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The relative influence of climate and housing development on current and projected future fire patterns and structure loss across three California landscapes

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A B S T R A C T

Climate and land use patterns are expected to change dramatically in the coming century, raising concern about their effects on wildfire patterns and subsequent impacts to human communities. The relative influence of climate versus land use on fires and their impacts, however, remains unclear, particularly given the substantial geographical variability in fire-prone places like California. We developed a modeling framework to compare the importance of climatic and human variables for explaining fire patterns and structure loss for three diverse California landscapes, then projected future large fire and structure loss probability under two different climate (hot-dry or warm-wet) and two different land use (rural or urban residential growth) scenarios. The relative importance of climate and housing pattern varied across regions and according to fire size or whether the model was for large fires or structure loss. The differing strengths of these relationships, in addition to differences in the nature and magnitude of projected climate or land use change, dictated the extent to which large fires or structure loss were projected to change in the future. Despite this variability, housing and human infrastructure were consistently more responsible for explaining fire ignitions and structure loss probability, whereas climate, topography, and fuel variables were more important for explaining large fire patterns. For all study areas, most structure loss occurred in areas with low housing density (from 0.08 to 2.01 units/ha), and expansion of rural residential land use increased structure loss probability in the future. Regardless of future climate scenario, large fire probability was only projected to increase in the northern and interior parts of the state, whereas climate change had no projected impact on fire probability in southern California. Given the variation in fire-climate relationships and land use effects, policy and management decision-making should be customized for specific geographical regions.

1. Introduction

As one of the most fire-prone places in the world, California is globally recognized for its long history of wildfire-related losses of homes and human lives. Wildfire is also important for shaping ecological structure and function (van Wagtendonk, 2018), but many of California's diverse fire regimes, as those across the world, are changing in response to past fire management (e.g., Steel et al., 2015), invasive species (e.g., Syphard et al., 2017a), land use change (e.g., Mann et al., 2016), and climate change (e.g., Westerling and Bryant, 2008). Climate and land use patterns, in particular, are expected to change dramatically in the coming century, raising concern about their effects on fire regimes and subsequent impacts to human communities across the world. California is expected to embody a wide range of these changes and their impacts, and the risk to human communities is complex because it requires predicting how and where climate or land use change will alter fire patterns, i.e., the long-term spatial and temporal characteristics of fire events on a landscape. Manifestation of change will depend upon both the nature and

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strength of the drivers and their relative impacts in different regions.

There is evidence from historical patterns and modeling studies that climate change will lead to large changes in fire extent and severity (e.g., Westerling et al., 2006; Jolly et al., 2015; Abatzoglou and Williams, 2016; Restaino and Safford, 2018). However, the relationships between climate and fire are nuanced and complex (Krawchuk et al., 2009; Bradstock, 2010; Doerr and Santín, 2016) and vary in nature and strength geographically (Littell et al., 2009; Hessl, 2011; Keeley and Syphard, 2017). One of the clearest factors that determines whether a fire becomes large is wind speed (Abatzoglou et al., 2018). Large, wind-driven fire events have been responsible for the vast majority of structures lost in California wildfires (Keeley et al., 2009), including the recent fires in 2017 and 2018. Beyond weather, climate controls fire size directly via temperature, and also via its short and long-term effects on fuel volume and moisture content, which are important controls on fire behavior (Keeley and Syphard, 2016). Thus, given that hot, dry conditions are generally associated with fire, and that temperatures and moisture deficit are projected to increase globally, there is widespread concern that climate change will lead to greater fire activity. However, feedbacks between climate, vegetation, and fire are likely to mediate these effects (Bowman et al., 2014; Parks et al., 2016; Syphard et al., 2018).

Adding to the complexity, changes in human land use and population are also expected to alter spatial and temporal characteristics of future wildfires, and these effects may also interact with climate-driven effects. Humans affect fire patterns in a variety of ways, including deliberate or accidental ignitions, prescribed burning and mechanical vegetation treatments, and suppression activities; humans also change fire behavior and extent through landscape fragmentation, cultivation practices, landscaping, and flammability of buildings. Given the diversity of these effects, recent studies highlight that one of the main problems for prediction of fire patterns and related human impact is that human presence may dampen or override the influence of climate in driving fire activity (Higuera et al., 2015; Ruffault and Mouillot, 2015; Mann et al., 2016; Syphard et al., 2017b). Another complexity is that the anthropogenic and biophysical factors that influence patterns of small fires have been shown to differ from the factors that drive large fires, particularly in areas where most fires are caused by humans (Syphard et al., 2008, 2017, Barros and Pereira, 2014). This is likely due to inherent geographical and biophysical differences between those fires that are easily suppressed and those that escape control (Moritz, 1997; Hantson et al., 2015).

In California, the vast majority of fires are human-caused (Syphard et al., 2007; Balch et al., 2017), but the spatial and temporal pattern of ignition causes and patterns varies widely across the state (Keeley and Syphard, 2018). Contrary to what might be expected, fire activity is not highest where population is highest. Instead fire frequency, and to a lesser extent, area burned, tend to peak at low- to intermediate population and housing density (Syphard et al., 2007; Westerling and Bryant, 2008; Mann et al., 2016); this relationship has also been observed in other areas across the globe (Syphard et al., 2009; Aldersley et al., 2011; Bistinas et al., 2013). This hump-shaped relationship reflects, in part the increased ignitions in rural and residential areas (compared to wildlands), balanced against lower potential for fire spread and/or greater suppression in urban areas (Butsic et al., 2015).

Beyond housing density's effect on fire patterns, studies have shown that structure loss in southern California is significantly correlated with low-to-intermediate housing density (Syphard et al., 2012, 2013, 2016). Other work in southern California and Colorado (Alexandre et al., 2016a), and a national analysis across the U.S. (Alexandre et al., 2016b), identified the spatial arrangement of housing development, in addition to topographic conditions, as consistently more important than vegetation-related variables in explaining structure loss to wildfire. Although small, isolated clusters of development were consistently associated with structure loss, in some cases, high housing density in those clusters contributed to higher structure loss. In addition, high-density development has been implicated in structure loss in some fires due to fire spread among structures (Cohen and Stratton, 2008; Price and Bradstock, 2013), as seen recently in the Coffey Park neighborhood in Sonoma County, CA in 2017 (Nauslar et al., 2018). House-to-house spread is also suspected for contributing to massive structure loss in the Camp Fire in Butte County in 2018. The role of building codes and ignition resistance has yet to be examined in such loss patterns, however.

Despite clear evidence of a nonlinear relationship between housing density and patterns of fire, and subsequently on patterns of structure loss, much is unknown regarding the scale and potential thresholds that define the relationship between housing density and fire. For example, Bistinas et al. (2013) reported regionally varying thresholds determining the shape of the nonlinear relationship between population density and area burned across the globe. Much more work is needed to identify the relative roles of climate and human presence in determining fire and structure loss patterns, and to determine the extent to which these relationships vary regionally. This is particularly critical considering there have already been rapid changes in both climate patterns (Swain et al. (2018)) and land use patterns in flammable landscapes (Radeloff et al. (2018)).

To better understand the relative importance of climatic and land use factors on long-term spatial and temporal patterns of fire and structure loss and how these patterns vary from region to region, we developed an integrated modeling framework to quantify variable importance and to map the distribution of current and future projected probability of fires and structure loss in three California study areas. These regions vary biophysically but have all experienced substantial residential losses from wildfire. We first developed statistical models and maps based on the association of climate, biophysical, and anthropogenic variables with small and large fire patterns, and then we modeled structure loss as a function of those variables and the projected probabilities of large fires. After quantifying and mapping current relationships, we projected future large fire and structure loss probability under different climate and housing growth scenarios. We address the following questions:

1) How do fire patterns vary by housing density and climate?
2) How do structure loss patterns vary by housing density and climate?
3) Do these relationships vary from region to region?
4) Which is likely to be the most influential driver of future change, climate or housing development, across our study regions?

2. Methods

2.1. Study areas

The northern coastal study area (NC) includes more than 1.4 million ha of land spanning all of Lake, Sonoma, and Napa Counties, in addition to small parts of Mendocino, Glenn, Colusa, Yolo, and Solano Counties (Fig. 1). The vegetation is characterized by a mosaic of oak woodlands, grassland, chaparral, and Douglas fir/hardwood ("mixed evergreen") forests, with montane conifer forests at higher elevations. Extensive exurban development has occurred in recent decades, and numerous homes have been destroyed by fire here; in particular, the 2017 'wine country' wildfires in this region resulted in 44 lost lives and nearly 9000 destroyed buildings.

The Butte and Plumas Counties study area (BP) included the full counties, plus a 20 km buffer to incorporate a larger urban-wildland gradient (2.2 million ha). Across this gradient spanning from the Central Valley to the northern cismontane Sierra Nevada, the vegetation transitions from grassland and chaparral to mixed evergreen and then pine- and fir-dominated forests, with a very small component of subalpine forest on the highest peaks (Fig. 1). Although the higher-elevation forests are mostly protected by the U.S. Forest Service and National Park Service, substantial residential development has been

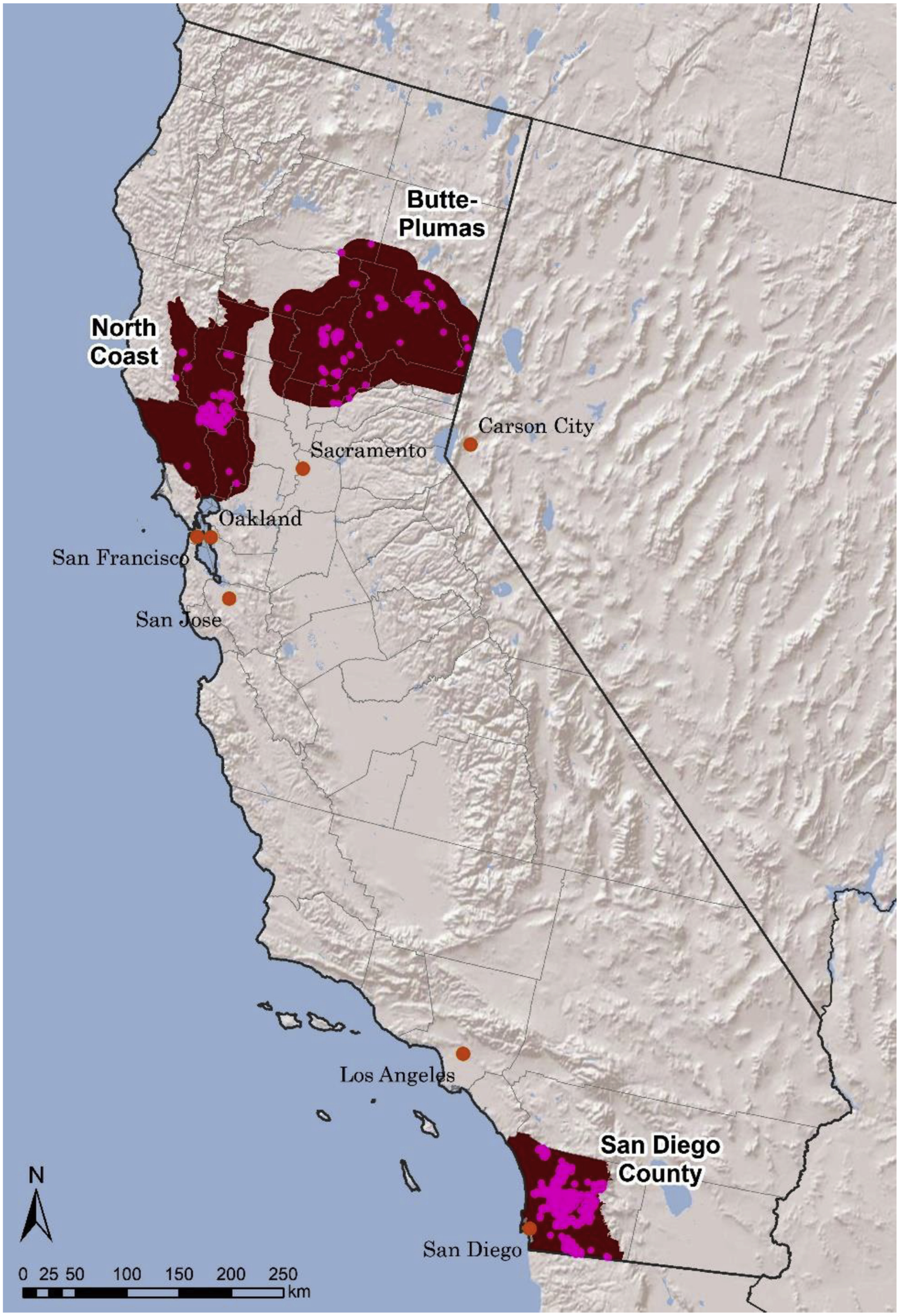

Fig. 1. Boundaries of three California study areas, with destroyed structure locations (2000–2015) in pink (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

occurring in the foothills. Wildfires destroyed more than 1000 structures here between 2000 and 2015 (the period we used for modeling); in 2018, the Camp Fire alone resulted in 86 fatalities and more than 18,000 destroyed structures. While all three study areas are characterized by Mediterranean climates, with warm to hot, dry summers and wet winters, BP is the only study area to receive substantial precipitation in the form of snowfall.

The third study area, coastal San Diego County (SD), is a rapidly developing, highly fire-prone region with an extensive wildland-urban interface. The majority of the study area is dominated by coastal sage and chaparral shrublands intermixed with grasslands and mixed oak woodlands, and some montane conifer forests at the highest elevations. Native shrubs are threatened by too-frequent fire, typically human-caused, which could lead to extensive replacement with more fire-prone herbaceous vegetation (Syphard et al., 2018b). Thousands of structures have been destroyed during large, Santa Ana wind-driven fire events (Keeley et al., 2009).

2.2. Data

For all dependent and independent variables (Table 1), we first assembled consistent statewide spatial data coverage, which we then clipped to the boundaries of the three study areas. We also rasterized all vector data, or resampled all grid data, to match the resolution of the climate variables (270 x 270 m).

2.2.1. Fire data

To determine whether different factors influence fire ignitions and large fire patterns across the study areas, we created statistical models based on two sources of data (Table 1). The first dataset included the location of origin for all fires of any size from the most recent decade of data available, 2003–2013 and was available via spatial coordinates indicating the point location of fire ignition. The data, from the National Interagency Fire Program Analysis, Fire-Occurrence Database (FPA FOD), include fire size and date as attributes and are publicly available for the whole country (Short 2014). Spatial clustering of points has the potential to lead to autocorrelation, which can inflate the accuracy of statistical distribution models (Veloz, 2009). Although we were less interested in model accuracy than we were in variable importance and maintaining comparability of model results, we nevertheless spatially filtered the presence data to ensure no duplicate points within a 500-m radius, as spatial filtering can reduce the effect of sample bias (Veloz, 2009). While this distance was not systematically determined, this was the radius used in Syphard et al. (2018) that best attained the appropriate number of samples per fire, using the method described in Davis et al. (2017).

We developed a second dataset for large fire locations using a separate comprehensive statewide fire perimeter database, provided by the State of California Fire and Resource Assessment Program (FRAP, http://frap.fire.ca.gov/data/frapgisdata-subset). We only considered large fires from these data (> =40 ha), and, based on the method developed by Davis et al. (2017), we generated a random sample of points within all fire perimeters from a baseline period of 1985–2015, the most recent 30 years available. That is, to calculate the number of random points to generate for each fire in the database, we took the square root of the ratio of the given fire's area to the area of the smallest fire in the study area as recorded in this dataset. Because a filter distance of 500 m resulted in too-small sample sizes for many of the fires, we reduced the filter distance to 400 m.

We considered the two fire datasets to capture two different processes, where each process potentially has its own set of drivers. The 'fire ignitions' dataset reflects the spatial patterns of ignitions (which is an outcome of fire initiation processes), whereas the 'large fires' dataset reflects a discrete sample of burnt locations (which is an outcome of fire spread processes).

2.2.2. Structure loss data

The dependent variable for the structure loss models was the location of any structure that had been destroyed in a fire from 2000 to 2015 (Table 1). The baseline data were developed by Alexandre et al. (2016), and included all destroyed structure locations across fires in the U.S. from 2000 – 2010. These data were created by examining, for all wildfires recorded in the Monitoring Trends and Burn Severity dataset (MTBS, https://mtbs.gov), Google Earth historical imagery from the closest dates before and after the fires. Within each fire perimeter, Alexandre et al. digitized all buildings before the wildfire; then, any building that had been completely removed in the post-fire image was considered destroyed. To update and extend these data, we followed the same methods using pre- and post-fire Google Earth imagery and digitized buildings in all three study areas that were present through 2015. Additionally, we selected all fires from the most recent Cal Fire historical perimeter database (2015 at the time of completion) and added new structures that may have been missed by Alexandre et al. (e.g., due to small fire size) or had occurred after 2010.

2.2.3. Topographic data

Terrain-related variables are typically included in fire behavior and distribution models due to their direct influence on fire behavior and indirect influence on fuel characteristics and flammability (Bond and van Wilgen 1996, Pyne 1996); and they have also been significantly associated with structure loss to wildfire due to exposure (Syphard et al., 2012, Alexandre et al. 2016). Therefore, we considered a range of topographic variables in both the fire and structure loss models, including slope, topographic variability, and topographic position (Table 1).

2.2.4. Climate data

We considered a range of historical and projected future climate variables, which were developed by Flint and Flint (2012) and updated through 2017 using the California Basin Characterization Model (https://ca.water.usgs.gov/projects/reg_hydro/basin-characterization-model.html (Table 1). The data were available annually at 270 m resolution. We processed the annual data to create 30-year baseline statistical summaries from 1981 to 2010 as well as decadal future projections from 2020 to 2050. To ensure consistency with state recommendations (Kravitz, 2017), we compared two scenarios of future climate conditions from complementary CMIP-5 General Circulation Model projections regarded as relevant for California. The scenarios were CNRM-CM5 and MIROC5, which represent "warm/wet" and "hot/dry" conditions, respectively. Despite this characterization both scenarios have substantial spatial and temporal variation in projected conditions, but should still provide meaningful bookends for representative climate spaces. For both scenarios, we used the RCP 8.5 "business as usual" emissions scenario (RCP scenarios are generally similar through 2050 and only diverge in the second half of the century).

For the fire models, we considered a combination of temperature and moisture-related climate variables that have had significant associations with fire patterns in other studies due to their effects on energy and moisture gradients that influence wildland fuel condition and abundance (e.g., Whitman et al., 2015; Parisien et al., 2016; Davis et al., 2017). We also included actual evapotranspiration (AET) and climatic water deficit (CWD) in all models, as these variables have been used to account for changes in fuel abundance (AET) and moisture (CWD) (Krawchuk et al., 2014, Parks et al., 2016, Mann et al., 2016). We did not include temperature and precipitation in the structure loss models because we assumed their influence on structure loss would be indirect, via their effects on large fire probability. On the other hand, given that AET and CWD served as proxies for vegetation, and that vegetation adjacent to structures could be influential beyond the effect on large fire probability, we did include these variables.

Table 1
Dependent and explanatory variables used to model fire and structure loss distribution in three California study areas.

Category	Fire models	Structure loss model	Data layer	Description and source	Time Variant
Dependent variable	x		Fire ignitions	Fire occurrence locations delineating point of ignition from 2003 - 2013 (Short 2014)	NA
	x		Large fires	Cal Fire fire perimeter database 1985 – 2015 (Department of Forestry and Fire Protection	NA
		x	Structure loss	Digitizing, Alexandre et al. (2016)	NA
Terrain					
	x	x	Slope	LANDFIRE, 30-m native resolution, aggregated by mean to 270m	No
	x	x	Topographic roughness	Range of slope values within 810-m radius from center cell (Derived from 30-m digital elevation model)	No
	x	x	Topographic position index	Index of slope position and landform, Jenness 2006 (Derived from 30-m digital elevation model)	No
	x	x	Topographic heterogeneity	Range of elevation values within 810-m radius from center cell (Derived from 30-m digital elevation model)	No
Climate					
	x		Temperature seasonality	Coefficient of variation across calendar year of temperatures (Derived from Flint and Flint, 2014)	Yes
	x		Annual precipitation	Sum over calendar year (mm) (Flint and Flint, 2014)	Yes
	x		Summer precipitation	Sum over June, July, August (mm) (Flint and Flint, 2014)	Yes
	x		Annual minimum temperature	Mean low temperature of coldest month (degrees C) (Flint and Flint, 2014)	Yes
	x	x	Actual evapotranspiration	Total annual water evaporated from surface and transpired by plants (Flint and Flint, 2014)	Yes
	x	x	Climatic water deficit	Annual evaporative demand exceeding water availability (Flint and Flint, 2014)	Yes
Land use					
	x	x	Housing density	Based on 2000 U.S. Census data using the baseline projection at 2009 (Mann et al., 2014)	Yes
		x	Housing cluster area	Boundaries around areas with housing density > = 0.02 units per ha (Derived)	Yes
		x	Distance to cluster edge	Mean Euclidean distance to boundary of housing clusters (Derived)	Yes
	x	x	Distance to populated places	Census populated places of at least 10,000 inhabitants in 2010 (Derived)	No
	x	x	Distance to roads	TIGER line files 2015, U.S. Department of Commerce, U.S. Census Bureau	No
	x	x	Distance to public land	Cal Fire land ownership database 2015 (Department of Forestry and Fire Protection)	No
Fire					
		x	Predicted large fire suitability	Output from large fire model (this paper)	Yes

2.2.5. Land use projections and anthropogenic data

Our primary source of land use data were maps of current and future projected housing density that were published in Mann et al. (2014). The historical data were collected from the U.S. Census long form with models trained using historical trends from 1940 to 2000 (the latest date that the long form was available). The predictions of housing density were provided in decadal time steps, and we used the 2009 forecast as our baseline here. Created using longitudinal census data, the model calculated the total number of new houses based on demographic forecasts at the national level, and then allocated them to split-block units based on a spatio-temporal estimate of housing density. We considered two scenarios, one with concentrated urban development ("urban scenario") and the other that favored rural expansion ("rural scenario"). In the "urban development" scenario, an additional 25% of all new housing was added into urban areas (density greater than 1 house per acre), while the "rural growth" scenario pushed the 25% into areas with less than 1 house per acre.

Housing density data were initially provided as vector data, with housing density listed as an attribute for each polygon. We converted these data into 270 m raster layers using housing density as the value to grid. In previous studies of structure loss to wildfire, two additional variables, the size of the housing cluster and the distance from each structure to the edge of development, were found to be highly significant (Syphard et al., 2012; Alexandre et al., 2016a, 2016b). Given that those data had been created using point locations of all structures, we developed an approach to devise similar housing clusters by thresholding and creating borders around polygons with at least 0.01 housing units per ha, which was the value that resulted in the best fit to the data created for San Diego County (Syphard et al., 2012). The housing density variables were available for the same time periods as the climate data, with 2009 representing current conditions, and decadal projections until 2050 for the two growth scenarios. Thus, for models using baseline climate data for 1981–2010, we used housing data from 2009; and for models using climate projections from 2019 to 2029, we used the housing projection for 2029, etc.

In addition to the housing projections, we included three other variables that have been significantly associated with fire occurrence patterns in other studies (e.g., Mann et al., 2016; Syphard et al., 2018). These included proximity to primary and secondary roads, which are often associated with human-caused ignitions (Syphard and Keeley, 2015); proximity to public land, which typically consists of large uninterrupted swaths of wildland vegetation; and distance to census populated places where the city includes at least 10,000 residences (Mann et al., 2016). These maps remained static for future projections.

2.3. Statistical modeling

We used Maxent 3.3.3k to estimate variable importance and project mapped probabilities of current and future fires and structures loss (Phillips and Dudik, 2008; Elith et al., 2011). A statistical machine learning method, MaxEnt estimates the best approximation of a distribution via iterative comparisons between values of the environmental predictor variables at the location of presence locations (i.e., all fires, large fires, destroyed structures) versus the values of the same variables at 10,000 randomly located background points. The best distribution is identified as the one with maximum entropy, and the model outputs a continuous grid with each cell assigned a relative suitability of occurrence from an exponential function. Recognized as one of the top-performing species distribution models (Elith et al., 2006), MaxEnt has also been successfully used in a range of wildfire analyses and mapping applications (e.g., Bar-Massada et al., 2012; Batllori et al., 2013; Parisien et al., 2016; Davis et al., 2017; Tracy et al., 2018).

We developed separate models for all fires and large fires to investigate potential differences in variable importance. We also tested the output of both models as potential predictors for the structure loss model, but we found significant correlation between the output of the small fire model and distance to roads. Given that most homes are destroyed in large fires, we decided to only use the output of the large fire probability model as a predictor variable for the structure loss model.

We initially developed all models with the full range of climatic, topographic, and anthropogenic explanatory variables to compare variable importance. For projecting future conditions, we employed a variable selection and model tuning process separately for each of the three study regions to ensure the best model fit. We first used ENMTools (Warren et al., 2010) to calculate Pearson correlation coefficients for all explanatory variables using current conditions (baseline) in each study area. For any pair of variables with a correlation coefficient of $r >= 0.8$, we retained the one that had a higher mean cross-validated receiver operating characteristic curve (AUC, Fielding and Bell, 1997), based on univariate models.

We used most of the default parameters for the MaxEnt modeling, except that we used only linear, quadratic, and product features for all models, and selected regularization multipliers, that avoid overfitting by penalizing complex solutions, by running models in 0.5 increments from 0.5 to 5. The final model was chosen by selecting the multiplier that resulted in the lowest Bayesian Information Criterion (BIC). For the baseline models of all and large fires, and structure loss, we ran five cross-validated model replicates to obtain mean permutation importance values and mean out-of-sample AUCs. We averaged the predicted values from the five replicate output maps to produce the baseline maps, which are interpreted as grids of mean predicted probability of large fires or structure loss given the environment in each study area.

After conditioning the models on the baseline time period, we then projected the averaged baseline models of large fires and structure loss onto maps representing future conditions at each time step for all combinations of future climate (two scenarios) and land use (two scenarios) projections. For each future time step, we first projected large fires, and then used those projections as input to the structure loss models.

2.4. Analysis

We averaged large fire probability and structure loss probability for all maps generated as model output by first summarizing the predicted probabilities across all grid cells in every map, then dividing this sum by the total number of cells in the maps of the three study areas. We calculated these numbers for all model replicates in all time periods and for all climate/land use scenario combinations. The probability averages for current conditions served as a baseline to compare with the probability averages of future scenarios, which allowed an overall estimate of whether fire or structure loss probability went up or down across the region.

To identify the housing density where most structure loss occurs in each study area, we extracted the housing density of destroyed structures from the baseline housing density maps generated by Mann et al. (2014). We then compared the mean housing density of destroyed structures in each study area with the underlying housing density in each region (i.e., all burned and unburned structures), which we determined by multiplying the area of each polygon in the study area by its housing density as indicated in the attribute table. This calculation assumed housing density was evenly distributed across polygons. For polygons that overlapped the study area boundary, we calculated the number of units in the entire polygon, then prorated by the percentage of the polygon within the study area. For both destroyed and the total structures in each study area, we plotted and compared their mean and distribution across housing density classes.

To compare the mean housing density data in our study areas to the recent destructive fire events of 2017 and 2018, we additionally acquired point locations for the destroyed structures in the 2017 Tubbs, Nunn, Atlas, and Pocket Fires in Sonoma and Napa Counties (number destroyed = 8022; http://sonomamap.maps.arcgis.com/apps/webappviewer/index.html?id=5af1dd01cb9b446db928abe51a259763), the 2018 Camp Fire in Butte County (number destroyed = 18,804; https://calfire.app.box.com/s/z03vd6hoikxa94ey25m0kuq2fsq2ln5e/folder/64813192070), the 2018 Carr Fire in Shasta County (number destroyed = 1614; https://www.arcgis.com/home/item.html?id=17d44552e0ea4c6ab2c43e80246e05b9), and the 2018 Woolsey Fire in Los Angeles and Ventura Counties (number destroyed = 1673; provided from Cal Fire to the National Park Service, Robert Taylor personal communication). All of these data were provided as part of the Cal Fire Damage Assessment and Fatality Totals (**DINS**) program. We used the same methods as above to calculate the mean housing density for destroyed and total number of structures. We calculated the total number of structures within the county boundaries where the fires were located.

To map geographical variation in structure loss probability by land use scenario, we subtracted the mapped probability of structure loss projected in the rural growth scenario models for year 2049 from the corresponding mapped probability of structure loss in the urban growth scenarios.

3. Results

3.1. Baseline statistics

From 2000–2015, there were 2081 structures destroyed in the NC study area. These destroyed structures were distributed across 17 out of a total of 202 fires during the same time period (based on the Cal Fire perimeter data). The mean size of fires where structures were destroyed (includes entire perimeters of those intersecting study area) was 5525 ha versus an overall mean fire size of 896 ha. In the BP study area, there were 451 destroyed structures that burned through 2015 in 39 out of 241 fires. The mean fire size with destroyed structures was 4018 ha versus a mean of 905 ha overall. In SD, 4338 structures were destroyed, across 20 fires out of a total 206 fires. The mean fire size when structures were destroyed was 150,647 ha versus a total mean of 1877 ha.

The mean density of destroyed structures was much lower than that of all structures in all study areas, by orders of magnitude (Fig. 2). This pattern was the same for density of destroyed structures versus all structures within counties in the recent fire events of 2017 and 2018 (Fig. 2), although the difference between destroyed and all structures was only about half for the Camp Fire and about a third for the 2017 North Coast fires. The distribution of housing density for both destroyed and all structures varied by study region, but destroyed structures were consistently located in low-density classes (Fig. 3).

Projected future trends in temperature and precipitation varied across regions for the two different climate scenarios, as did the overall housing density change. In the NC and BP study areas, the mean annual precipitation resulted in conditions with consistently more moisture in the CNRM scenario and consistently drier conditions in the MIROC scenario by 2049, with slight geographical variability (Fig S1a&b). Both GCMs projected decreased annual precipitation in the SD study area, but the drying was stronger for the MIROC scenario (Fig. S1c). The changes in summer precipitation showed much more geographical variability within study regions, but the differences in GCMs were flipped such that CNRM was projected to be drier in the summer than MIROC (Fig. S2a-c). Annual temperature was projected to increase much more substantially in the MIROC than the CNRM scenario for all three study areas by 2049, with substantially more geographical variation in the CNRM scenario (Fig. S3a-c). Decadal fluctuations, reflecting idiosyncrasies of the model run, were strongest in MIROC in the North Coast.

Changes in projected housing density patterns from 2009 to 2049 show substantial geographical variability across all three study regions (Fig. 4). For all regions, the rural scenario showed a larger areal increase of housing densities within the range where houses have been destroyed historically (Fig. 4); but the difference in rural versus urban scenarios was most substantial in NC, followed by SD, then BP. In the rural scenario, most of this increase in low-density housing occurred via growth (i.e., increased housing density) across more rural parts of the landscape, whereas in the urban scenario, a larger portion of exurban areas declined in housing density as there was a shift to more

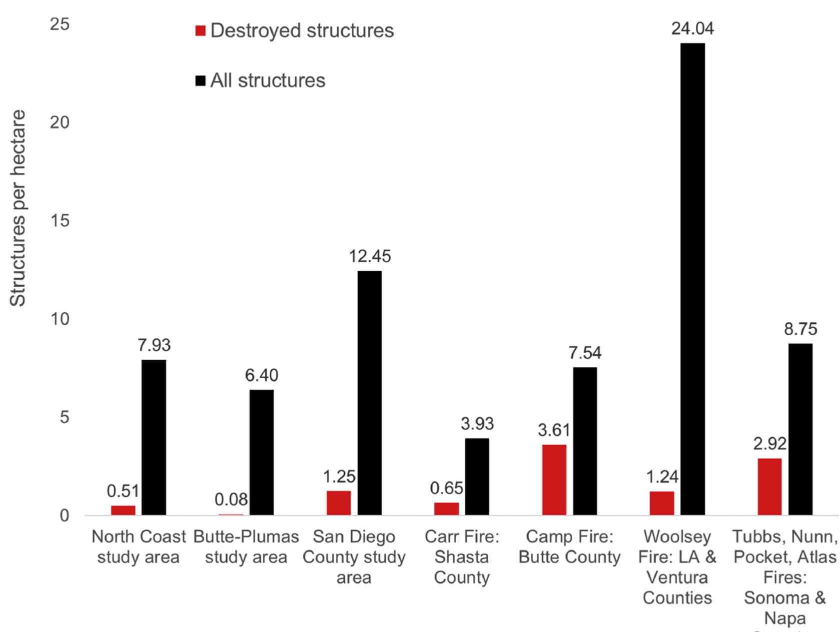

Fig. 2. Mean housing density for destroyed and all structures in three California study areas (using data through 2015) and for the four largest destructive fire events in 2017 and 2018.

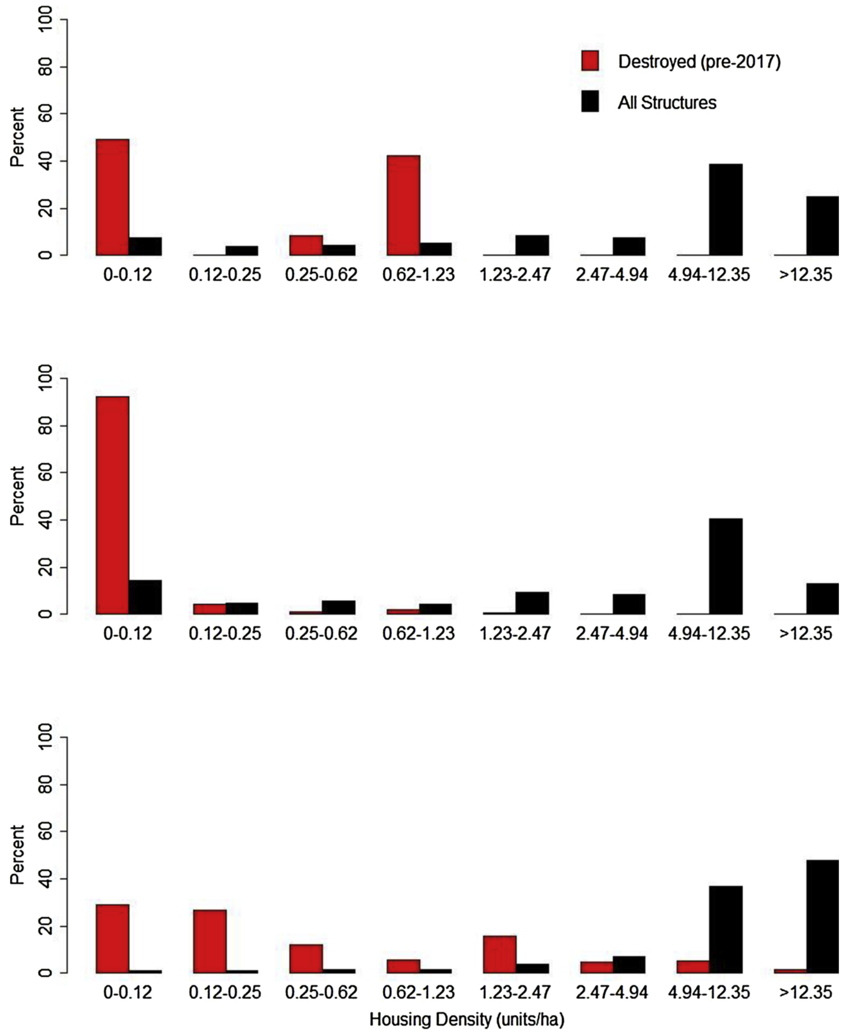

Fig. 3. Distribution of housing density classes (structures/ha) for destroyed and all structures in the a) North Coast, b) Butte-Plumas, and c) San Diego County study areas.

concentrated high-density housing near urban areas (Fig.4). One exception is the northern coastal portion of the SD study area, where there was some housing density decline in the rural scenario.

3.2. Variable importance

There were large differences in model variable importance for fire ignitions vs. large fires for all three study areas, and these were much larger than differences among regions (Table S1 – S2,Fig. 5). In particular, anthropogenic variables, particularly proximity to roads, dominated the patterns of fire ignitions, whereas topography and climate variables dominated the patterns of large fires, except in SD, where both housing density and distance to roads had about the same importance as topography and climate for large fires. In SD, housing density was almost equally as important as climate for explaining large fires. The directions of relationships differed such that fire ignitions tended to occur in close proximity to roads or populated places, but large fires occurred closer to public lands and farther from roads and populated places.

Whereas climate variables had a strong influence on fire ignitions and especially large fires, the vegetation productivity and moisture variables (AET and CWD) were not important for explaining structure loss patterns in NC or BP (Table S3 – S4, Fig. 5), and were less important than fire suitability for SD. Instead, housing variables and large fire suitability were the two most important factors explaining structure loss across all regions, with higher structure loss Univariate response curves showing the probability at low housing density (Fig. 6). SD was again different than NC or BP in that housing variables were more important than fire suitability.

3.3. Future projections

Overall, NC had a slightly lower baseline probability of large fires across the study area (Fig. 7a) than BP or SD, which had similar baselines (Fig. 7 b & c). Projections of future large fire probability were higher than the baseline for most time periods and climate scenarios for both the NC and BP study areas, except for MIROC in 2029 and 2049 in NC and CNRM 2019 in BP, and the results from these decades reflected oscillations that stemmed from decadal variability in the climate model projections. Large fire probability did not significantly change under either climate scenario in SD (Fig. 7c), but there was also slight decadal variability in the model run for CNRM. In all cases, differences in projected large fire suitability between the two land use scenarios were virtually absent due to the small relative importance of these variables to the model.

Compared to NC and BP (Fig. 8a & b respectively), SD had a relatively high baseline structure loss probability across the landscape (Fig. 8 c). Differences in structure loss probability for the two climate scenarios in NC and BP generally mimicked the large fire probability results in ranking and magnitude, and the decadal variability in fire

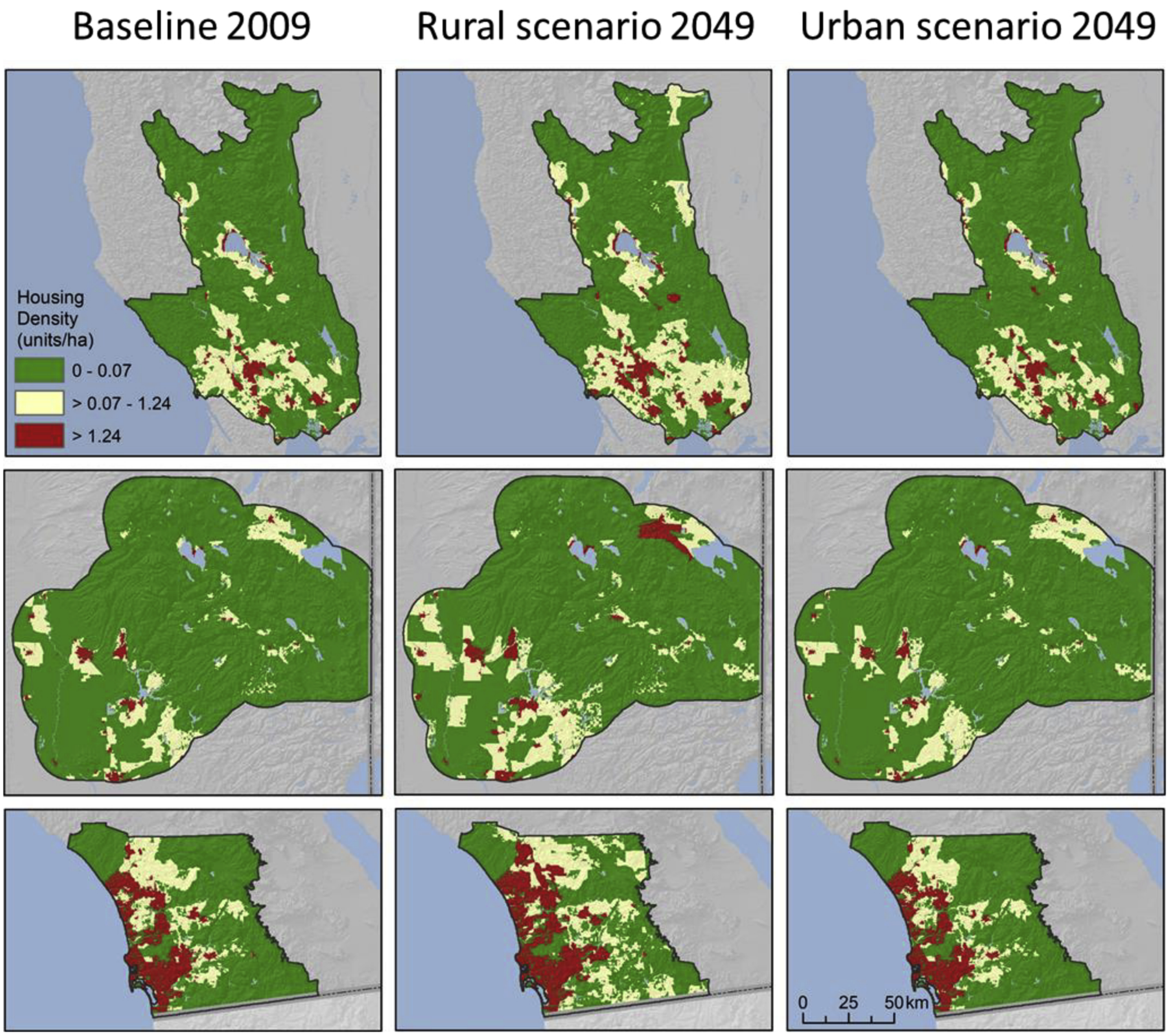

Fig. 4. Classified housing density in 2009, 2049 for the rural, and 2049 for the urban scenarios in the a) North Coast, b) Butte-Plumas, and c) San Diego County study areas. The middle (yellow) class represents the housing density range across the three study areas where structures have been destroyed in the past (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

probability for SD that came from climate model projections was reflected in the CNRM result. Compared to large fire probability, there was a much stronger effect of land use scenario on structure loss projections, and more variation in which scenarios exceeded baseline for NC (Fig. 8a) and SD (Fig. 8b). BP showed little variation in either climate or land use scenario probabilities. In NC, the rural land use scenario had a much larger probability of structure loss overall, and for CNRM, this difference generally determined whether probability would increase or decrease relative to the baseline. The rural scenario also resulted in higher overall structure loss probabilities in SD, but this was mostly apparent in 2049.

While structure loss was higher overall across regions and climate scenarios in the rural land use scenario (Fig. 8), there was considerable spatial heterogeneity in the effect of the land use scenario (Fig. 9). Comparing the rural land use scenario to the urban scenario in NC and SD, there were small changes to structure loss probabilities across most of the currently semi-urban and urban areas and large increases in structure loss probabilities in the currently rural areas (compare Fig. 9 to Fig. 4). In contrast, BP had locations of large increases and decreases in structure loss probabilities under the rural land use scenario compared to the urban land use scenario. However, all three regions had higher predicted structure loss in areas where there was an increase in low-density housing.

4. Discussion

Our projections suggest that both climate and land use will drive future changes in patterns of wildfire and subsequent likelihood of structure loss; but the relative importance and strength of different drivers will vary across and within different regions. Future changes will depend upon the nature and degree of change in both climate and land use relative to current conditions. For example, locations with increased low density rural housing are likely to see increased structure loss even in decades with lower large fire probabilities (compare decades 2029 and 2049 in Figs. 7a and 8a). Changes will also vary according to the strength and nature of regional relationships among climate, land use, fire patterns, and structure loss, with potential feedbacks among these drivers. Despite these complexities, which underscore the importance of customizing policy and management by geographical location (Keeley et al., 2009; Moritz et al., 2014), there were also key commonalities across regions. In particular, structure loss mostly occurred at fairly low housing densities. While more work needs to be done to create models that incorporate short-term weather conditions, such as wind, and feedbacks among drivers, we believe that the central importance of housing density to structure loss may be generally applicable to fire-prone landscapes.

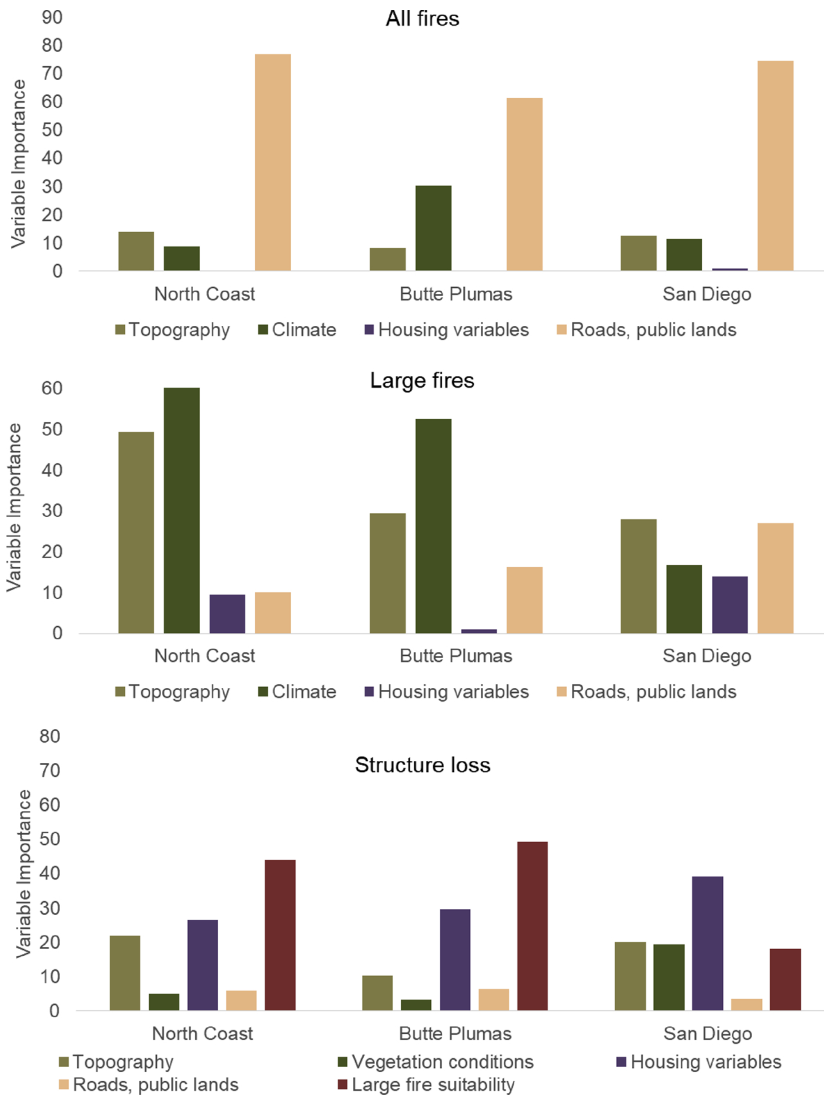

Fig. 5. MaxEnt variable permutation importance for fire and structure loss models in three California study areas, with variables grouped into categories. The fuel category for structure loss consisted of actual evapotranspiration and climatic water deficit.

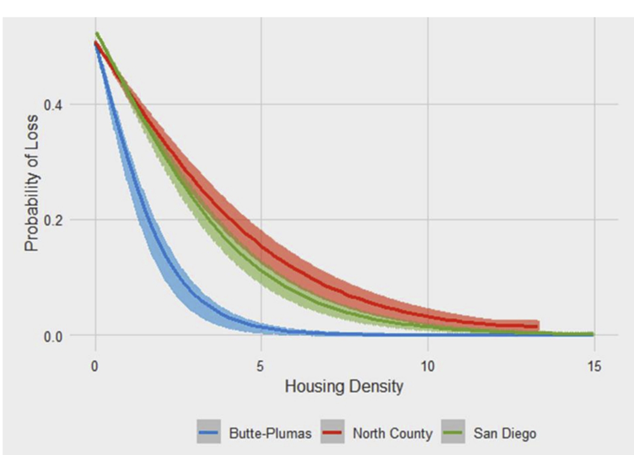

Fig. 6. Probability of structure loss relative to housing density (units/ha) for three California study areas, averaged across 5 model replicates.

4.1. High anthropogenic variable importance for fire ignitions, but not large fires

One commonality across regions was that anthropogenic variables were most important in explaining patterns of fire ignitions, whereas large fires were more related to topography, climate, and fuel (via AET and CWD). This finding is not surprising given that most fires in California are started by humans (Syphard et al., 2007; Balch et al., 2017), near human infrastructure (Syphard and Keeley, 2016). The finding is also consistent with other studies that have shown differences between the drivers of small and large fires (e.g., Syphard et al., 2008, 2016, Barros and Perreira, 2014; Abatzoglou et al., 2018) and that large fires are more likely to occur in remote areas where fuel continuity is greater, with severe winds better able to propagate fires via long-distance ember production, and access to suppression is lower (Gray et al., 2014). The consistency with other studies, and across divergent regions in this study, has important considerations for management. For example, ignition prevention efforts may be most effective if geographically concentrated near roads and development. Thus, land use change may generally be the biggest concern for preventing fires from starting; but climate change, in addition to weather and fuel patterns, may be more critical in the consideration of large fire behavior. One exception is that, unlike other human-caused fire sources, powerline-

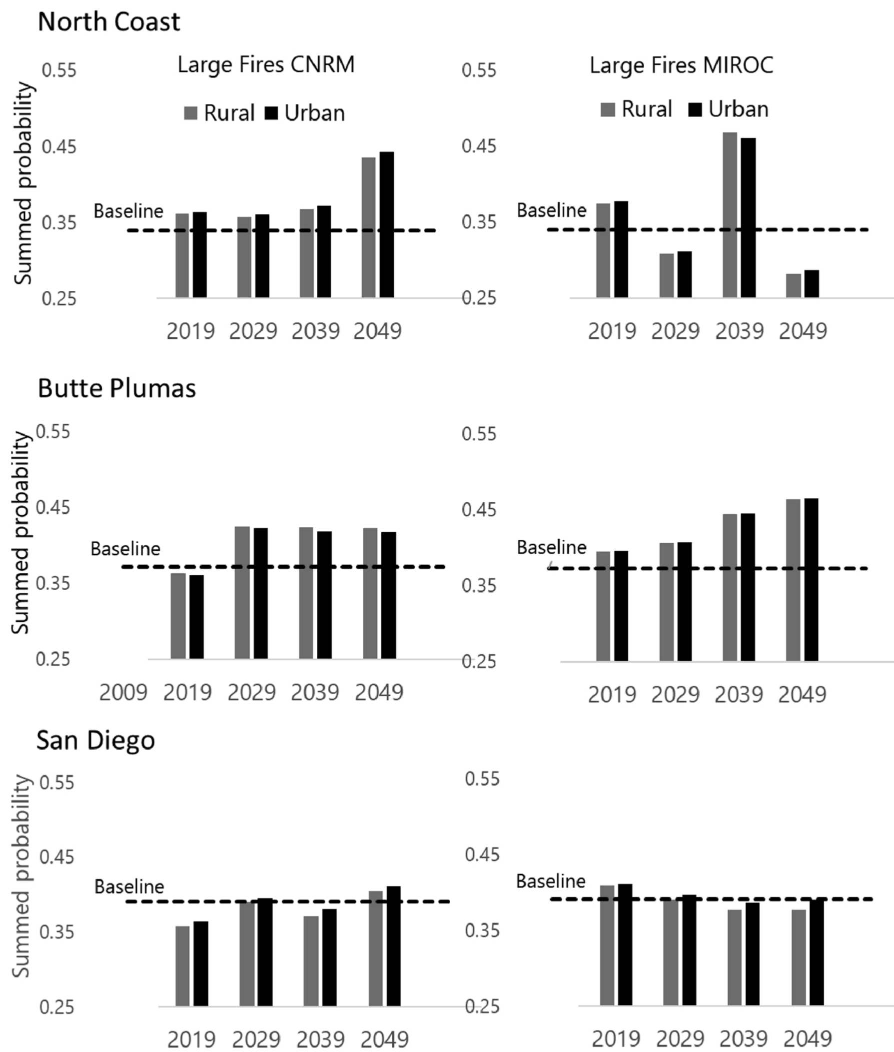

Fig. 7. Total projected probability of large fires under two climate and two land use scenarios for a) North Coast, b) Butte Plumas, and c) San Diego.

ignited fires tend to occur in more remote areas during severe weather, and these fires often result in large areas burned with substantial human losses (Keeley and Syphard, 2018). Understanding the relative importance of anthropogenic variables is critical given expected changes in human land use with resulting downstream impacts on deliberate or accidental ignitions, prescribed burning, mechanical vegetation treatments, and fire suppression.

The timing of ignitions, particularly corresponding with extreme fire weather, may be the most important variable to consider in determining whether fires become large and potentially destructive to human assets (Syphard et al., 2016; Abatzoglou et al., 2018). Historical analysis has also shown there to be an overall low correlation between fire frequency and area burned in California (Keeley and Syphard, 2018). Thus, small, frequent fires caused by human ignitions do not necessarily lead to highly destructive fires. Instead, the fires most likely to cause structure loss tend to be ignited in low-intermediate population or housing density (Syphard et al., 2007, 2009), adjacent to areas of high fuel loading.

Studies of historical fire-climate relationships in California (Keeley and Syphard, 2015, 2016) and across the U.S. (Littell et al., 2009; Parisien and Moritz, 2009; Syphard et al., 2017a; Littell et al., 2018) show differences in the strength and nature of climatic control over fire activity. In particular, those areas where fire is most strongly explained by climate in California are in northern, higher-elevation parts of the state, whereas in southern CA, fire-climate relationships have historically been weak (Keeley and Syphard, 2016). Other studies have shown fire-climate relationships to be weaker in areas with higher human presence (Higuera et al., 2015; Ruffault and Mouillot, 2015; Mann et al., 2016; Syphard et al., 2017b), and this is supported in our results, with the SD study area having both the highest overall housing density and the weakest link between climate and large fire suitability. SD was also the study area with the strongest relationship between anthropogenic variables and patterns of large fire suitability.

4.2. Predicted future wildfire varied less across scenarios than structure loss

Given the weak ties between climate and large fire suitability in SD, there were no major changes projected for large fires here, which is an important result given widespread concern that climate change will be responsible for increasing future fire activity across the western U.S. (Westerling et al., 2006; Barbero et al., 2015; Abatzoglou and Williams, 2016). Nevertheless, there could be other types of indirect climate change effects on fires in southern CA, such as long-term drought (Keeley and Zedler, 2009), vegetation type conversion facilitated by drier conditions (Jacobsen et al. (2007); Park et al., 2018; Syphard et al., 2018b), or changes in wind patterns (Guzman-Morales et al. (2016)). For the other two study areas, climate change was projected to increase large fire probability by the middle of the century, which corresponded to at least part of the increase in structure loss probability in these regions. In all regions, it is important to acknowledge that,

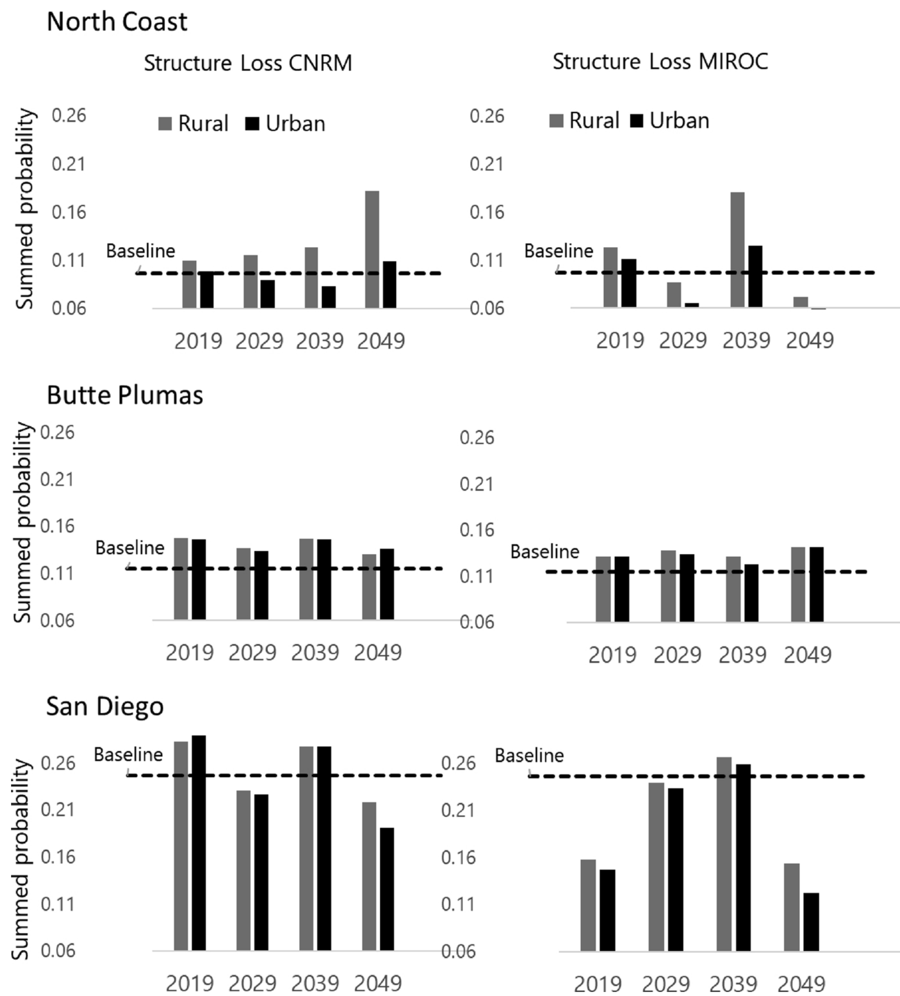

Fig. 8. Total projected probability of structure loss under two climate and two land use scenarios for a) North Coast, b) Butte Plumas, and c) San Diego.

despite inclusion of AET and CWD as proxies for fuel amount and condition, fire-vegetation feedbacks or vegetation type changes were not accounted for, and these could play an important, yet undetermined role in future fire activity (Syphard et al., 2018).

Particularly in the NC study area, land use change scenario played a major role in differences in structure loss probability, due to the significant relationships found in the baseline models as well as the nature of projected change in the rural versus urban scenarios. That is, there was substantially more expansion of low-density housing in the rural scenario versus the urban scenario in the NC study area, corresponding with the densities where most structures have been destroyed (i.e., the middle class in Fig. 4). This was true in BP and SD as well, but to a lesser extent. Also, for the urban scenario projections in all regions, and the rural projections for SD, there were both increases and decreases in housing density across the landscape; this patchwork of change may have dampened the apparent effect of land use on future projections of either fire or overall structure loss probability. Another important consideration is that structure loss probability may shift over time in response to changing density patterns. In other words, as some lower-density developments fill in with new homes, they may become less susceptible in the future; this is the likely reason that structure loss probability was projected to decline in some scenarios and time periods.

In modeling the decadal projections, we attempted to understand how different growth trajectories influenced model outcomes. For example, a region may initially experience low-density housing development in 2020–2030 that transitions to high density development by 2050. We hypothesized that either large fire or structure loss probability might thus vary through time as a function of the underlying housing density. However, given that land use was not one of the most important predictors of large fires, we did not observe a strong effect of oscillating housing density on fire projections. Instead, the up and down behavior in large fires, particularly in NC under MIROC, was due to idiosyncratic oscillations in climate projections that resulted from the climate model. For projections of structure loss, there was continued growth of low-density housing in the rural scenario for NC, which resulted in consistently higher structure loss probabilities over time. On the other hand, some areas of low-density development converted into high density development in San Diego County, which led to a net decline of structure loss probability by 2049. Overall, however, the biggest differences in effect of housing density was via the higher concentration of high-density development in the urban versus rural scenarios.

It is important to clarify that the land use scenarios were not meant to reflect precise changes but were designed to emphasize possible differences based on housing density and general trends towards urban or rural development. The land use change model tended to emphasize temporal and spatial spillovers; that is, any projection of housing density change in largely uninhabited areas first required either a history of growth or a spillover of growth from neighboring polygons, and this may have limited spatial expansion of housing in those areas. In other words, the model results, particularly for the rural growth scenario may understate the risks associated with low-density development. Further, we also assumed that road proximity, the distance to urban areas (areas with $\geq$ 10,000 residences), and the proximity to public land would remain unchanged over time, suggesting the results here are conservative.

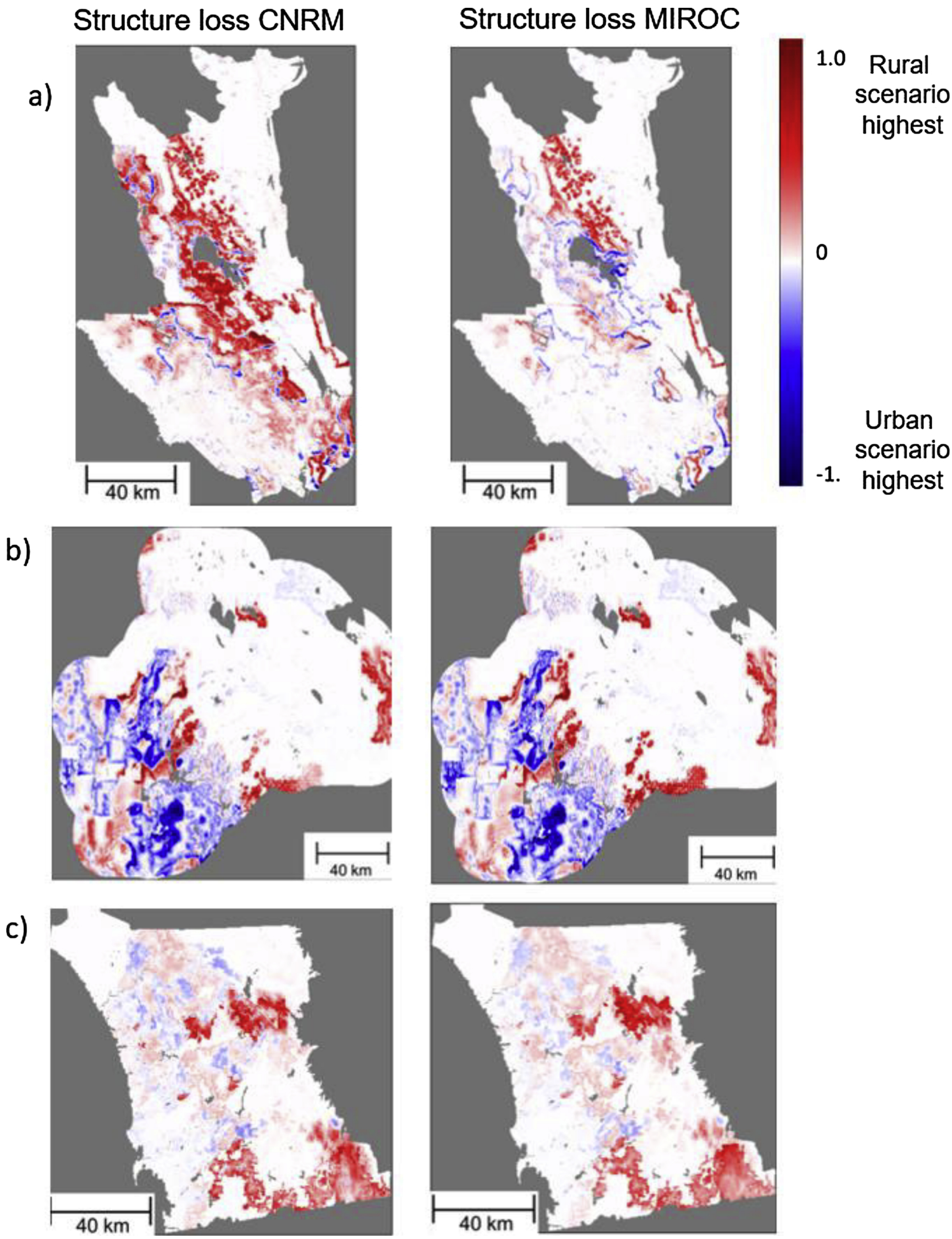

Fig. 9. Projected differences in structure loss probability at 2049 between the rural and urban density land use scenarios for CNRM and MIROC in the a) North Coast, b) Butte Plumas, and c) San Diego study areas.

4.3. Higher structure loss was seen in low density development

Regardless of future projections, one of the striking commonalities in the results was that observed structure loss occurred in larger fires and at lower housing densities than the averages for the regions. There are two different statistics related to housing density that are closely related but distinct. The first is the probability of structure loss for any house given its density (i.e., Fig. 6), and the other is the total number of structures lost at different housing densities (i.e., Fig. 3). Our results showed that probability of structure loss is negatively related to housing density in all regions, and while most destroyed structures were located in lower housing density classes, some structures were also destroyed at high densities. The association between structure loss and housing pattern has been documented in recent studies (Syphard et al., 2012, Alexandre et al. 2016, Kramer et al., 2018), and there has long been an assumption that fire risk is highest at the Wildland-Urban Interface (WUI), where houses meet or intermingle with wildland vegetation, both in the U.S. (e.g., Radeloff et al., 2018, Mell et al., 2010) and internationally (e.g., Lampin-Maillet et al., 2010; Montiel Molina and Galiana-Martín, 2016; Argañaraz et al. (2017)). However, the occurrence of several highly catastrophic wildfire events within high-density developments (e.g., Cohen and Stratton, 2008; Price and Bradstock, 2013; Nauslar et al., 2018), including recent California events, combined with previous lack of data associating changes in fire losses to changes in development patterns (McCaffrey et al. https://fireadaptednetwork.org/fire-narratives-accurate/) have led to questions and debate over which are the most dangerous development patterns.

Thus, one of the most important results of this study is that, even considering the massive numbers of structures that were destroyed in the last two years in wind-driven fire events, the overall mean housing density where houses are most likely to be destroyed (0.08 to 2.01 structures/ha pre-2015 and 1.24–3.61 in recent events) was more than an order of magnitude lower than the average housing density on the landscape for most cases (except the Camp Fire where the destroyed structure density was about 50% lower and the 2017 North Coast Fires, where the destroyed structure density was about 66% lower than total structures). The recent wildfires were uncharacteristic in the sheer number of structures and lives lost relative to historical numbers, in addition to the fact that wildfires did reach and enter parts of high-density urban areas in Coffey Park (Tubbs Fire), Paradise (Camp Fire), and the city of Malibu (Woolsey Fire). Thus, a lot more research is needed to understand how and why so many structures were lost. One clear factor were the wind speeds in these events, in addition to apparently substantial structure-to-structure spread and incendiary ember ignitions in which the houses themselves were more flammable than the nearby vegetation. Nevertheless, the losses in urban areas were still only a portion of the total number of structures destroyed in these fires, and thus they do not change the main conclusions of our study: overall, most structure loss tends to occur in areas of low-density development. One caveat is that we calculated housing density using data from the 2000 Census projected to 2009 as a baseline, and thus housing density has likely changed since then. However, the relative comparisons likely still hold because we consistently used the same housing data. Another recent study reported that the majority of threatened and destroyed structures from the last 30 years in the U.S. were located within the WUI; furthermore, when destroyed houses were not located in the WUI, the most common reason was that the housing density was lower than that in the WUI definition (Kramer et al., 2018).

The most likely explanation for this striking consistency is that housing patterns largely reflect exposure to wildfire. That is, wildfires typically burn through vegetation; and thus, those homes most interspersed with vegetation are most likely to encounter a wildfire in the first place, or be hit by incendiary embers. The reason for occasional catastrophic wildfire losses in high density areas is that, once exposed to a fire, a community with closely spaced homes made of flammable materials can lead to rapid house-to-house spread, particularly during severe weather conditions. In these cases, like the Tubbs fire in 2017 and Camp fire in 2018, the house itself becomes the fuel that propagates the fire.

Therefore, in terms of addressing conflicts between housing and wildfire in the future, the most effective mitigation may be land use and urban planning decisions that reduce the exposure of homes to wildfires (Syphard et al., 2013, 2016, Butsic et al., 2017). However, mitigation measures focused on defensible space and fire-safe construction materials, particularly when houses are closely spaced, are also critical for preventing future losses (Syphard et al., 2015, 2017c), as are other traditional fire management practices such as fire suppression and strategic location of fuel breaks to allow safe firefighter access to defend homes.

4.4. Conclusion

Looking at fire ignitions, large fires, and structures burned, we explored the importance of climatic and human variables for explaining fire and structure loss patterns across three diverse California landscapes, under current and future climate (hot-dry or warm-wet) and land use (rural or urban residential growth) scenarios. Across regions, we found that housing and human infrastructure were more responsible for explaining fire ignitions and structure loss probability. Large fires were better explained by climate, topography, and fuel variables. The differing strengths of these relationships interacted with the climate and land use scenarios, resulting in variability across regions in the relative importance of climate and housing patterns on fire and structures burnt. Focusing only on empirical housing density and structures burnt, we found that most structure loss occurred in areas with low housing density (from 0.08 to 2.01 units/ha), and as such, expansion of rural residential land use generally increased projected structure loss probability in the future. Both the historical results and the future projections highlight that future changes are likely to be complex and will result from a range of interacting factors. Climate change will be important to consider for managers and policy makers in some, but not all regions. In all areas, land use change merits increased attention, as local policy decisions can influence future patterns of development and exposure of structures to risk of loss in large wildfires.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.gloenvcha.2019.03.007.

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