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Post-Disaster Housing Recovery Estimation: Data and Lessons Learned from the 2017 Tubbs and 2018 Camp Fires

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Abstract

Post-wildfire housing recovery is a complex process for which systematically collected data remains scarce. Consequently, our ability to anticipate obstacles and plan for housing recovery from future events is limited. This study leverages housing permit datasets collected in Santa Rosa and Unincorporated Sonoma County, impacted by the 2017 Tubbs Fire, and Paradise, impacted by the 2018 Camp Fire. Permit and tax assessor data are combined to gain insights into the recovery processes for these communities. Although the percentage of rebuilt destroyed homes varies significantly between regions, the peak construction demand occurs around 1.5 years after each wildfire, with a substantial decline in the reconstruction rate after 2.5 years. Moreover, the pace of transition from permit application to reconstruction completion is similar across all three regions. Using this finding, we propose a methodology to forecast the number of parcels rebuilt per unit of time based on observations from prior events. A proof-of-concept application of the proposed methodology indicates that it estimates long-term housing recovery patterns based on permit application data collected within one year of the event. These findings indicate that a longitudinal housing recovery data database would help forecast housing recovery from future disasters by providing a source for early empirical validation of predictive models.

1 Introduction

The combined effects of climate change, multi-decade fire suppression, and increasing development in wildland-urban interfaces (WUI) make wildfires an increasing threat to communities across the globe, with quickly growing event frequencies and resulting impacts [e.g., 84, 6]. In California, wildfire risk has become so significant that the biggest home insurers are halting the sale of new policies [75]. Wildfires cause extensive damage to physical and social infrastructure within a community and have long-lasting impacts. Post-wildfire recovery for communities is a complex multi-year process where quick decisions must be made to address societal needs and mitigate future risks. There is a growing effort to start recovery planning before an event to improve equity in recovery outcomes [e.g., 41, 29, 55, 58].

Significant empirical work documents factors that impede successful post-disaster housing recovery for individuals and demographic groups after disasters [e.g., 80, 95, 5]. Recent efforts to document disaster recovery longitudinally have increased. Robust longitudinal studies of disaster recovery have been launched by interdisciplinary teams [e.g., 93], and the International Journal of Mass Emergencies and Disasters recently dedicated a special issue to longitudinal recovery research [45]. However, to what extent lessons from one disaster or community can be transferred to new contexts is unclear. While community-level factors dictate some aspects of housing recovery, others are a function of individual characteristics [e.g., 1, 64, 21]. With the increasing need to better plan for future disasters, we need tools to gain insights into potential yet previously unobserved phenomena.

Scholars have suggested that computational models can complement knowledge from empirical studies, allowing decision-makers to anticipate disaster recovery patterns better. Existing models tend to represent housing recovery

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as a two-step process. Models often assume that housing recovery may be delayed due to a lack of resources (e.g., financing) and homeowners' capacity and willingness to stay in the community before a building permit is obtained. After obtaining the permit, housing recovery is often modeled as a zero-sum game where homeowners compete for limited resources (e.g., skilled workers and construction materials). Although several housing recovery models have been proposed recently [e.g., 26, 69, 2], only a few are validated (e.g., [7]). Moreover, housing recovery is a complex problem influenced by multiple forces, as discussed in the following section. Thus, it is challenging to represent these dynamics properly using computer models.

This study makes three contributions to housing recovery modeling efforts. First, we collect and analyze housing recovery data from three municipal regions: Santa Rosa and Unincorporated Sonoma County, impacted by the 2017 Tubbs Fire, and Paradise, struck by the 2018 Camp Fire. These data are combined with tax assessor and demographic data. We investigate disparities in the housing recovery outcomes between these communities, considering community and individual factors, and common patterns across all communities. The insights from these analyses can guide the development and improvement of housing recovery models for similar events. Second, we publicly share anonymized permit application and reconstruction completion data from these communities to foster the development of a publicly available database of post-disaster housing recovery curves. Third, we propose and evaluate a methodology that uses permit application data collected in the initial months following a disaster to estimate long-term housing recovery patterns. The proposed approach implicitly accounts for the community context because it builds on local recovery patterns. Thus, the proposed approach can be used to gain insights into future housing recovery rates or to calibrate more sophisticated housing recovery models deployed after a disaster.

2 Housing Recovery: Empirical Evidence and Existing Models

This section provides an overview of post-disaster housing recovery literature, focusing on empirical and simulation-based studies. Wildfire-related studies are emphasized, though studies that focus on other hazards are discussed when their findings are likely transferable to wildfire contexts.

2.1 Empirical Studies of Post-Disaster Housing Recovery

Studies of post-disaster housing recovery based on surveys, interviews, and secondary data sources (e.g., satellite imagery, postal code changes, and Census data) highlight multiple community-level factors that influence recovery outcomes [e.g. 67, 33, 47]. Disasters may increase community cohesion and collaborative action among individuals [56, 61], but also tend to create conflicts between the community and local and federal agencies [16, 62]. Post-disaster conflict may result in cascading social effects, increasing inequalities in recovery between those who can fund their own rebuilding project and those who must rely on government aid [35, 70]. Long-term recovery groups (LTRGs) and voluntary organizations active in disasters (VOADs) can play key roles in building community engagement in the post-disaster recovery process by serving as a bridge between affected individuals and local organizations, non-profits, funding sources, and government agencies [40, 60]. In addition to helping shape recovery policies, they identify and address various unmet needs including immediate food and shelter, blind spots of financial assistance, and emotional support [66, 71]. Significant differences in post-fire recovery are also observed between rural and urban areas. Citizen-agency conflicts in rural areas may persist for years [16, 78]. In rural areas, where destroyed homes are few and far apart, economies of scale for recovery are often absent, leading to increased repair costs compared to urban environments [83, 51]. Regional and national economic conditions may also influence post-fire patterns of housing recovery, redevelopment, or resettlement. Groups that benefited or lost financially from a series of 2008 fires in Trinity County, California, were partly influenced by that year's recession [28]. New development (rather than reconstruction) is often observed after wildfires [1], and house prices often increase in communities affected by wildfires, as in the Colorado Front Range [63].

Recovery for disaster-impacted homeowners may also be delayed due to factors such as underinsurance: an insurance policy that does not cover the home's replacement cost due to home appreciation, post-disaster price surges, or required improvements from enhanced building codes [12, 54, 77, 68]. Place attachment (individuals' deep bonds with their communities) also influences recovery [27, 68, 81], particularly in rural areas [3]. Place attachment may motivate individuals to rebuild to support their community [49], or to leave if community ties are disrupted and landscapes are irreversibly damaged [72, 34, 79]. Housing type and ownership also impact post-disaster recovery [59, 85, 23, 95]. Post-disaster financing in the US prioritizes owner-occupied homes, making it more difficult to fund rental unit repairs

[22, 95]. Federal program objectives, decision-making methods, and eligibility prerequisites may limit an individual's access to housing recovery financing [88].

2.2 Predictive Models for Post-Disaster Housing Recovery

Predictive models may complement empirical studies by simulating potential recovery scenarios before disasters and informing preventive action. Although each model's number of recovery stages varies, many proposed models split recovery into pre- and post-permit stages [e.g. 2, 7, 57, 94]. The pre-permit stage includes initial damage assessment, securing financial assistance, and permit review. The post-permit stage represents subsequent activities until the completion of construction, including physical reconstruction and inspection of the constructed structure. Some factors affect both stages, but may have different effects. For instance, heavily damaged structures may be prioritized in the pre-permit phase [2] but require longer inspection times when completed [53].

Pre-permit stage models consider constraints such as utility loss [7, 65], severity of damage [2, 30, 7, 53], post-disaster inspector availability [30, 57, 94], and availability of reconstruction crew and materials [2, 94], along with non-tangible factors such as sense of community [7], permit processing time [94, 57], household income [94, 7, 57], and insurance coverage [87, 7, 65]. Household decision-making models for this stage often emphasize sociodemographic factors [73, 7, 8].

Predictive models for the post-permit stage focus on the availability of construction crews and materials. Some develop supply and demand models to capture the dynamics of labor and physical resources [31], while others introduce the scarcity of these resources as a constraint (i.e. a unit household or agent cannot proceed to the next sub-step without securing these resources) [26, 25, 57, 90]. The duration of the post-permit process is often simulated based on theoretical [94] or empirical [7, 2] distributions of reconstruction time due to the difficulty in capturing these dynamics.

Due to the complexities highlighted above, there are no consensus best practices for housing recovery modeling, partly because it is difficult to validate or demonstrate that models are transferable across hazards and regions. Moreover, existing models often include many parameters that must be calibrated to an application, and systematic calibration methods are unavailable. Consequently, state-of-the-art regional risk assessments [e.g., 52] still employ standard but less sophisticated approaches (e.g., the Hazus methodology [38]) because they do not require data beyond the damage state of a building. As such, a gap exists regarding validated and generalizable approaches for predicting post-disaster housing recovery.

3 Wildfire Events and Data

This section discusses empirical data collected for this study. We consider three California regions recently impacted by wildfires: Santa Rosa, Unincorporated Sonoma County, and Paradise. The City of Santa Rosa is located in Sonoma County. Unincorporated Sonoma County (referred to as 'Sonoma' in subsequent sections) encompasses multiple townships around the City of Santa Rosa. We distinguish the post-fire recoveries in Santa Rosa and Sonoma because different authorities managed them. These three regions are studied because each lost more than 1,500 structures, faced significant recovery challenges, and have systematically documented data on their reconstruction processes.

3.1 Tubbs Fire

The October 2017 Tubbs Fire destroyed 5,636 structures [9], including more than 3,000 homes in Santa Rosa—approximately 5% of the city's housing inventory [82]. In Sonoma, impacts were concentrated in the more rural towns of Glen Ellen and Kenwood. Figure 1 shows the locations of destroyed parcels and parcels undergoing recovery. (In the following discussion, we use parcels to refer to plots of land that also include the homes built on them and structures to refer to the homes themselves.) There are destroyed structures that have not yet begun reconstruction (red points in the left panel of Figure 1 with no corresponding point in the right panel), as well as new development on plots of land affected by the wildfire (blue or green points without a corresponding red point). FEMA issued a Presidential Major Disaster Declaration following the wildfire event (FM-5215-CA) [36], and the direct losses were estimated to be $7.9 billion [15]. At the time, the Tubbs Fire was the most destructive wildfire in California's history.

In the weeks following the Tubbs Fire, the VOADs in Sonoma County jointly created a long-term recovery group called Rebuilding Our Community (ROC) Sonoma County that comprised more than 60 nonprofit organizations. The ROC linked residents and the local government by identifying the most vulnerable populations, particularly renters at high risk of migrating and initiated the conversion of affordable dwelling units to provide shelter. Particularly relevant to housing recovery are the housing committee, which helped secure numerous Department of Housing and Urban Development (HUD) grants and provide rental assistance not limited to rebuilding, and the construction committee, which helped residents navigate the evolving building codes and provided realistic estimates of reconstruction costs through a team of dedicated construction analysts [17].

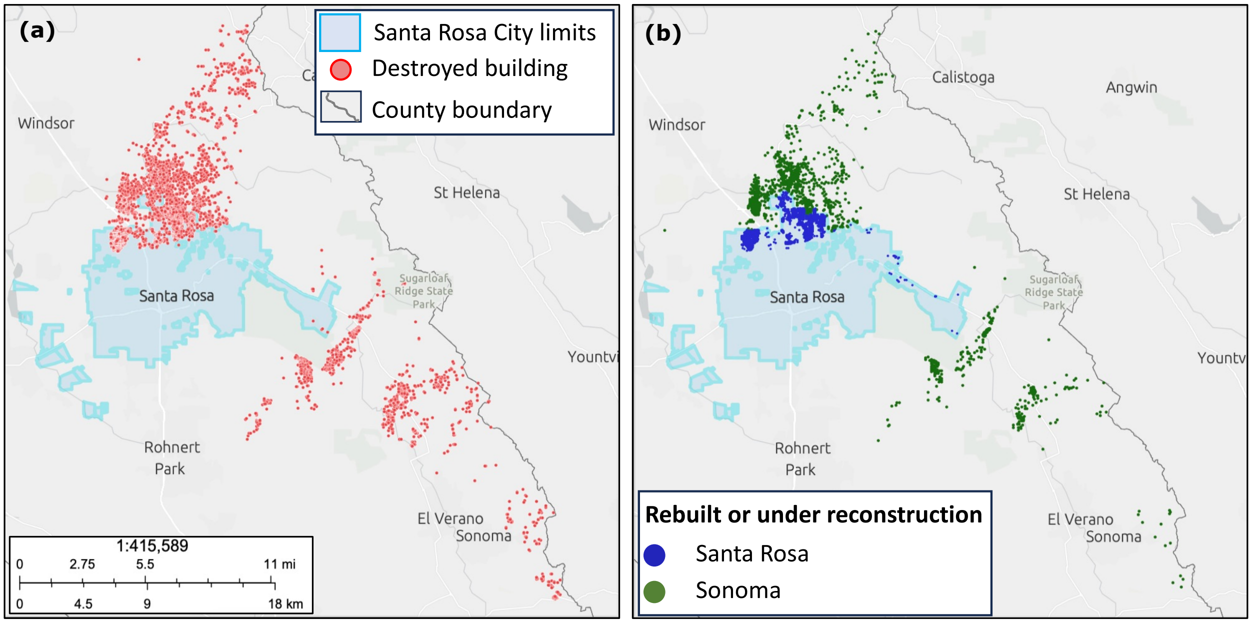

Figure 1: Parcels affected by the Tubbs Fire. (a) Destroyed by the wildfire and (b) rebuilt or under reconstruction. Note the different color scatter to denote independent jurisdictions.

3.2 Camp Fire

The November 2018 Camp Fire burned roughly 18,000 structures near Paradise and Concow—approximately 95% of the cities' housing stock [10]. Figure 2 shows the locations of destroyed parcels and parcels undergoing recovery in Paradise. FEMA issued Major Disaster Declaration FM-5278-CA [37] in response to the fire. In addition to structural losses, the Camp Fire severely affected infrastructure and disrupted basic services in Paradise, including its water supply, power supply, and access to healthcare. The claims filed for direct losses five months after the wildfire were estimated at $8.5 billion by the California State Insurance Commissioner [13].

Based on a year-long series of meetings from 2018 to 2019, the Town of Paradise created a long-term community recovery plan nicknamed "Make It Paradise." This plan outlined the key long-term recovery goals and delineated town-led and partner-led projects [91]. Key voluntary LTRGs included the Rebuild Paradise Foundation and North Valley Community Foundation, which provided grants, and Camp Fire Collaborative, which provided extensive disaster case management to residents [91, 66]. To alleviate the housing needs of residents in a one-stop-shop approach, the town initiated a building resiliency center in October 2019 that connected residents to partner organizations, including CalOES, North Valley Community Foundation, HCD-Community Development Block Grant Program (CDBG), FEMA, and the State of California Insurance Commissioner. The center addressed hurdles throughout the housing recovery process, from site issues and insurance to home financing and final permitting [39].

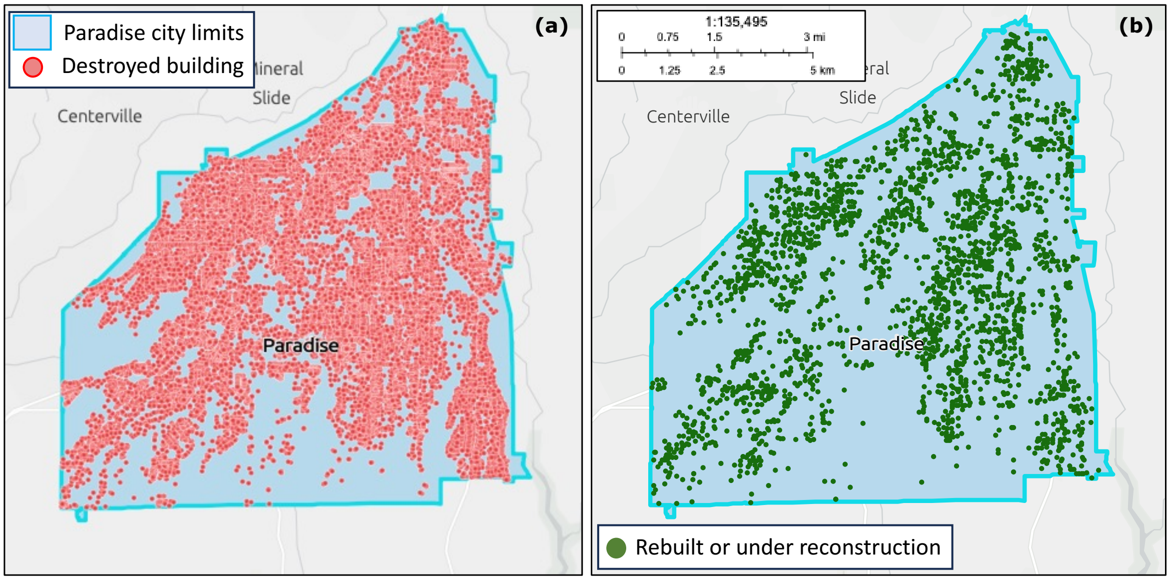

Figure 2: Parcels affected by the Camp Fire. (a) Destroyed by the wildfire, and (b) rebuilt or under reconstruction.

3.3 Housing Recovery Data

We consider data quantifying the reconstruction of single-family housing as of October 15, 2022, which corresponds to 60 months after the Tubbs Fire and 47 months after the Camp Fire. Data used in this analysis include the locations of parcels destroyed by the fires, the dates of construction permit applications for parcels that have started reconstruction, tax assessor data indicating the value of the parcel and whether the owner or a renter occupies the structure, and aggregate information about the demographics of each region.

Permit data were collected via personal communication with city officials and data portals for disaster recovery for Santa Rosa [20], Sonoma [89], and Paradise [18]. Although each region tracks different milestones in the recovery process, all three provide dates for the initial construction permit application and the completion of construction, so we use those two dates for the subsequent analysis. When a parcel had a permit application date but no construction completion date, we assumed that the parcel had not yet finished reconstruction. We also used 2022 tax assessor data to determine whether a parcel was an owner-occupied primary home based on tax deductions and to determine the appraised value of structures on the land [43, 74]. We note that tax assessor data may be influenced by the shifting political and economic dynamics that may shape the process and timing of the post-disaster tax assessment. Consequently, the 2022 tax assessor data are an imperfect proxy of the housing stock in 2017. Not all destroyed parcels are in the data sets available for this study. The subsequent analyses focus on the parcels that applied for a permit by the time of data collection.

Table 1 presents aggregated statistics for each region. Santa Rosa had the highest population density at 7,587 persons per square mile compared to less than 400 persons per square mile in Sonoma and Paradise. Paradise had the highest percentage of owner-occupied homes and a median household income approximately 2/3 of that of Santa Rosa and Sonoma (consistent with national trends of regions with high home values having lower ownership rates [44]). Approximately 84% of Paradise's housing units were insured before the Camp Fire, versus more than 98% in Santa Rosa and Sonoma [14, 48] before the Tubbs Fire. These differences in damage and demographics result in substantial differences in the housing recovery by October 2022. While Santa Rosa and Sonoma rebuilt 57% and 36% of the destroyed housing stock, Paradise had rebuilt only 9% of its destroyed homes. We note that less time had passed since the damages to Paradise at the time of the data collection. However, in July 2024, Paradise rebuilt only 17% of its homes, reinforcing that recovery is slower in the city than in Santa Rosa and Sonoma [92]. To capture potential correlations between the community-level and individual-level factors on the overall recovery progress, statistical analyses are conducted on (a) the relationship between permit application time T_p and repair time T_r as well as (b) the potential effects of homeownership status, home value, and neighborhood density on permit application time T_p and total recovery time T. All three factors are statistically significant in some cases, but the trends vary based on each region. For additional discussion, the reader is directed to the Appendix.

Table 1: **Summary of aggregated demographic and damage statistics for the three study regions.** As throughout the manuscript, “Sonoma” refers to Unincorporated Sonoma County townships around the City of Santa Rosa.

	Santa Rosa	Sonoma	Paradise	Source
Population	176,938	5,187	5,268	US Census
Population density [persons/sq. mi]	7,587	145	320	US Census
Owner rate [%]	55.3	62.8	72.2	US Census
Median household income [$]	84,823	72,861	51,396	US Census
Median home value [$]	598,700	577,400	287,400	US Census
Insurance penetration [%]	98	99	84	CDI/US Census
Parcels destroyed	3,043[1]	1,963	14,352	Municipality[3]/Cal Fire [19, 89, 11]
Parcels in dataset	2,693	1,423	2,544	Municipality[3]
Parcels with a permit[2]	1,856	880	1,524	Municipality[3]
Parcels rebuilt[2]	1,733	719	1,322	Municipality[3]
Parcels with permit [% of destroyed][2]	61	45	11	Municipality[3]
Parcels rebuilt [% of destroyed][2]	57	36	9	Municipality[3]

[1]: Santa Rosa tracks structures destroyed, while Sonoma and Paradise track parcels.

[2]: Among those with complete records.

[3]: Data obtained from each municipality is based on a cutoff date of October 15, 2022.

4 Analysis of Post-Wildfire Housing Recovery

Consistent with the previous sections, we treat recovery as a two-stage process, as shown in Figure 3. The first milestone in the collected data is the permit application, which we use as a proxy for the decision to rebuild. The time between the disaster and the permit application is denoted T_p in the following. The time between the permit application and the completion of reconstruction and the repair is denoted by T_r. After the permit is obtained, we assume that homeowners actively seek to rebuild their homes, competing for limited access to skilled workers and resources. Thus, T_r may be extended if available reconstruction resources are insufficient to meet the demand. In the following, we refer to T_p as ”permit application time” and T_r as ”repair time.” The total recovery time, T, is defined as as

$$T = T_p + T_r \tag{1}$$

Figure 4 shows statistics of housing recovery times for each region. Figure 4a shows the number of permit applications and parcels rebuilt in each region over time. Note that we compare the first four years of the recovery in each region. For Santa Rosa and Sonoma, the four-year period represents 2017-2021, and for Paradise, 2018-2022. Santa Rosa rebuilt the most parcels (1,733) and the highest percentage of destroyed parcels (57%). Paradise rebuilt more parcels than Sonoma (1,322 versus 719) within four years of the disasters. However, this represents only 9% of Paradise’s destroyed parcels, compared to 36% rebuilt in Sonoma. Figure 4b shows the ratio of the of parcels rebuilt, as a percentage of those that had obtained a permit to reconstruct by October 2022, $\rho(t)$, calculated as

$$\rho(t) = \frac{R(t)}{P_{all}} \tag{2}$$

where $R(t)$ is the number of buildings rebuilt at time t, and P_{all} is the number of permit applications in the dataset. In this case, all regions have similar recovery curves. This indicates that once a homeowner starts their reconstruction process, their timeline to complete it is similar across the regions. However, there are large differences in the number of households initiating and engaging in the reconstruction across the regions.

Figure 5 shows histograms of permit application time T_p, repair time T_r, and total recovery time T. The vertical dashed lines indicate the medians for each region. The median time to permit application in Paradise is about 0.5 years later than in the other two regions. Conversely, the distributions of total recovery time are similar across the three regions, with medians of about 2.5 years. This is partly explained by Paradise’s shorter repair times. The Spearman correlation coefficients between permit application time and total recovery time are 0.70, 0.56, and 0.78 for Santa Rosa, Sonoma, and Paradise, respectively. As expected, this indicates that as permit application time increases, total

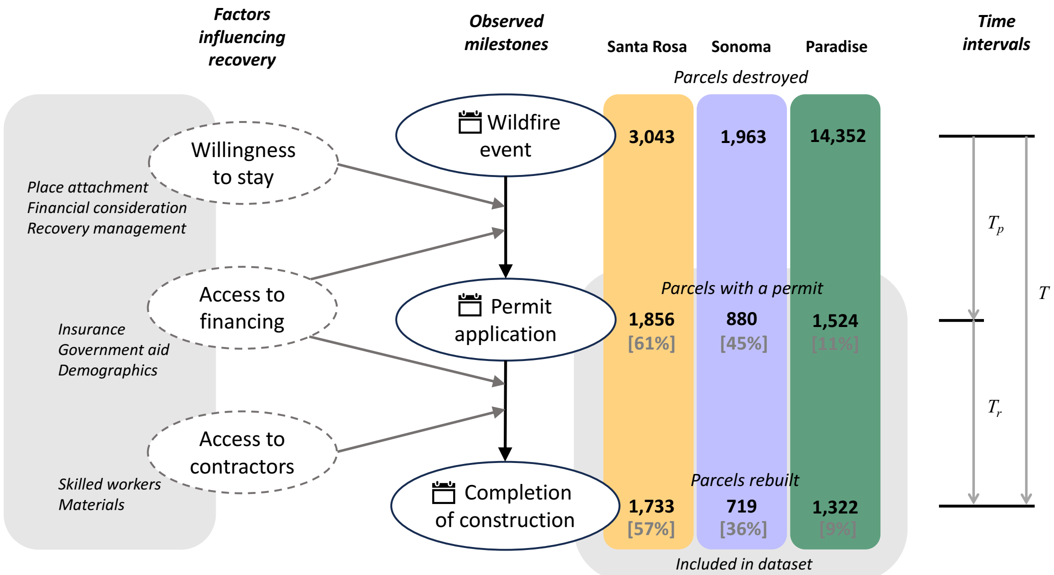

Figure 3: Schematic representation of a household's post-disaster housing recovery process. Note that only those parcels that applied for a permit are considered in the dataset which includes data up to October, 15 2022. Values in percentages are with respect to the total number of parcels destroyed for each region shown in the top row.

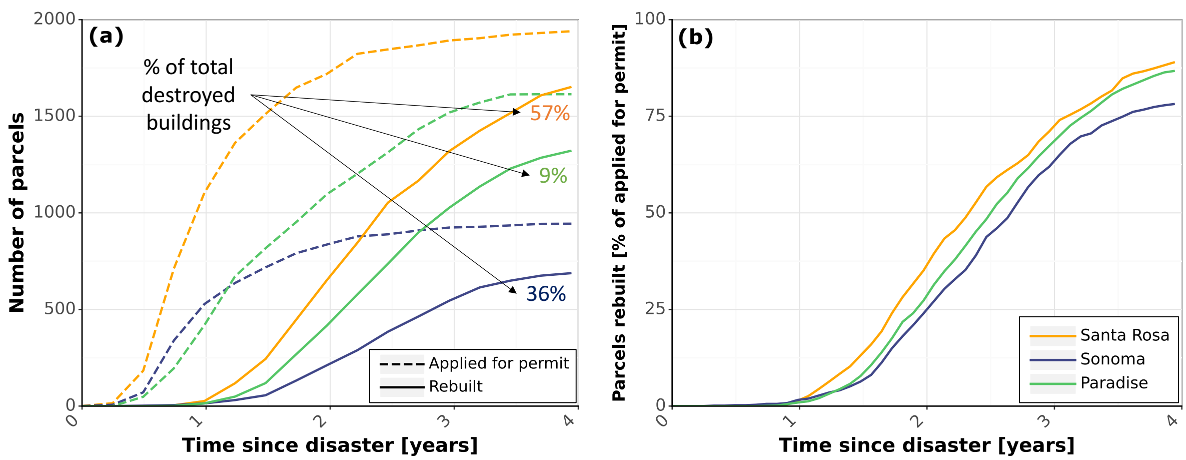

Figure 4: Housing recovery progress based on data available in October 2022. (a) Number of parcels with a permit and/or rebuilt (b) number of reconstructed parcels as a percentage of those with a permit application.

recovery time tends to increase. Interestingly, the Spearman correlation coefficients between permit application and repair time are 0.09, -0.01, and -0.33 for Santa Rosa, Sonoma, and Paradise. This shows that homeowners who applied for a permit later did not complete their reconstruction significantly more slowly.

Figure 6 provides insights into the demands for permit processing, construction workers, and materials. Figure 6a shows the number of permit applications applied for per 90-day period. For Santa Rosa and Sonoma, most homeowners with approved permits applied within the first year, and the peak in applications happened six months after the Tubbs Fire. In Paradise, the to-date peak occurred approximately one year after the Camp Fire. Figure 6b shows the number of parcels rebuilt per 90-day period, showing that the curves flattened around the 1.5-year mark in all regions. This suggests that the demand exceeded the region's reconstruction capacity, and the rates of housing completions were limited for this period by available capacity. Figure 6c shows the number of parcels with a permit but not yet fully reconstructed. The maximum number of parcels that meet these criteria occurs 1.25 years after each disaster for

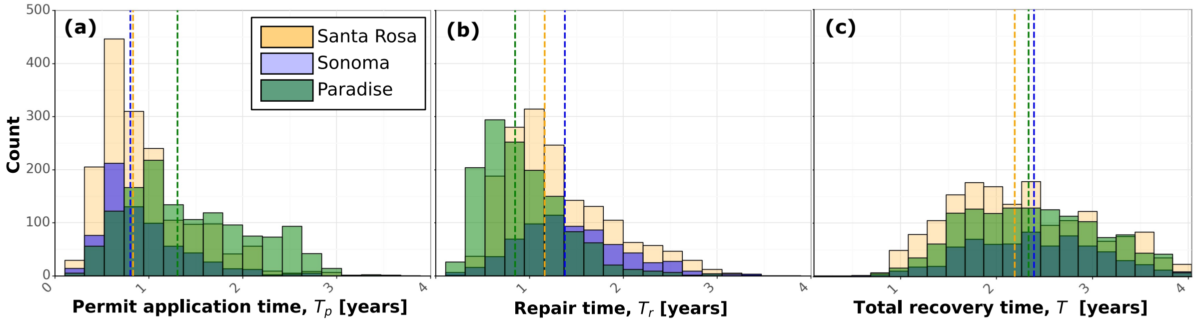

Figure 5: Histograms of duration in recovery process. (a) Permit application time, (b) repair time, and (c) total recovery time. Dashed vertical lines indicate the median values from each histogram.

all regions. At this peak, 1,029 parcels in Santa Rosa (34% of the destroyed parcels) had permits but had not been repaired. Assuming that the owners of these parcels were actively seeking to rebuild their homes at this period, this is a proxy for the peak demand for construction materials and contractors. This similarity across regions and disasters suggests some predictability in expect peak demands for workers and materials.

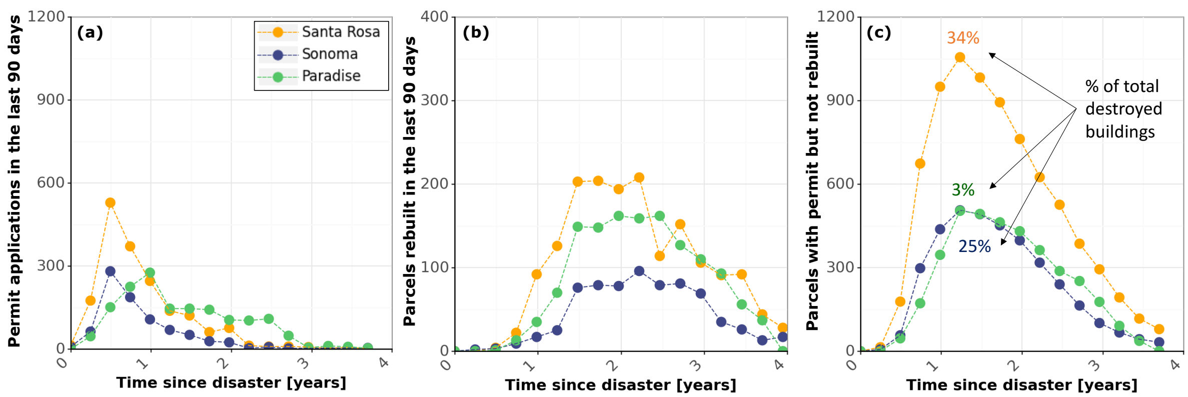

Figure 6: Indicators of variation in demand during the recovery process. (a) Permit processing, (b) construction workers, and (c) materials.

An Appendix provides additional analyses of how recovery times correlate with characteristics such as number of neighbors and housing value.

5 Forecasting Housing Recovery Using Early-Stage Data

In this section, we use permit application statistics from the early stage of the recovery process to anticipate the rate of housing reconstruction. Figure 4 shows that, although the number of rebuilt parcels varied, around 75% to 85% of homeowners who applied for a permit in each region could rebuild within 4 years. Figure 5a shows that substantial data on permit application times are available within one year of the events, while 5c shows that data on reconstruction completions are scarce.

Figure 7 summarizes the proposed methodology to forecast reconstruction progress based on permit applications. Step 1 is to develop a database of housing recovery data from past disasters containing information on the ratio of rebuilt parcels to parcels with a permit over time for each event. We anticipate that this will become available as cities and researchers systematically collect housing recovery data [e.g. 93, 76]. The data in Figure 4 are initial contributions to this database and can be accessed through the DesignSafe Data Depot at [50]. Steps 2 and 3 focus on estimating housing recovery for a new event. Step 2 is to collect early housing permit data for the new event (e.g., within the first year) of the recovery process and use this data to forecast the rate of permit applications over the subsequent years,

$P_{new}(t)$. Finally, Step 3 combines the estimated permit application data with recovery curves from previous disasters to estimate the rate of housing reconstruction for the new event. These steps are described in detail in the following.

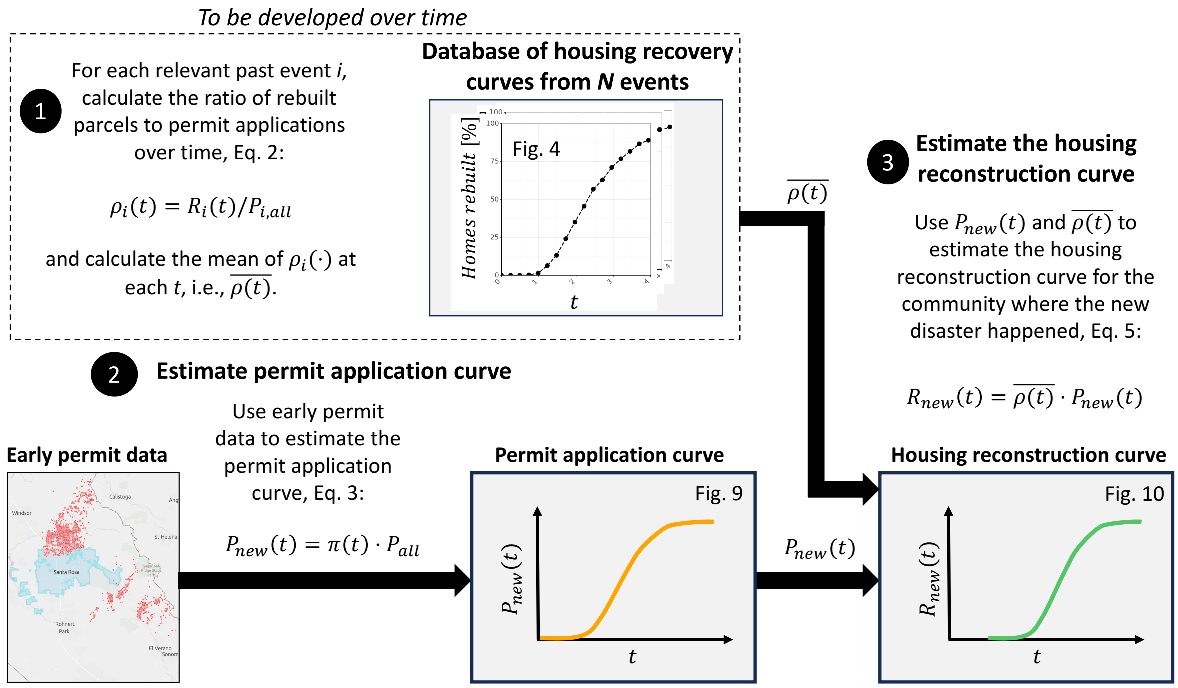

Figure 7: Workflow to forecast housing reconstruction rates based on early permit application data.

5.1 Developing a Database of Housing Recovery Curves

Recent efforts to collect longitudinal disaster recovery data, including those in this paper, will result in a database of housing recovery curves similar to the example shown in Table 2. Recovery curves from multiple events can be stored in a matrix where columns represent events, E_*, and the rows are time intervals since the disasters, t_*. Suppose permit and reconstruction data are collected for each event-time pair. In that case, the database can store the ratio of the parcels rebuilt as a percentage of those that had applied for a permit (i.e., $\rho(t)$ in Equation 2). Finally, the database can be screened to select only events relevant to the current situation (e.g., in terms of severity, hazard, or geography). Earthquake engineers use a similar process when designing a new building. They select the most relevant events from a database of ground motion records for the new building's site. We believe that best practices for selecting events from a database of recovery curves will be developed over time. In this case, the mean $\rho_*(t)$ across selected events can be calculated at each t:

$$\overline{\rho(t)} = \frac{1}{m}\sum_{i=1}^{m}\rho_i(t) \tag{3}$$

where m is the number of selected events, and $\rho_i(t)$ are the ratio of parcels rebuilt as a fraction of parcels with permits, from Table 2.

Table 2: Database of housing recovery information to be built over time. Columns indicated with E_* are past relevant events.

Time	E_1	E_2	$\vdots$	E_m	Row mean
t_1	$\rho_1(t_1)$	$\rho_2(t_1)$	$\vdots$	$\rho_m(t_1)$	$\overline{\rho(t_1)}$
t_2	$\rho_1(t_2)$	$\rho_2(t_2)$	$\vdots$	$\rho_m(t_2)$	$\overline{\rho(t_2)}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
t_n	$\rho_1(t_n)$	$\rho_2(t_n)$	$\vdots$	$\rho_m(t_n)$	$\overline{\rho(t_n)}$

5.2 Estimating the Permit Application Curve for a New Event

In Step 2 of Figure 7, we must estimate the permit application curve, $P_{new}(t)$, that specifies the number of applications received at any point in time:

$$P_{new}(t) = \pi(t) \cdot P_{all} \tag{4}$$

where $\pi(t)$ is the fraction of applications that are received by time t, and P_{all} is the expected number of permit applications at the end of the period of interest. The observed applications in the first year following a disaster are used to estimate these parameters and permit application curve.

Figure 8 illustrates the procedure used to estimate $\pi(t)$. The histograms in Figure 8 show distributions of permit application times available after one year (in gray) and the entire dataset (in color). A lognormal probability distribution fitted to the data available within one year would result in the dash-dot lines in each panel. This "naïve model" does not account for future permit applications that have not yet been received, and so is unsuitable for forecasting. Instead, we log-transform the available data and fit a truncated normal distribution to the data. This process results in the fitted distributions shown as solid lines in Figure 8 (and labeled as "proposed model"). These distributions fit the entire dataset histograms well, despite not using the data with times greater than one year. Integrating these probability density function curves over the study period yields cumulative distribution functions that quantify the probability that a permit application will happen within t time of the event, $\pi(t)$.

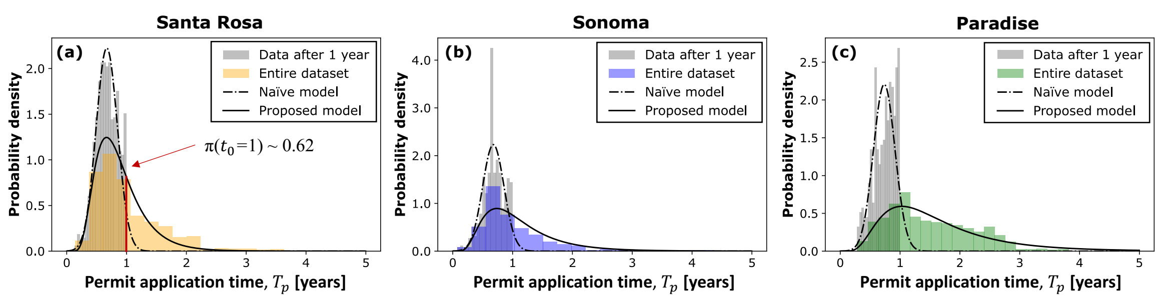

Figure 8: Fitting of distributions to available permit application data. Note that the naïve and proposed curves are fitted with data after 1 year (gray). The entire dataset (color) is only shown for comparison.

We next need to estimate P_{all}. At the time of the analysis, t_0, we know how many permit applications have been made, $P_{new}(t_0)$, and the probability that a randomly selected building applied for a permit in this period, $\pi(t_0)$, is obtained from the proposed model in Figure 8. With this, we estimate P_{all} as

$$P_{all} = \frac{P_{new}(t_0)}{\pi(t_0)} \tag{5}$$

Using Santa Rosa as an example, 1,130 permit applications were received within one year, and Figure 8a shows that $\pi(t_0 = 1) = 0.62$, so we estimate $P_{all} = 1,130/0.62 = 1,818$ permit applications in Santa Rosa. This procedure is repeated for Sonoma and Paradise, and the results are summarized and compared to their empirical counterparts in Table 3, showing good agreement between estimated and actual values of P_{all} for these cases.

Table 3: Summary of estimated recovery parameters for each region after one year of each event. As throughout the manuscript, "Sonoma" refers to Unincorporated Sonoma County townships around the City of Santa Rosa.

Region	$\pi(1)$	$P_{new}(1)$	Estimated P_{all}	Empirical P_{all}
Santa Rosa	0.62	1,130	1818	1856
Sonoma	0.63	560	887	880
Paradise	0.28	445	1594	1524

With the $\pi(t)$ function estimated using a procedure like in Figure 8, and P_{all} estimated using Equation 5, Equation 4 can be evaluated for the event of interest.

The abovementioned procedure can be employed at different t_0 times after a disaster. However, with less data, the method will perform worse. Figure 9 presents the forecasts based on limited data and compares them to the empirical permit application curves. From left to right, the panels use 0.5, 0.75, and 1 year of permit application data to fit the models. The agreement between the empirical data and the model increases the more data are used. A substantial increase in model accuracy is obtained between panels Figure 9a and Figure 9b, but diminished returns are observed between Figure 9b and Figure 9c suggesting that the model can perform well if employed 0.75 years (i.e., 9 months) after these disasters. However, in the results in Figure 9c the model performs better at representing the shape of the curves.

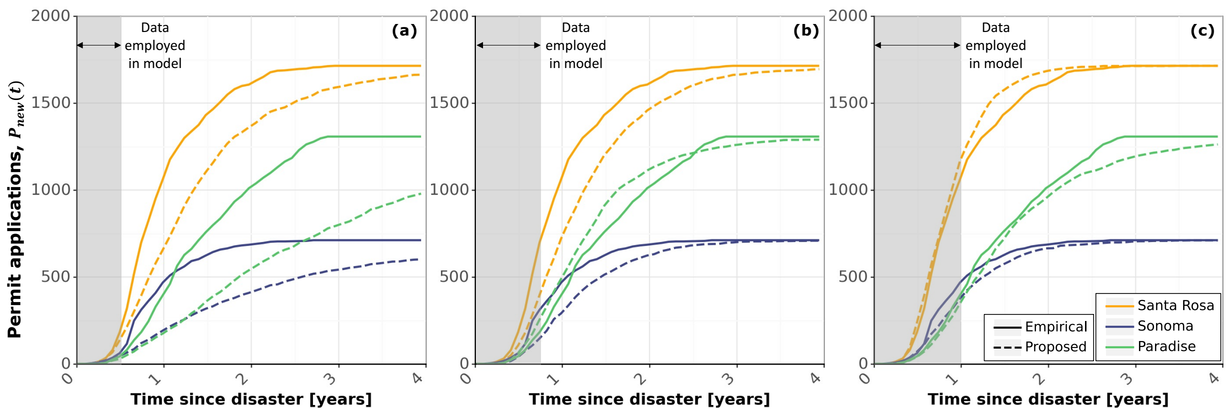

Figure 9: Estimate rates of permit applications, based on early-stage data. Empirical observations (solid lines) and forecasts using the proposed model (dashed lines). Colors indicate each region. The shaded areas indicate the portion of the empirical curves (i.e., 0.5, 0.75, and 1 year) used to fit the models.

It is worth noting that this transition rate may not be so similar between disparate events (e.g., between housing recovery following tornadoes and wildfires), and thus, the user should select the most relevant set of events to the current situation from the database of housing recovery curves as discussed in Section 5.1.

5.3 Estimating the Housing Recovery Curve for a New Event

The final step of the procedure is to estimate the permit application curve, $R_{new}(t)$. Figure 4b showed that the transition rate from permit application to reconstruction completion was similar following the three regions investigated in this study. Here, we posit that the user identified a subset of relevant events and that the rate of transition from permit application to completion is similar among this subset. With this, the number of reconstructed buildings overtime after a new event, $R_{new}(t)$, is a fraction of the number of permit applications, $P_{new}(t)$. This fraction is the ratio of parcels rebuilt to parcels with a permit in Table 2. With this, $R_{new}(t)$ is estimated as

$$R_{new}(t) = \overline{\rho(t)} \cdot P_{new}(t) \tag{6}$$

where $\overline{\rho(t)}$ comes from Equation 3 and $P_{new}(t)$ comes from Equation 4.

As a proof of concept, Figure 10 shows a forecasted recovery rate for a given community (e.g., Paradise) using early permit data from that community to estimate $P_{new}(t)$ and recovery curves from the two events to estimate $\overline{\rho(t)}$ using Equation 3. The forecasts obtained with the proposed approach are similar to the empirical results available later in time, and improve as more permit data are used to estimate the number of parcels rebuilt. It is also worth noting that the estimates are relatively consistent between Figure 10b and Figure 10c. This suggests that the proposed approach has the potential to provide valuable insights into long-term reconstruction based on data available within 0.75 years of the event.

The results in Figure 10 are only a proof of concept because they relied on data that would not have been available at the time of the fires. But if a new region is struck by a wildfire in the future, data from Santa Rosa, Sonoma, and Paradise can be used as predictors in Equation 6. As more longitudinal housing reconstruction data sets are available, the proposed procedure can rely on a larger data set tailored to particular event conditions.

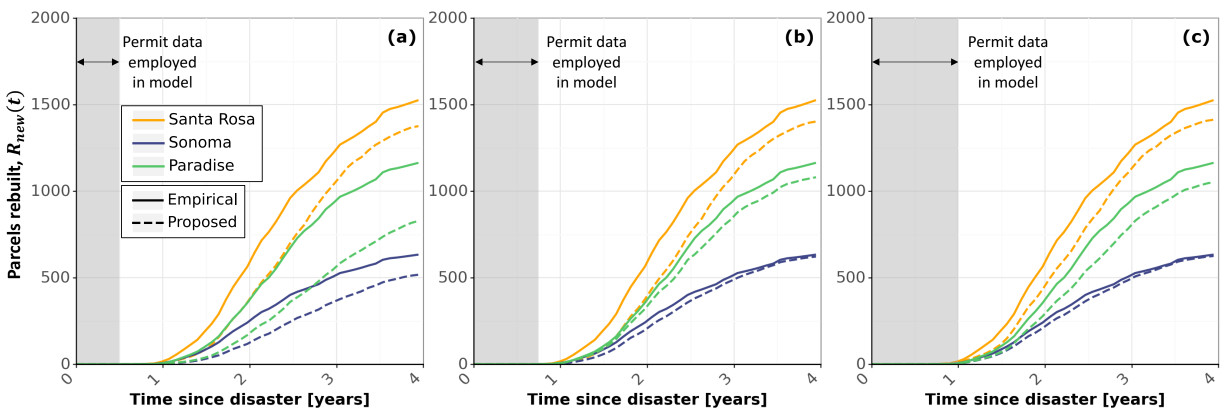

Figure 10: Estimate rates of reconstruction rate, based on early-stage data. Empirical observations (solid lines) and forecasts using the proposed model (dashed lines). Colors indicate each region. The shaded areas indicate the portion of the empirical permit application curves (i.e., 0.5, 0.75, and 1 year) used to fit the models.

5.4 Limitations

Due to the available data, we only investigate the recovery of single-family housing. Empirical studies suggest that the recovery process for multi-family housing is more complex [46, 42, 86, 24]. Consequently, the observation that data collected in the first few months of the recovery process can anticipate long-term housing recovery trends merits a critical assessment if applied to communities where multi-family buildings represent a large fraction of the housing stock.

Similarly, we did not have data regarding households that never applied for a permit. With sufficient data (e.g., nine months or more), Equation 6 represents well the number of households that will eventually rebuild, providing an indirect estimate of the number that will not rebuild. However, our methodology cannot identify the root causes for this outcome. We envision that the proposed methodology can be used to anticipate if many households will not rebuild, triggering an in-depth study with community members.

Finally, by reducing the recovery process to the permit application and building reconstruction phases, the methodology cannot explicitly capture some of the nuances of the housing recovery process. For example, households may face difficulty obtaining financing, delay reconstruction due to economic reasons (e.g., assessing the housing market), disaster impacts on neighborhood amenities, and personal preferences, among other things. Thus, the proposed methodology is a support tool for recovery planning but should be employed alongside other strategies for understanding community and household needs and challenges.

6 Conclusions

In this study, we investigate housing reconstruction after recent wildfires using housing permit data collected over more than four years in Santa Rosa and Unincorporated Sonoma County, following the 2017 Tubbs Fire, and in Paradise, following the 2018 Camp Fire. We analyze the numbers and timing of permits to understand how the recovery process unfolded and propose a predictive model that can forecast the timing of reconstruction over multiple years based only on the rate of permit applications in the first few months following a disaster.

We consider two milestones in the housing reconstruction process: permit application and reconstruction completion. Comparing the housing reconstruction processes in these regions four years after each event highlights their differences. While Santa Rosa and Sonoma rebuilt 36% and 57% of their destroyed parcels, respectively, only 9% of the destroyed parcels in Paradise were rebuilt within four years. However, we identify similarities across regions when focusing only on rebuilt parcels. The peak of the reconstruction demand occurred after 1.5 years, and the median reconstruction time was close to 2.5 years in all regions. Moreover, the rate of reconstruction plateaus after 1.5 years, indicating that the reconstruction processes did not progress as quickly as they could. This observation is corroborated by news articles indicating that labor shortages limited the reconstruction processes in these communities [4, 32].

We then propose a methodology that uses permit application data available within the first year since a disaster to project the rate of housing reconstruction completion for the subsequent years. The methodology relies on a database of housing reconstruction curves, which we envision will become available as more longitudinal housing recovery studies are deployed. This study contributes to the development of this database by publicly sharing three such housing reconstruction curves [50]. For the considered cases, the methodology provides valuable insights based on data available within six months of a disaster. Using permit data available nine months after each disaster, the methodology accurately forecasts the empirical permit application and housing reconstruction curves. Since the peak demand for reconstruction in each region happened more than one year after the event, the methodology can help recovery planners anticipate this demand. With this information, local authorities can take actions such as facilitating the influx of contractors and industry agreements for the supply of reconstruction materials that can minimize the likelihood of resource shortages and bottlenecks in the recovery processes.

Another feature of the proposed methodology is that it employs local data and trends from previous disasters. Thus, the methodology partially captures aspects specific to the community and disaster being investigated. However, the methodology cannot explain the local trends in the observed recovery, nor can it identify causal relationships between reconstruction speed and community or household characteristics. We envision that the methodology can uncover that a community is experiencing a slower-than-anticipated recovery process and trigger a more robust assessment to identify the root causes (e.g., by engaging with community members). Another alternative would be to employ more sophisticated models built upon lessons from previous disasters, such as those discussed in Section 2.2 to gain insights on the potential causal relationships. We envision that the proposed methodology can help calibrate sophisticated models by providing constraints on the long-term rate of recovery based on empirical data available in the short term. Then, sophisticated models can be used in 'what-if' analyses to evaluate the benefits of target actions in improving recovery. This synergistic combination of approaches can improve our ability to manage post-disaster housing recovery in future events.

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A Appendix

The following sections discuss additional results from the analyses carried out in Section 4. Section A.1 analyzes correlations between the permit application time T_p and repair time T_r. The remaining sections study the effects of homeownership status, home value, and neighborhood density on permit application time T_p and total recovery time T. While all three factors are statistically significant in some cases, their effects vary in degree, and in some cases direction (i.e., leads to an increase in duration in one community while a decrease in other), across the three regions. These data sets thus do not provide clear evidence of strong relationships between these factors and recovery times.

Appendix A.5 illustrates fitting of the truncated lognormal distribution discussed in Section 5.2 in greater detail.

A.1 Repair Time as a Function of Application Time

Figure 11 shows the relationship between permit application time and median repair time. For instance, the left-most dots in Figure 11 are obtained by grouping all parcels within each region that applied for a permit within 0.5 years after the respective wildfires and finding the median repair times of these parcels. To compute an accurate median value, we account for the fact that data are censored (i.e., some parcels have not completed reconstruction within the available timeframe, $T > 4$ years). We thus consider all parcels that have applied for a permit after x years, even those that have not yet completed the repair, when computing the median. For example, if 100 parcels applied for a permit within 0.5 years in one of the regions and only 70 completed reconstruction at the time of analysis, we still set the median as the repair time of the 50$^{\text{th}}$ parcel in the sorted list (recognizing that the remaining 30 parcels have large repair times). An increase in median repair time for permit application times of 0.5-1.5 years is seen across the three municipalities. This increase matches the peak demand for workers shown in Figure 6. Beyond this period, the median repair times are relatively constant, which indicates a minor influence from resource constraints.

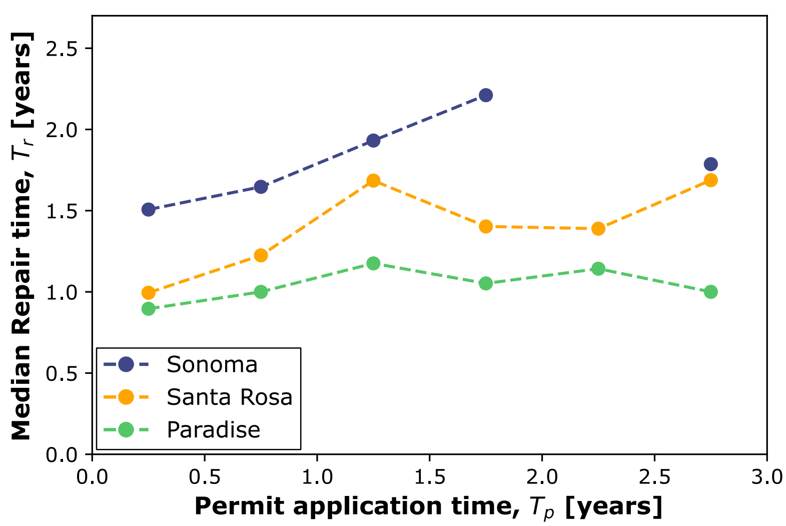

Figure 11: Median repair time (T_r) of households binned by permit application time (T_p). Some dots for Sonoma do not appear because the data censoring due to incomplete construction prevents the calculation of a median repair time.

A.2 The Effect of Homeownership Status on Housing Recovery

Figure 12 highlights differences in permit application time T_p and total recovery time T for renter-and owner-occupied homes. The boxes in Figure 12 indicate the 25$^{\text{th}}$-percentile and 75$^{\text{th}}$-percentile of the metrics in the ordinate axis. The black horizontal line within each box is the median, and outliers are marked as individual scatter points. The lefthand side panel shows only parcels that applied for a permit—61% in Santa Rosa, 45% in Sonoma, and 11% in Paradise. Among these, 52%, 60%, and 45% are owner-occupied in Santa Rosa, Sonoma, and Paradise, respectively. The panel indicates that, on average, renter-occupied parcels were slower to apply across the three regions, with Paradise showing the largest disparity. Moreover, in all regions, the 75th percentile is higher for renter-occupied parcels, indicating more variability in the application times for these parcels. The right-hand side panel shows the total recovery time including only parcels that have completed reconstruction—57% in Santa Rosa, 36% in Sonoma, and 9% in Paradise. There are negligible disparities in averages or percentiles in Santa Rosa and Sonoma; however, renter-occupied parcels were slower to reconstruct in Paradise.

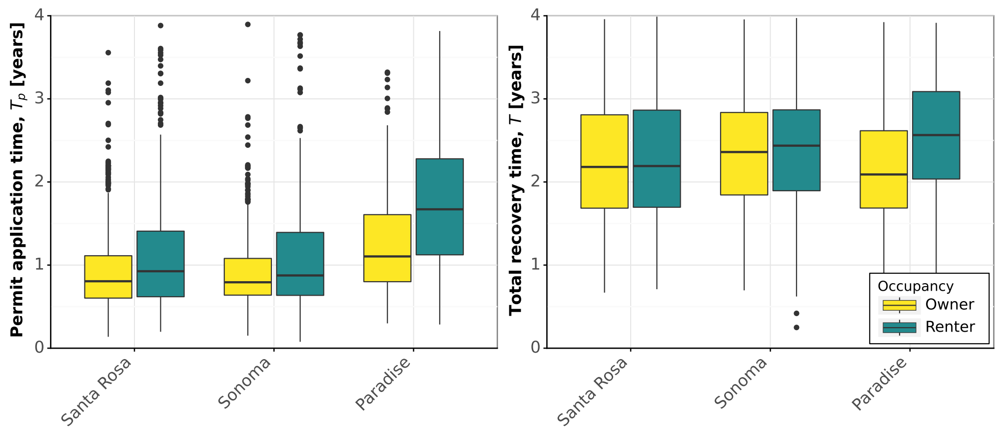

Figure 12: Recovery progress as a function of occupancy. Permit application time (left), total recovery time (right).

A.3 The Effect of Home Value on Housing Recovery

Figure 13 shows the influence of the destroyed structure's improvement value on recovery time. Improvement value refers to a parcel's total value minus the value of the land. We expect highly valued structures to be owned by wealthier households with more resources to reconstruct, but also to be more expensive to rebuild. All three regions display significant differences in the mean permit application times between the below-median and above-median improvement value groups ($p < 0.01$). However, the above-median (i.e. higher value) groups generally took less time to apply for a permit in Sonoma and Paradise, while the opposite is true for Santa Rosa. In Santa Rosa, the above-median group also took longer to complete reconstruction, as seen in the bottom left plot of Figure 13. Although not shown in the figure, parcels with improvement value above median have fewer neighbors in Santa Rosa. That is, highly valued structures tend to be in less dense regions. This may explain the unique trend observed, as parcels with fewer neighbors tended to take longer to apply for a permit and reconstruct, as seen in Figure 14.

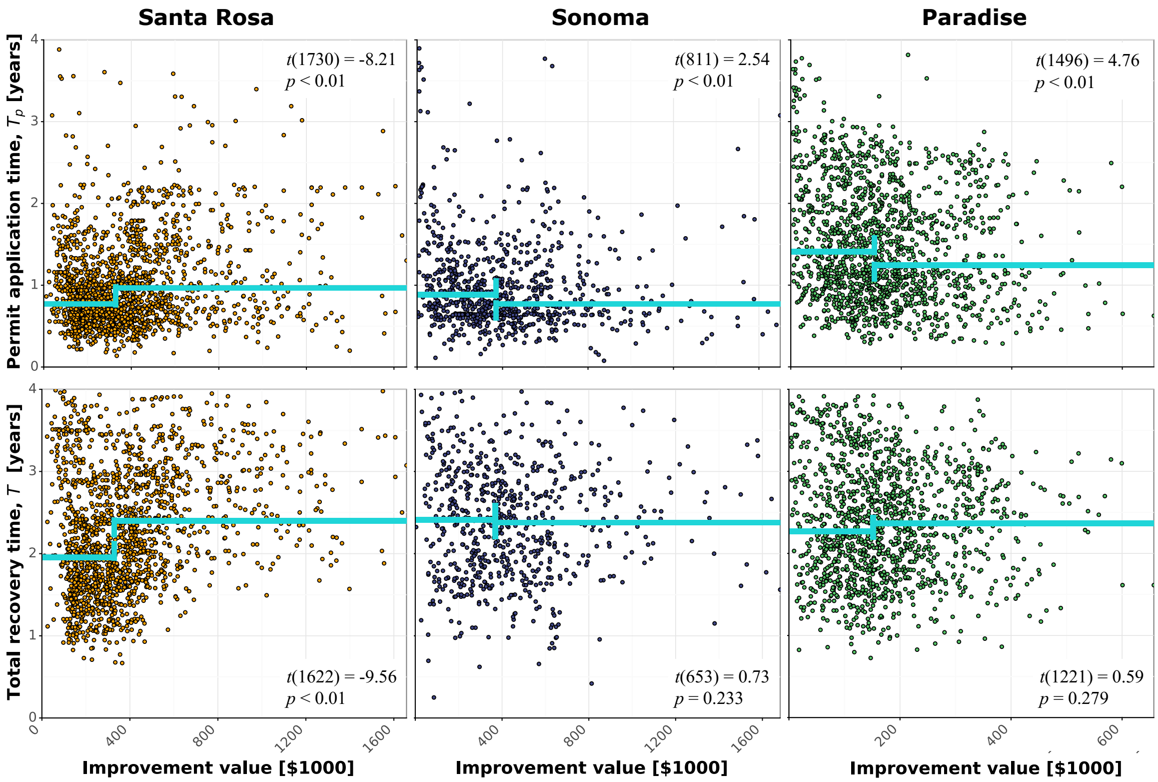

Figure 13: Recovery progress as a function of improvement value. Permit application time on top, total recovery time below. The projections of the horizontal lines on the ordinate axis represent the median times for the parcels with improvement values below (left) or above (right) average. The median improvement value is the point on the abscissa axis where the horizontal lines meet. The results of Welch's t-test comparing T_p and T for parcels with below-median and above-median improvement values are shown in the respective panels.

A.4 The Effect of Neighborhood Density on Housing Recovery

Figure 14 shows how proximity to other destroyed parcels affected the recovery in each region. Clusters of destroyed structures can create an economy of scale for reconstruction services and facilitate recovery. Conversely, it can also act as a barrier due to competition for resources and a reduced sense of community due to the extent of the damage. The plots consider the number of destroyed parcels within a one-kilometer radius, called *neighbors* in the following. The plots show that parcels with more neighbors applied for a permit and recovered faster in Santa Rosa and Sonoma. To test for statistical significance, we conduct Welch's t-test on the means of the two groups in each region (i.e., below vs. above average neighbors). The differences are significant in Santa Rosa and Sonoma for both permit application time and total recovery time ($p < 0.01$). The similarities between Santa Rosa and Sonoma are interesting because the damage in Santa Rosa, although heavy, was concentrated in a few blocks, as indicated by many parcels with more than 500 neighbors in Figure 14. In contrast, the impact in Sonoma was mostly in sparsely populated areas, as indicated by most parcels having fewer than 100 neighbours in Figure 14. No meaningful differences across the number of neighbors are observed for Paradise, where losses were distributed and severe.

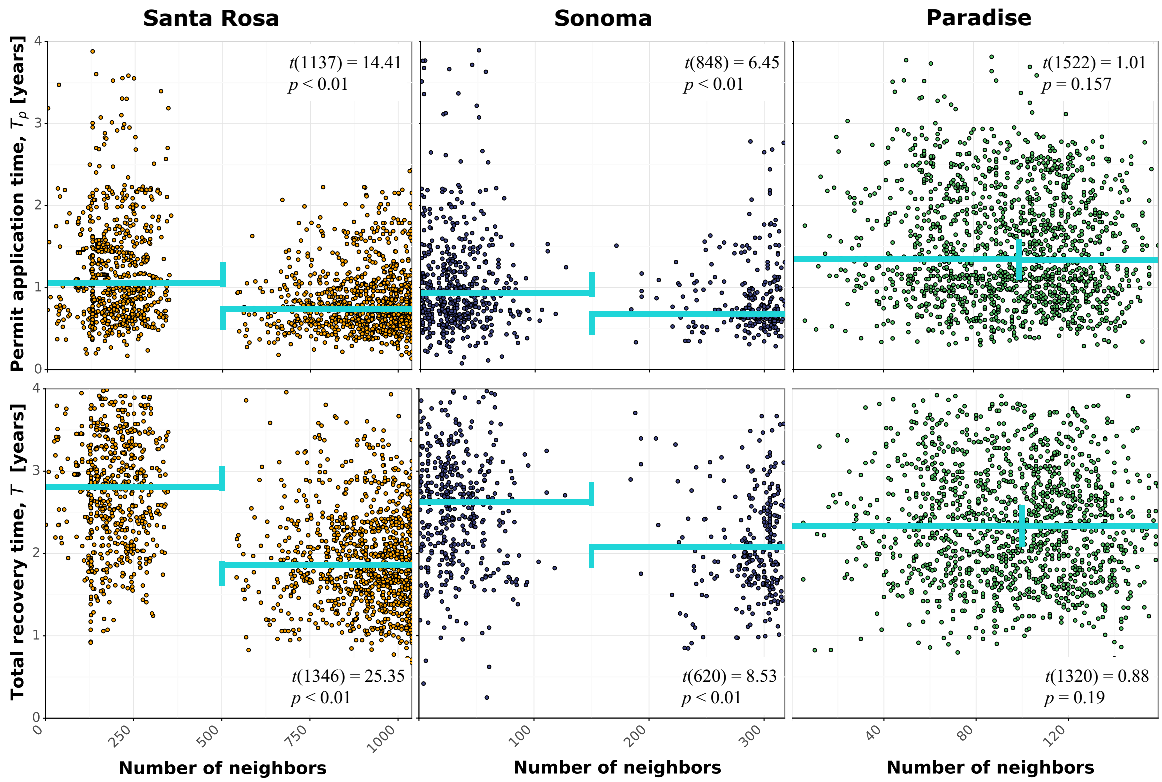

Figure 14: Recovery progress as a function of number of neighbors (i.e., destroyed parcels within 1 km). Permit application time is on top, and total recovery time is below. The projections of the horizontal lines on the ordinate axis represent the median times for the parcels with fewer (left) or above (right) average neighbors. The point on the abscissa axis where the horizontal lines meet defines the below-average and above-average number of neighbors. The results of Welch's t-test comparing T_p and T for parcels with below-average and above-average neighbors are shown in the respective panels.

A.5 Truncated Lognormal Distribution Fitting

In this section, we illustrate the fitting of the truncated lognormal distribution to estimate housing recovery curves described in Section 5.2 in greater detail using Santa Rosa as an example. Figure 15(a) shows a histogram of the distribution of permit application times for Santa Rosa, as seen in Figure 8. The corresponding log-transformed version of the histogram is shown in Figure 15(b). The lognormal distribution to the original data T can be obtained by finding a normal distribution to the log-transformed data $\ln(T)$. In order to fit this normal distribution, we employ the maximum likelihood estimation. Under maximum likelihood estimation, we find a set of optimal parameters that define a statistical distribution (mean μ_{lnT} and standard deviation σ_{lnT} for a normal distribution) that will yield the highest likelihood of obtaining the given set of observations.

In order to account for data truncation, we place a numerical upper bound for which any values greater than the upper bound will have a zero probability. In this case, the upper bound is set to $ln(T_p = 1year) = 0$, as shown in Figure 15(b). We observe that the proposed model shown in solid lines provides a better fit than the naïve model shown in dash-dot lines. The normal distribution parameters can be converted to equivalent lognormal parameters via the following relationship:

$$\mu_{lnT} = \ln \mu_T - \frac{1}{2}\sigma_{lnT}^2 \tag{7}$$

$$\sigma^2_{lnT} = \ln\left(\frac{\sigma^2_T}{\mu^2_T} + 1\right) \tag{8}$$

The curves fit using the method above are probability distributions (i.e. they have been normalized such that the area under the distribution sums up to 1). As such, the corresponding cumulative distributions plateau at 1, with an example for Santa Rosa shown in Figure 15(c). We transform this cumulative distribution into a curve that estimates raw permit application counts. For Santa Rosa, we observed 1,130 permit applications after one year. The proposed cumulative distribution has a value of 0.62 at one year, suggesting that 62% of the total households that would apply would have done so by one year. Thus, the cumulative distribution is scaled by $1130/0.62$ which yields the curve in Figure 15(d). The estimated number of permit applications after four years is 1818, compared to 1856 in the empirical data. Estimates are obtained for Sonoma and Paradise using a similar approach.

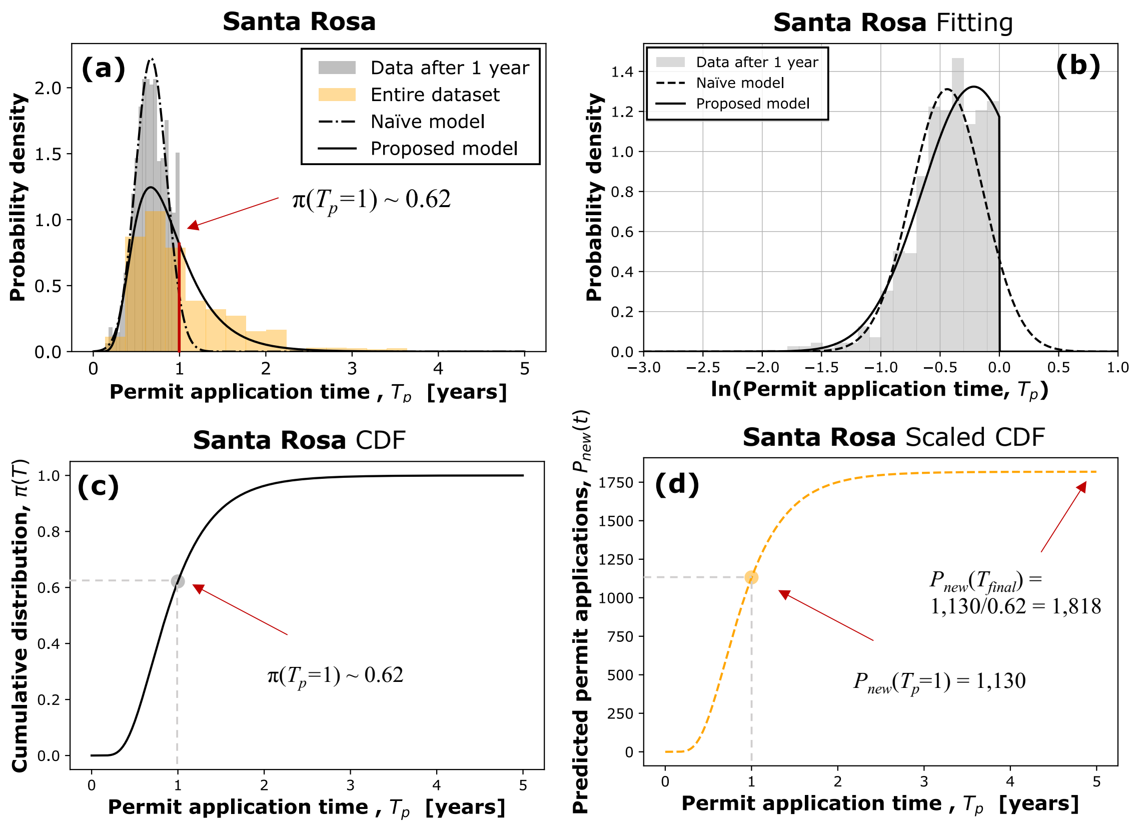

Figure 15: Illustration of truncated lognormal distribution fitting for Santa Rosa

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