A Methodology to Estimate Post-disaster Unmet Housing Needs Using Limited Data: Application to the 2017 Californian Wildfires

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Abstract

In the US, assistance from the Department of Housing and Urban Development (HUD) plays an essential role in supporting the post-disaster recovery of states with unmet housing needs. HUD requires data on unmet needs to appropriate recovery funds. Ground truth data are not available for months after a disaster, however, so HUD uses a simplified approach to estimate unmet housing needs. State authorities argue that HUD's simplified approach underestimates state's needs. This paper presents a methodology to estimate post-disaster unmet housing needs that is accurate and relies only on data obtained shortly after a disaster. Data on the number of damaged buildings are combined with models for expected repair costs. Statistical models for aid distributed from the Federal Emergency Management Agency (FEMA) and the Small Business Administration (SBA) are then developed and used to forecast funding provided from those agencies. With these forecasts, the unmet need to be funded by HUD are estimated. The approach can be used for multiple states and hazard types. As validation, the proposed methodology is used to estimate the unmet housing needs following disasters that struck California in 2017. California authorities suggest that HUD's methodology underestimated the state's needs by a factor of 20. Conversely, the proposed methodology can replicate the estimates by the state authorities and provide accounts of losses, the amount of funding from FEMA and SBA, and the total unmet housing needs without requiring data unavailable shortly after a disaster. Thus, the proposed methodology can help improve HUD's funding appropriation without delays.

1 Introduction

Studies of housing recovery after previous disasters have identified that disadvantaged persons are more likely to occupy deteriorated homes in hazard-prone neighborhoods and have the least resources to restore their livelihoods.

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These conditions have led to an unequal distribution of disaster impacts due to income [e.g., 27, 38, 41], race [e.g., 3, 12, 25], homeownership [e.g., 16, 18, 22, 39], and other demographic factors. To partly address inequalities in disaster impacts, governmental disaster assistance programs are often designed to assist the most vulnerable [e.g., 5, 17, 20, 42]. In the US, the Department of Housing and Urban Development (HUD) has increasingly supported the recovery of uninsured, low-income, disaster-affected families. As HUD's role in supporting disaster recovery in communities increased over the last decades, criticisms have been raised regarding their limited and slow funding disbursement. In some cases, for reasons sometimes beyond their control, HUD's role in disaster recovery was deemed to have worsened socioeconomic inequalities [14, 23, 32].

One way HUD's recovery assistance programs negatively impact recovery outcomes is the strict criteria to estimate the funds needed by a disaster-struck state. HUD defines unmet housing needs as the difference between the home repair costs (i.e., losses) and the funding a state is expected to received from insurance, Federal Emergency Management Agency (FEMA), or the Small Business Administration (SBA) for housing repairs. HUD uses the number of FEMA funding applications as a proxy for the number of households with unmet housing needs. This approach has been criticized because it implicitly assumes those who do not apply for FEMA assistance do not have any unmet needs [4]. However, the FEMA assistance application is complicated, results in small grants, and many are disincentivized from applying. Previous research with Black households identified that they did not apply because FEMA 'was not for them'; other research points to racial minorities' distrust in government institutions which can lead to the households not seeking needed resources [2, 7]. Another problem is that HUD limits its assistance to renter-occupied homes that are affordable to low-income renters. In areas with high costs of living, most housing may not be affordable to low-income persons. However, without assistance landlords may not be able to repair, reducing the available rental housing and further increasing rental costs [27]. Combined, these factors lead to an under-estimation of unmet needs [4, 11].

However, obtaining better estimates of post-disaster unmet housing needs is challenging. HUD must combine information from FEMA with detailed data from other sources, including other federal agencies, private insurance claims payments, and possibly charitable assistance, to have a clear picture of unmet needs. Often, these data are unavailable for months after a disaster. For this reason, HUD grantees must produce an Action Plan for using the HUD funding, which includes re-calculating unmet needs conducted months after the disaster. Although the Action Plans still rely on often inaccurate or insufficient data, they provide a better representation of the unmet needs [21]. A problem is raised if there is a significant discrepancy between the HUD-allocated funding and the grantee-estimated needs. For example, after the 2017 California Wildfires, a survey was conducted to assess homeowners' needs and define priorities resulting in delays in funding disbursement [4]. From this perspective, estimating unmet housing needs shortly after a disaster can help HUD allocate appropriate funding and communities to better plan their disaster recovery.

This paper presents a methodology that uses computational simulations to estimate post-disaster unmet housing needs using data that can be collected shortly after a disaster. Computational simulations have provided a multilevel understanding of relationships between factors influencing disaster impacts [24]. Disaster financing data from the Federal Emergency Management Agency Individual Assistance Program (FEMA IAP) and the Small Business Administration Homeowner and Personal Property Loan (SBA HPPL) programs are used to build probabilistic models to estimate the expected approval rate and approved amount for these programs. The models account for hazard type (e.g., flood, wildfire, earthquake), state, and applicant demographics (e.g., income, insurance status, home-ownership, and residence type). These models are combined with a methodology to estimate housing reconstruction costs based on FEMA guidelines and used to estimate post-disaster unmet housing needs. Thus, this paper provides two contributions. First, we develop statistical models to probabilistically estimate post-disaster assistance from the FEMA IAP and SBA HPPL programs. Second, we develop an improved methodology to estimate post-disaster housing needs that utilized only data available shortly after a disaster. A case study application of the methodology to the 2017 California wildfire-related disasters shows that the proposed approach can replicate the losses, assistance, and unmet housing needs following these disasters.

2 Summary of Post-disaster Housing Recovery Financing in the US

Multiple sources of financing are available to support reconstruction of privately-owned housing following a disaster. These sources differ in their approval criteria, maximum amount, and disbursement time. The following briefly reviews the primary sources of post-disaster housing recovery financing in the US.

Insurance against disasters is an add-on to a standard homeowner's insurance policy and often the first source of coverage for disaster losses. Insurance coverage varies by hazard. Homeowners exposed to perils perceived more frequently tend to have higher insurance coverage [40]. In some at-risk regions, disaster insurance is a requirement for a mortgage. Insurance covers the home's reconstruction cost minus a deductible, usually between 10% and 25% of the reconstruction cost. However, the insurer assesses the home reconstruction cost and does not account for post-disaster price surges or any required improvements [19, 26]. As consequence, even insured households may rely on other sources of financing to repair their homes [4].

The Federal Emergency Management Agency (FEMA) provides small grants to homeowners with uninsured or under-insured needs due to a disaster through its Individuals Assistance Program [33]. After a disaster, FEMA inspects the impacted homes and assesses FEMA Verified Losses (FVL). The FVL reflects the funds needed to repair the home to an occupiable state rather than to reestablish its pre-disaster state. These grants are capped at $36,000 per applicant and are aimed at low-to-moderate income persons [9]. Homeowners deemed able to repay a loan are steered away from FEMA IAP assistance and recommended to seek loans.

The Small Business Administration (SBA) Home and Personal Property Loans (HPPL) program provides low-interest loans to cover losses not fully covered by insurance or other means [28]. The interest rate is capped at 4% for applicants unable to obtain credit elsewhere, and 8% for those who can obtain credit elsewhere. Unlike the FEMA IAP grants, SBA loans are aimed at repairing homes to their pre-disaster state, and the maximum SBA loan is $200,000. These loans are designed to be more accessible than bank loans, but household income and credit history are still considered in the decision process.

Households may procure a private bank loan if an SBA loan is insufficient. These loans have more strict approval criteria: borrowers must demonstrate the capacity to repay the loan, e.g., through their credit history or by providing collateral. The interest rates for these loans can significantly exceed those of the SBA loans. Hence, bank loans are more accessible to higher-income homeowners who are more likely to be approved, have assets to provide as collateral, and can obtain shorter maturity loans with lower interest rates. Because the estimate of unmet housing needs is focused on homeowners of lower socioeconomic status, bank loans are generally not included in the calculation.

Homeowners unable to cover their losses using the abovementioned programs may rely on federal funding from the Department of Housing and Urban Development (HUD), which is provided through the Community Development Block Grants for Disaster Recovery (CDBG-DR). HUD's CDBG-DR program is the backstop for many homeowners and can be the only financing mechanism available to uninsured, low-income homeowners [21]. Congress allocates CDBG-DR funding based on the losses and the impacted region's demographics [1]. It requires the approval of an Action Plan developed by state housing authorities. However, the approval of CDBG-DR funds can be slow, often taking more than a year for homeowners to receive the first payments [15, 30]. To determine the amount of funding to be provided, HUD relies on an estimate of the unmet housing needs for the disaster [36]. In the following, we discuss how unmet housing needs are currently calculated by HUD and by state authorities.

2.1 HUD's Post-disaster Unmet Housing Needs Estimation

To estimate post-disaster unmet housing needs, HUD uses the FEMA Verified Losses to categorize each building into one of five damage categories: (1) minor, (2) minor high, (3) major low, (4) major high, or (5) severe damage. HUD considers that only buildings at major low, major high, or severe damage categories have unmet housing needs. Among owner-occupied homes, only uninsured homeowners are eligible. Among renter-occupied homes, only those that are affordable to households with income below 50% of the area median income are eligible. Thus, using HUD's criteria, the serious unmet housing needs in a disaster-impacted community are

$$U = L_T - F_{insurance} - F_{FEMA} - F_{SBA} \tag{1}$$

where L_T are the total housing losses for the eligible homes, and $F_{insurance}$, F_{FEMA}, and F_{SBA} are the funding coming from insurance, FEMA, and SBA, respectively. Note that under HUD's criteria, $F_{insurance}$ is zero since only uninsured homeowners are assumed to have unmet needs.

The challenge for HUD is that F_{FEMA} and F_{SBA} are not known by the time funds need to be appropriated because homeowners may not apply for FEMA and SBA immediately after a disaster and because these applications take weeks-to-months to be processed. Thus, HUD's initial appropriation employs a simplified approach in which the serious unmet housing are estimated as

$$U^* = \sum_{dc=3}^{5} H_{dc} \cdot M_{dc} \tag{2}$$

where H_{dc} is the number of FEMA IAP applicants in each damage category dc, and the multiplier M_{dc} is the amount of unmet needs per home, empirically estimated by HUD. The multipliers M_{dc} are defined per state and per year. In 2017, the minimum cost multipliers across all Major Disasters were M_3 = \$40,323, M_4 = \$55,812, and M_5 = \$77,252.

2.2 Limitations of the HUD Methodology

HUD's simplified method (Eq. 2) has been criticized by CDBG-DR grantees. Eq. 2 implicitly assumes that homeowners who do not apply for FEMA IAP assistance do not have any unmet needs. However, the FEMA IAP application can be complicated and often results in grants smaller than \$5,000, as we demonstrate later. These factors lead to an under-representation of disaster impacts if unmet needs are estimated by Eq. 2 [4, 11]. Recent disasters in Texas, Florida, and California show that the grantee-calculated unmet needs (using Eq. 1) can be between 3 and 20 times higher than the initial HUD estimate (Eq. 2). In a recent review of multiple CDBG-DR programs, [21] suggests that improved certainty about unmet needs and federal resources could improve the initial allocation and disbursement time without compromising the quality of the programs. These limitations of the current approach and the observations by [21] motivate the current study.

3 Unmet Housing Needs after the 2017 Disasters in California

Once HUD funding is approved by Congress and allocated to the state authorities, the grantees must design an Action Plan which includes a thorough estimate of unmet housing needs. To do so, grantees estimate the number of impacted homes and their respective losses and compare that to the state's funding from insurance claims, FEMA grants, and SBA loans. In this section, we discuss the Action Plans designed in response to the 2017 Disaster in California to exemplify this process.

In October 2017, a series of wildfires spanned from the north coast of the San Francisco Bay Area to the northern Central Valley and Orange County in California. More than 200,000 acres burned, and 8,922 structures were destroyed.

In response to the fires, FEMA issued Major Disaster Declaration DR-4344 in October 2017. In December of the same year, another series of wildfires burned 308,383 acres across Southern California. The wildfires were followed by heavy rains, mudflows, and debris flows which compounded the devastation. In December 2017, FEMA issued Major Disaster Declaration DR-4353 in response to these events. The disaster declarations led to a Presidential Disaster Declaration and the subsequent Congressional Appropriation of Funds, and on August 14th, 2018, HUD published the Federal Register allocating $124 million to California [35]. These funds were destined for three programs. The Owner Occupied Housing Rehabilitation and Reconstruction Program received $47.63 million to repair single-family owner-occupied homes. The Multifamily Housing Program received $66.7 million to be used for reconstructing apartment complexes and mixed-use developments, with preference given to displaced individual renter households. Lastly, $3.5 million was destined to repair critical infrastructure via the FEMA-Public Assistance Match Infrastructure Program.

3.1 HCD's Post-disaster Unmet Housing Needs Estimation

In response to the 2018 HUD allocation, the California Department of Housing and Community Development (HCD) prepared an Action Plan for Disaster Recovery [4], published on March 15th, 2019. The HCD obtained data from the California Department of Forestry and Fire Protection (CAL FIRE), which identified that 7,640 homes were impacted: 137 severely damaged and 7,503 destroyed. The HCD estimated the average replacement cost for a home in California to be $300,000. The HCD assumed that the repair costs are a fraction of the replacement costs, between 50% and 75% for severely damaged homes and 100% for completely damaged homes. With this, the HCD estimated the total losses per county as

$$L_T = \$300,000 \cdot \Big(\sum_{i=1}^{NS} \frac{0.75+0.5}{2} + \sum_{i=j}^{NC} 1 \Big) \tag{3}$$

where *NS* and *NC* are the number of severely and completely damaged homes, respectively. Using this approach, the HCD estimated the total losses to be $2.283 billion. The HCD identified that many homeowners were not insured or held policies that did cover the total building replacement costs. Some fully insured homeowners had significant unmet needs due to increased materials and labor costs. Moreover, HCD advocated that HUD's criteria limiting the analysis to homes affordable to low-income households did not reflect the high-living-cost areas involved in these disasters. Thus, the HCD included all losses in calculating unmet housing needs. The HCD collected data from FEMA and SBA to estimate funding from these sources, i.e., F_{FEMA}=20.7 million and F_{SBA}=163.2 million. However, more than a year after the disasters, the HCD could not collect reliable data on insurance funding, and so estimated the upper bound of the unmet housing needs using $F_{insurance} = 0$. Thus, Eq. 1 provided an unmet needs estimate of

$$
\begin{aligned}
U &= \$2.283 \text{ billion} - \$0 - \$20.7 \text{ million} - \$163.2 \text{ million} && (4) \\
&= \$2.098 \text{ billion} && (5)
\end{aligned}
$$

Comparatively, applying Eq. 2 using HUD's simplified approach with its more restricted criteria yields $80 million in unmet housing needs. Due to the mismatch of unmet needs and available funding, HCD implemented a program survey period before launching its Owner Occupied Rehabilitation and Reconstruction Program to accurately measure owner households with unmet housing recovery needs. The survey was necessary but incurred delays in the funding allocation process.

Figure 1 presents a timeline of events following the 2017 Disasters in California. The highlighted period between the FEMA 4353 Disaster Declaration and the Notice of Appropriation could have been reduced if the HUD appropriation of funds was completed more quickly. The second highlighted period, between the approval of the State Action Plan and the Initial Program Awards, could have been reduced if the initial appropriation provided sufficient funding and the survey period was unnecessary.

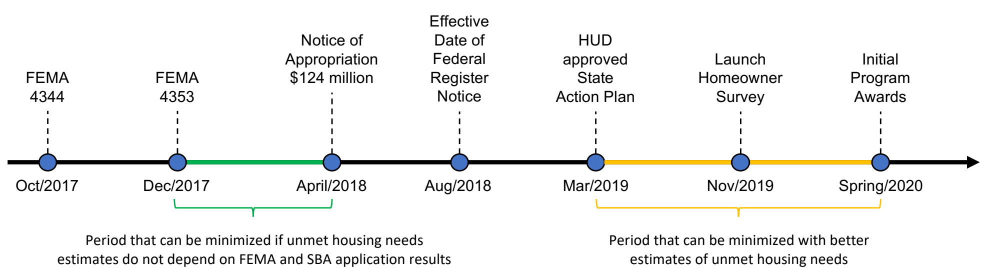

Figure 1: Timeline of CDBG-DR funding allocation following FEMA Disasters 4344 and 4353.

3.2 Limitations of the HCD Methodology

The HCD methodology accounts for community and disaster-specific contexts and yields unmet housing needs estimates more representative of the impacts of the 2017 Disasters. However, there are some limitations to the HCD approach. First, it could not consider financing from insurance, so it only estimates the upper bound of the unmet housing needs. Second, the HCD estimated the average replacement cost for any home is $300,000. However, home values in California vary significantly per county. For example, the average home value is $167,300 in Lake County, but $503,000 in Napa County [34]. Third, the HCD approach requires data on processed FEMA grants and SBA loans, which only become available several months after a disaster. Thus, the HCD approach cannot be applied shortly after a disaster to inform HUD funding appropriation.

4 Proposed Approach to Estimate Post-disaster Unmet Housing Needs

This section introduces the proposed approach to estimating unmet housing needs, which overcomes some of the limitations of the Department of Housing and Urban Development (HUD) and California Department of Housing and Community Development (HCD) approaches. Fig. 2 presents a schematic representation of the three approaches. The top panel shows HUD's methodology, which estimates unmet housing needs based on FEMA IAP data and the multipliers dependent on damage categories. The center panel presents the methodology used by the HCD, which uses data from multiple sources to estimate unmet housing needs using Eq. 5. In Fig. 2, the shaded boxes indicate data unavailable for some months after a disaster. The boxes associated with damage information are half shaded because rapid damage assessments tools exist for specific hazards [e.g., 37].

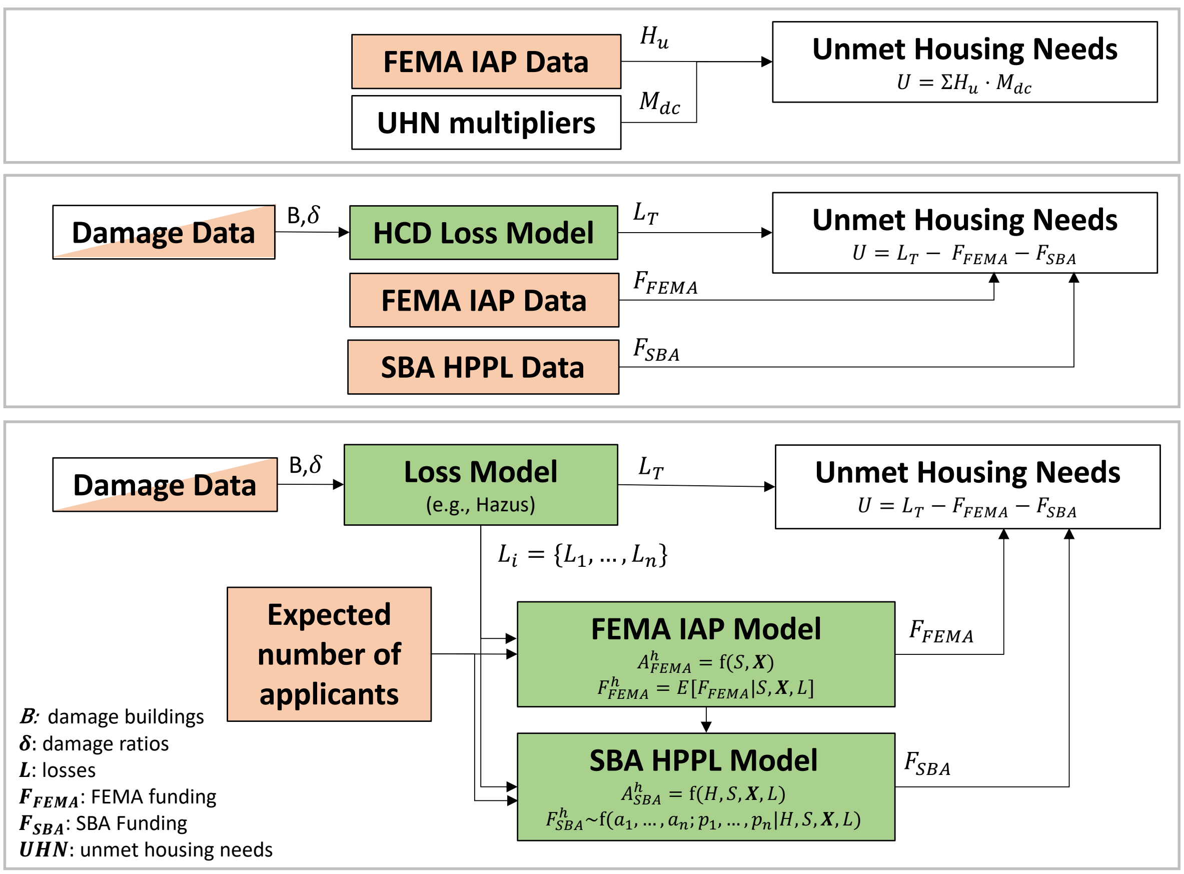

Figure 2: Overview of the unmet housing needs methodologies. Orange boxes indicate required input data. Green boxes are models that replace the need for input data.

The bottom panel in Fig. 2 shows the proposed approach and shares the reliance on damage estimates in the HCD approach. The proposed approach also depends on an estimate of the number of households expected to apply for FEMA and SBA funding. We discuss the implications of this dependency and alternative ways to obtain these data later in this communication. The FEMA IAP Model estimates the approval rate, A^h_{FEMA}, and the amount of financing received F^h_{FEMA} by approved households. Similarly, A^h_{SBA} and F^h_{SBA} represented the approval rate and expected amount received by a household from the SBA HPPL program. The sum of the losses and the total funding from FEMA IAP and SBA HPPL across all households are used to estimate the total unmet housing needs in the community. We note that the proposed approach does not include a model for insurance funding, similar to the HCD approach. Later in this communication, we discuss potential alternatives to overcome this limitation.

4.1 Loss Model

The first step in analyzing the unmet housing needs is to determine losses. While collecting data on the number of buildings damaged can be done quickly after a disaster, estimating losses is not trivial due to the variability in the building portfolio. Here, we employ a methodology developed by the Federal Emergency Management Agency to estimate the replacement costs of homes in the United States. The methodology was designed to be used within FEMA's Hazus Loss Assessment tools [8] and is henceforth called the Hazus Loss Model. The replacement cost is the cost of repairing a structure to its pre-disaster state. It is often smaller than the home value, which includes land value and appreciation. Using the Hazus methodology, the replacement cost for a building (B_{rc}) is

$$B_{rc}(county) = A_{main} \cdot C_{main}(county) + \mathbf{1}_{bsm} \cdot A_{bsm} \cdot C_{bsm}(f, county) + \mathbf{1}_g \cdot A_g \cdot C_g(f, county) \tag{6}$$

where A_{main}, A_{bsm}, A_g are the areas of main floor, basement, and garage in square feet, $C_{main}(county)$, $C_{bsm}(f, county)$ and $C_g(f, county)$ are the cost to replace one square foot of main area, basement, and garage based on the quality of the finish, f, and $\mathbf{1}_{bsm}$ and $\mathbf{1}_g$ are an indicator functions which return the unity if the home has a basement or garage, or they return zero otherwise. The replacement costs are based on 2018 RSMeans estimates [6]. Note that the replacement costs vary per county, making the building replacement cost a function of the county where the building is located. Tables that are used to determine A_{main}, A_{bsm}, A_g, $C_{main}(county)$, $C_{bsm}(f, county)$ and $C_g(f, county)$ are available in [8] for all regions of the US.

4.2 The FEMA Individual Assistance Program (IAP) Model

Data on recent Major Disaster Declarations from the OpenFema portal [10] are used to estimate the funding coming from the FEMA IAP grants. These data include accounts of losses, assistance received, and some basic demographic information on the applicants impacted by Hurricanes Harvey, Irma, Maria, Laura, Ida, Michael, and the 2021 Texas Winter Storm. We exclude entries where the verified losses are missing, zero, or the building type is 'Mobile Home.' Entries for Puerto Rico are also removed, as the median applicant income for Puerto Rico is \$12,000, less than half that of the state with the lowest median applicant income (\$25,200 in Louisiana) and about one-third of the median income for applicants in the continental US (\$34,000). The final data set contains 430,908 FEMA IAP applications.

In our data set, 38.4% of all applications with any amount of verified losses received some assistance from FEMA IAP. The maximum assistance one household can receive for repairs or replacement is about \$36,000. However, 53% of the successful applicants in our data set received less than \$5,000, and 3.8% received more than \$30,000. Figure 3 provides a breakdown of the amount received by FEMA IAP applicants for repairs and replacement.

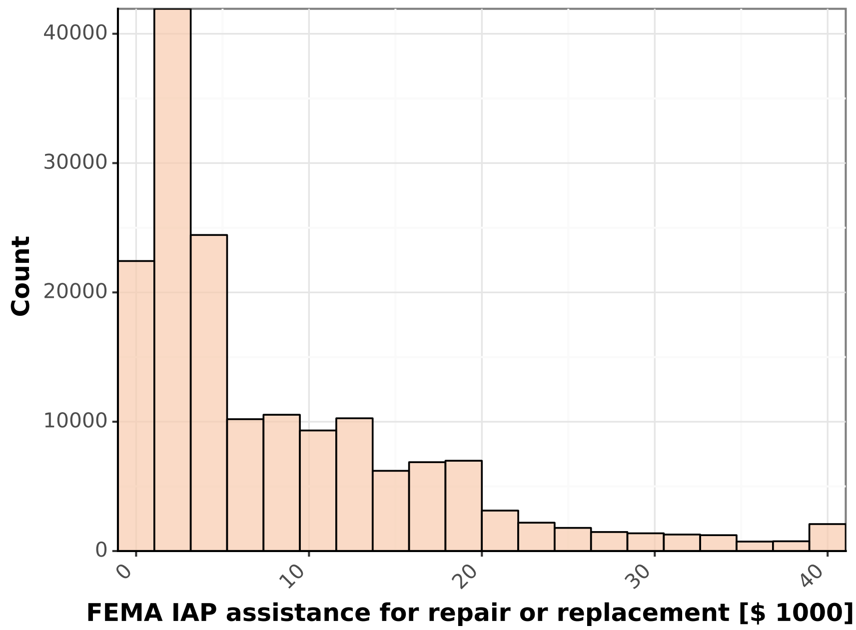

Figure 3: FEMA IAP funding received by successful applicants impacted by Hurricanes Harvey, Irma, Maria, Laura, Ida, Michael, and the 2021 Texas Winter Storm to repair or replace housing.

In Fig. 4, we evaluate the influence of multiple variables on approval rates and households' approved amounts. Insured households tend to receive more on average. Except for condominiums, there is also a tendency for high-income households to receive more assistance. The residence type appears to have a negligible effect on the amount received. However, the residence type has a strong effect on the approval rate. Houses and duplexes have slightly higher rates of approval overall. The positive correlation between income and home value can explain these observations since, all else equal, losses are a consequence of home value. Income has a minor effect on approval rates, and insurance decreases one's approval rate. These observations reinforce the idea that higher approved amounts for higher income households are tied to these households experiencing higher losses.

Considering the insights from Fig. 4, we estimate the approval rate for a household of interest ($A_{FEMA,h}$) in state S_h, with loss L_h, and demographics $\mathbf{X}_h$ (i.e., income, housing type, and insurance status), as

$$A_{FEMA,h}(S_h, \boldsymbol{X}_h, L_h) = \frac{\sum_{i=1}^{N} \mathbf{1}(S_i = S_h) \cdot \mathbf{1}(\boldsymbol{X}_i = \boldsymbol{X}_h) \cdot 1(L_i \sim L_h) \cdot 1(F_{FEMA,i} > 0)}{\sum_{i=1}^{N} \mathbf{1}(S_i = S_h) \cdot \mathbf{1}(\boldsymbol{X}_i = \boldsymbol{X}_h) \cdot 1(L_i \sim L_h)} \tag{7}$$

where N=430,908 is the number of FEMA IAP applicants in the OpenFEMA database, and $1(\cdot)$ is an indicator function

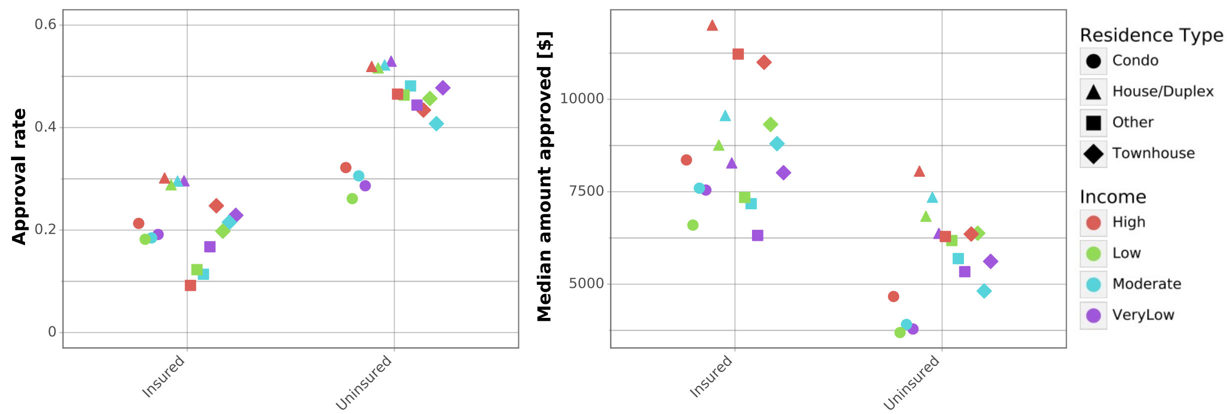

Figure 4: Summary of approval rates (left) and approved amount (right) by household and housing characteristics

that returns 1 if the condition within the parenthesis is true and 0 otherwise. The condition $\mathbf{1}(S_i = S_h)$ if household i has is in the same state as the household of interest, h. The condition $\mathbf{1}(\boldsymbol{X}_i = \boldsymbol{X}_h)$ is true when households i and h have the same income, housing type, and insurance status. The condition $1(L_i \sim L_h)$ indicates that the losses experienced by households i and h are similar, namely, within a \$5,000 range. $F_{FEMA,i}$ is the FEMA IAP funding received by household i.

Using a similar approach, we estimate the amount of FEMA IAP financing that a household is expected to get, $F_{FEMA,h}$, as

$$F_{FEMA,h}(S_h, \boldsymbol{X}_h, L_h) = \frac{\sum_{i=1}^{N} \mathbf{1}(S_i = S_h) \cdot \mathbf{1}(\boldsymbol{X}_i = \boldsymbol{X}_h) \cdot 1(L_i \sim L_h) \cdot F_{FEMA,i}}{\sum_{i=1}^{N} \mathbf{1}(S_i = S_h) \cdot \mathbf{1}(\boldsymbol{X}_i = \boldsymbol{X}_h) \cdot 1(L_i \sim L_h) \cdot 1(F_{FEMA,i} > 0)} \tag{8}$$

and the expected total amount of FEMA IAP assistance across all impacted households is

$$F_{FEMA} = \sum_{h=1}^{H} A_{FEMA,h}(S_h, \boldsymbol{X}_h, L_h) \cdot F_{FEMA,h}(S_h, \boldsymbol{X}_h, L_h) \tag{9}$$

where H is the total number of households that apply for FEMA IAP in the community.

4.3 The SBA Home and Personal Property Loans (HPPL) Model

We collected two data sets to gain insights into the approval rates and amounts for SBA loans. The first data set was obtained and made publicly available by [13] through the Freedom for Information Act. This data set, henceforth called the Goldstein data set, contains only individual SBA applications. However, in areas with few applicants, the SBA aggregates data at the zip code level to protect privacy. Thus, the Goldstein dataset contains a subset of all SBA loans from 2001 through 2018. Moreover, the Goldstein data set is split into approved and denied applications and does not contain data on the losses. Thus, this data set helps calculate approval rates, A_{SBA}, but does not provide insights on the loan-to-loss ratios. Figure 5 provides an overview of the approved loans in the Goldstein data set, showing that loans below \$50,000 are the most common.

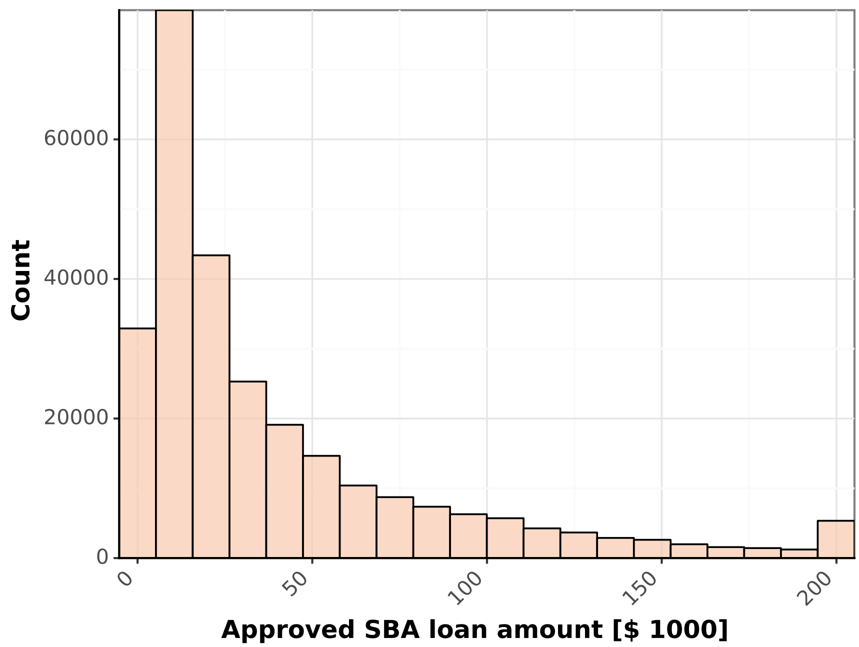

Figure 5: SBA approved loan amounts in the Goldstein data set.

The second data set was collected from the OpenSBA portal [29]. The OpenSBA data contains all approved loans between 2008 and 2019. This data set includes entries representing individual applicants (like the Goldstein data set) and aggregated entries that protect applicants' privacy. The entries representing individual applicants in the OpenSBA data set contain data on losses and loans received, allowing us to derive loan-to-loss ratios. Figure 6 shows the loan-to-loss ratios for different hazards. The dots indicate the mean loan-to-loss ratio, and their size represents the number of loan applications available for a hazard-state pair, i.e., sample size. The vertical lines are bounded between the 10th and 90th quantiles. The shading of each dot indicates the state. For example, the leftmost dot shows that SBA loans to repair earthquake damage have only come from California. The loan-to-loss ratios are between 0.55 and 1.0, and fewer than 300 applications match this hazard-state pair.

Table 1 summarizes the data available from each data set. The Goldstein data set covers 18 years compared to the 11 years in the OpenSBA data. For this reason, the Goldstein data set across all disasters represents a higher total approved amount. When focusing on FEMA declarations 4344 and 4353, it is noticeable that the Goldstein data set is not comprehensive, with \$60 million of approved funds compared to \$152 million from OpenSBA.

Table 1 highlights the issue with aggregation in the OpenSBA data set. For example, for the 2017 Disaster there are only 105 entries that represent individual applications. To obtain more individual application data, we employ the procedure described in Fig. 7. For a given hazard H and state S (e.g., wildfire and California), we create a histogram

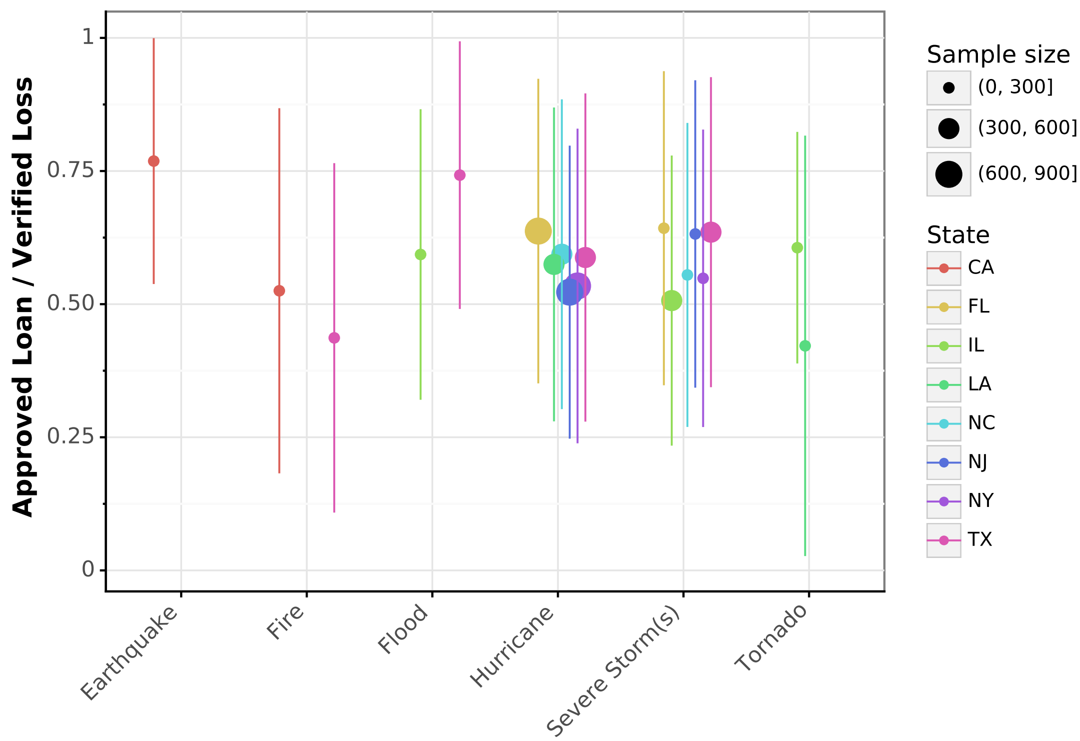

Figure 6: Approved loan *vs* verified loss by hazard from the OpenSBA dataset.

Table 1: Summary of SBA data.

Disasters	SBA Goldstein (2001-2018) Entries	Approved amount Mean[$]	Approved amount Total[$million]	OpenSBA (2008-2019) Entries	Approved amount Mean[$]	Approved amount Total[$ million]
All	553,471	54,886	15,200	16,842*	–	9,890
California	7,738	64,427	260	183*	–	630
FEMA 4344 & 4353	966	96,405	60	105*	–	152

* some entries represent multiple applicants.

as the one in Fig. 5 and describe the probability that the loan amount for a given approved loan, L_{SBA}, is within a $25,000-interval. That is, the amount received from SBA, L_{SBA}, is approximated as a multinomial distribution given by

$$L_{SBA} \sim f(a_1, \ldots, a_n; p_1, \ldots, p_n | H, S) \tag{10}$$

where the probability that the amount received is in the interval a_* (e.g., a_1=[$0, $25,000) and a_2=[$25,000, $50,000)) is p_*. Next, the OpenSBA data is separated into individual and aggregated entries. Entries with approved loan amount larger than $200,000 are considered to represent more than one successful applicant, i.e., an aggregated entry. Using the OpenSBA individual loans, for a given hazard, H, state, S, and eligible loss L, the loan-to-loss ratio, R_{LL}, is modeled as a multinomial distribution, that is

$$R_{LL}^{ind} \sim f(a_1,\ldots,a_n;p_1,\ldots,p_n|H,S,L) \tag{11}$$

Certain H-S combinations may yield small sample sizes and result in poor models for L_{SBA} and R_{LL}. To avoid these situations, one of the conditions the data grouping may be relaxed, for example by using data from all hazards for one state S.

The last step is splitting the aggregated loans into the OpenSBA data set. Consider an aggregated entry with a total loan amount of L^{agg}=\$2 million. First, a loan amount is sampled from the Eq. 10 L_{SBA} distribution (e.g., $L_{SBA,1}$ =\$150,000). Next, a loan-to-loss ratio with distribution R_{LL} (Eq. 11) is assigned to $L_{SBA,1}$. The loan $L_{SBA,1}$ is then added to a list of split loans. The loan amount for $L_{SBA,1}$ is subtracted from L^{agg}, and the process is repeated until L^{agg} is completely split into loans smaller than \$200,000. The procedure is performed for all aggregated entries in the OpenSBA data set. Finally, all split loans are combined with the original list of individual loans. This procedure expands the number of loan data points available for the 2017 California disaster from 97 to 12,769, while ensuring that the loans split from aggregated entries have statistical characteristics that are consistent the the individual loan data. Note that the procedure in Fig. 7 assumes that in the OpenSBA data set, the individual and aggregated loans are identically distributed.

Finally, the expanded OpenSBA data set containing split and individual loans is used to estimate the amount of funding a household in state S will received from SBA as result of L eligible losses incurred by hazard H as

$$F_{SBA,h} \sim f(a_1,\ldots,a_n;p_1,\ldots,p_n|H,S,L) \tag{12}$$

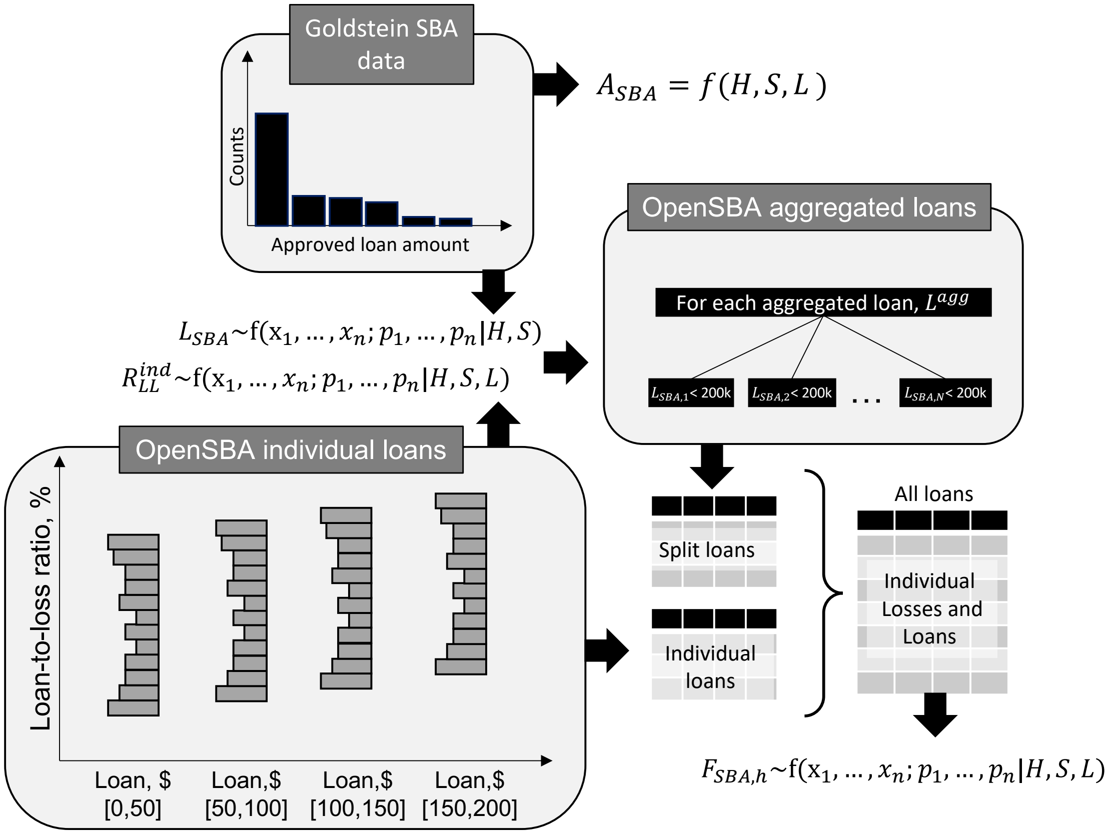

Figure 7: SBA data processing. Individual loan amounts from the Goldenstein data set and the loan-to-loss ratio from the OpenSBA data set are used split aggregated data in the OpenSBA data set into individual loans.

4.4 Insurance

As discussed earlier, HUD does not include insured homeowners in their estimate of serious unmet housing needs (see 2), and state authorities face difficulties obtaining reliable insurance data, even several months after a disaster. Unlike federal grants and loans, insurance coverage may vary significantly by location and hazard. For example, while Californians in flood-prone areas may be required to purchase flood insurance, only 13% of the homes in California have earthquake insurance [31]. Even if county-level insurance statistics are available, these may not be sufficient (e.g., for wildfires, insurance penetration may differ in wildland-urban interface areas). Thus, developing an $F_{insurance}$ model for Eq. 1 that can be employed soon after a disaster is challenging. However, because the proposed approach provides detailed estimates of the building replacement costs (e.g., Eq. 6), it can be used to estimate insurance financing probabilistically as

$$F_{insurance,h}(county) = P(I|B,H,S,\boldsymbol{X}) \cdot I(B|H,S,\boldsymbol{X}) \cdot B_{rc}(county) \tag{13}$$

where $P(I|B,H,S,\boldsymbol{X})$ is the probability that a home is insured conditioned on building type (B), hazard (H), location

S (e.g., state or county), and demographics of the owner household ($\boldsymbol{X}$), and $I(B|H,S,\boldsymbol{X})$ is the insurance coverage as a percentage of the building value. For applications to specific disasters, the values of $P(I|B,H,S,\boldsymbol{X})$ and $I(B|H,S,\boldsymbol{X})$ should be defined by the state authorities in collaboration with community and insurance-sector specialists. Note that although $F_{insurance,h}$ could be integrated into the HCD methodology, Eq. 1, the assumption that the building replacement cost is homogeneous within the state (i.e., \$300,000) would limit the accuracy of the estimates. Thus, the possibility to calculate $F_{insurance,h}(county)$ using $B_{rc}(county)$ is another improvement of the proposed approach.

5 Application to the 2017 California Fires

We employ the proposed methodology to hindcast the impact and unmet housing needs following the 2017 California Disasters (FEMA Disaster Declarations 4344 and 4353). Although the disaster events are months apart and affected different counties, we evaluate their collective impact because they resulted in a single funding allocation by HUD. The proposed methodology (Fig. 2) is employed to estimate losses, funding from FEMA IAP and SBA HPPL, the subsequent unmet housing needs, and to compare the results with the findings and estimates provided by the California Department of Housing and Community Development (HCD). Only FEMA and SBA data from 2017 or earlier (i.e., data available at the time of the disasters) are used to fit the models to replicate the available data after the disasters. Table 2 lists the inputs to the case study. The limitations incurred by the need for this information and alternatives to improve the model are discussed later.

Table 2: Input parameters from 2017 California disasters required by the proposed approach.

Parameter	Value	Source
Severely damaged buildings	137	CAL FIRE
Completely damaged buildings	7,503	CAL FIRE
FEMA IAP applicants with verified loss	3,048	FEMA, reported by HCD
SBA HPPL applicants with verified loss	3,971	SBA, reported by HCD

Table 3 lists the empirical outputs that we aim to replicate using the proposed approach. The values come from FEMA and SBA directly or from data collected and reported by the HCD in their Community Development Block Grant-Disaster Recovery Action Plan published on March 2019 [4]. We emphasize that these data require the processing of FEMA IAP and SBA HPPL applications and are not available for months after a disaster. The proposed approach is probabilistic as the approval rates and approved amounts are uncertain. To gain insights on the variability of the results, the workflow in Fig 2 is run 1,000 times; that is, 1,000 estimates are collected for each variable. The results are presented in the following sections.

Table 3: Impact of FEMA 4344 & 4353 disasters and financing received by California.

Parameter	Value	Source
Total housing loss	\$2,283,300,000	Estimated by HCD
	\$2,578,607,000	Estimated by SBA, reported by HCD
Total FEMA IAP funding	\$15,247,000	OpenFEMA
Total SBA funding	\$152,000,000	OpenSBA*
Unmet housing needs	\$2,584,349,091	–

* total for 2018

5.1 Estimated Losses

We estimated losses using the the number of damaged buildings, replacement costs, and estimated loss ratios. The replacement costs are estimated using Eq. 6 with one modification due to the data available for the case study being compiled at the County level, not at the Census tract level. Without Census tract-level data, the building replacement costs estimated with Eq. 6 do not capture the variability across all counties investigated. To partially correct this, we adjust the estimated replacement costs in each county based on the home values available from the 2020 American Community Survey [34]. The adjusted building replacement cost is

$$B_{rc}^{adj}(county) = B_{rc}(county) \cdot \frac{HV_{ACS}(county)}{HV_{ACS}(CA)} \tag{14}$$

where $HV_{ACS}(county)$ and $HV_{ACS}(CA)$ are the home values for the county and for California, respectively. Table 4 compares the loss estimates provided by the HCD (i.e., Eq. 3) to the estimates yielded by the proposed approach. Two empirical data are provided for comparison: (i) home values from the American Community Survey (ACS), and (ii) total losses reported by SBA. The ACS home values include the value of land and appreciation. Thus the replacement costs should be consistently smaller than home values. The proposed approach yields results between 45% and 80% of the ACS home values. Conversely, the HCD approach yields replacement costs up to 166% of the ACS home values. The HCD approach is not designed to yield accurate results at the county level; hence this finding is not surprising.

The SBA losses are calculated from the reported losses by applicants. Figure 8 shows that the loss estimates using the proposed approach partially capture the trends in the SBA data. Each dot in Fig. 8 represents one county in Table 4. The size of the dot reflects the number of damaged buildings in the county. The proposed loss model yields better results for Sonoma county, which had the most damaged buildings. In consequence, the proposed approach total loss estimates (e.g., \$2.812 billion) are closer to the values reported by the SBA (e.g., \$2.782 billion) when compared to the HCD total estimated losses (e.g., \$2.658 billion).

Table 4: Comparison of losses from empirical data and two estimation models.

					Loss model			
					HCD		Hazus	
County	Buildings	Insured buildings[a] [count (%)]	ACS home value [$ 1,000]	SBA total loss [$ 1,000]	RC[b] [$ 1,000]	Total loss [$ 1,000]	RC[b] [$ 1,000]	Total loss [$ 1,000]
Butte	38	16 (42)	229	5,092	300	6,115	103	3,844
Lake	131	97 (74)	167	20,174	300	15,436	74	9,657
Los Angeles	75	63 (84)	465	11,775	300	23,457	267	19,533
Mendocino	313	200 (64)	319	75,746	300	70,344	141	43,802
Napa	626	472 (75)	503	199,694	300	221,237	403	251,823
Nevada	29	32 (1)	356	5,249	300	7,269	220	6,105
San Diego	116	70 (60)	455	25,636	300	36,900	267	31,144
Santa Barbara	255	42 (16)	480	71,655	300	73,909	283	62,015
Sonoma	5,154	4,963 (96)	465	1,850,286	300	1,685,488	373	1,919,231
Ventura	762	627 (82)	481	287,274	300	256,575	388	292,851
Yuba	143	107 (75)	191	26,026	300	19,201	113	16,307
All	7,642	6689	–	2,578,607	–	2,415,932	–	2,656,314

[a] the number of insurance claims is used as a proxy for the number of insured buildings.

[b] per-building replacement cost.

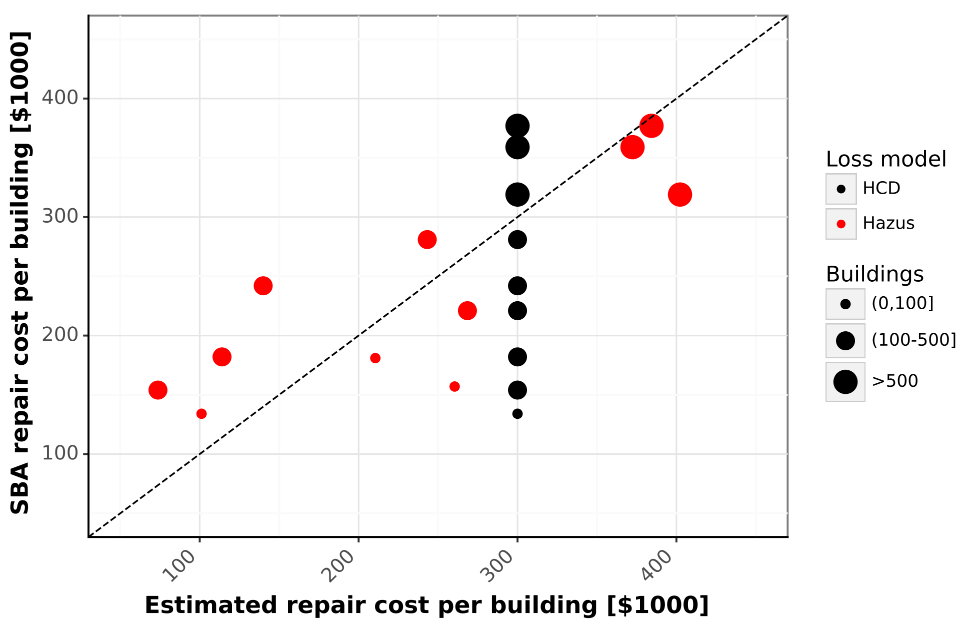

Figure 8: Comparison between SBA reported losses and estimates using the HCD loss model and the proposed loss model. Each point in the figure represents per-building losses for a single county.

5.2 Funding from Insurance

There are limited data regarding housing insurance for these disasters. The best information available was provided by the California Department of Insurance (CDI) to the HCD. These data consist of the total sum of all insurance claims (i.e., residential, personal property, life, and automotive) and counts of the residential insurance claims per county, shown in Table 4. Thus, there is no available information on the amount of insurance funding provided for housing reconstruction. In the face of these limitations, three scenarios are tested regarding insurance penetration. The 'None Insured' scenario represents the extreme case where no resident has insurance. Conversely, the 'All insured' scenario considers all residents are insured with coverage equal to 85% of their home repair costs, i.e., full coverage for expenses that exceed a deductible of 15%. These two scenarios capture extreme cases and have the advantage of not requiring any further empirical data. The third 'CDI-based' scenario assumes that the number of insurance claims provided by the CDI (Table 4) represents the number of insured homes. This assumption overestimates the number of insured buildings since, in some counties, e.g., Nevada County, insurance claims exceed the number of damaged buildings. For this scenario, we assume that insurance will cover 50% of the repair costs. This assumption reflects the findings from the HCD regarding the issues with underinsurance. Because this scenario uses data that would not otherwise be available shortly after a disaster, it is presented as a benchmark. That is, it can be used to test whether the more rapidly available 'None Insured' or the 'All Insured' scenarios better represent the empirical results.

5.3 Funding from FEMA's Individual Assistance Program

The model described in Section 4.2 is used to generate 1,000 estimates of the FEMA IAP funding received by Californians following the 2017 Disasters. Figure 9 shows the results obtained from all insurance scenarios. For reference, the vertical dashed line shows the empirical estimate of $15.3 million in assistance obtained from the OpenFEMA portal. The results show that at least one simulation from the 'CDI-based' and the 'None insured' scenarios replicate the empirical results. However, the empirical result is a relatively extreme value for both distributions. This finding can be explained by the fact that the wildfires caused complete damage to most homes, which would be expected to result in the maximum FEMA IAP funding of about $34,000. However, Fig. 3 demonstrated that only 3.8% of FEMA IAP applicants received more than $30,000. Lastly, the 'All insured' scenario does not replicate the empirical results, showing that the assumptions in this scenario do not represent the reality of the households impacted by the 2017 Disasters in California.

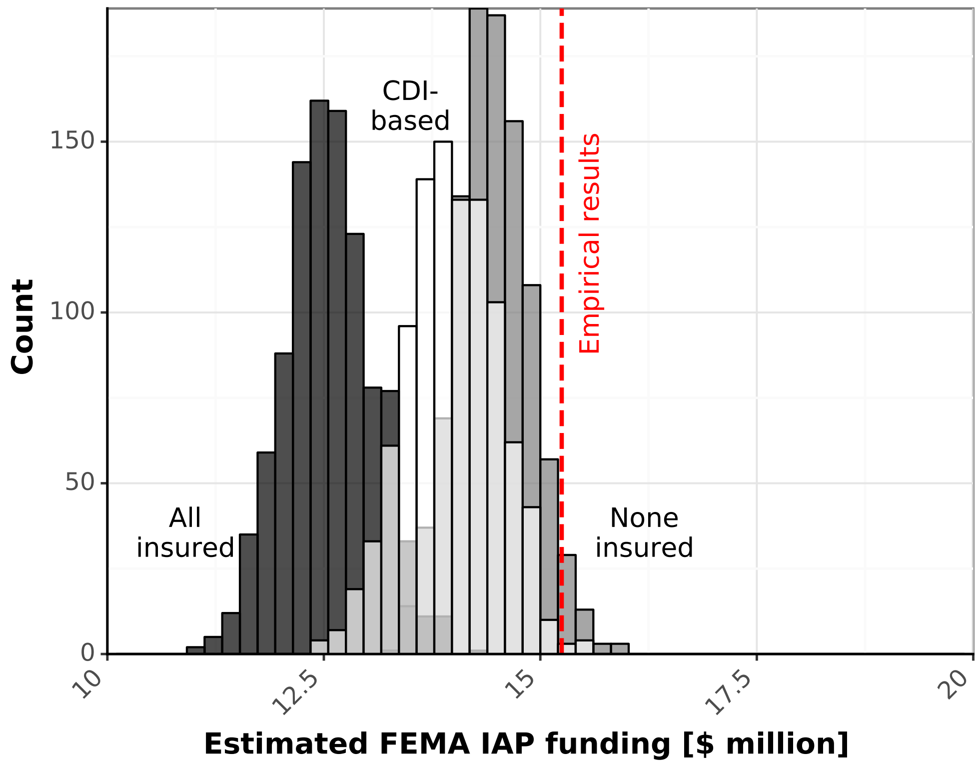

Figure 9: Results from 1,000 estimates of the total FEMA IAP funding received by California in response to FEMA Disasters 4344 and 4353 using the proposed approach. The vertical dashed line indicates empirical results after the event, as collected from the OpenFEMA portal [10].

5.4 Funding from SBA's Homeowner Personal Property Loan Program

Figure 10 shows the results from 1,000 simulations of the SBA funding using the method described in Section 4.3. Because SBA loans exclude losses covered by insurance, the SBA estimates are strongly influenced by assumptions regarding insurance penetration. The dashed vertical line indicates the empirical value obtained after the event (2,371 successful SBA applicants from California received $152 million between 2017 and 2018, according to the OpenSBA portal [29]). The results in Fig. 10 indicate that the 'All insured' scenario underestimates SBA funding by a factor of 3. Although consistently overestimated, the 'None insured' results are significantly closer to the empirical values. Lastly, the mode of the results from the 'CDI-based' scenario perfectly matches the empirical results. These results indicate that most who applied for an SBA loan following the 2017 Disasters were either uninsured or underinsured, i.e., had significant remaining losses after insurance payments were received.

The OpenSBA data are also available per-county basis allowing us to assess the proposed approach in finer detail. Figure 11 compares the SBA funding per county estimated using the proposed approach (on the abscissa axis) to the OpenSBA data (on the ordinate axis). The 'None insured' results are not presented due to the low accuracy shown in Fig. 10. The size of the dots indicates the number of damaged buildings per county. Combined with the results in Fig.

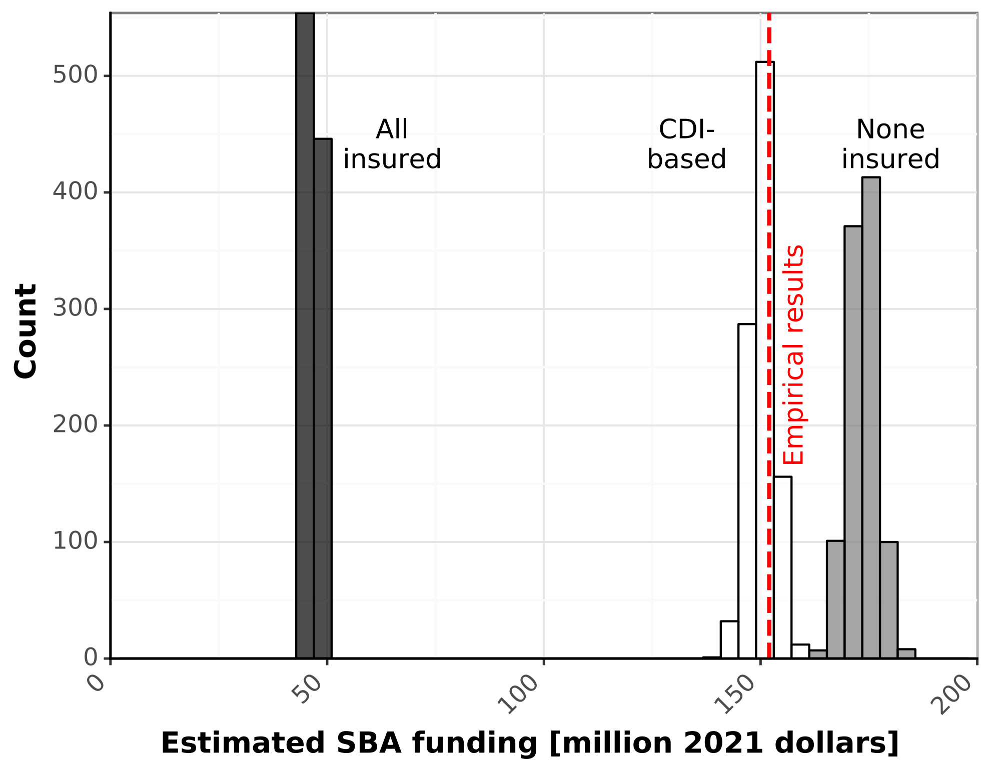

Figure 10: Results from 1,000 estimates of the total SBA HPPL funding received by California in response to FEMA Disasters 4344 and 4353 using the proposed approach. The vertical dashed line indicates empirical results collected from the OpenSBA portal [29].

10, the results Fig. 11 provide two insights. First, the proposed approach can capture the overall expected funding and its county distribution. Second, the proposed methodology can estimate the expected SBA funding with relative accuracy by using the 'None insured' assumption.

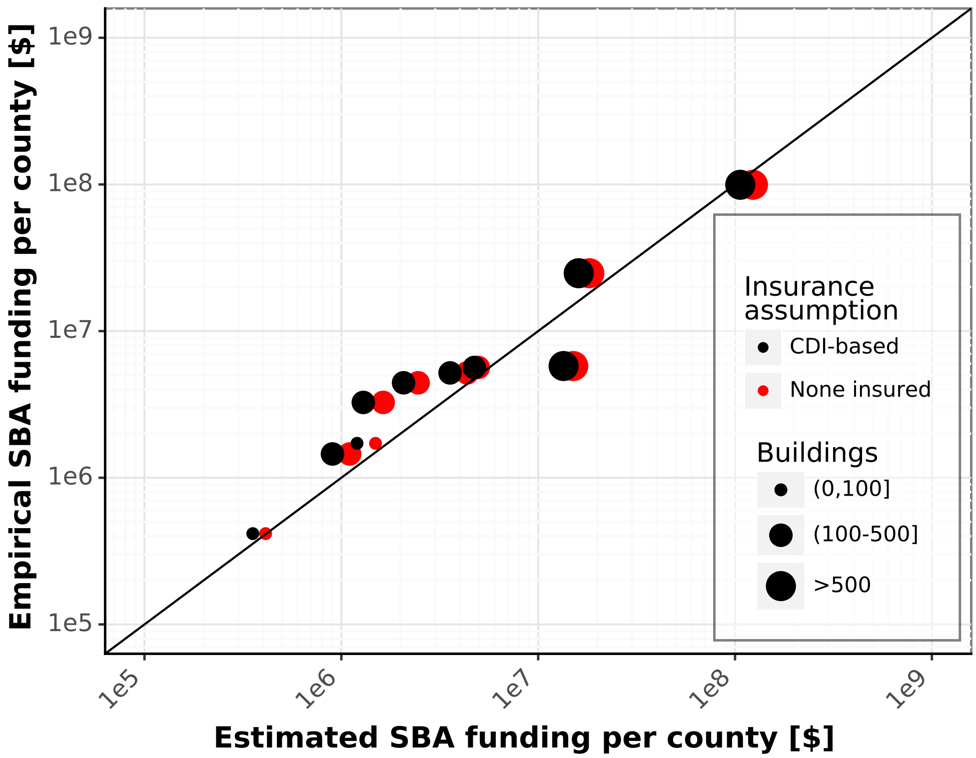

Figure 11: Comparison of the SBA funding received per county estimated using the that assumption all applicants are insured to empirical data from the OpenSBA portal considering all approved loans in 2018.

5.5 Estimated Unmet Housing Needs

Finally, the losses summarized in Table 4 are combined with the results from Figs 9 and 10 to estimate the total unmet housing needs. Figure 12 presents the mean unmet housing needs estimated using the proposed approach and compares it to the $2.58 billion unmet housing needs calculated by the HCD and the $124 million total CDBG-DR funding in HUD's initial allocation. The 'All insured' and the 'CDI-based' scenarios reinforce the empirical evidence that the HUD-estimated unmet housing needs underestimate reality. Even under optimistic assumptions in these scenarios, the results in Fig. 12 show that the HUD significantly underestimated the unmet housing needs for the 2017 Disasters. On the other hand, the results from the 'None insured' scenario closely replicate the HCD estimates. However, the proposed approach could produce these estimates shortly after the disaster and does not require data from FEMA or SBA. Thus, the proposed approach can significantly expedite the estimation of unmet housing needs without significantly reducing the accuracy of the current HCD approach.

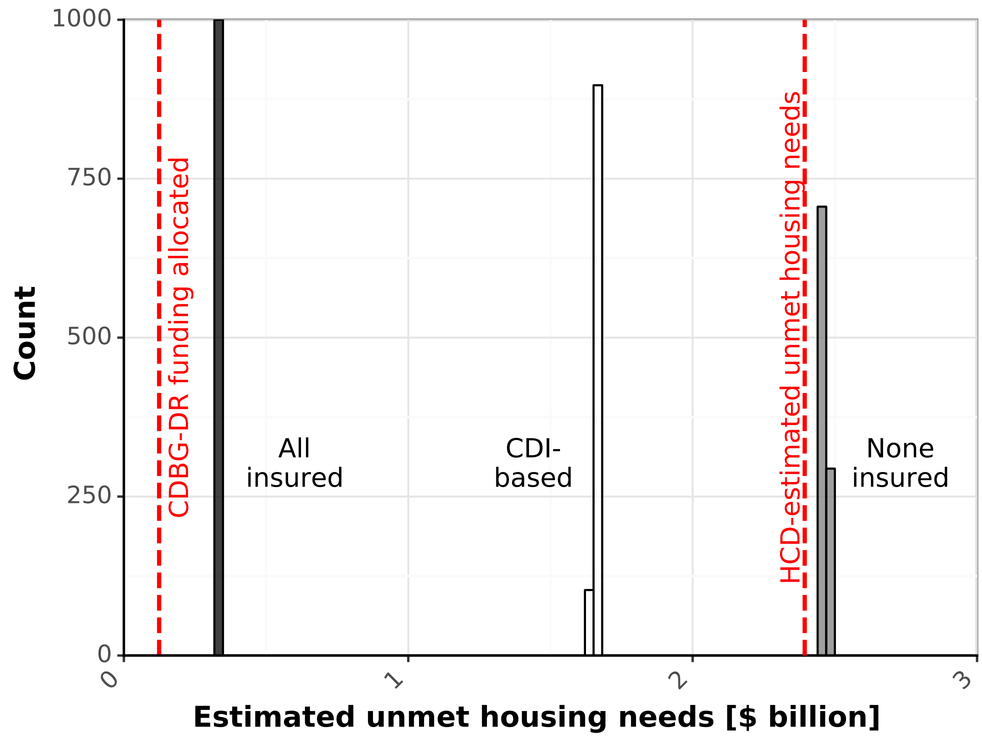

Figure 12: Results from 1,000 estimates of the unmet housing needs using the proposed approach. The vertical dashed line represents the estimate by the California Department of Housing and Community Development.

5.6 Limitations

Although the proposed approach presents significant advantages compared to existing methodologies, it has limitations in addressing a complex problem. The proposed methodology does not include a model to estimate the funding from insurance payments directly–a limitation also present in the existing methodologies. Insurance penetration and coverage are community-dependent and hazard-dependent. Thus, developing a generic model for insurance funding may not be feasible. However, if local authorities have data on insurance penetration and coverage for specific hazards, the proposed methodology can incorporate this information. The methodology also requires information about the number of persons expected to apply for FEMA and SBA assistance - not the result of the applications. Future work may be devoted to evaluating previous disasters and establishing relationships between the number of impacted persons and the number of FEMA and SBA applicants. Alternatively, the impacted population may be quickly surveyed after a disaster to establish their intention of applying for FEMA and SBA assistance. Surveying this information would still be considerably faster than waiting for FEMA and SBA to process the applications and report results.

6 Conclusions

This study proposes a methodology to estimate post-disaster unmet housing needs in U.S., accounting for losses and funding from the Federal Emergency Management Agency (FEMA) and the Small Business Administration (SBA). Rapid estimates of unmet housing needs are essential for the Department of Housing and Urban Development (HUD) to allocate Community Development Block Grants for Disaster Recovery (CDBG-DR) funding. However, current approaches to accurately estimate unmet needs rely on data not available until months after a disaster. The methodology proposed in this paper uses data from the OpenFEMA and OpenSBA portals regarding assistance provided after major disaster in the US in the last 20 years to build predictive models for the approval rate and approved amount from each agency. Thus, the proposed methodology can be used shortly after a disaster and provides accuracy equivalent to the state-of-the-art approaches. We envision that the proposed methodology can be used by state housing authorities after a disaster to gain insights into the magnitude of unmet housing needs or to inform the appropriation of funds by HUD. The methodology could also be used with regional loss estimation tools to assess the unmet housing needs following hypothetical disasters and inform pre-disaster recovery planning initiatives. Thus, the proposed methodology can help communities better prepare and respond to a disaster by providing accurate and quick estimates of unmet housing needs.

A case study methodology application is used to estimate unmet housing needs after a combination of disasters that struck California in 2017 (i.e., FEMA DR-4344 and FEMA DR-4353). Unmet housing needs estimates provided by the California Department of Housing and Community Development (HCD) using data collected about one year after the disaster are used as benchmarks. The case study demonstrates that the proposed methodology can replicate the HCD estimates while using only data available much sooner after the Disasters. Moreover, while the HCD results are only accurate if aggregated over all impacted counties, the proposed methodology provides accurate per-county estimates of loss and funds received. One of the challenges of the case study is that although insurance was the primary source of housing recovery financing, even a year after the disaster, the HCD could not obtain accurate data regarding insurance. We demonstrate that with basic information regarding the insurance penetration rate and average coverage, the accuracy of the proposed methodology is increased significantly. This finding reinforces the confidence in the proposed approach but also suggests that collecting and maintaining information regarding housing insurance can significantly help communities understand their residents' recovery needs after a disaster.

7 Funding

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8 Data Availability

All data used in this study are publicly available from the referenced sources. These data and the code to run the analyses described in this paper are provided here.

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