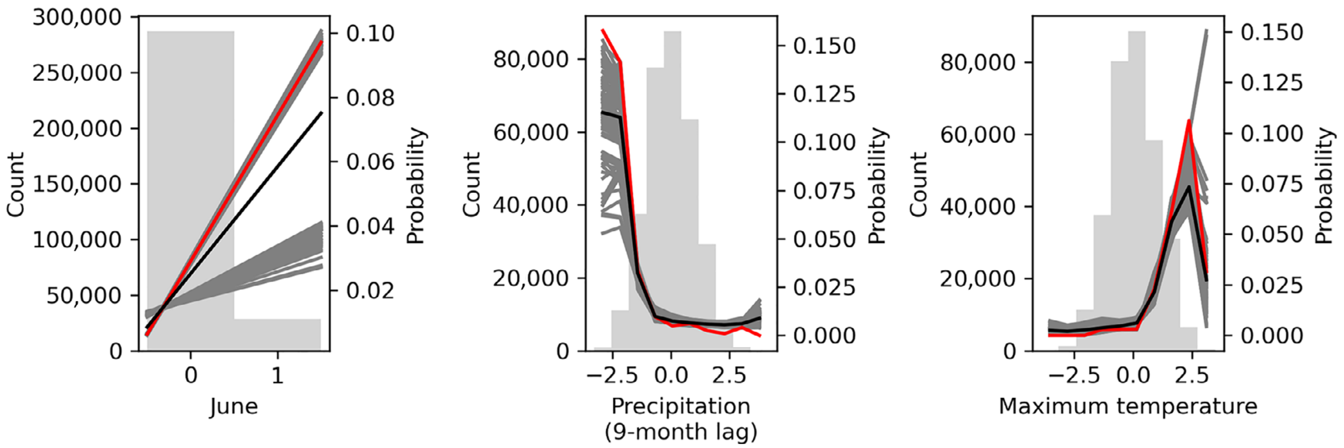

FIGURE 4 Histograms and partial dependence of the top three predictors selected. Red lines show the observed response, black lines show the mean of random forests predictions, and gray lines show the partial dependence calculated using individual decision trees within the random forests model.

The maximum of predictions was often substantially larger than the observed amount, up to 260% greater than the maximum observed burned area, and up to 376% greater than the maximum observed exposure (equivalent to 7270 km^2 of burned area and 14,671 homes at risk per year).

We used decadal averages to visualize the spatial patterns in the random forests predictions for burn probabilities (Figure 5). In the 1990s, burn probabilities were relatively low for the entire study area but increased in the 2000s and again in the 2010s. Especially pronounced increases were predicted in the southern and eastern parts of the ecoregion. Spatial patterns of risk were difficult to visualize across the study area but track gradients in burn probabilities and housing densities when shown at a scale relevant to regional and local planning and zoning (Figure 6).

The patterns of predicted burned area across WUI categories and decades were similar to observed but overestimated in the 1990s (Figure 7). Consequently, predicted change rates were lower than observed change rates from the 1990s to the 2000s. Predicted burned area increased from the 1990s to the 2000s by 140% and again by 27% in the 2010s (Table 3; Figure 7), and increases were even higher in the WUI (218% for 1990–2000 and 38% for 2000–2010). Across all land use categories, predicted risk increased by 231% from the 1990s to the 2000s and again by 28% from the 2000s to the 2010s (Table 3; Figure 7). In the WUI, predicted risk increased from the 1990s to 2000s by 335% and again by 7% from the 2000s to 2010s. Predicted changes in risk in very low housing density and wildland vegetation also increased, but at a lower rate than in the WUI from the 1990s to 2000s (106%) and at a greater rate from the 2000s to 2010s (85%).

The relative influence of changing burn probabilities and housing growth on risk

Changes in burn probability were primarily a result of changes in weather because the predictors selected by the random forests model were almost entirely related to weather; however, changes in predicted risk were related to increases in both burn probability and housing density (Table 3). Overall, predicted changes in risk were greatest using observed changes in weather and housing. Changes

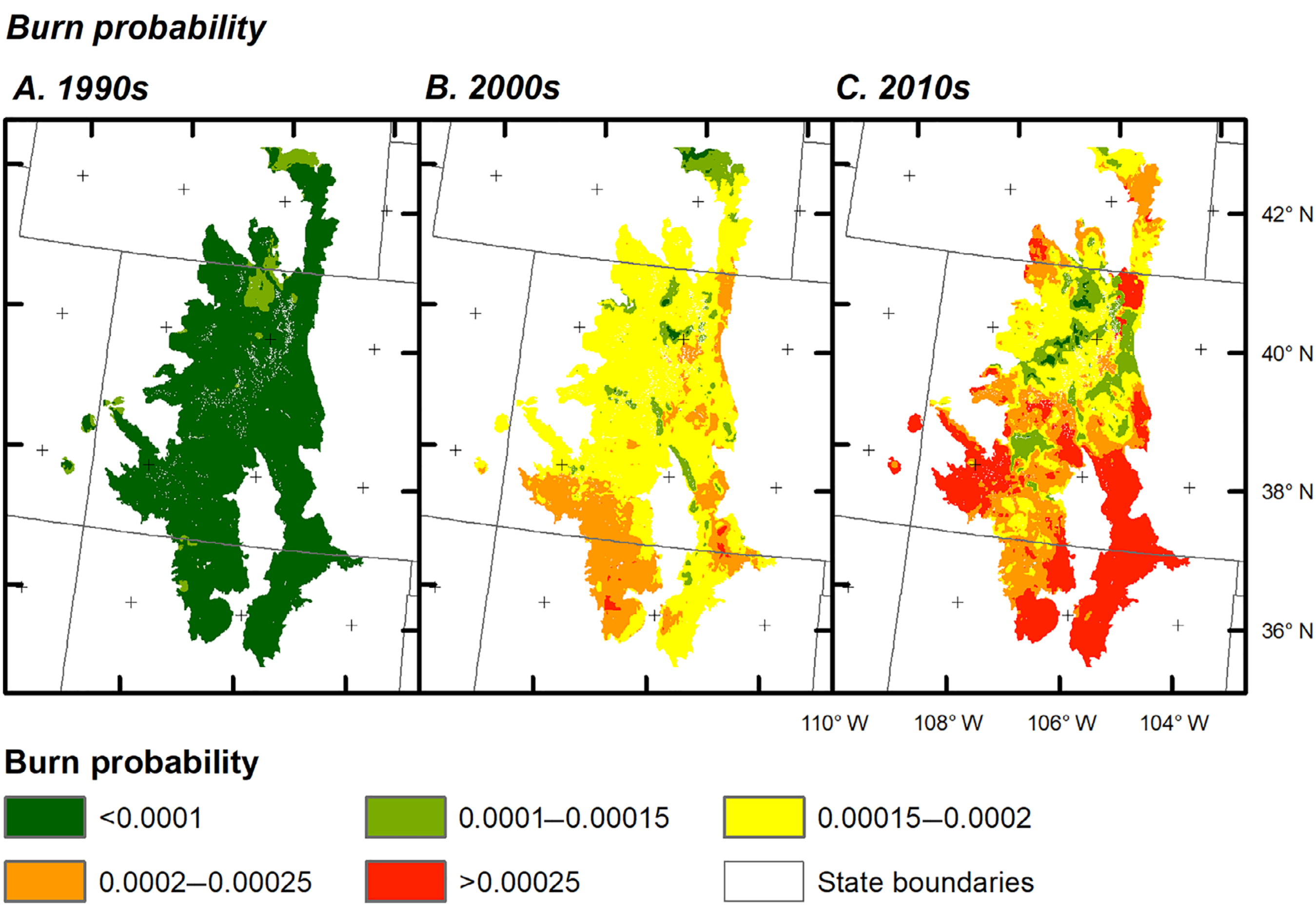

FIGURE 5 Decadal averages of predicted burn probabilities.

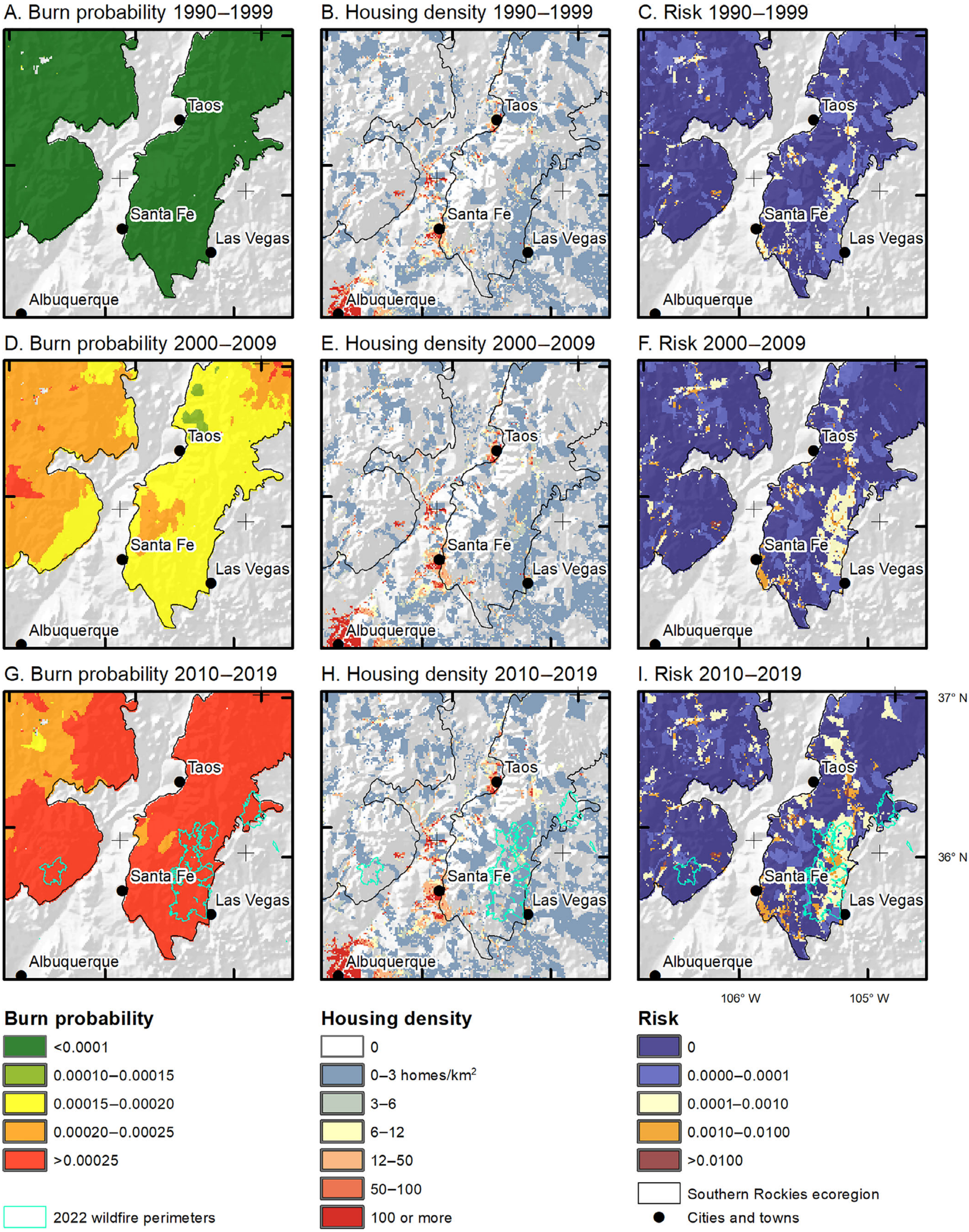

FIGURE 6 Examples of decadal averages of predicted burn probability, observed housing density, and predicted risk for northern New Mexico with 2022 wildfires perimeters (as of June 3, 2022).

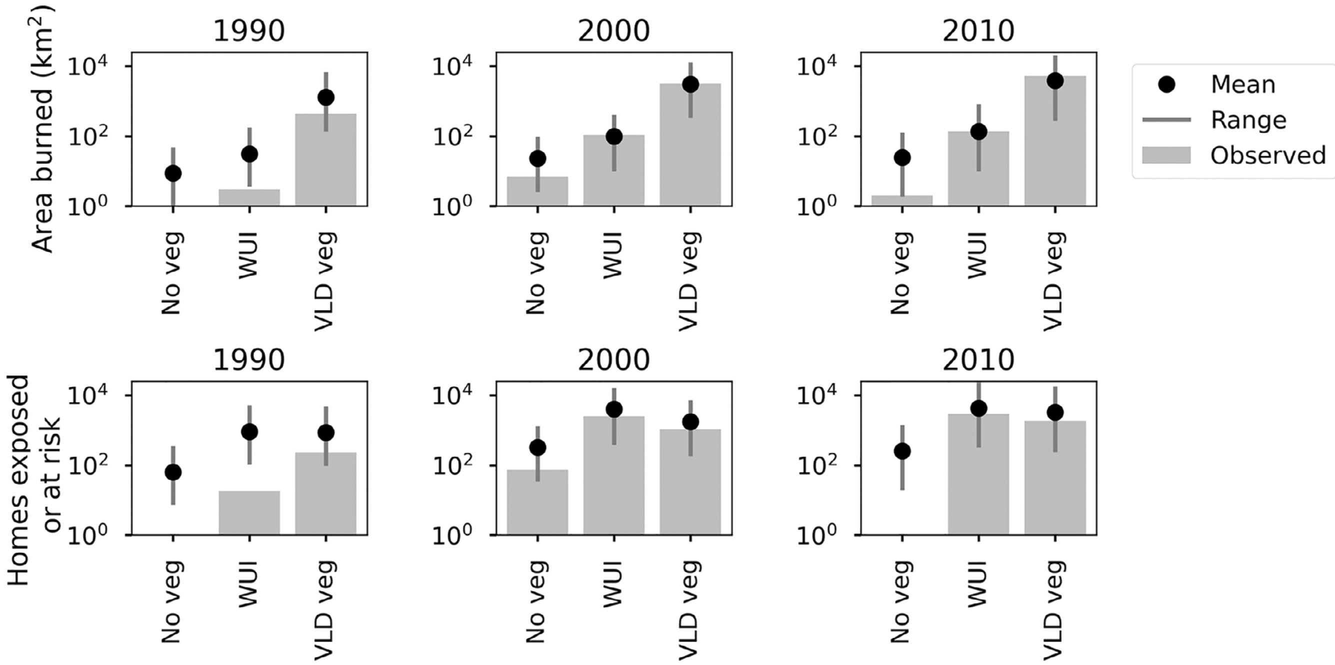

FIGURE 7 Decadal trends in observed and predicted burned area and risk across land use categories. Gray bars represent observed values. Mean and range of predictions are shown by black dots and error bars, respectively. VLD, very low housing density and wildland vegetation (veg); WUI, wildland–urban interface.

TABLE 3 Predicted burned area (in square kilometers) and risk (homes) by decade for weather and housing growth scenarios.

	Burned area (km^2)			Risk (no. homes)		
Scenario	**1990s**	**2000s**	**2010s**	**1990s**	**2000s**	**2010s**
Changing weather, changing housing	1325	3182 (140%)	4029 (27%)	1844	6101 (231%)	7800 (28%)
1990s housing (changing weather)	1325	3182 (140%)	4029 (27%)	1844	4631 (151%)	4949 (9%)
1990s weather (changing housing)	1325	1325 (0%)	1325 (0%)	1844	2429 (32%)	2951 (21%)

Note: Increases from the previous decade are shown in parentheses.

in risk were lower in the two scenarios where 1990s housing and 1990s weather were held constant. Differences between the scenarios indicated that increases in risk from the 1990s to 2000s were primarily driven by changes in weather as increases in risk were greater in the 1990s housing scenario (151%) than in the 1990s weather scenario (32%). However, changes in risk from the 2000s to 2010s were primarily driven by changes in housing; increases in risk were 21% in the 1990s weather scenario compared with 7% in the 1990s housing scenario.

DISCUSSION

Similar to many other parts of the western United States, the Southern Rockies witnessed a substantial increase in annual burned area starting in the 2000s. The increase in annual burned area continued into the 2010s, but at a lower rate (Hawbaker et al., 2020; Picotte et al., 2016). The spatial patterns of burn probability predicted by our models matched observed patterns and trends over the course of three decades. Predicted burn probability was highest in forests and ecosystems at lower elevations and the south part of the Southern Rockies ecoregion (Figure 5), matching known patterns and providing confidence in our modeling approach (Kulakowski & Veblen, 2007; Sibold et al., 2006; Veblen et al., 2000).

Exposure was greatest for homes within the WUI in the Southern Rockies, containing 62.7% of all exposed homes, whereas 36.4% were outside the WUI in very low housing density and wildland vegetation areas. Within the WUI, most homes exposed were in the intermix

(61.7% of all homes), not in the interface (1.0%). This corroborates findings by Kramer et al. (2018) that 59% of all exposed buildings were in the WUI from 2000 through 2013 across the conterminous United States, and by Caggiano et al. (2020) that 86% of all buildings destroyed in large fires were in the WUI from 2000 through 2018. Averaged over all years in our analysis, 58.4% of homes at risk were in the WUI.

Burned area and exposure both increased over time in the Southern Rockies and at a much greater rate than housing growth; however, the relationship between the burned area and exposure varied. Exposure was correlated with burned area in the 1990s and the 2000s. That correlation weakened in the 2010s, even though there was more burned area and homes exposed than in the 2000s. Our modeling approach captured the relative changes, showing increases in potential burned area from the 1990s to the 2000s and again to the 2010s. Homes in the WUI had limited exposure in the 1990s, but exposure increased in the 2000s in WUI areas. Our predictions of risk had similar changes in the WUI but overpredicted in the 1990s, related to overprediction of burned area in the WUI in the 1990s.

The discrepancy between observed and predicted risk patterns may be a result of the limited amount of data available to train our random forests model or natural variation and stochasticity expected in long-term fire data. The 1990s had much less burned area than the 2000s and 2010s, and the random forests model captured years with a large amount of burned area but overpredicted in years with a minimal amount of burned area. This suggests that future efforts building on our approach may benefit from using longer time series of observed data and additional predictors that better differentiate conditions in the 1990s where burned area tended to be low from the 2000s and 2010s where burned area was greater.

Drivers of burn probability and burned area

Our model selected monthly relative humidity, precipitation, and temperature, and lagged precipitation as important predictors, indicating the influence of near-term fuel moisture conditions on fire behavior and spread but also long-term drought conditions on fuel moisture and vegetation productivity (Littell et al., 2016; Riley et al., 2013; Veblen et al., 2000). The only additional predictor selected was the indicator for June, representing seasonal variability in burning unrelated to the other weather-related predictors. June is the month with the lowest precipitation and humidity values and the greatest burned area in our study area. It is also the start of the summer tourist season in the Southern Rockies and just before the start of the summer monsoon when lightning ignitions are more common. Thus, the June indicator may represent patterns of human activity that affect ignition rates and thereby burned area, especially in and near public lands.

Another surprising result of the predictor selection were the variables not included. The random forests model selected none of the predictors representing human influences, even though we tested WUI classes and other predictors related to human activities that influence ignition patterns and variability in fire management and suppression actions (Prestemon et al., 2002; Rideout & Omi, 1990). These predictors were not selected by our model, indicating that the influence of human development and activities on burned area is minimal or lacks spatial and temporal variability in this region at the 1-km^2 resolution of our analysis. Initial predictor selection included variables characterizing land cover or forest type, wildland vegetation connectivity, and past fire activity. Howee predictors also removed during model fitting represented variability in fuel loads and structure (Keane, 2015), spatial differences in vegetation connectivity (Mansuy et al., 2019; Parisien et al., 2012), and how past fires affect subsequent ones (Coop et al., 2016; Hurteau et al., 2019; Parks, Holsinger, et al., 2015). We rescaled all input data to a 1-km^2 resolution primarily to maintain computational efficiency. However, this may have limited the influence of variability in vegetation types and connectivity; nearly the entire study area is connected at 1-km^2 resolution. Indicators of past fire occurrence not being selected by the random forests model suggests that previously burned areas were either not extensive enough or burned vegetation recovered too quickly to have an effect, a result confirmed by previous studies (Kulakowski & Veblen, 2007; Parks, Holsinger, et al., 2015; Sibold et al., 2006).

Risk changed over time in response to development patterns and weather changes. The alternate scenarios we evaluated demonstrated that changes in weather between the 1990s and 2000s contributed substantially more to risk (151% increase) than housing growth (32% increase). The combined influence of changing weather and housing growth (231%) was greater than either driver individually. The 2000s marked the beginning of long-term drought in the western United States (McCabe & Wolock, 2021; Williams et al., 2020) and continued WUI expansion (Radeloff et al., 2018). Drought conditions persisted in the 2010s and coincided with increases in wildfire occurrence observed across the western United States, also beginning around the year 2000 (Abatzoglou & Williams, 2016; Hawbaker et al., 2020). Because drought conditions persisted, weather conditions in the 2010s were similar to conditions in the 2000s, but housing growth continued. Consequently, our scenarios showed that housing growth had a greater influence than weather conditions on increases in risk from the 2000s to the 2010s (21% for housing growth and 7% for changing weather).

Implications for assessing and mitigating wildfire risk

Risk can only be predicted using models, and models need to be closely tied to observed data to be relevant to management. Our approach is unique in that it allowed us to quantify relative differences in burn probability and risk over space and time. By accounting for the case–control sampling strategy in our random forests model predictions, our predicted burned probabilities summed across the study area resulted in burned area estimates on the same scale as the observed burned area at any time step. Our estimates are thus not just relative but also absolute estimates. Similarly, calculating risk as the product between housing density and predicted burn probabilities provided a pixel-level risk measure that summed to the regional count of homes at risk. These summations provide regional estimates of burned area and homes at risk with uncertainties that are directly comparable with observed exposure, allowing us to estimate and validate trends in potential fire occurrence and risk in given conditions of each month, year, or decade. Predictions of the burned area (in km^2) and the number of houses at risk are more valuable than just predictions of higher or lower risk on an uncalibrated and thereby relative scale. Thus, the estimates resulting from our approach can help homeowners, communities, and land managers visualize and evaluate risk in comparison to historical trends across a range of spatial and temporal scales.

An additional benefit of using random forests, and ensemble models in general, is the ability to estimate uncertainties using the range and percentiles of predictions from individual models in the ensemble (Meinshausen, 2006). When we calculated these ranges, the observed burned area and risk were within the range of predictions in all years. This demonstrates that our approach can recreate past patterns but also that extensive burning could have occurred in most years. For example, in extreme years such as 2002 and 2012, the maximum uncertainty interval from our predictions was more than 260% greater than the maximum observed burned area, and risk was 376% more than the maximum observed exposure; indicating there is potential for much greater burned area and exposure than has been recently observed in the Southern Rocky Mountains. Ager et al. (2021) reported similar findings for the western United States based on 10,000 fire spread simulations; historical burned area and exposure were exceeded by 278% and 1255%, respectively, in the most extreme simulation.

The modeling approach demonstrated here for the Southern Rockies could be applied to other regions; however, predictor importance and model performance are certain to vary. We expect our approach would capture spatial patterns well in most regions where wildfire occurrence is common. We also expect our approach would capture temporal variability well in regions where wildfire occurrence is primarily driven by weather conditions. However, temporal patterns may be more difficult to capture in regions where wildfire occurrence is primarily influenced by variables with low rates of change and when the effects of change may not be immediately apparent, such as changes in management, land use/land cover, development patterns, and vegetation.

Our approach differs from some studies that used response curves relating fire intensity metrics to potential damage to buildings as part of their risk metric (Scott et al., 2013; Thompson et al., 2013). We took a more expansive view of risk considering the short- and long-term impacts of wildfires on communities extend beyond damage and loss to buildings. However, that does not preclude use of our results for incorporating potential for damages or losses. Our results could be combined with additional models to estimate potential damages to buildings in fires that do not rely on fire intensity data. For example, previous studies assessed individual building loss in fires in relation to outreach programs, WUI classification, building density, building materials, distance to vegetation and vegetation cover, topography, and other predictors (Alexandre et al., 2016; Caggiano et al., 2020; Kramer et al., 2019; Meldrum et al., 2022; Papathoma-Köhle et al., 2022).

Many existing studies have used statistical and machine learning approaches to predict wildfire occurrence (Jain et al., 2020; Taylor et al., 2013; Xi et al., 2019), but these models are not without limitations. Our random forests model predicted burn probabilities in areas where other simulation models cannot because the detailed fuel information that fire simulation models need is lacking there (e.g., the WUI); however, our model did not directly simulate wildfire behavior. This may explain why our random forests model did not select predictors related to fuels that would be responsive to fuel treatments: a practice commonly used by land management to mitigate wildfire risk (Prestemon et al., 2002; Rideout & Omi, 1990). Fuel treatments are designed to change surface and crown fire behavior and spread, and ultimately alter burn probabilities and fire sizes (Cochrane et al., 2012). Our approach provides spatially and temporally explicit predictions of burn probability and risk and can help prioritize locations for mitigation efforts. However, not including predictors related to fuel treatments may limit the use of our modeled results for directly evaluating the effectiveness of different fuel treatment strategies. Instead, our model selected weather-related predictors that often have a larger influence on fire behavior than fuels (Bessie & Johnson, 1995; Coen et al., 2018; Moritz et al., 2010). The annual duration of weather conditions favoring wildfire occurrence and spread has increased substantially (Jolly et al., 2015) and changes in weather conditions and subsequent increases in fire activity have been linked to human-caused climate change (Abatzoglou & Williams, 2016). Furthermore, increases in risk were related to both increases in burn probability and housing density. This suggests that policies and initiatives to reduce wildfire risk may also benefit from considering natural climate solutions to mitigate climate change (Fargione et al., 2018) and managing growth and building codes in fire-prone areas (Moritz et al., 2014).

Ultimately, agencies and communities need to determine the optimal approach to reduce risk and protect lives and property by asking what mitigation actions are most appropriate and likely to succeed in their local context (Mockrin et al., 2020; Moritz et al., 2014; Schoennagel et al., 2017). Financiers and insurance underwriters of housing development, utilities, and infrastructure may also benefit from considering changing patterns of fire occurrence and risk in long-term strategies of economic growth and gain. Agencies and communities can use our model results to determine whether risk patterns have changed and whether past mitigation efforts to protect homes remain in optimal locations to reduce risk or whether additional mitigation efforts are needed. The burn probability and risk uncertainties estimated by our model also provide the information needed to help agencies and communities determine the range of variability in conditions that they might need to plan for. Finally, scenarios like those we evaluated could determine which additional areas may require mitigation in response to future housing development or changing weather conditions.

The WUI is one of the fastest growing areas in the United States, and that growth will likely continue (Radeloff et al., 2018). Increases in the frequency of weather conditions favoring wildfire occurrence and spread are expected under most climate change scenarios (Liu & Wimberly, 2016; McKenzie & Littell, 2017; Stavros et al., 2014). The results of our analyses considered in light of the projected changes in the WUI and weather conditions suggest that risk analyses would benefit from considering the influence of both changing weather conditions and housing growth on patterns of risk in the future.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

This research was based on publicly available datasets, cited in this publication. Please see Appendix S1 for full citations and links for data access. Data produced from this study are available from the U.S. Geological Survey Science Base Catalog (Hawbaker et al., 2022; https://doi.org/10.5066/P9237EQ3), including Python scripts for preprocessing data, sampling data, fitting models, and generating model outputs.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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