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Post-wildfire neighborhood change: Evidence from the 2018 Camp Fire

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HIGHLIGHTS

- Wildfire destruction was predicted by building type, tenure, and value.
- Building value-destruction association was explained by density and proximity to roads.
- Post-fire reconstruction was predicted by building type, tenure, and value.
- Findings suggest housing stock filtering and cost-burden gentrification.

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ABSTRACT

As the number of highly destructive wildfires grows, it is increasingly important to understand the long-term changes that occur to fire-affected places. Integrating approaches from social and biophysical science, we document two forms of neighborhood change following the 2018 Camp Fire in the United States, examining the more than 17,000 residential structures within the burn footprint. We found that mobile or motor homes, lower-value residences, and absentee owner residences had a significantly higher probability of being destroyed, providing evidence that housing stock filtering facilitated socially stratified patterns of physical damage. While the relationship between building value and destruction probability could be explained by measures of building density and distance to nearby roads, building type remained an independent predictor of structure loss that we could not fully explain by adding environmental covariates to our models. Using a geospatial machine learning technique, we then identified buildings that had been reconstructed within the burn footprint 20 months after the fire. We found that reconstructed buildings were more likely to have been owner-occupied prior to the fire and had higher average pre-fire property value, suggesting an emerging pattern of cost-burden gentrification. Our findings illustrate the importance of examining the built environment as a driver of socially uneven disaster impacts. Wildfire mitigation strategies are needed for mobile and motor home residents, renters, low-income residents, and dense neighborhoods.

1. Introduction

The impacts of wildfires on the built environment are growing increasingly acute. In the U.S., the number of housing units exposed to wildfire grew more than twofold in recent decades (Radeloff et al., 2023), and wildfire events in the western U.S. had a 160% higher structure loss rate between 2010 and 2020 compared to the previous decade (Higuera et al., 2023). Concerns over growing wildfire destruction are echoed internationally, with a recent United Nations report emphasizing “the rising threat of extraordinary landscape fires” across many continents (United Nations Environment Programme, 2022). As the number of highly destructive wildfires grows, it is increasingly important to understand the long-term changes that occur to fire-affected places.

Existing research on the dynamics of wildfire and the built environment has documented an extensive set of physical characteristics that influence building destruction outcomes (Alexandre et al., 2016; Gibbons et al., 2012; Syphard et al., 2012, 2014, 2017). A small but growing area of research has further described macro-level trends in post-fire building reconstruction (Alexandre et al., 2015; Kramer et al., 2021; Mockrin et al., 2015). We advance this area of study by integrating key concepts from social science research on neighborhood

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change - shifts in a place's built environment, population, or economy over time - to examine socioeconomic differentiation of building destruction and subsequent reconstruction (Zuk et al., 2015).

Our study examines two forms of physical neighborhood change that have not been investigated widely in the context of wildfire: housing stock filtering and cost-burden gentrification. We do so in a case study of the 2018 Camp Fire, which destroyed nearly 19,000 structures in northern California and remains one of the most destructive wildfires in U.S. history. In our study, we test whether socioeconomic-related characteristics of buildings exposed to the fire - building type, building value, and building tenure - were associated with heightened or reduced probability of destruction and subsequent reconstruction. Through this fine-grained examination of the built environment immediately following the Camp Fire and again, 20 months after the event, we illustrate how wildfire can facilitate neighborhood change at different periods of time through a restructuring of the physical landscape.

Social science research on disasters has long emphasized that social, political, and economic processes fundamentally shape how environmental hazards affect residents, often reinforcing existing social inequalities (Tierney, 2019; Wisner et al., 2014). Scholarship focused on wildfires and social inequality has described the co-occurrence of wildfire risk and community demographic characteristics (Davies et al., 2018; Lambrou et al., 2023; Palaiologou et al., 2019; Wigtil et al., 2016). It has further highlighted ways that residents' capacity to prepare for wildfire or to adapt to post-fire conditions differ across demographic groups (Méndez et al., 2020; Paveglio et al., 2015). Building on existing wildfire social vulnerability scholarship - which has primarily examined characteristics of people - we show how the dwellings where people live can further drive socially uneven disaster outcomes through physical neighborhood change.

1.1. Neighborhood change and environmental hazards

Neighborhood change research broadly investigates the ways that the population, economy, or built environment of a place change as the result of public policies, private capital flows, and residential movement (Zuk et al., 2015). Our study follows prior neighborhood change research that focuses specifically on the physical environment, using tools such as Google Street View imagery (Hwang & Sampson, 2014) and video-recording (Raudenbush & Sampson, 1999) to document the physical attributes of neighborhoods. We build on this tradition, using a combination of property records and aerial imagery to investigate how wildfire can influence neighborhood change through impacts to the built environment.

Prior research on environmental hazards and the built environment suggests that wildfires may influence two distinct neighborhood change processes. First, certain buildings may be more sensitive to being destroyed or damaged in a fire as a result of a process known as "filtering." As housing stock ages and physically declines, researchers have documented that the residents living in those structures also shift. Namely, lower-income and non-White residents are often sorted into lower-value housing stock (Baer & Williamson, 1988; Peacock et al., 2014). In turn, residents living in lower-quality housing can subsequently face heightened exposure to damage from environmental hazards (Chakraborty et al., 2019; Kamel, 2012; Ma & Smith, 2019). The filtering of housing stock can thus reflect patterns of socioeconomic and racial segregation, which then intersect with specific disaster events (Madden, 2021).

In a changing climate, it is likely that filtering will exacerbate social inequalities in the built environment, as older housing stock is less likely to be designed to withstand intensifying environmental hazards and retrofits can be costly (Fussell & Castro, 2022). In the U.S., wildfire mitigation is generally approached as an individual responsibility; as such, residents with fewer resources are less likely to have the capacity to address fire risk where they live (Wigtil et al., 2016). When considering housing tenure, scholars have suggested that not only do renters have little incentive to invest in hazard mitigation on property that they do not own, but further, that it may be difficult for owners of rental properties to recoup costs of hazard mitigation investments (Burby et al., 2003). Further, Chase and Hansen (2021) report that renters affected by the Camp Fire had lower average income than homeowners, suggesting they likely had fewer financial resources to put towards mitigation. As a result of these income and housing tenure dynamics, one of few case studies on this topic found that low-income and renting households were less likely to engage in fire mitigation practices (Collins, 2008). Such patterns are in keeping with broader environmental hazard research, which finds more generally that lower-income residents and renters have less capacity to engage in disaster preparedness and mitigation (Fothergill & Peek, 2004; Lee & Van Zandt, 2019).

The second avenue through which we hypothesize wildfires can influence neighborhood change is in the building reconstruction process through a form of post-disaster gentrification. We draw on a typology advanced by Keenan et al. (2018), who outline distinct pathways through which environmental hazards can influence property markets. While these authors emphasize the connection between climate change and housing, their proposed gentrification pathways can be applied more broadly to environmental hazards such as wildfires, which can result from a combination of factors including climate change, land use patterns, and, human- or utility-caused ignitions (Balch et al., 2017; Goss et al., 2020). In their case study of Miami-Dade County, Florida, Keenan et al. (2018) find that residential property values at higher elevations - where they were better protected from nuisance flooding - appreciated at a higher rate. In short, capital moved away from hazardous places. However, the authors point out that hazard-driven gentrification can also function inversely, wherein more affluent residents are able to afford the costs of remaining in a hazardous place, while less affluent residents cannot, and subsequently move away.

Termed "cost-burden gentrification" (Keenan et al., 2018), this form of hazard-related neighborhood change is especially plausible in a U.S. wildfire context given the common co-occurrence of desirable landscape amenities with heightened wildfire risk (Winkler & Rouleau, 2020). In other words, more resourced residents may seek to remain in place and adapt to fire risk, rather than moving to a lower-risk area. We also know from research across different hazard types that the financial burden of post-disaster rebuilding can be high (Fothergill & Peek, 2004). This past research led us to hypothesize that cost-burden gentrification is a likely post-fire trajectory. Yet, to our knowledge, existing research has not investigated such patterns of neighborhood change following fires. Further, cost-burden gentrification has received little scholarly attention relative to other, more commonly-documented avenues of hazard-related gentrification.

To investigate whether there is evidence of cost-burden gentrification following the Camp Fire, we examined patterns of building reconstruction. Compared to research on wildfire damage, analyses of post-fire building reconstruction are far fewer. The limited research in this area tends to describe general trends of whether rebuilding is considered "fast" or "slow," and often reports the overall proportion of burned structures that have been rebuilt within a particular timeframe (Alexandre et al., 2015; Kramer et al., 2021; Mockrin et al., 2015). This line of inquiry has yet to deeply investigate post-fire reconstruction through the lens of neighborhood change or gentrification. As a result, there is still limited understanding of which types of buildings in which neighborhoods are reconstructed more quickly, and why reconstruction rates vary across different fires. Research on post-fire reconstruction has been further limited by its reliance on manual techniques for identifying buildings. This time-intensive approach limits researchers' ability to analyze extremely destructive events, such as the Camp Fire, or to examine differences in reconstruction across many fire events. Recognizing a need for more efficient techniques of identifying reconstructed buildings, we developed a methodological strategy that draws on aerial imagery and machine learning to semi-automatically detect buildings within a landscape.

1.2. Research objectives

Our study investigates the following hypotheses of neighborhood change following wildfire:

Housing stock filtering

- H1.1: Compared to single-family residences, multi-family residences and mobile or motor homes were more likely to be destroyed in the fire. Compared to owner-occupied residences, renter-occupied residences were more likely to be destroyed. Lower-value homes were more likely to be destroyed than higher value homes.
- H1.2: Differences in destruction probability observed in H1.1 can be explained by examining additional covariates known to be associated with structure loss.

Cost-burden gentrification

- H2.1: Compared to single-family residences, multi-family residences and mobile or motor homes were less likely to be reconstructed. Compared to owner-occupied residences, renter-occupied residences were less likely to be reconstructed. Lower-value homes were less likely to be reconstructed than higher value homes.

We conclude by reflecting on how our empirical findings can inform future directions for wildfire mitigation planning. Our paper's primary contribution is to document how wildfire can drive neighborhood change, showing first how characteristics of the built environment facilitate socially stratified hazard impacts, and second, how post-disaster reconstruction is similarly uneven.

2. Methods

2.1. Study site

The 2018 Camp Fire occurred in Butte County, California, which is situated in the broader Sierra Nevada bioregion (Figs. 1 and 2). This region is considered a predominantly Mediterranean climate, with substantial precipitation during winters and dry summers, leading to flammable fuel loads. Primary vegetation in the affected region include a range of conifer species, mixed evergreen, and chaparral. These conditions mean that fire has always been a part of the Sierra Nevada landscape (Knapp et al., 2021; van Wagtendonk et al., 2018).

The Camp Fire destroyed nearly 80% of buildings in its path, and, to date, is one of the most destructive wildfires in U.S. history. The majority of buildings destroyed were located in the Town of Paradise, with surrounding communities of Concow, Magalia, Yankee Hill, and Butte Creek Canyon all severely affected as well (Chase & Hansen, 2021). This area is locally referred to as "the Ridge," a term that we use to reference the communities affected by the fire.

Fig. 1. Reconstruction on the Ridge in Butte County, California. Photo taken by K. McConnell circa spring 2022.

2.2. Measuring building socioeconomic proxy characteristics

We tested our hypotheses by integrating building-level data from CAL FIRE's Damage Inspection Data from the Camp Fire (hereafter "CAL FIRE Damage Inspection Data") (California Department of Forestry and Fire Protection, 2018) with administrative property records, a suite of biophysical characteristics calculated in R computing software, and indicators of post-fire building reconstruction derived from aerial imagery. We constrained our analysis to exclusively residential structures (N = 17,536) in order to focus on residential neighborhood change processes.

Our hypotheses focus on three characteristics of buildings that, while not direct measures of buildings' residents, can be considered proxy variables for socioeconomic status and have been used in several previous studies of wildfire and social vulnerability (Lambrou et al., 2023, p. 7). Our primary socioeconomic variables included: (1) building type (single-family residence, mobile or motor home, or multi-family home), (2) building tenure (renter- or owner-occupied), and (3) building value. We determined building type from the CAL FIRE Damage Inspection Data, and building tenure and value from 2017 Butte County public property records obtained from the financial analytics company CoreLogic.

To estimate building value, we used the "total value" measure, which combines land value and improvement value (*Client Welcome Toolkit: A Guide to Better Understand CoreLogic Property Data*, 2019, p. 32). To account for the small number of parcels that had a large number of residential structures (<1%) - and which primarily were sites of mobile home parks - we adjusted the total value measure by the number of residential structures per assessor's parcel number (APN).

A structure is considered to have an absentee owner if the owner lives at a different location (Client Welcome Toolkit: A Guide to Better Understand CoreLogic Property Data, 2019, p. 32). This measure has been used to identify rental properties in prior research (Einstein et al., 2022). While it is possible that the absentee owner variable may have captured some second homes or vacation rentals, estimates that approximately 30% of Paradise residents rented prior to the fire (Chase & Hansen, 2021, p. 1569) were in line with our data's estimates, suggesting that this variable predominantly captured renters living on the Ridge. Among residential structures, 90.0% included a designation of either "owner" or "absentee owner" status.

2.3. Measuring additional building covariates

In addition to our primary socioeconomic variables described above, we computed a suite of additional building-level characteristics to investigate Hypothesis 1.2 (Table 1). These covariates primarily included landscape, terrain, and building arrangement characteristics that have been published in past fire science literature (Alexandre et al., 2016; Gibbons et al., 2012; Syphard et al., 2012), as well as interaction terms that could be associated with destruction outcomes (additional details in Appendix A).

Many variables were determined based on buildings' spatial location and without the need for additional data, however landscape-level variables were derived using the 2016 National Land Cover Database (NLCD) (Dewitz, 2019). We followed Alexandre et al. (2016) in reclassifying NLCD raster data into three primary classes: highly flammable, flammable, and non-flammable (Appendix A). From these three classes, we calculated additional variables within 2500 m of each building point. Summary statistics of continuous covariates are reported in Appendix B.

Fig. 2. Location of the Camp Fire in Butte County, California. Burn footprint from the Monitoring Trends in Burn Severity (MTBS) database (Eidenshink et al., 2007).

2.4. Identifying destroyed buildings

CAL FIRE Damage Inspection Data were created through in-person field inspections and document an ordinal damage measure for each structure within the Camp Fire burn footprint. We calculated a binary measure of whether a structure was destroyed or not destroyed as the primary outcome variable, where all categories with less than 50% destruction were classified as "not destroyed." Out of 17,536 residential structures, 13,974 were destroyed (79.7%), 54 experienced 1–50% damage (0.003%), and 3,048 experienced no damage (17.4%). Maps of all destroyed and surviving structures are shown in Appendix C.

Our study builds on research conducted by Knapp et al. (2021) and Troy et al. (2022), who also utilize CAL FIRE Damage Inspection Data. While there is some overlap in variables examined in these studies and our research, a fundamental difference between all three is the population of buildings included in analysis. Knapp et al. randomly sample 400 structures, selecting only from single-family residences within the Town of Paradise (Knapp et al., 2021, p. 4). Troy et al. (2022) conduct two sets of analysis, the first of which analyzes all destroyed structures within the burn footprint, including both residential and nonresidential structures. In addition to analyzing a broader set of structures, the comparison group used in this analysis is distinct from ours, and is composed exclusively of partially damaged structures, rather than structures that survived with no damage (Troy et al., 2022, p. 589). This study's second analysis analyzes a sample of 1,404 properties based within the Camp Fire footprint but outside the Town of Paradise (Troy et al., 2022, p. 590). Our analysis uses a distinct set of observations, which includes the full population of documented residential structures within the burn footprint.

2.5. Identifying reconstructed buildings

To create the binary outcome indicating whether a building had been reconstructed after the fire, we integrated high-resolution imagery from the U.S. Department of Agriculture's National Aerial Imagery Program (NAIP) and Microsoft's open-access database of building footprints in the United States (see Appendix D for additional details). NAIP images have been previously used to classify land cover types with relatively high accuracy (U.S. Department of Agriculture Farm Service Agency, n.d.; Maxwell et al., 2017), while Microsoft's Building Footprints database has been used to quantify building counts within hazard-prone areas (Huang & Wang, 2020; Microsoft, 2022). We paired these two data sources in Google Earth Engine's (GEE) cloud computing platform (Gorelick et al., 2017).

We first accessed 35 pre-fire NAIP scenes captured on July 18, 2018 directly from GEE, and upload 48 post-fire NAIP scenes captured on July 9, 2020, which had not yet been ingested into the GEE platform. We then mosaicked each collection of scenes together to create a single pre-fire and a single post-fire image covering the entire Camp Fire burn footprint. Next, to classify the post-fire NAIP image mosaic, we trained a support vector machine (SVM) algorithm on pre-fire imagery with Microsoft Building Footprints, NAIP's primary spectral bands (red, green, blue, and near infrared), and the Normalized Difference Vegetation Index (NDVI) (a combination of red and near infrared bands). We trained the SVM by sampling 1000 random points from each land cover class - "building" and "non-building" - which were defined by Microsoft Building Footprints on the pre-fire aerial image mosaic. We then removed sample points with an NDVI value higher than 0.2 to avoid misclassifying occasional overhanging tree pixels as building class. This process yielded 812 total sample points for the building class. Non-building points were sampled from pixels within the burn footprint which had been masked to exclude Microsoft Building Footprint polygons and buffered roads.

After training and testing the classifier on the pre-fire NAIP mosaic, we then used the algorithm to classify the post-fire NAIP mosaic (Fig. 3). Points of buildings designated by Damage Inspection Data as destroyed were then overlaid on the 2020 classified image, and each point was determined to be rebuilt or not rebuilt based on the class of the pixel on which it was located. See Appendix D for details on SVM models and our multi-step validation process.

2.6. Modeling bivariate destruction and reconstruction outcomes

To test Hypothesis 1.1 and 2, we utilized a series of linear probability models (LPMs) to estimate the probability that a structure was destroyed or reconstructed. In these models, we exclusively analyzed socioeconomic proxy characteristics of structures - building type, pre-fire building value, and building tenure - to evaluate whether certain building types were disproportionately impacted by the fire (Hypothesis 1.1) or disproportionately more likely to have been reconstructed (Hypothesis 2), regardless of the cause. LPMs took the form:

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

Where Y_i is the binary outcome variable that indicates whether building

Table 1
Covariates used in Hypothesis 1.2.

Variable	Description	Measurement Scale	Source
Building type	Categorical indicator of single-family residence, multi-family residence, or mobile or motor home	Building level	CAL FIRE Damage Inspection Data
Absentee owner status	Binary indicator of whether a building owner lives at a different location (absentee owner/renter) or lives in the home (owner-occupied)	Building level	Public property records
Pre-fire building value (logged)	Total dollar value of building adjusted for count of residential structures per APN	Building level	Public property records
Slope	Slope in degrees	Building level	Computed with R statistical software (sf, elevatr, and raster packages)
Aspect	Compass direction of slope	Building level	Computed with R statistical software (sf, elevatr, and raster packages)
Southwestness	Derived from aspect, ranges from + 1 (southwest) to −1 (northeast)	Building level	Computed with R statistical software (sf, elevatr, and raster packages)
Topographic Position Index (TPI)	Topographic position of a given point in relation to its general neighborhood (e.g. valleys, slopes, flat areas, ridges) retained in continuous form	Building level	Computed with R statistical software (sf, elevatr, and raster packages)
Distance to nearest building	Continuous variable measured in meters and calculated with both residential and non-residential structures	Building level	Computed with R statistical software (sf and nngeo packages)
Count of buildings within 40 m radius	Continuous variable based in a 40 m buffer from each building point, calculated with both residential and non-residential structures	Building level	Computed with R statistical software (sf and nngeo packages)
Distance to any road	Continuous variable measured in meters and calculated with Census Bureau's TIGER/Line Shapefile	Building level	Computed with R statistical software (sf, nngeo, and tigris packages)
Distance to major road	Continuous variable measured in meters and calculated with state-recognized roads in Census Bureau's TIGER/Line Shapefile	Building level	Computed with R statistical software (sf, nngeo, and tigris packages)
Post code change	Binary indicator of whether a structure was built in 2008 or later after the adoption of updated California Building Code	Building level	Calculated from year of construction, CAL FIRE Damage Inspection Data
Distance to cluster edge	Continuous measure of meters from building point to the edge of cluster, where cluster is defined by merging overlapping 100-meter buffers from each building point (see Alexandre et al., 2016)	Cluster level	Computed with R statistical software (sf and nngeo packages)
Contagion Index	Measures the "clumpiness" of raster cells in categorical maps, including both the extent to which differing patch types are intermixed and their spatial distribution (McGarigal, 2015)	Landscape level (within a 2500 m radius)	Land cover map of the National Land Cover Database; computed with R statistical software (sf, raster, and exactextractr packages)
Mean canopy cover	Measure of the average pixel value, where each cell represents a continuous measure of the percent tree canopy (0–100)	Landscape level (within a 2500 m radius)	U.S. Forest Service Science Tree Canopy Cover, National Land Cover Database; computed with R statistical software (sf, raster, and exactextractr packages)
Proportion highly flammable land cover	Proportion of cells within the radius classified as highly flammable	Landscape level (within a 2500 m radius)	Land cover map, National Land Cover Database; computed with R statistical software (sf, raster, and exactextractr packages)
Count of non-flammable, flammable, and highly-flammable patches	Number of unique patches of each flammability class within the radius	Landscape level (within a 2500 m radius)	Land cover map, National Land Cover Database; computed with R statistical software (sf, raster, and exactextractr packages)

i was destroyed (1) or survived (0) in the case of Hypothesis 1.1, and reconstructed (1) or not reconstructed (0) in the case of Hypothesis 2. β_0 represents the intercept; x_i is a vector of observed socioeconomic proxy characteristics; and ε_i represents residual errors. β_1 is the coefficient of interest, indicating whether a given building characteristic is associated with structure loss or reconstruction. Our preferred threshold for statistical significance is $p < .01$. To address the potential for LPMs' residuals to be heteroscedastic, we computed HC1 robust standard errors. We elected to use LPMs rather than non-linear probability models (NLPMs), such as logistic regression, because NLPMs do not produce comparable coefficients in nested models that use the same outcome variable, as our research design does (Breen et al., 2018). However, we present alternative model specifications in logistic form in Appendix E to ensure the robustness of our findings.

2.7. Modeling multivariable destruction outcomes

To test Hypothesis 1.2, we introduced a series of covariates into our multivariable model from Hypothesis 1.1 in forward stepwise fashion (Table 3, Models 1–7). We incorporated 16 additional covariates (Table 1), nearly all of which have been documented in prior fire science literature to influence structure loss. At each step, we examined whether the coefficient on building type, building value, or building tenure changed in magnitude, direction, or significance. Given our focus on understanding socioeconomic predictors of structure loss, we placed greater emphasis on understanding changes to these coefficients and less emphasis on interpreting the added covariates.

In addition to our stepwise procedure, we asked whether any of our socioeconomic predictors were included in a final "best fit" model (Table 3, Model 8). If so, this would suggest that socioeconomic characteristics of buildings were associated with structure loss independently from the range of established structure loss predictors included in our models, and may be especially important to include in future wildfire destruction research. We utilized a LASSO regression on a non-spatial, full multivariable model to select covariates for inclusion in our "best fit" model, using the glmnet package in R (Friedman et al., 2023). The LASSO operates by adding a shrinkage penalty to a least squares regression, such that coefficients of covariates with less predictive power are "shrunk" to zero, effectively being removed (James et al., 2013). The LASSO yielded the following covariates in the final model: building type, distance to nearest building, count of buildings within 40 m, distance to nearest road, post-code change, and Contagion Index. We removed distance to nearest road, which was non-significant in the final spatial error model. The LASSO model should address potential correlation between covariates by selecting only one of multiple correlated variables. To ensure this was the case, we tested the Variance Inflation

Fig. 3. Support vector machine classification procedure. Top image shows pre-fire NAIP imagery of the Town of Paradise. Middle image shows post-fire NAIP imagery of the Town of Paradise. Bottom image shows support vector machine-classified grid derived from post-fire NAIP imagery that designates built hard-scape (black) and non-building (white). Red circles illustrate how the algorithm was able to successfully detect buildings in NAIP imagery. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Factor (VIF) of the final set of covariates selected by the LASSO, and confirmed that all variables had a VIF of 2 or lower.

Finally, to assess whether our data were spatially autocorrelated, we tested the residuals of our full multivariable model. Results of this test suggested that there was positive autocorrelation in our data (Moran's I = 0.444). Lagrange Multiplier tests indicated that a spatial error or a spatial lag model would be similarly well-suited to address this autocorrelation. We opted to include a spatial error term in our models, given that this approach is theoretically better-suited to address cases in which known explanatory variables are not included in the models (Chi & Zhu, 2020, p. 78).

We fit a series of stepwise spatial error models and a spatial "best fit" model which took the form:

$$Y_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \varepsilon_i$$

$$\varepsilon_i = \lambda W \varepsilon_i + v_i$$

Where Y_i is the binary outcome variable that indicates whether building i was destroyed (1) or survived (0). β_0 represents the intercept; and x_{ij} is the j-th predictor for the i-th observation over p independent variables. The error term, ε_i, includes both an autoregressive spatial error term, $\lambda W \varepsilon_i$, which accounts for spatial autocorrelation in either measurement error or unobserved variables as well as a random error term, v_i (Anselin & Bera, 1988). These models were produced using a three-nearest neighbors spatial weights matrix, which we selected after examining which of a series of neighbor counts (K = 3, 5, 10, and 15) reflected the highest spatial dependence (Chi & Zhu, 2020, pp. 40–41). Additional model robustness checks are reported in Appendix F.

3. Results

3.1. Disproportionate probability of destruction across building type, tenure, and value

We first posited in Hypothesis 1.1 that certain structures would be disproportionately more likely to have been destroyed in the fire, namely, multi-family residences, mobile or motor homes, renter-occupied residences, and lower-value residences. Our findings support most components of this hypothesis. Examining different residential building types, we found that mobile or motor homes were significantly more likely to have been destroyed than single-family residences, with 87.1% of mobile or motor homes destroyed compared to 77.5% of single-family residences ($p < .001$) (Table 2, Model 1). However, in contrast to our expectation, we found that multi-family residences were significantly less likely to have been impacted than single-family residences, with 69.2% having been destroyed ($p < .001$) (Table 2, Model 1). The magnitude of both of these differences was substantial. Examining building tenure, we found that renter-occupied residences were significantly more likely to have been destroyed in the fire compared to owner-occupied residences (Table 2, Model 2). While the three-percentage point difference was smaller in magnitude than differences observed for building type, it was significant ($p < .001$). Examining buildings' pre-fire value, we found a negative relationship with probability of destruction, where the higher value the building the less likely it was to be destroyed ($p < .001$) (Table 2, Model 3).

Given the likelihood that our three socioeconomic proxy characteristics were collinear, we fit a full multivariable model with building type, tenure, and value (Table 2, Model 4). This model indicates whether our three variables predict destruction probability independently from one another. Here we found that multi-family residences remained significantly less likely to have been destroyed compared to single-family residences ($p < .001$), and pre-fire building value continued to significantly predict destruction probability ($p < .001$). However, mobile or motor homes and renter-occupied homes were no longer significantly more likely to have been destroyed. This was due to collinearity with building value, in which mobile or motor homes were substantially lower in total value than any other building type, at $65,663 on average compared to $185,416 for the average single-family residence. A similar pattern occurred among absentee owner structures, in which this variable no longer significantly predicted destruction in the multivariable model of residential structures. As with mobile or motor homes, this was the result of collinearity with building value, in which absentee owner residential buildings were, on average, $63,048 less than owner-occupied residential buildings.

3.2. Correlates of differential building destruction

Hypothesis 1.2 posits that we can explain differences in destruction outcomes observed in Hypothesis 1.1 by including additional building characteristics in our model. Our aim in this modeling approach was to identify which specific physical characteristics may be associated with different socioeconomic characteristics of buildings, in turn causing them to be more physically sensitive to structure loss. If Hypothesis 1.2 were correct, building type, building value, and building tenure would

Table 2
Probability of residential building destruction.

	Dependent variable:			
	Destroyed			
	(1)	(2)	(3)	(4)
Intercept	0.775***	0.799***	1.524***	1.488***
	(0.004)	(0.004)	(0.042)	(0.065)
Multi-Family Residence (reference = Single-Family)	−0.083***			−0.124***
	(0.023)			(0.027)
Mobile or Motor Home (reference = Single-Family)	0.096***			−0.004
	(0.006)			(0.009)
Absentee Owner (reference = Owner-Occupied)		0.035***		0.010
		(0.007)		(0.007)
Pre-Fire Building Value (log scale)			−0.061***	−0.058***
			(0.004)	(0.005)
Observations	17,536	15,704	16,881	15,704
Log Likelihood	−8,810	−7,616	−7,943	−7,496
Akaike Inf. Crit.	17,626	15,235	15,889	15,002

Note: *p < 0.05; **p < 0.01; ***p < 0.001.

have non-significant coefficients in our multivariable models. If Hypothesis 1.2 were incorrect, we would still observe significant coefficients on these variables, indicating that our models did not fully account for the underlying reasons why these structures were more susceptible to destruction. To test Hypothesis 1.2, we introduced a spatial error term and a range of primarily environmental covariates to our socioeconomic proxy models to determine whether we could explain the heightened probability of destruction observed among mobile or motor homes, renter-occupied residences, and lower-value residences.

First, we fit the same multivariable socioeconomic model from Table 2 (Model 4), but included a spatial error term to address spatial autocorrelation (Table 3, Model 1). Here we found similar trends in that multi-family residences were significantly less likely to be destroyed than single-family residences ($p < .01$), building value was negatively associated with destruction probability ($p < .001$), and there were no significant differences among owner- and renter-occupied residences. However, in contrast to our non-spatial models, we found that mobile or motor homes were significantly more likely to have been destroyed even after accounting for structure value ($p < .001$).

In stepwise additions of covariate sets across Models 2 through 7, we found strong consistency in the significance and direction of building type as a predictor of structure loss. Across all models, multi-family residences were significantly less likely to have been destroyed ($p < .01$ for Models 1-2, $p < .001$ for Models 3-8) and mobile or motor homes were significantly more likely to have been destroyed ($p < .001$) compared to single-family residences. Counter to Hypothesis 1.2, we were not able to explain the disproportionate impacts across building types by accounting for differences in terrain, development density, distance to roads, building code standards, building location within a cluster, or landscape characteristics.

We also observed similar consistency in the coefficient on renter-occupied structures, which was non-significant across all stepwise models. The heightened probability of renter-occupied structures being destroyed in the bivariate non-spatial model (Table 3, Model 2) can be best accounted for by differences in building value, and subsequent consideration of environmental characteristics did not change this explanation.

Pre-fire building value was the only socioeconomic variable that we were able to fully explain through the inclusion of additional covariates (Fig. 4). The significance and magnitude of the building value coefficient remained almost exactly the same after the addition of terrain characteristics ($p < .001$) (Table 3, Model 2), and then shrank in magnitude and became significant at a larger p-value threshold ($p < .05$) after adding building density characteristics (Table 3, Model 3). This indicates that some of the relationship between building value and destruction could be explained by building density, in which buildings located in denser developments were both lower value and more likely to have been destroyed. These trends held across all three building types (Fig. 4). In the next stepwise addition (Table 3, Model 4), the inclusion of distance to nearest road and to nearest major road rendered the coefficient on building value non-significant. Higher value single-family residences and mobile or motor homes were more likely to be a greater distance from roads, and structures farther from roads were less likely to have been destroyed (Fig. 4). The coefficient on building value remained non-significant in all subsequent stepwise models (Table 3, Models 5–7).

After examining changes in socioeconomic variable coefficients across stepwise regressions, we report a “best fit” model selected through LASSO regression (Table 3, Model 8). This model tells us which sparse combination of variables best predicts destruction probability. Here we found that building type was retained as a key predictor, along with building density measures, the building code change indicator, and landscape Contagion Index. As with previous stepwise models, mobile or motor homes were significantly more likely to have been destroyed ($p < .001$) and multi-family residences were significantly less likely to have been destroyed ($p < .001$) than single-family residences.

While our primary hypotheses focus on understanding the relationships between socioeconomic-related building variables and susceptibility to destruction, we briefly comment on the additional covariates in the full multivariable model here (Table 3, Model 7). As described above, building density and distance to roads significantly predicted probability of structure loss ($p < .001$). Additionally, the building code change variable indicates that residences built after the adoption of updated building codes in 2008 were significantly less likely to have been destroyed ($p < .001$). Finally, a number of landscape-scale vegetation metrics (all of which were measured within a 2,500 m radius of each structure) all significantly predicted structure loss; mean canopy cover, proportion of highly flammable land cover, and count of highly flammable patches were all positively and significantly associated with structure loss ($p < .001$). Contagion Index was negatively associated with structure loss, indicating that patchier, less-contiguous land cover was associated with a higher probability of destruction ($p < .001$). Finally, the significant interaction term between distance to nearest neighboring

Table 3
Correlates of differential building destruction.

	Dependent variable:							
	Destroyed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.051***	1.069***	0.894***	0.940***	0.889***	0.786***	−0.807***	1.069***
	(0.055)	(0.058)	(0.060)	(0.060)	(0.061)	(0.062)	(0.189)	(0.016)
Multi-Family Residence (reference = Single-Family)	−0.074**	−0.076**	−0.084***	−0.093***	−0.087***	−0.082***	−0.111***	−0.087***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.021)
Mobile or Motor Home (reference = Single-Family)	0.041***	0.042***	0.034***	0.039***	0.034***	0.036***	0.045***	0.060***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Absentee Owner (reference = Owner-Occupied)	0.004	0.004	0.004	0.004	0.003	0.003	0.005	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	
Pre-Fire Building Value (log scale)	−0.022***	−0.021***	−0.009*	−0.007	−0.002	−0.002	−0.003	
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	
Slope		−0.005*	−0.002	−0.002	−0.002	−0.001	0.001	
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Aspect		−0.0001	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001	
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Topographic Position Index (TPI)		0.016	0.040	0.064	0.019	0.051	0.143	
		(0.105)	(0.105)	(0.105)	(0.106)	(0.106)	(0.106)	
Southwestness		0.014	0.010	0.009	0.007	0.005	0.003	
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	
Meters to Building			−0.001***	−0.001***	−0.001***	−0.001***	−0.005***	−0.0003***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0001)
Building Count within 40 m			0.017***	0.016***	0.017***	0.015***	0.011***	0.016***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Meters to Major Road				−0.00002***	−0.00002***	−0.00001***	−0.00004***	
				(0.00000)	(0.00000)	(0.00000)	(0.00001)	
Meters to Any Road				−0.001***	−0.001***	−0.001***	−0.0001	
				(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Post-Code Change					−0.101***	−0.097***	−0.083***	−0.113***
					(0.018)	(0.018)	(0.018)	(0.016)
Meters to Cluster Edge						0.0002***	0.00000	
						(0.00002)	(0.00003)	
Contagion Index							−0.020***	−0.009***
							(0.002)	(0.0004)
Mean Canopy Cover							0.006***	
							(0.001)	
Proportion Highly Flammable Landcover							2.765***	
							(0.289)	
Count of Non-Flammable Patches							0.0003	
							(0.001)	
Count of Flammable Patches							0.0002	
							(0.0004)	
Count of Highly Flammable Patches							0.003***	
							(0.0003)	
Slope*Aspect		0.00001	0.00001	0.00001	0.00001	0.00001	0.00000	
		(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	
Meters to Building*Proportion Highly Flammable							0.005***	
							(0.001)	
Spatial Error	0.588***	0.586***	0.570***	0.562***	0.562***	0.556***	0.516***	0.551***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	15,704	15,704	15,704	15,704	15,426	15,426	15,221	17,176
Log Likelihood	−4,4331	−4,425	−4,309	−4,270	−4,187	−4,147	−3,749	−4,588
σ^2	0.091	0.091	0.091	0.090	0.090	0.090	0.088	0.090
Akaike Inf. Crit.	8,880	8,874	8,6465	8,572	8,407	8,330	7,549	9,194

Note: *p < 0.05; **p < 0.01; ***p < 0.001.
Models present results of linear probability models with spatial error term.

structure and proportion of highly flammable vegetation at the landscape scale (p <.001) indicated that, as buildings became more distant from each other, the influence of landscape-level flammable vegetation on destruction probability was stronger.

3.3. Disproportionate probability of building reconstruction across building type, tenure, and value

Finally, we tested Hypothesis 2.1 for evidence of cost-burden gentrification, positing that multi-family residences, mobile or motor homes, renter-occupied residences, and lower-value residences would be less likely to have been reconstructed within the 20-month study period. We found mixed evidence in support of this hypothesis.

First examining building type, results did not support our hypothesis; we found instead that there was no difference in reconstruction probability between multi-family and single-family residences. While mobile or motor homes were slightly less likely to have been replaced than single-family residences in the bivariate model (p <.05) (Table 4, Model 1), the difference was very small in magnitude and did not meet our preferred p-value threshold of 0.01. Further, after controlling for building value in the full multivariable model (Table 4, Model 4), mobile or motor homes were *more* likely to have been rebuilt (p <.01), which may speak to mobile or motor homes being faster to place back on a lot, as opposed to the lengthier process of constructing a new building.

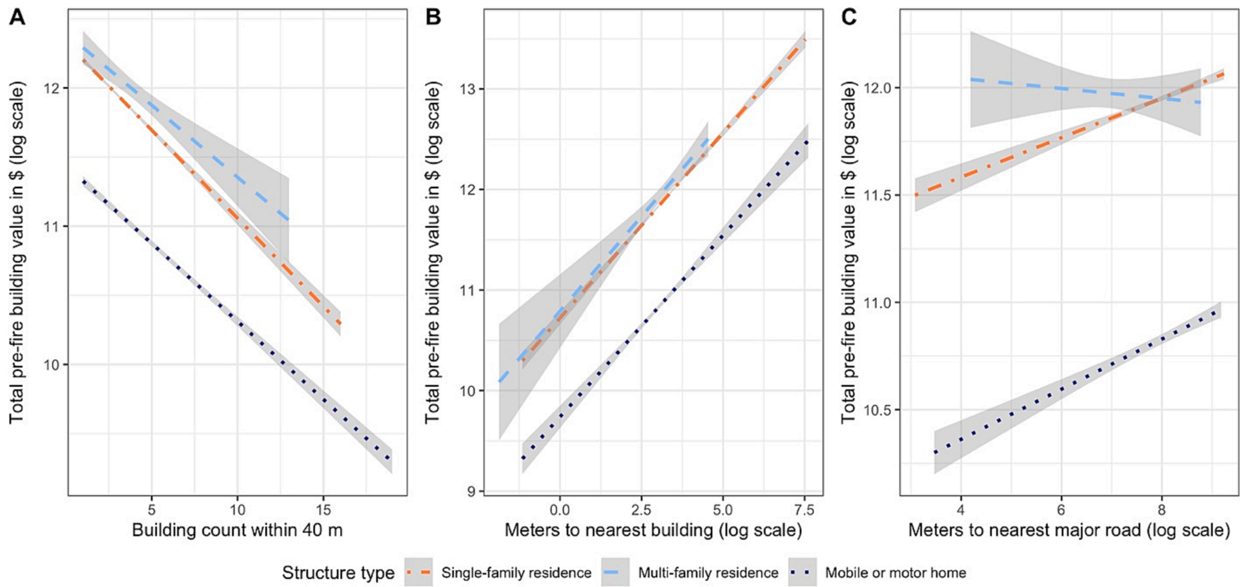

Fig. 4. Correlations between total pre-fire building value (log scale) and (A) building count within a 40 m radius, (B) meters to the nearest building (log scale), and (C) meters to the nearest major road (log scale).

Table 4
Probability of post-fire residential building reconstruction.

	Dependent variable:			
	Rebuilt			
	(1)	(2)	(3)	(4)
Intercept	0.039***	0.046***	−0.089***	−0.076*
	(0.002)	(0.002)	(0.018)	(0.031)
Multi-Family Residence (reference = Single-Family)	−0.010			0.012
	(0.010)			(0.013)
Mobile or Motor Home (reference = Single-Family)	−0.007*			0.013**
	(0.003)			(0.005)
Absentee Owner (reference = Owner-Occupied)		−0.028***		−0.026***
		(0.003)		(0.003)
Pre-Fire Building Value (log scale)			0.011***	0.010***
			(0.002)	(0.003)
Observations	13,972	12,699	13,704	12,699
Log Likelihood	3,562	2,988	3,590	2,996
Akaike Inf. Crit.	−7,118	−5,971	−7,176	−5,981

Note: *p < 0.05; **p < 0.01; ***p < 0.001.

However, when we examined residence tenure and building value, findings provided evidence of an emerging trend of cost-burden gentrification. Renter-occupied dwellings were three percentage points less likely to have been reconstructed than owner-occupied dwellings ($p < .001$) (Table 4, Model 2), a trend that remains similar in the multivariable model (Table 4, Model 4). Pre-fire building value was positively and significantly associated with reconstruction probability in both bivariate and multivariable models ($p < .001$) (Table 4, Models 3 and 4), indicating that higher value residences were more likely to have been reconstructed in the study period.

An important caveat to these findings is that we only documented reconstruction patterns within the first 20 months after the fire. While analyzing a relatively short timeframe is common in disaster scholarship, further work is needed to determine whether the patterns observed here will persist into the future.

4. Discussion

4.1. Wildfires and neighborhood change

The scale of wildfire impacts to the built environment is growing, raising the question of how places and communities change following highly destructive fires (Higuera et al., 2023; Radeloff et al., 2023; United Nations Environment Programme, 2022). Through a close examination of the 2018 Camp Fire, we showed how wildfire can facilitate physical neighborhood change, first at the stage of building destruction and again through the process of building reconstruction.

We found evidence supporting our first hypothesis of physical neighborhood change, that the filtering of housing stock prior to a disaster event contributed to uneven physical hazard impacts; mobile or motor homes, renter-occupied residences, and lower-value residences were significantly more likely to have been destroyed in the Camp Fire compared to single-family residences, owner-occupied residences, and higher-value residences. These findings on the sensitivity of specific building types and building value are in keeping with Troy et al.'s (2022) analysis of non-residential and residential structures within the burn footprint. Our residential-specific models show that the negative association between building value and destruction probability is not driven by high-value non-residential structures, but is consistent among residential structures as well.

Our findings on housing stock filtering are in keeping with prior research documenting the link between housing stock quality and environmental hazard damage (Chakraborty et al., 2019; Kamel, 2012; Ma & Smith, 2019). But beyond identifying disproportionate impacts, we were able to identify built environment characteristics that in part explain observed disparities in Hypothesis 1.1. We found evidence that the physical sensitivity of lower-value buildings can be explained by their density and proximity to roads, in which lower-value residences were more likely to be closer to other buildings and closer to roads, which in turn were characteristics associated with a higher probability of destruction. Our findings on density build on Knapp et al.'s analysis of a sample of single-family residences in the burn footprint (Knapp et al., 2021); we show that building density was associated with structure loss across all residential structure types and for the full population of residential structures affected by the Camp Fire.

In contrast to our findings on building value, we were not able to explain the heightened susceptibility of mobile or motor homes to destruction by accounting for their spatial location within the burn footprint or by proximate environmental characteristics. This indicates that there were some characteristics of mobile or motor homes or their surrounding environment that made them uniquely susceptible to wildfire destruction. Understanding this sensitivity is a critical area for future study.

These observed differences in residential building sensitivity illustrate one avenue through which wildfire can facilitate neighborhood change. Existing physical differences among residential structures meant that certain structure types were more likely to be destroyed when exposed to wildfire than others. Further, the structure types we observed to be more sensitive to wildfire exposure were also those that are more likely to house residents with less adaptive capacity in a disaster context - those who rent, reside in mobile homes, and those who have less household wealth (Lambrou et al., 2023). As a result, neighborhood change occurred through disproportionately high loss of structure types that likely housed more socially vulnerable residents.

Finally, we showed how building reconstruction further facilitated neighborhood change through cost-burden gentrification in the first years following the fire. Compared to all buildings that were destroyed during the Camp Fire, the estimated 643 buildings that had been reconstructed by July of 2020 were more likely to have been owner-occupied before the fire and were, on average, higher in pre-fire value. While further research is needed to track how reconstruction dynamics will play out over a much longer timeframe, the observed slower rate of building reconstruction among lower-value and renter-occupied residences suggests that cost-burden gentrification is a possible trajectory of neighborhood change following wildfires. This is a distinct pathway of gentrification, wherein capital does not leave high hazard areas, as has been shown in the case of chronic flooding (Keenan et al., 2018), but instead, the costs of adapting in place mean that less affluent residents cannot afford to do so. This less-documented form of gentrification suggests that different hazards can trigger diverging pathways of neighborhood change, requiring attention to specific hazard contexts in future research.

Our case study answers a broad but underexplored question: how does a place change after it experiences a highly destructive wildfire? While scholars have investigated physical predictors of wildfire structure loss (Alexandre et al., 2016; Gibbons et al., 2012; Syphard et al., 2012, 2014, 2017) and broad trends in post-fire building reconstruction (Alexandre et al., 2015; Kramer et al., 2021; Mockrin et al., 2015), few have systematically examined finer-grained processes of neighborhood change following wildfire events. While wildfire science on whole has predominantly emphasized biophysical dynamics of wildfire impacts (Lambrou et al., 2023), social scientists have tended to emphasize residents' demographic characteristics and adaptive capacity, attending far less to how the physical sensitivity of residential buildings can shape overall vulnerability to wildfire and socially uneven post-disaster trajectories. We showed that dwellings which we would expect to house more socially vulnerable residents were also more physically susceptible to being destroyed in the fire and less likely to have been reconstructed after the fire. By integrating biophysical and social scientific approaches, we demonstrate the importance of considering the built environment at the individual structure level in developing a more comprehensive understanding of wildfire vulnerability.

4.2. Limitations and future research directions

There are several limitations to our study which we anticipate can be addressed in future research. First, there are limits to which our findings on the physical mechanisms of building destruction (Hypothesis 1.2) can be considered causally identified, given our descriptive research design. However, this limitation is not unique to our study; most research we reviewed on the determinants of wildfire-related building loss were, like ours, descriptive analyses. Such research designs are always susceptible to the effects of omitted variables. Like most existing research in this area, we examined a subset of relevant and available structure loss predictors, however we did not capture all known factors associated with wildfire-related building destruction. Due to data limitations, we did not include known predictors of structure loss such as defensible space (Syphard et al., 2014). Our relatively coarse vegetation measurements from the NLCD (which are observed at 30 m pixel resolution) only capture landscape-level trends, and do not capture finer-scale patches of vegetation within a near radius from a structure. Additionally, we did not include data on direction of fire approach, weather conditions (Gibbons et al., 2012), dwelling construction materials (Syphard et al., 2017), or protective responses taken by residents or firefighters. Given the exceptional detail of the CAL FIRE Damage Inspection Data, we anticipate that much can still be learned from further investigation of these data paired with different sets of loss predictors, much as our research builds on existing examinations of Camp Fire structure loss (Knapp et al., 2021; Troy et al., 2022).

A second limitation of our work is its exclusive analysis of dwellings rather than the residents who live within them. This focus on officially-documented residential properties means that we do not capture wildfire impacts among unhoused residents or those who lived in informal dwellings - populations that tend to be overlooked in studies of wildfire (Chase & Hansen, 2021). Our use of buildings further limited our ability to investigate whether destruction or reconstruction outcomes differed across demographic groups. Much prior research on neighborhood change emphasizes racial segregation (Zuk et al., 2015), documenting the ways that racial discrimination is embedded in different stages of property ownership (Korver-Glenn, 2018). Given findings from this body of work, we would expect similar racial disparities to exist in the context of post-wildfire changes to the built environment. Further research is needed to investigate whether this is the case.

Examining longer-term neighborhood change - on the scale of years and decades - following wildfires is one of the most important directions for future research following our study. Our research documents reconstruction in a relatively short period of time (20 months) after the Camp Fire. While it is possible that the trajectory of stratified reconstruction patterns we observed may continue into the future, it is also possible that this trend could change. Efforts such as the local not-for-profit Rebuild Paradise Foundation's work to support low- and middle-income residents in rebuilding (Rebuild Paradise Foundation, n.d.) and government-funded affordable housing projects (Weber, 2023) could change who is able to return and live on the Ridge and the types of buildings that are constructed there. Longer-term examinations of neighborhood change should account for post-fire changes in property ownership, in which new building construction may not reflect the previous resident rebuilding, but rather construction undertaken by a new property owner.

In addition to substantive findings, our study presented a method for semi-automatically detecting reconstructed buildings within high-resolution aerial imagery, which allowed us to evaluate building reconstruction more efficiently and in a much higher volume than prior research has done using manual techniques. This algorithm may continue to be honed in the future to enhance its precision at the building level, for instance through the inclusion of LiDAR data that measure building heights. Looking forward, our building detection technique could be scaled up to evaluate post-fire neighborhood change across multiple disaster sites to investigate comparative research questions. Are some places rebuilt more quickly after a disaster than others? If so, what does this suggest about the allocation of capital into the built environment following major disasters? Answering questions about the long-term trajectories of disaster-affected regions will become increasingly important as the scale of destruction - from wildfires and from many other environmental hazards - continues to increase under climate change.

4.3. Policy and planning implications

Findings from our study point to several areas where wildfire planning and policies could be adapted to serve a broader range of fire-affected communities. The disproportionate destruction outcomes we observed among certain types of residential buildings suggest that wildfire mitigation guidance could be better tailored to address the specific needs of low-income residents, renters, and mobile or motor home residents. As prior researchers have pointed out, the financial costs of wildfire mitigation mean that more socially vulnerable residents may be less able to reduce physical risk where they live (Collins, 2008; Wigtil et al., 2016). Strategies such as installing fire-resistant roofs and residential sprinklers, upgrading windows to be dual-paned, planting firewise landscaping, and keeping vegetation well-maintained can all incur financial costs that may not be manageable for many residents. In geographic regions that are both at high fire-risk and home to substantial populations of low-income residents, costly wildfire mitigation strategies are unlikely to be widely adopted without subsidization. Further, wildfire mitigation efforts that broadly target homeowners may be less successful in communities with a large share of renters, given that these residents and even rental property owners do not have the same capacity or incentive structure to invest in hazard mitigation (Burby et al., 2003; Lee & Van Zandt, 2019).

Mobile or motor homes stand out in our analysis as uniquely sensitive to being destroyed compared to single-family or multi-family residences. Part of this susceptibility can be explained by the density of mobile home parks, as the Camp Fire spread through structure-to-structure burning, in which radiant heat exposure from an already burning structure ignited neighboring structures (Keeley & Syphard, 2019; Knapp et al., 2021). This positive association between building density and probability of destruction poses a challenge for defensible space guidelines, which advise that flammable materials be removed from close proximity (e.g. 30–40 m) of structures (Gibbons et al., 2012). Most often, the flammable materials emphasized are vegetation or movable objects such as wood piles or propane tanks. However, in structure-to-structure burning, buildings themselves act as fuels. In the case of the Camp Fire, it was not possible for many of the densely co-located buildings on the Ridge to meet defensible space guidelines given their close proximity to neighboring buildings. Planning and design innovations are badly needed for dense developments, such as mobile home parks, in which residences do not have large lots that can be defensibly cleared of all possible fuel sources. However, density could not fully explain mobile or motor homes' heightened sensitivity to destruction in our analysis. While further research is needed to determine the specific mechanisms of this susceptibility, planners should be aware of this heightened risk and place greater emphasis on mitigation planning for mobile or motor home residents and mobile home parks in particular.

In addition to preemptive wildfire mitigation planning, our analysis also has implications for post-wildfire policy and planning. The slower reconstruction of lower-value and renter-occupied residences suggests that, as researchers have documented in studies of other environmental hazards, the costs of post-disaster rebuilding can be a major obstacle for lower-income residents seeking to return to their communities (Fothergill & Peek, 2004; Lee & Van Zandt, 2019). As such, housing affordability and access should be a major focus for planners who seek to support equitable post-disaster recovery.

5. Conclusions

While wildfires have always been an important part of the landscape, the number of buildings exposed to and destroyed by fires is growing (Higuera et al., 2023; Radeloff et al., 2023). As wildfire impacts to the built environment become more common, it is important to understand their long-term effects on places and the people who live there. We integrated social and biophysical science approaches to examine physical neighborhood change following the 2018 Camp Fire, finding evidence that housing stock filtering led to uneven patterns of wildfire destruction and that near-term housing reconstruction was on an early trajectory of cost-burden gentrification. These findings demonstrate the importance of examining the built environment as a driver of socially uneven disaster impacts.

Our findings further highlight key wildfire policy and planning approaches in need of innovation. Wildfire mitigation plans that rely primarily on individual residents making changes to their dwellings are likely to be less successful in communities where many residents rent or have less household wealth. Additionally, dense neighborhoods and mobile home parks need mitigation planning and design strategies that account for the close proximity of buildings and subsequent potential for structure-to-structure burning. Finally - and as we have seen emerging in initiatives on the Ridge in the wake of the Camp Fire - post-fire recovery resources should address obstacles for return and rebuilding among residents who rent and those with fewer financial resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Public data sources and R packages used to calculate specific measures are described in the study's Methods.

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Appendices.

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