Post-disaster Housing Recovery Simulation via an Agent-based Model

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Abstract

As climate change increases the frequency and severity of disasters, proactive planning for post-disaster housing recovery is essential to mitigate long-term social and economic disruption. Computational models can support this planning by simulating potential recovery trajectories, yet many existing approaches are limited by overly idealized data requirements or narrow applicability to past events. Here, we introduce RAAbIT (Recovery Assessment using Agent-based Tools), a novel agent-based model designed to simulate housing recovery using data available within weeks of a disaster. RAAbIT models individual households, insurers, and contractors as agents governed by empirical behavior rules, and incorporates modifiable system-level constraints, such as contractor availability, to reflect context-specific recovery dynamics. We demonstrate the model's utility by hindcasting two California wildfires—the 2017 Tubbs Fire in Santa Rosa and the 2018 Camp Fire in Paradise—and capturing their divergent recovery trajectories. Despite similar hazards, the two communities experienced significantly different reconstruction outcomes, with Santa Rosa rebuilding 57% of destroyed homes by 2022 and Paradise only 9%. RAAbIT can reproduce temporal and spatial patterns of recovery observed in building permit and construction data. By balancing generalizability with data realism, RAAbIT provides a flexible and transferable tool for post-disaster recovery planning, supporting more effective decision-making under uncertainty and enhancing community resilience in the face of escalating climate risks.

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Editorial Notes

The perhaps unconventional format is due to the venue where we aim to publish the paper, which requires that the main text (not including Abstract, Methods, References and Figure legends) should be limited to 5,000 words. The maximum title length should be 15 words. The abstract — which should be no more than 200 words long and contain no references — should serve both as a general introduction to the topic and as a brief, non-technical summary of the main results and their implications.

The main text of an Article should begin with a section headed Introduction of referenced text that expands on the background of the work (some overlap with the abstract is acceptable), followed by sections headed Results, Discussion (if appropriate) and Methods (if appropriate). The Results and Methods sections should be divided by topical subheadings; the Discussion should be succinct and may not contain subheadings. Methods are typically less than 3000 words. Figure legends are limited to 350 words each. As a guide, references should not exceed 70. Footnotes are not used.

1 Introduction

Proactive planning for post-disaster housing recovery is critical to mitigating the long-term social and economic consequences of disasters, particularly as climate change exacerbates the frequency, scale, and unpredictability of extreme natural events. Ad hoc recovery efforts often result in delayed reconstruction, increased displacement, and a deepening of existing inequalities [42]. For example, the recovery from the 2018 Camp Fire in California was hindered by the lack of affordable and temporary housing solutions, which led to prolonged displacement. Many lower-income and elderly residents were unable to return due to high rebuilding costs and inadequate insurance coverage. Moreover, the failure to integrate long-term housing planning with disaster preparedness limited the community's capacity to manage residual risk, leaving it vulnerable to future events. The shortcomings of ad hoc recovery management can be mitigated with pre-disaster planning, enabling governments and communities to establish clear recovery frameworks, streamline resource allocation, and prioritize the needs of marginalized populations, thereby reducing recovery time and enhancing resilience.

However, planning for disaster recovery is a challenging task because it involves predicting the uncertain impacts and the effectiveness of targeted actions. While lessons learned from previous disasters can be helpful in this planning, their effectiveness is limited when it comes to possible but previously unseen events. In this context, computational simulations of post-disaster recovery have been proposed as a tool to support decision-making [38]. These models facilitate 'what-if' analysis under simulated futures, allowing decision-makers to understand extreme values of impacts and tipping points for recovery. Simulations can provide insights into post-disaster needs and help allocate resources effectively, facilitating the development of a roadmap to guide short-term relief and long-term action.

Disaster recovery is a complex, non-linear, spatially distributed process that comprises multiple heterogeneous physical and societal systems and agents with bounded rationality (i.e., they do not have perfect information nor make optimal decisions). Consequently, it is a difficult problem to simulate using approaches based on general equilibrium, graph theory, or optimization. Recent developments in this area have highlighted the use of agent-based models (ABM) due to the approach's versatility [40]. Agent-based models represent individual agents — such as people or organizations — with defined behavioral rules that interact within a specified environment. These models are used to explore how macro-level patterns and dynamics emerge from micro-level interactions, often providing insight into complex, adaptive systems [36]. Although ABMs tend to be complex to build and explain, be computationally expensive, and require more granular data, they excel at simulating complex, heterogeneous, non-linear, spatial problems and do not rely on strict boundary conditions [24, 48]. In the last decade, agent-based models have been developed to study disaster recovery under different hazards [3, 20, 30, 39]. Some models focus on the recovery of subcomponents of a community (e.g., housing or infrastructure), other efforts seek to simulate all systems within a community simultaneously. While these efforts have highlighted the potential of ABMs for simulating recovery, existing models have limitations. On the one hand, many existing models have been designed for and deployed only under examples with unconstrained data, such as virtual testbeds [23]. While a valid exercise, this approach underestimates the complexities of obtaining reliable data, particularly if the model is being used to plan recovery shortly after a disaster. On the other hand, certain models were developed to hindcast recovery from a previous disaster. In these cases, models tend to employ data specific to that disaster, making them overfit to a particular application, and their transferability is not proven.

This study presents a novel agent-based model for simulating disaster housing recovery called RAAbIT (Recovery Assessment using Agent-based Tools). While housing recovery is intertwined with the recovery of other community functions (e.g., infrastructure, services), limiting RAAbIT's scope to housing allows us to work with fewer variables and better understand emerging behaviors, a challenge in ABM. The philosophy behind developing RAAbIT is that it should only require data that is accessible within weeks of a disaster and that all of its agents' behaviors are modeled according to the best available statistical data. If these goals are achieved, RAAbIT can be employed for planning before or shortly after a disaster, and it is not overfit to one case study. We consulted recovery action plans developed by state housing authorities in the US to determine that the number of homes impacted and the extent of damage can be realistically estimated within weeks of a disaster. RAAbIT also requires American Community Survey statistics and insurance penetration rates from the previous year, which we assume are available. To model agents' behaviours using historical data, we rely on publicly available datasets to develop conditional probability models. When reliable data are not publicly available, 'levers' are included in the model based on empirical observations of past disasters. These levers (e.g., availability of contractors) allow users to control aspects of the simulation to best represent their expectations of the community's recovery process (e.g., recovery is expected to be limited by contractor availability or not).

To demonstrate RAAbIT's versatility, we present two case studies where the model was used to hindcast recovery in Santa Rosa (CA) after the 2017 Tubbs Fire and Paradise (CA) after the 2018 Camp Fire. Although the triggering hazard is the same, the immediate impact and recovery from these disasters differ substantially. Table 1 presents aggregated statistics for each region, highlighting differences in demographics and extent of damages. The October 2017 Tubbs Fire destroyed 5,636 structures [4], including 3,040 homes in Santa Rosa—approximately 5% of the city's housing inventory [43]. FEMA issued a Presidential Major Disaster Declaration following the wildfire event (FM-5215-CA) [25], and the direct losses across Sonoma County, where Santa Rosa is located, were estimated to be $7.9 billion [10]. The November 2018 Camp Fire burned roughly 18,000 structures near Paradise and Concow — approximately 95% of the cities' housing stock [5]. FEMA issued Major Disaster Declaration FM-5278-CA [26] 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 were estimated at $8.5 billion by the California State Insurance Commissioner [9]. These case studies are selected due to the availability of empirical recovery data and differences in the extent and outcomes of the recovery process in these communities. While Santa Rosa rebuilt 57% of the destroyed housing stock by October 2022, when data were collected, Paradise had rebuilt only 9% of its destroyed homes during this period. We note that less time had passed since the damages to Paradise at the time of the data collection.

Table 1: Summary of aggregated demographic and damage statistics for the study regions.

	Santa Rosa	Paradise	Source
Population	176,938	5,268	US Census[3]
Population density [persons/sq. mi]	7,587	320	US Census[3]
Median household income [$]	84,823	51,396	US Census[3]
Median home value [$]	598,700	287,400	US Census[3]
Insurance penetration [%]	70	84	HCD/CDI
Buildings destroyed	3,043[1]	14,352	Municipality[4]/Cal Fire [6, 14, 46]
Buildings in dataset	2,693	2,544	Municipality[4]
Buildings with a permit[2]	1,855	1,524	Municipality[4]
Buildings rebuilt[2]	1,733	1,322	Municipality[4]
Buildings with permit [% of destroyed][2]	61	11	Municipality[4]
Buildings rebuilt [% of destroyed][2]	57	9	Municipality[4]

[1]: Santa Rosa tracks buildings destroyed, Paradise track parcels.
[2]: Among those with complete records.
[3]: From year before the disaster.
[4]: Data obtained from each municipality is based on a cutoff date of October 15, 2022.
HCD: California Department of Housing and Urban Development.
CDI: California Department of Insurance.
Cal FIRE: California Department of Forestry and Fire Protection.

We quantify the reconstruction of single-family housing 60 months after the Tubbs Fire and 47 months after the Camp Fire. We assume one building per parcel and use these terms interchangeably. The data used to validate the analysis include the recovery plans developed by the California Department of Housing and Community Development [7, 8], the locations of buildings destroyed by the fires, and the dates of construction permit applications for buildings that have begun reconstruction. Permit data were collected via personal communication with city officials and data portals for disaster recovery for Santa Rosa [15] and Paradise [13]. Although each region tracks different milestones in the recovery process, they provide dates for both the initial construction permit application and the completion of construction, which we use for subsequent analysis. These data did not include buildings that had not applied for a permit. Our subsequence analysis must be interpreted with this limitation in mind. When a building had a permit application date but no construction completion date, we assumed that the building had not yet finished reconstruction. Figure 1 shows the empirical recovery curve (**a**) and spatial distribution of recovery (**b**) in Santa Rosa following the 2017 Tubbs Fire. These data include 1,855 buildings (i.e., approximately 61% of the destroyed buildings). The bottom panels show the equivalent data for Paradise following the 2018 Camp Fire. While the counts are similar, the 1,524 that obtained a building permit in Paradise represent only 11% of the destroyed buildings. Figure 1.e highlights that Paradise residents took longer to apply for reconstruction permits on average but that once a permit was obtained, the physical reconstruction of buildings was similar to Santa Rosa's.

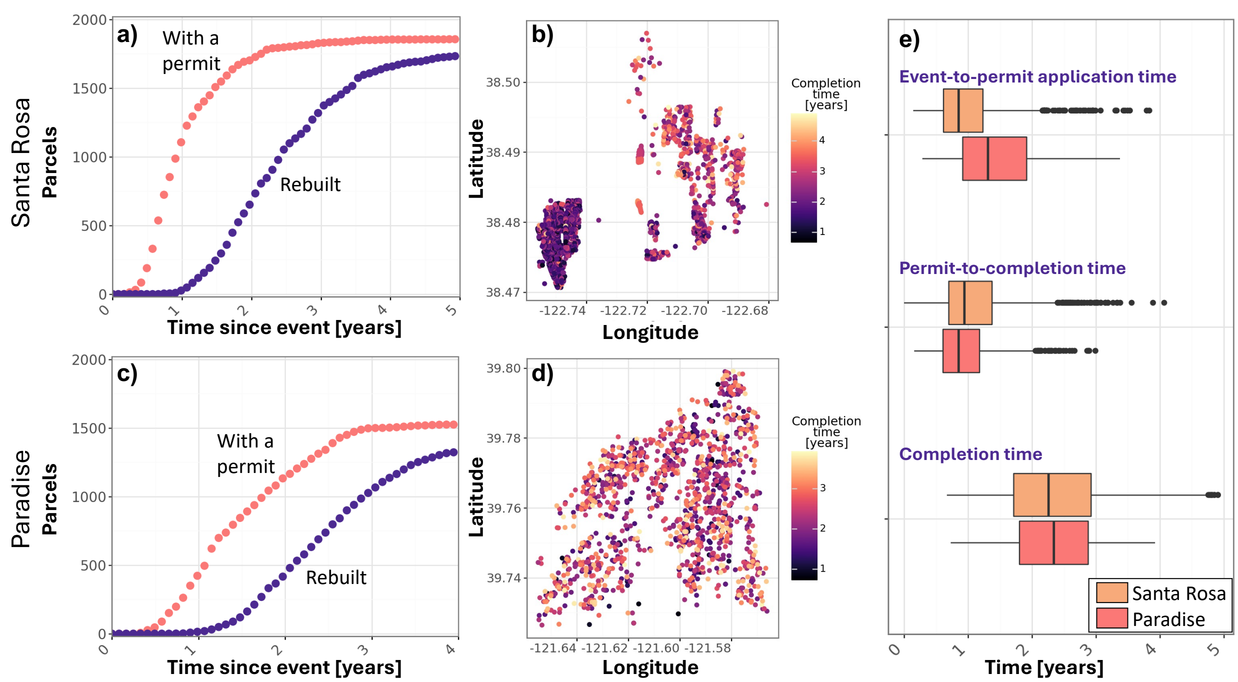

Figure 1: Housing recovery in Santa Rosa after the 2017 Tubbs (**a**-**b**) Fires and Paradise after the 2018 Camp Fire (**c**-**d**). **a** and **c**, Number of buildings rebuilt over time. **b** and **d**, Spatial distribution of recovery times. **e**, Comparison of recovery progress between Santa Rosa and Paradise.

In the subsequent analysis, RAAbIT is used to hindcast recovery in these communities. The simulated results are benchmarked against the empirical data Fig. 1. Lastly, we provided an example of how we envision RAAbIT can be used for recovery planning through 'what-if' scenario analysis, where the community can take actions to expedite reconstruction and guarantee the availability of skilled workers.

2 Results

The following analyses investigate RAAbIT's ability to hindcast the empirical results in Fig. 1. In these simulations, only data that would have been available shortly after the disaster is input into RAAbIT (e.g., the number of destroyed buildings and Census data from the previous year). Multiple scenarios are simulated, in which a few model parameters are modified to gain insights into the influence of each parameter on RAAbIT's estimates. For each scenario, 1,000 realizations (i.e., model runs) are generated to simulate housing recovery and capture uncertainties. In each realization, random variables dictate the agents' behaviors and decisions.

2.1 RAAbIT Average Housing Recovery Curves Match Benchmark Data

The first analysis examines how assumptions about contractor availability over time affect RAAbIT's simulation results. The results for the recovery in Santa Rosa after the 2017 Tubbs Fire are summarized in Fig. 2. Fig. 2.a shows the results obtained if uncertainty about contractor availability is significantly reduced. To obtain these results, we calculated the number of building completions per 90-day period and used this time series to estimate the number of contractors in the community. RAAbIT's results align with the empirical values, highlighting the model's performance when uncertainty about contractor availability is reduced. However, the contractor availability data would be unavailable in a practical application. To provide flexibility, RAAbIT includes two other alternative models for contractor availability.

The results in Fig. 2.b assume contractor availability is constant during the simulated period. Under this assumption, a fixed number of Local Contractor Agents are responsible for the reconstruction, and no Out-of-town Contractor Agents exist in the simulation. The number of individuals working in the construction sector in the year before the disaster is obtained from the Bureau of Labour Statistics `https://www.bls.gov/oes/current/oes_ca.htm` (last accessed February 11, 2025) and used as a reference value. In each realization, this reference value is multiplied by a uniformly random number between 0.5 and 1.5 to add variability. The mean results for this scenario, shown as a solid red line, indicate that RAAbIT estimates align relatives well with empirical results under this modeling assumption. However, the arbitrarily selected uncertainty bounds (i.e., 0.5 and 1.5) add substantial uncertainty that is not minimized over time.

The last modeling alternative in RAAbIT is to use the supply-demand relationship. In this case, the recovery will be entirely driven by Out-of-town Contractor Agents attracted to the community due to a surge in demand. The willingness of contractors to come is a value between 0 (i.e., none come) and 1 (i.e., one contractor comes per unit of unmet demand). At the beginning of each realization, one value is chosen in this interval and held constant. The results in Fig. 2.c indicate that this modeling approach approximates the pace of recovery over time well, and uncertainty is reduced over time, yielding accurate results at the five-year mark. The subsequent analyses utilize this assumption due to its relative agreement with the empirical results and the advantage of eliminating the need to estimate the number of contractors in the community before the disaster.

The simulations described above are repeated for Paradise in Figure 2.d Figure 2.e, and Figure 2.f. The key difference in Paradise is that RAAbIT underestimates the start of the recovery process when using the constant and supply-demand dynamic assumptions for contractor availability. The Camp Fire's impact on Paradise was devastating, resulting in the loss of most homes and infrastructure. Consequently, the decision to rebuild for Paradise homeowners was expected to be a complex process. As such, the contribution of $T_{decision}$ is likely underestimated by RAAbIT's default assumption (e.g., $T_{decision} < T_{finance}$). A more sophisticated assumption for $T_{decision}$ would shift the start of the recovery to the right and better approximate the empirical curve. This highlights the importance of assessing the context of community and disaster when employing RAAbIT.

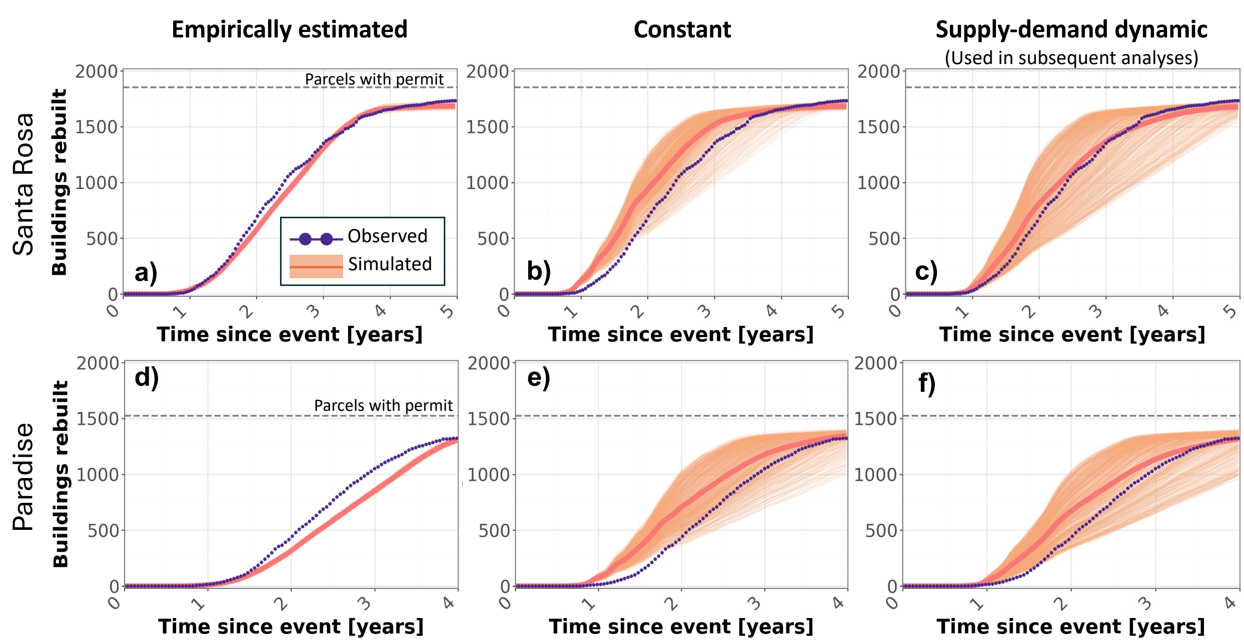

Figure 2: Estimated housing recovery curves for Santa Rosa (**a-c**) and Paradise (**d-f**) for difference assumptions regarding contractor availability. **a** and **d** use empirically-estimated time series of available contractors. **b** and **e** use a randomly selected constant number of available contractors. **c** and **f** use supply-demand relationships to dynamically estimate contractor availability.

2.2 RAAbIT Anticipates Housing Recovery Financing Sources

Estimating losses, recovery financing from different sources, and the expected unmet needs is helpful for recovery planning because it can anticipate the pace of recovery and potential inequalities (e.g., post-disaster indebtedness). Figure 3 shows the RAAbIT-estimated losses and federal assistance received by Santa Rosa after the 3.a-d, and in Paradise following the Camp Fire, 3.e-h. The leftmost panels show losses. The dashed and dotted lines represent estimates developed using methodologies from the California Department of Housing and Community Development (HCD) and the US Small Business Administration (SBA), which were used for recovery planning purposes. The methods yield different values because they account for slightly different steps needed for housing reconstruction. The gray bars represent the results of 1,000 RAAbiT realizations. The variability in RAAbIT's loss estimates is small. Hence, the histogram appears as a single bar.

Figures 3.b-d and Figures 3.f-h compare the simulated FEMA Housing Assistance (HA) and SBA Household, Personal Property Loss (HPPL), and CDBG-DR funding estimates to the amounts received by Santa Rosa and Paradise from these sources, respectively. The simulated estimates are uncertain due to random variables dictating Household Agents' behaviors (e.g., apply or not). The red dashed lines represent benchmark values collected from the OpenFEMA `https://www.fema.gov/about/reports-and-data/openfema` (last accessed February 11, 2025) and OpenSBA `https://data.sba.gov/dataset/disaster-loan-data` (last accessed February 11, 2025) portals, and have been linearly scaled down, as our database contains only a fraction of the destroyed buildings. Despite small discrepancies, the simulated results are within 25% of the benchmark values.

The CDBG-DR estimates for single-family, owner-occupied housing reconstruction were collected from the disaster recovery action plans developed by the HCD for each disaster [7, 8]. In both cases, HCD made an initial allocation of CDBG-DR funds towards single-family, owner-occupied housing reconstruction programs, which was later revised due to these programs being undersubscribed. The initial and final allocations are shown. The RAAbIT estimated values are closer to the final allocations, indicating that the model can better anticipate the real CDBG-DR needs than the HCD methodology.

Detailed descriptions of the process to obtain the benchmark values are shown in Appendix 8.4.

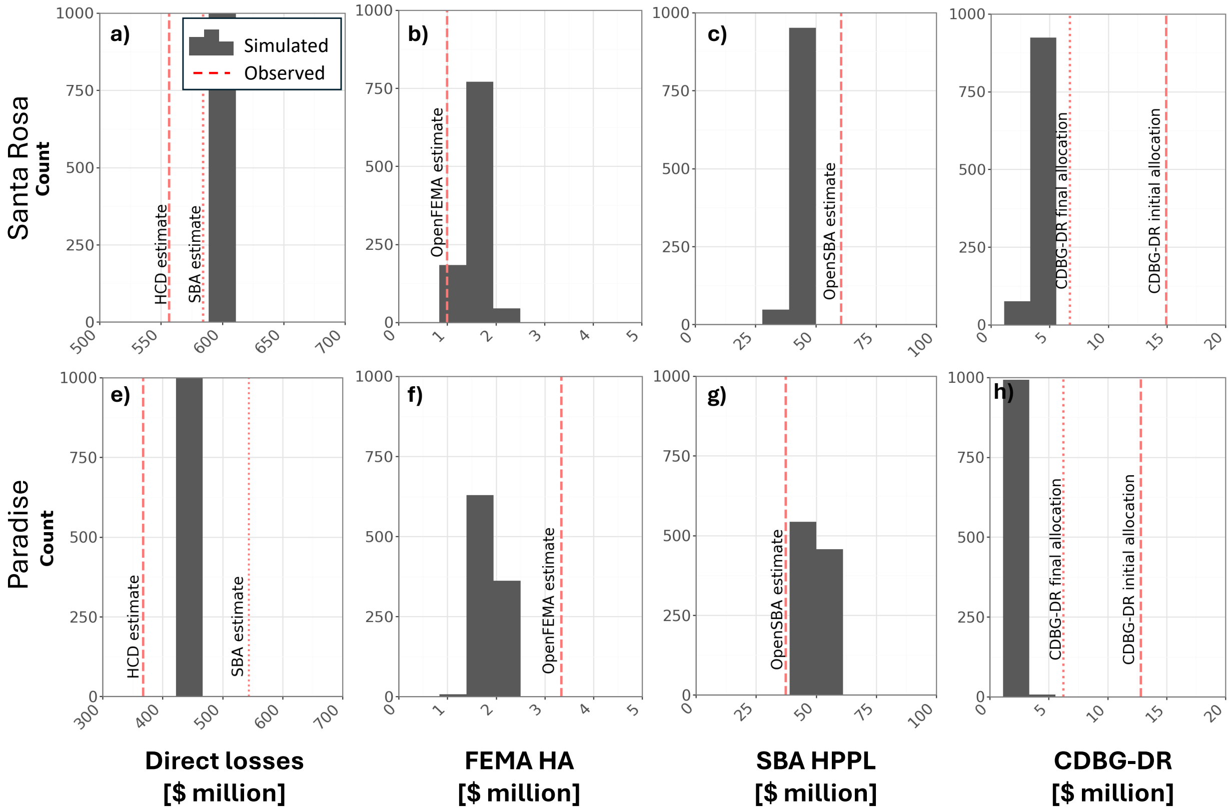

Figure 3: Estimated housing recovery losses for Santa Rosa **a-d** and Paradise **e-h**. **a** and **e**, Direct losses. **b** and **f**, FEMA Housing Assistance. **c** and **g**, SBA Household Personal and Property Loans. **d** and **h**, CDBG-DR allocation. The dashed lines represent benchmark values estimated from empirical sources as described in Appendix 8.4.

2.3 Capturing Spatial Recovery Patterns Requires Integrating Other Models

The final verification is whether simulation results can capture spatial patterns in recovery. Spatial patterns are expected in housing recovery due to uneven distribution of damages, resources, and demographics [e.g., 31, 41]. However, these spatial dependencies are likely strongly tied to the context of community and disaster, making it challenging to develop a model that can generally capture these patterns. In RAAbiT, the only variable that affects this pattern is the behavior of the contractor agents. As discussed in Section , three modeling alternatives are available to simulate how contractors prioritize the jobs they accept: urban density, first-come-first-serve, or random. Figure 4.a-c shows the results obtained with each modeling approach for Santa Rosa. The plots compare the spatial lag of the empirical recovery time (ordinate axis) to the spatial lag of the simulated results (abscissa axis). Each dot represents a building. For a building at location l, the spatial lag is calculated as the average recovery time for the five closest buildings to l. The agreement between empirical and simulated results is indicated by the dots aligning along the red dashed line, and it can be measured using a linear correlation metric, such as Pearson's correlation coefficient, ρ. While none of the modeling approaches yields close to perfect correlation (i.e., 1), assuming that contractor agents prefer to work in denser areas substantially increases the model's capacity to capture spatial patterns in housing recovery in Santa Rosa, reflecting the faster recovery in the denser southwest portion of the impacted area as shown in Fig. 1.b. Figure 4.d-f presents the same estimates for Paradise. Unlike in Santa Rosa, RAAbIT cannot capture the spatial correlation in Paradise's recovery under any assumptions. While the first-come-first-served assumption results in higher ρ, it does not capture the variability in results. As discussed earlier, Paradise's housing recovery appears tied to its infrastructure recovery. Because infrastructure recovery is not modelled in RAAbIT, it cannot capture the recovery spatial patterns in Paradise. Improving these results will require including models to represent the availability of utilities, services, and other community capitals.

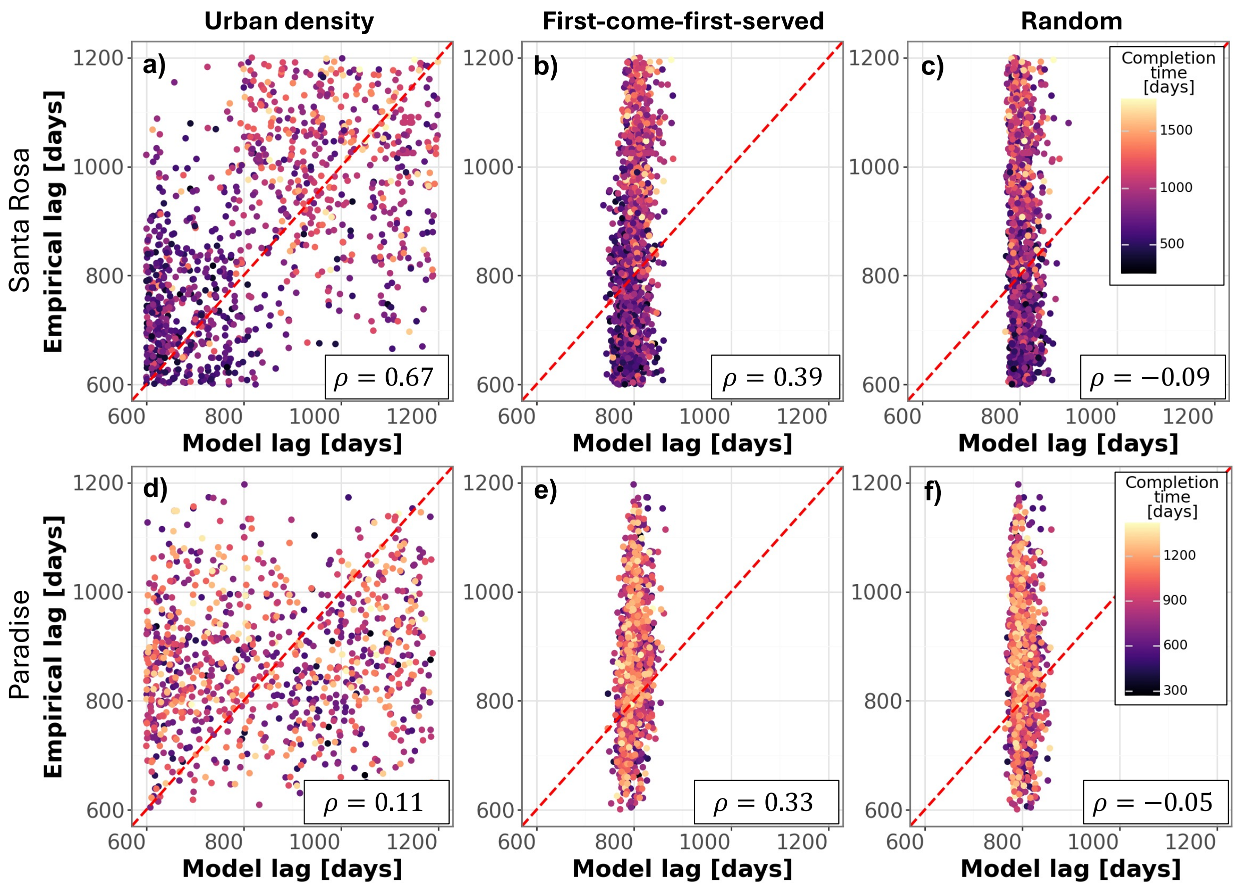

Figure 4: Estimated spatial correlation of recovery times for Santa Rosa (**a-c**) and Paradise (**d-f**). **a** and **d**, Assumes contractors prioritize jobs in denser areas. **b** and **e**, Assumes contractors prioritize jobs based on a first-come-first-served basis. **c** and **f**, Assumes contractors randomly select among the potential jobs.

2.4 Simulations Provide Insights on How Housing Recovery Can Be Improved

Finally, we discuss how RAAbIT can be used to deepen our understanding of recovery by evaluating the effects of 'what-if' scenarios. Figure 5 shows the mean results from 1,000 realizations under the different assumptions. The black lines represent the baseline simulated results, i.e., the red lines in Fig. 2.c-f. The blue line represents a scenario where building rebuild times do not exceed one year. This is achieved by redistributing the probability of ”13 or more” in Table 5 to the other alternatives, which can be implemented in practice by improving supply chains and expediting the occupancy permitting process. The yellow line shows a scenario where the city can attract more out-of-town contractors, i.e., R in Eq. 22 is $R \sim U(0.5, 1)$, instead of $R \sim U(0.25, 0.75)$ in the baseline scenario. Finally, the red curve combines the improvements in take-up rates and contractor availability. Increasing contractor availability expedites recovery but does not affect the number of rebuilt buildings in the long term. While reducing rebuild times and improving contractor availability have benefits, when both improvements are implemented simultaneously, they act synergistically, resulting in an expedited and more robust recovery process. For example, under the scenario with both improvements, there are nearly 75% more buildings rebuilt two years after each disaster. While the results Fig. 5 reflect how recovery could have been different in a past event, a similar exercise during recovery planning for a new event could evaluate the potential benefits of recovery-improving decisions, reducing uncertainty for decision-makers.

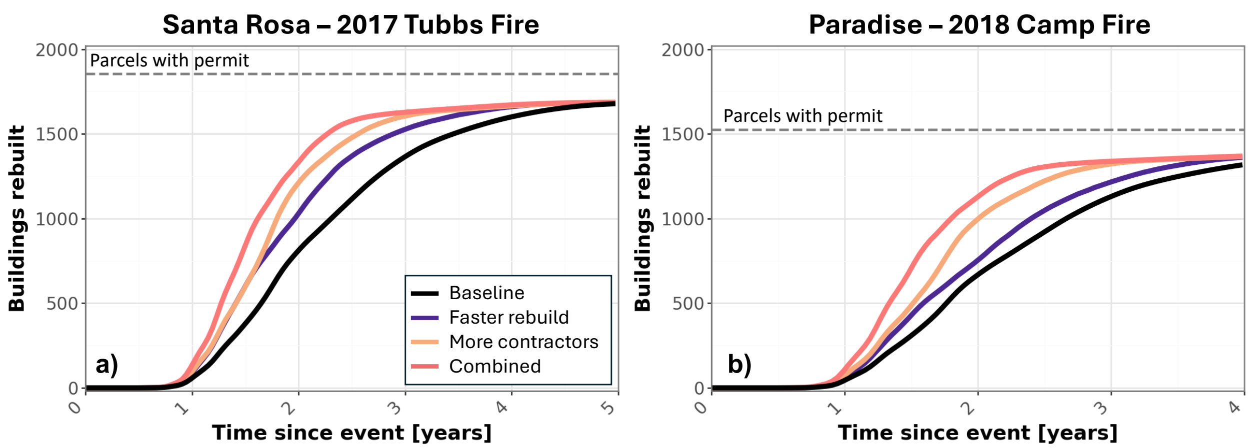

Figure 5: Estimated housing recovery curves under alternative scenarios. **a**, Results for Santa Rosa after the 2017 Tubbs Fire. **b**, Results for Paradise after the 2018 Camp Fire.

3 Discussions

We demonstrate that our proposed model can approximate well empirical housing recovery trends following two disasters. Beyond estimating recovery trends under the status quo, access to a housing recovery model enables decision-makers to assess the potential benefits and drawbacks of recovery-enhancing strategies. For example, after the 2017 Tubbs Fire, the HCD decided to use CDBG-DR funds to provide grants of up to $150,000. However, after the 2018 Camp Fire, these grant’s cap was $200,000. A practical application of RAAbIT could be to forecast recovery trends in the 2025 Los Angeles Fires and investigate whether recovery can be enhanced if an eventual CDBG-DR allocation is used to provide $150,000 to more individuals or $200,000 to potentially fewer households. In this context, RAAbIT can inform decisions and help minimize the long-term impacts of inefficient resource allocations. Accurate estimates of recovery progress can also help communities prepare for increased demand for skilled workers or materials, allowing them to train professionals locally if a shortage is expected and establish supply chain contracts for the provision of reconstruction materials.

Another practical use of RAAbIT is estimating unmet housing needs to inform CDBG-DR fund allocation under limited information. Currently, estimations of unmet needs rely on processing FEMA IA and SBA HPPL applications, which can take several months, as well as data from insurance claims that state housing authorities may not easily access. Moreover, individuals who do not apply for FEMA assistance are not accounted for in HUD's estimates of unmet housing needs. Incorrect estimates of unmet housing needs have led to delays in implementing CDBG-DR programs in past events [e.g., 18]. As shown in Fig. 3, RAAbIT's estimates of the required CDBG-DR, which can be obtained as soon as the number of damaged buildings is determined, align well with the revised calculations conducted by HCD about several years after the Tubbs and Camp Fires when better data were available.

The models and applications discussed in this study, as shown in Fig. 6, primarily focus on an application in the US. However, RAAbIT is versatile and can be adapted to other contexts. An application in another context (e.g., Canada) could be achieved by replacing the US-specific agents (e.g., FEMA, SBA, and HUD agents) with agents that represent local financing organizations (e.g., Public Safety Canada). Moreover, RAAbIT is hazard-agnostic as long as structural damage is the main driver of repair time; however, this may not be the case in applications where water damage is the main concern. Consequently, RAAbIT can be easily integrated into a workflow with other software dedicated to estimating regional disaster losses, [e.g., 22]. We anticipate this versatility will be a key feature for RAAbIT's adoption.

While we strive to develop an accurate model in this study, any computational model will incur simplifications. Post-disaster housing recovery is a complex problem, and predicting exact outcomes may be unrealistic, especially at the individual household level. Despite the good performance shown in this study, we argue that models such as RAAbIT are best suited for relative comparisons of trends across 'what-if' scenarios. Consider the example above where RAAbIT is used in the forecast recovery after the 2025 Los Angeles Fires and investigate the ideal cap for CDBG-DR grants. RAAbIT's limitations would be a common factor in the $150,000 and $200,000 cap scenarios. Thus, the impact of these limitations on the relative simulation results (e.g., ratio of results) is minimized, making the relative results a more robust metric.

Despite our efforts to collect empirical data to validate our model, we acknowledge limitations in the validation process. The first issue is that the permit data we employ for validation only includes buildings that had applied for a reconstruction permit when the data were collected. Thus, our data likely overrepresent buildings with a less challenging housing recovery process. Understanding the decision process for homeowners who did not rebuild requires a different type of model that focuses on individuals rather than buildings. Another issue relates to mismatches between official data reports. For example, FEMA assistance figures reported by HCD and FEMA diverge. Thus, it is challenging to confidently determine the benchmark values that indicate our model is accurate. In cases of divergence, we adopted the values closest to the source, e.g., FEMA in the case of FEMA assistance, but acknowledge this is a limitation.

Another limitation of our study is that RAAbIT, in its current implementation, lacks variables that capture spatial correlations in the housing recovery process. As a process, housing recovery is closely intertwined with the recovery of infrastructure and social networks, community services (e.g., schools, healthcare, employment opportunities), and macroeconomic and political factors. By simulating housing recovery as a resource-constrained, homeowner-driven process, RAAbIT does not fully capture some of these nuances, particularly in building-level results, as shown in Fig. 4. However, as shown in this study, this approach can capture aggregate metrics of recovery that are useful for planning recovery at the community level.

4 Conclusions

In this study, we develop an agent-based model to evaluate the long-term impact of disasters on communities and simulate the reconstruction of its building stock. The model simulates how owners of destroyed buildings interact with financing agencies to obtain funds (e.g., grants or loans) and service providers (e.g., contractors) to reconstruct their homes. The interactions between these relatively simple agents and their competition for limited resources allow us to partially capture the complexity of the simulated process. The model provides insights regarding housing recovery curves (i.e., the number of buildings rebuilt over time) and the expected unmet housing recovery needs (i.e., the gap between losses and the aggregated financing capacity of impacted homeowners). Thus, our agent-based model can be used in hindcasting exercises to understand how recovery could have been improved in previous disasters and deepen our understanding of this process, or in ’what-if’ scenario analysis to forecast the potential impact of different decisions on improving housing recovery.

The performance of our model is tested in a hindcast exercise where the model is used to predict housing recovery from two past disasters: the 2017 Tubbs Fire and the 2018 Camp Fire. To simulate data constraints, the model inputs include only data that would have been available within weeks of each event, such as past-year statistics and the number of destroyed buildings. Empirical housing recovery data from these events, comprising dates of reconstruction permit applicant and construction completion, serve as the benchmarks for the pace of recovery. Data from the US Federal Emergency Management Agency, the US Small Business Administration, the California Department of Insurance, and the California Department of Housing and Community Development are benchmarks for the unmet needs assessment. We demonstrate that our agent-based model can closely approximate both the housing recovery curves of fires and estimations of unmet needs. While the model performs well at estimating aggregating metrics (i.e., averages across the entire community), it has limitations in its capacity to predict recovery patterns at the building level.

5 Methodology

Figure 6 presents an overview of the agents in RAAbIT and their interactions. Household Agents are the drivers of the simulation. These agents represent households whose homes were affected by the disaster and who wish to rebuild their homes. For certain housing types, the reconstruction of the housing unit and the household's post-disaster state may be decoupled (e.g., rental housing). RAAbIT does not simulate this process. Hence, the Household Agents in RAAbIT are better interpreted as the household responsible for the costs of the building reconstruction - i.e., homeowners of owner-occupied homes or landlords. The first step in the reconstruction process for Household Agents is to secure the required financing. To do so, they interact with finance provider agents. The primary attributes of finance provider agents include their approval criteria, maximum amounts, and disbursement time. The approval criteria are a function of the requesting households' socioeconomic status and losses, which may lead to inequalities in access to financing. Household Agents may interact with one or multiple finance provider agents. In Fig. 6, finance provider agents represent organizations that exist in the US. The types of existing finance provider agents may change for applications outside the US. If a Household Agent obtains sufficient funds, they procure a contractor to conduct the physical repairs or reconstruction of the housing unit. In RAAbIT, the Job Market Agent tracks the supply and demand for contractors. This agent can create Contractor Agents if demand exceeds supply (e.g., a contractor comes to the community) or remove contractors (e.g., a contractor leaves the community) if supply exceeds demand. Service provider agents possess behaviors enabling them to prioritize specific households and benefit themselves, creating inequalities in the recovery process. While the behaviors of Finance Provider Agents are primarily adopted from previous work, Household and Service Provider Agents and their interactions are novel in this study. The following sections provide a detailed description of these agents.

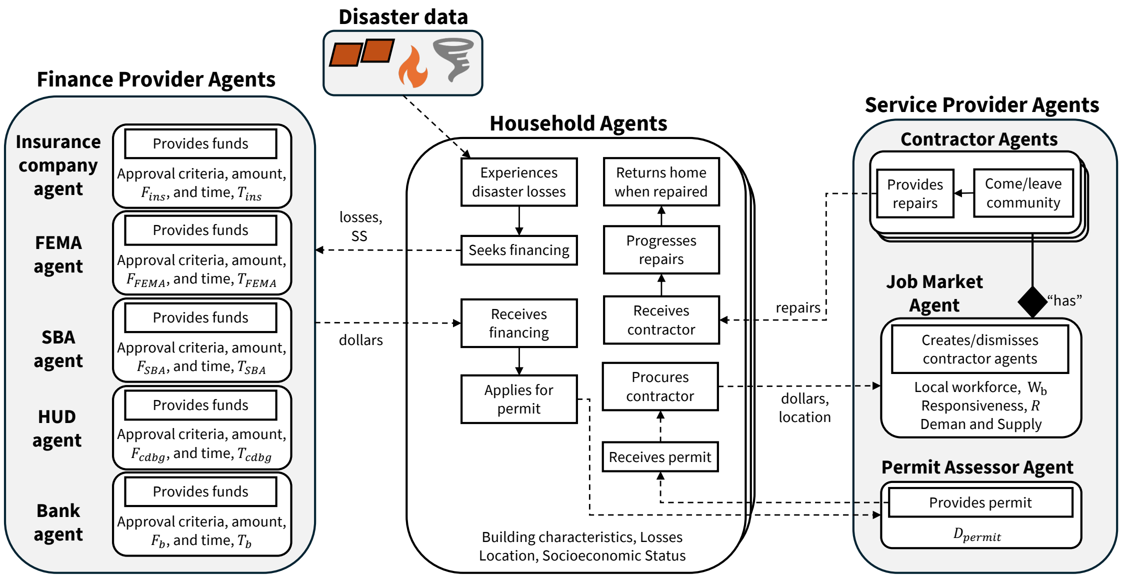

Figure 6: Overview of agents in RAAbiT.

5.1 Household Agents

Household Agents are central to RAAbIT. They represent the individuals in a community and the processes they must follow to repair or rebuild their homes after a disaster. The housing recovery process for each Household Agent comprises multiple steps. Each step has a duration associated with it, which is a function of the losses experienced, demographic characteristics of the households, and community features (e.g., availability of contractors). The total housing recovery time, T, is simulated as

$$T = \begin{cases} T_{decision} \\ T_{finance} \end{cases} + D_{permit} + \begin{cases} D_{materials} \\ D_{contractor} \end{cases} + T_{repair} \tag{1}$$

where $T_{decision}$ is the time to make a decision regarding repair or rebuild, $T_{finance}$ is the time to secure funds, D_{permit} is the time to obtain a building permit, $D_{materials}$ is the time to procure materials, $D_{contractor}$ is a delay due to unavailability of workers, T_{repair} is the time to conduct the repairs or rebuilt the building. These parameters are discussed in detail below. Other steps in the recovery process (e.g., clean up) are assumed to overlap with and take less time than the events explicitly included in Eq. 1.

5.1.1 Building Replacement Cost

The Federal Emergency Management Agency's methodology for estimating the replacement costs of homes is employed to estimate replacement costs [27]. The methodology splits costs into those associated with repairing main areas, garages, and basements and estimates the replacement cost for a building, B_{rc}, as

$$B_{rc}(ir) = A_{main} \cdot C_{main}(f, ir) + A_{bsm} \cdot C_{bsm}(f, ir) + \mathbf{1}_g \cdot C_g(f, cars, ir) \quad (2)$$

where A_{main}, A_{bsm} are the areas of the main floor and basement in square feet, $C_{main}(ir)$, and $C_{bsm}(f, ir)$ are the cost to replace one square foot of the main area, and basement based on the quality of the finish, f. For garages, a flat value, $C_g(f, cars, county)$, is added to the building replacement cost based on the presence of a garage, the quality of the finish, and the size of the garage, *cars*=1, 2, or 3 cars. The indicator function 1_g returns 1 if the building has a garage and zero otherwise. Tables that are used to determine A_{main}, A_{bsm}, C_{main}, C_{bsm} and C_g are available in the 2021 Hazus Inventory Manual [27] for all regions of the US. The tables are based on 2018 RSMeans estimates [17]. Inflation should correct the replacement cost estimates for applications in different years. The last factor in Eq. 2 is the income ratio, *ir*, defined as the ratio between the median income of the county and the census region where the building is located.

5.1.2 Decision Time

The decision time accounts for the household's decision to reconstruct. Households' decisions may be influenced by attachment to their community, the post-disaster housing market, and the community's availability of services and utilities, among other factors. In Eq. 1, the decision time $T_{decision}$ is considered different from the time to secure funds, $T_{finance}$. This decision to treat $T_{decision}$ and $T_{finance}$ differently in RAAbIT is due to the availability of data to model $T_{finance}$, as discussed below. However, decoupling $T_{decision}$ and $T_{finance}$ may be challenging because access to funds may expedite the decision to rebuild. Consequently, developing a universal model to estimate $T_{decision}$ may be unfeasible. For this reason, RAAbIT assumes $T_{decision} = 0$, resulting in a model that consistently underestimates housing recovery. Users have the alternative to include $T_{decision}$ as a fixed value or a probability distribution from which random draws are used to assign a $T_{decision} > 0$ for each Household Agent.

5.1.3 Financing Time

Household Agents may seek funds from multiple Finance Provider Agents. The first step in this process is to assess whether a Household Agent will apply for funding from a given source. Empirical studies show that a convoluted application process or the expectation of small grants can deter potential applicants [2, 21]. Moreover, studies indicate that lower-income households are overrepresented among grant applicants. To account for this, RAAbIT allows users to input the expected percentage of applicants for a given financing source. The model attributes lower-income households a higher probability of applying, defined as

$$P(Apply = yes) = 1 - LN((H_{inc} - \bar{H}_{inc})/S_{inc}); s, l, sc) \quad (3)$$

where $LN()$ is a lognormal distribution, H_{inc} is the household income, and $\bar{H}_{inc}$ and S_{inc} are the median and standard deviation of the household income. This model's shape, s, location, l, and scale sc parameters can be calibrated using historical application data for a given source.

The financing time, $T_{finance}$, represents the time Household Agents need to raise funds to rebuild their home. Household Agents interact with Finance Provider Agents sequentially until they have obtained the required funding or interacted with all selected Financing Agents based on Eq. 3. The amount of funding and the disbursal time are specific to each Financing Agent and are discussed in detail in subsection 5.2. The funding available to a Household Agent at time t is

$$F(t) = \sum_{i=1}^{F} \mathbf{1}_A(\boldsymbol{X}) \cdot \mathbf{1}_D(t) \cdot F_i(\boldsymbol{X}, Loss) + F_{savings} \tag{4}$$

where $\boldsymbol{X}$ is a vector of household demographics, $\mathbf{1}_A(\boldsymbol{X})$ is an indicator function that returns 1 if the application for funding from source i is successful, $\mathbf{1}_D(t)$ is an indicator function that returns 1 the disbursal time for funding source i is less than t, and $F_i(\boldsymbol{X}, Loss)$ is the amount of funding to be received from source i conditional on losses. Consequently, the financing time, $T_{finance}$, is

$$T_{finance} = \begin{cases} \min(t|F(t) \geq RC) & \text{if } \exists\, t \text{ where F(t)} \geq \text{RC} \\ \infty & \text{otherwise} \end{cases} \tag{5}$$

where RC is the repair cost for the building. Consequently, Household Agents that cannot secure sufficient funding are assumed unable to repair or rebuild their homes (i.e., $T_{finance} \approx \infty$). The term $F_{savings}$ represents the estimated savings estimated as,

$$F_{savings} = \mathbf{1}_s(H_{inc}) \cdot F_{stocks} \cdot m^s_{us \to r} + \mathbf{1}_r(H_{inc}) \cdot F_{retirement} \cdot m^r_{us \to r} \tag{6}$$

and a household's capacity to get a loan may be affected by its equity, estimated as

$$F_{equity} = \mathbf{1}_e(H_{inc}) \cdot F_{home} \cdot m^e_{us \to r} \cdot m^e_{r \to c} + \mathbf{1}_l(H_{inc}) \cdot F_{rental} \cdot m^l_{us \to r} \cdot m^l_{r \to c} + \mathbf{1}_o(H_{inc}) \cdot F_{other} \cdot m^o_{us \to r} \cdot m^o_{r \to c} \tag{7}$$

where F_{stocks} and $F_{retirement}$ are the average savings related to stocks and retirement accounts, and F_{home}, F_{rental}, and F_{other} are the average equities from own home, rental home, and other assets. Each Household Agent is assigned an income H_{inc} and a probability of having funds from source F_*. The indicator functions $\mathbf{1}_*(H_{inc})$ return 1 if a household with income H_{inc} has access to funds from a given source, and 0 otherwise. The multipliers $m^*_{us \to r}$ convert national averages to averages at the Census region (e.g., West for California). The 2020 values used in Eq. 6 and Eq. 7 are obtained from `https://www.census.gov/data/tables/2020/demo/wealth/wealth-asset-ownership.html` (last accessed February 2025) and corrected by the consumer price index in application in other years.

5.1.4 Service Delays

The time it takes for a Household Agent to obtain a permit, D_{permit}, hire a contractor, $D_{workforce}$, and get construction materials, $D_{materials}$, are called "delays" to emphasize that they are calculated differently from the other variables in Equation 1. Delays have a baseline value (i.e., potentially zero) but can be dynamically extended due to supply-demand imbalances. Thus, delays are a consequence of competition for limited resources and the behaviors of the Service Provider Agents. Details about the implementation of Service Provider Agents are discussed in Sec. 2.3.

5.1.5 Repair Time

The repair time T_{repair} represents the time between the start and completion of physical repairs for a building. The repair time is conditional on the level of damage. Five levels of damage are used based on the Hazus MH 4.2 [28]: none, minor, moderate, severe, and complete. We use repair times provided by Hazus for damage states ranging from none to severe. For complete damage, Hazus suggests that it takes 180 days to rebuild a home, which is significantly less than the average start-to-completion time for new residential construction in the US, as reported by the Census Bureau [11]. Consequently, we build a multinomial distribution based on the Census data to replace the Hazus estimate when the damage is complete. With this, the repair time T_{repair} is

$$T_{repair} \sim \begin{cases} 0 & \text{if no damage} \\ 2 & \text{if minor damage} \\ 30 & \text{if moderate damage} \\ 90 & \text{if severe damage} \\ f(a_1,\ldots,a_n;p_1,\ldots,p_n) & \text{if complete damage} \end{cases} \tag{8}$$

where a_* are time ranges, and p_* is the percentage of completions within the range in the Census data [11]. As an example, the values for a_* and p_* for California from 2015 to 2021 are presented in Appendix 8.1. Assuming linear progress in the recovery status of a home, the amount of per analysis time step, $R(t+\Delta t)$, is

$$R(t+\Delta t) = \min\left(\frac{1}{T_{repair}}\sum_{t=0}^{T_f} \mathbf{1}_C(t)\cdot\Delta t, 1\right) \tag{9}$$

where $\mathbf{1}_C(t)$ is an indicator function that returns 1 if a contractor crew was allocated to the building at time t, and Δt, is the simulation time step. The building is considered recovered when the recovery rate $R(t)$ equals the unity. At that time, the Household Agent dismisses the Contractor Agent allocated to the building.

5.2 Finance Provider Agents

RAAbIT includes multiple agents representing public and private organizations that can provide Homeowner Agents funding. The behaviors of the Finance Provide Agents mimic the criteria employed by their real-world counterparts to provide funds to a given homeowner. The approval probability and the amount received from each Finance Provider Agent are functions of the losses and attributes of the Homeowner Agents. Homeowner Agents interact with Finance Provider Agents sequentially; e.g., they wait for a decision from a grant agency before seeking a loan. It is assumed that homeowners prefer to seek funding from grants and low-interest loans before committing to market-rate loans. Some Finance Provider Agents are not activated for several months after the disaster. In this case, Homeowner Agents who can obtain funding from other sources, even at a higher cost, will not wait. The Finance Provider Agents are described in the following.

5.2.1 Insurance Company Agent

The Insurance Company Agent represents the insurance market in the community. One Insurance Company Agent is expected to be included in a simulation, and its behaviors approximate the average behavior of individual companies. The main attributes of the Insurance Company Agent are its deductible (d_{ins}), coverage (c_{ins}), and disbursal time ($T_{insurance}$. Insured Homeowner Agents submit a claim after a disaster. The Insurance Company Agent covers losses exceeding the deductible and up to the policy coverage equal to 100% of the replacement cost by default. This is an optimistic assumption since underinsurance is a common problem for disaster-struck households [34]. Deductibles are hazard-dependent but tend to be between 1% and 15% for fires. By default, the c_{ins} equals the pre-disaster home replacement cost. If post-disaster replacement costs are expected to be higher, users can reduce c_{ins} to simulate underinsurance. The disbursal time for insurance funds is modeled as a lognormal variable given by [1]

$$T_{ins} \sim lognormal(\mu_{ins} = 42 \text{ days}, \beta_{ins} = 1.11 \text{ days}) \tag{10}$$

5.2.2 FEMA Agent

The FEMA Agent provides grants that mimic the Federal Emergency Management Agency Individuals and Households Program (FEMA IHP). Housing Assistance (HA) grants for emergency home repairs are relevant for simulating housing recovery. The maximum HA grant is corrected annually for inflation, e.g., $41,000 in 2023 [35]. To estimate approval rates and approved amounts from the FEMA HA Model, we employ models developed by [18] based on historical data available from the OpenFEMA Portal [29]. The models estimate the probability that the outcome of an application for housing assistance is positive, $P(O_{FEMA,h} = yes)$, as

$$P(O_{FEMA,h} = yes|\boldsymbol{X}) = \begin{cases} o_1(\boldsymbol{X}) & \text{if } Loss < 5{,}000 \\ o_2(\boldsymbol{X}) + o_3(\boldsymbol{X}) \cdot Loss & \text{otherwise} \end{cases} \tag{11}$$

where o_1, o_2, and o_3 are constants that depend on the characteristics of the applicant households ($\boldsymbol{X}$), i.e., insurance status and income, and L is the disaster-induced loss (or repair cost). Similarly, the mean FEMA HA grant received by a successful applicant with characteristics defined by $\boldsymbol{X}$ are approximated as

$$F_{FEMA}(\boldsymbol{X}) = a_1(\boldsymbol{X}) \cdot L^2 + a_2(\boldsymbol{X}) \cdot L + a_3(\boldsymbol{X}) \tag{12}$$

where a_1, a_2, and a_3 are coefficients that depend on the household characteristics. The average time for a FEMA IHP grant is 37 days [47]. Here, we assume that the disbursal time for the FEMA Agent could vary $\pm$ 10 days, that is

$$T_{FEMA} \sim U(a = 27, b = 47) \text{ days} \tag{13}$$

where $U(a,b)$ is a uniform random variable between a and b. Successful Homeowner Agent applicants receive F_{FEMA} dollars after T_{FEMA} days. Parameters used in Equations 11 and 12 are provided in the Appendix 8.2.

5.2.3 SBA Agent

The SBA Agent provides low-interest loans to households affected by disasters. The approval criteria, loan characteristics, and disbursement time mimic those of the Small Business Administration Household and Personal Property Loans (SBA HPPL) Program. Data on SBA HPPL applications between 2008 and 2019 were collected and used to develop a model to estimate the likelihood of success conditioned on experienced losses, $P(O_{SBA,h} = yes|L)$, as

$$P(O_{SBA,h} = yes|L) = \begin{cases} min(1, \exp(-0.0053 \cdot \ln(L)^2 + 0.2394 \cdot \ln(L) - 2.2594)) & \text{if } L > 0 \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

The amount provided by the SBA Agent to a successful application is estimated by a linear relationship based on summary statistics provided by [16] from 285,260 SBA-approved loans. However, as its real-world counterpart, the SBA Agent does not fund expenses covered by insurance or FEMA grants. Combining the criteria above, we estimate the amount of SBA funding as

$$F_{SBA} = \begin{cases} min(SBA_{cap}, L - F_{insurance} - F_{FEMA}, 1891.9 + 0.4692 \cdot L) & \text{if non-failed} \\ 0 & \text{otherwise.} \end{cases} \tag{15}$$

where SBA_{cap} is the maximum loan (i.e., \$500,000 since August 2023, and \$200,000 earlier `https://disasterloanassistance.sba.gov/ela/s/article/Home-and-Personal-Property-Loans` (Last accessed February 2025)), $F_{insurance}$ is the funding from insurance, and F_{FEMA} is FEMA IHP funding. The disbursement time for SBA loans is given by

$$T_{SBA} \sim lognormal(\mu_{SBA} = 45, \beta_{SBA} = 0.57) \text{ days} \tag{16}$$

, and it is assumed that successful applicants receive F_{SBA} dollars after T_{SBA} days.

5.2.4 Bank Agent

The Bank Agent is a proxy for the private institutions that provide loans. The loanee's (i.e., Homeowner Agent) gross debt-to-income ratio limits the Bank Agent's loans which must be backed by collateral [e.g., 12]. The loan is calculated as a new mortgage, that is

$$P = G \cdot \Big(H_{\text{inc}}/12\Big) \cdot \Big((1+r)^M - 1\Big) / \Big(r \cdot (1+r)^M\Big) \tag{17}$$

where P is the maximum loan amount, G is the maximum gross debt-to-income ratio that the Bank Agent accepts, H_{inc} is the annual loanee income, r is the monthly interest rate, and M is the loan maturity in months. To receive the loan P, a household must have collateralizable assets that amount to P. In RAAbIT, a homeowner's collateral, C, is at least equal to home equity, discounted from disaster-induced repair costs. It is assumed that an asset cannot be used as collateral more than once. Consequently, funding from SBA loans is also discounted from the home equity. Thus, the maximum loan provided by the Bank Agent is

$$F_{\text{bank}} = \min(P, E_h - L - F_{SBA}, L - F_{insurance} - F_{FEMA} - F_{SBA}) \tag{18}$$

where E_h is the home equity discounted of losses and SBA loans. The disbursal time for loans provided by the Bank Agent is modeled as [1]

$$T_{bank} \sim lognormal(\mu_{bank} = 60, \beta_{bank} = 0.68) \text{ days} \tag{19}$$

Suggested values for the parameters in Equations 17, and 19 are provided in the Appendix **??**.

5.2.5 HUD Agent

The HUD Agent represents the US Department of Housing and Urban Development (HUD) and provides funding to households mimicking the Community Development Block Grant for Disaster Recovery (CDBG-DR) grants program [32]. HUD does not interact directly with households affected by disasters. They provide funding to state housing authorities, which they disburse to the most impacted areas. As such, the HUD Agent represents the state housing authority in managing the CDBG-DR funding. We opted to call it the HUD Agent to indicate the funding source. The HUD Agent's behaviors are defined by the HUD's Homeowner Compensation Program (HCP) criteria. Consequently, the HUD Agent cannot cover expenses funded by insurance, FEMA IHP, or SBA HPPL funding to avoid duplication of benefits. Thus, the maximum a household may receive from HUD's CDBG-DR, F_{CDBGDR}, is

$$F_{CDBGDR} = min\Big(\underbrace{L - F_{insurance} - F_{FEMA} - F_{SBA}}_{\text{unmet needs}}, CDBG_{max}\Big) \tag{20}$$

where $CDBG_{max}$ is a cap established by the state housing authority. The disbursal of CDBG-DR funds comprises multiple tasks. Funds are first appropriated by HUD ($\Delta T_{\text{appropriation}}$), then allocated by Congress ($\Delta T_{\text{allocation}}$), then awarded to state authorities (ΔT_{award}), and disbursed to households over time ($\Delta T_{\text{first}} + u(0,1) \cdot \Delta T_{90\% \text{ expenditure}}$). Considering this, the disbursal time for the CDBG-DR Agent is modeled as

$$T_{\text{CDBG-DR}} = \Delta T_{\text{appropriation}} + \Delta T_{\text{allocation}} + \Delta T_{\text{award}} + \Delta T_{\text{first}} + u(0,1) \cdot \Delta T_{90\% \text{ expenditure}} \tag{21}$$

where $u(0,1)$ is a uniformly distributed random variable and $\Delta T_{90\% \text{ expenditure}}$ is a proxy of the duration of the program. Parameters used in Equations 20 and 21 are provided in the Appendix 8.3.

5.3 Service Provider Agents

5.3.1 Permit Assessor Agents

The Permit Assessor Agent reflects the community's capacity to process permit applications. A generic model for permit application delays may misrepresent aspects of the disaster and the community of interest. Thus, such a model is not offered in RAAbIT. Instead, RAAbit provides three alternatives (i.e., modes) for user input models. The simplest model requires a constant value to be provided, $D_{permit} = constant$. The second alternative is to draw values from a user-provided probability distribution, $F_X()$, that is, $D_{permit} = F_X^{-1}(U(0,1))$. The final alternative is inputting a time series of delays comprised of pairs $\{$t:$D_{permit}(T = t)\}$ and Household Agents that apply for a permit at time t will be assigned a delay as a function of t, $D_{permit} = f(t)$.

5.3.2 Materials Provider Agents

RAAbIT does not include a model to account for delays due to construction materials shortages. That is, by default, $D_{materials} = 0$ in Eq. 1. Properly estimating $D_{materials}$ would require simulating the supply chain for various materials and household reconstruction decisions (e.g., rebuild to the pre-disaster standard or not). Disasters affect supply-demand patterns, may impact community access and block supply chains, or lead to a change in the types of materials used, making pre-disaster data a limited predictor of post-disaster demand. In the absence of a detailed model of material availability, RAAbIT offers users the ability to input a probability distribution that represents the expected delays due to materials shortage. We believe that data from previous disasters can help build such a model.

5.3.3 Job Market and Contractor Agents

The Job Market Agent is a supporting agent whose main purpose is to simulate the contractor supply and demand. Its main attribute is its responsiveness, R. If the market is fully responsive, $R = 1$, for each unit of contractor demand, one new Contractor Agent is added to the simulation. Similarly, for each unit of contractor surplus, one Contractor Agent is removed from the simulation. If $R = 0.5$, two units of demand are required for a new contractor to be added to the simulation. If $R = 0$, no contractors are added or removed. The Job Market Agent may also have a baseline number of contractors which permanently exist in the simulation. More broadly, the number of contractors to be added in a given simulation is step, C_{new}, is

$$C_{new}(t+\Delta t) = R \times \underbrace{\Big(C_a(t) + C_h(t)\Big)}_{demand} - \underbrace{\Big(C_a(t) + C_w(t)\Big)}_{\text{supply}} \tag{22}$$

where negative numbers indicate a surplus of contractors.

Contractor Agents represent the workforce available in the community. In job markets with $R < 1$, demand may exceed the supply of Contractor Agents, forcing them to prioritize requests from certain Household Agents. Contractor Agents may prioritize based on *density*, causing them to prioritize requests from Household Agents in denser areas. Empirical studies of post-disaster housing recovery demonstrated that denser areas tend to recover more quickly [33, 44]. Multiple factors may contribute to these patterns, including easier access, quicker reestablishment of critical infrastructure, and economies of scale. In RAAbIT, a Gaussian kernel density estimator (KDE) is used to determine the density of damaged buildings around a location $\boldsymbol{z}$ as,

$$KDE(\boldsymbol{z}) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{2\pi}\frac{1}{|\boldsymbol{H}|}\exp\Big(-\frac{1}{2}\big(\boldsymbol{z}-\boldsymbol{z_i}\big)^T\boldsymbol{H}\big(\boldsymbol{z}-\boldsymbol{z_i}\big)\Big) \tag{23}$$

where $\boldsymbol{H}$ is a two-dimensional bandwidth matrix that smooths the Gaussian kernels centered at $\boldsymbol{z}$. Silverman's rule [45] is used to determine $\boldsymbol{H}$. The density of damaged neighbours is calculated for each building at the beginning of the simulation and used by the contractor agents to assign priority, i.e., higher density equals higher priority. If Contractor Agents behavior is set to *first-come-first-served*, they will prioritize requests as they are received, implicitly prioritizing Household Agents with more access to funding since this will lead to earlier requests. Lastly, if the behavior is set to *random*, Contractor Agent will randomly select a Household Agent among those seeking a contractor at time step t.

6 Data Availability

The data required to replicate the results of this study are available via Zenodo at `https://doi.org/10.5281/zenodo.15586155`.

7 Code Availability

The files with custom code required to replicate the results of this study are available via Zenodo at `https://doi.org/10.5281/zenodo.15586155`.

8 Appendix

This Appendix provides detailed information regarding default values for parameters in RAAbIT to facilitate replication of the results in this study.

8.1 Household Agents

This section describes the default values used in RAAbIT's Household Agent. Table 2 provides the average dollar values for different sources of home equity and savings in the US by income quintile. Table 3 provides the US average percentage of households with home equity and savings. Table 4 provides multipliers to convert national averages to Census area averages. For example, the average Californian in the West Census area has 2.3 times more stocks and shares than the average American. The values in Tables 2, 3, and 4 are obtained from `https://www.census.gov/data/tables/2020/demo/wealth/wealth-asset-ownership.html` (last accessed February 2025). Lastly, Table 5 shows the distribution of time to build new single-family homes in the US per year, which is used to estimate the reconstruction time for destroyed buildings.

Table 2: Constants used to estimate the dollar value of savings and equity for Household Agents based on national averages.

Income quintile	Stocks & shares [$] ($F_{stocks}$)	Retirement accounts [$] ($F_{retirement}$)	Home equity [$] ($F_{home}$)	Rental equity [$] ($F_{rental}$)	Other equity [$] ($F_{other}$)
Lowest	10,000	22,000	100,000	140,000	38,800
Second	19,000	25,000	120,000	110,000	55,000
Third	20,000	40,000	130,000	105,000	50,000
Fourth	21,000	74,000	150,000	156,000	70,000
Highest	75,200	220,000	218,000	226,000	120,000

Table 3: Constants used to estimate the percentage Household Agents with savings and home equity based on national averages.

Income quintile	Stocks & shares [%]	Retirement accounts [%]	Home equity [%]	Rental equity [%]	Other equity [%]
Lowest	7.3	17.4	37.1	2.1	2.5
Second	14.5	44.5	53.4	4.1	4.7
Third	22.2	63.5	62	5.2	6.6
Fourth	30.8	79.2	74.1	7.8	10.2
Highest	50.8	89.8	83	15.2	16.9

Table 4: Multipliers used to convert savings and home equity national averages to Census area values.

Census region	Stocks & shares ($m^s_{us \to r}$)	Retirement accounts ($m^r_{us \to r}$)	Home equity ($m^e_{us \to r}$)	Rental equity ($m^l_{us \to r}$)	Other equity ($m^o_{us \to r}$)
Northeast	2.50	2.32	1.52	1.43	1.60
Midwest	1.25	1.90	0.85	1.14	1.10
South	1.50	1.53	0.95	1.38	1.44
West	2.30	2.00	2.00	2.38	2.00

Table 5: Distribution of time to build new single-family homes in the US [11].

	Percent distribution[1]						
Months	2015	2016	2017	2018	2019	2020	2021
3 or less	5	1	4	4	2	2	0
4 to 6	21	19	22	16	8	13	16
7 to 9	26	29	25	21	17	14	20
10 to 12	14	18	13	19	20	26	23
13 or more	34	34	36	40	54	44	40

[1]May not add to 100 due to rounding.

8.2 Federal Emergency Management Agency Housing Assistance Grants

The FEMA HA model is based on previous work by the authors [18, 19] and parameters established by the Federal Emergency Management Agency at `https://www.federalregister.gov/documents/2024/01/22/2024-00677/individual-assistance-program-equity`[1] (Last accessed February 2025) and `https://www.fema.g` ov/press-release/20240216/what-expect-after-applying-fema[2] (Last accessed February 2025). The parameters of this model are shown in Tables 6 and 7.

Table 6: Parameters used in Eq. 11 to estimate FEMA IA approval rates.

Insurance status	Income	Equation parameter o_1	o_2	o_3
Uninsured	Very low	0.527	0.838	-3.3e-6
Uninsured	Low	0.523	0.829	-2.2e-6
Uninsured	Moderate	0.519	0.799	-1.9e-6
Uninsured	High	0.518	0.756	-7.9e-6
Insured	Very low	0.294	0.577	-2.8e-6
Insured	Low	0.290	0.556	-4.2e-6
Insured	Moderate	0.297	0.541	-3.8e-6
Insured	High	0.303	0.481	-3.9e-6

All fits resulted in R-squared > 0.95

Table 7: FEMA Agent Attributes

Attribute [units]	Default value	Source
[1]Current cap[$]	42,500 in 2024	1
[2]Disbursement time [days]	U(10,30)	2

8.3 HUD CDBG-DR Grants

To estimate $T_{\text{CDBG-DR}}$, we calculate the averages of data collected by [37], where $T_{\text{appropriation}} = 0.6$ years, $\Delta T_{\text{allocation}} = 0.2$ years, and $T_{\text{award}} = 0.2$ years. The grant caps for the Tubbs Fire and Camp Fire are collected from the action plans developed by the California Department of Housing and Community Development available at https://www.hcd.ca.gov/grants-and-funding/disaster-recovery-and-mitigation/action-plans-and-federal-register-notices-frns (last accessed February 2025).

Table 8: HUD Agent Attributes

Attribute [units]	Model value Santa Rosa	Paradise
Grant cap [$]	150,000	200,000
Appropriation delay [year]	0.6	0.6
Allocation delay [year]	0.2	0.2
Award delay [year]	0.2	0.2
1^{st} expenditure delay [year]	0[1]	0
Program duration [year]	1.9[1]	1.9

[1]For housing repair expenses.

8.4 Benchmark Recovery Financing Values

For the Tubbs Fire, the action plan developed by the California Department of Housing and Community Development (HCD) provides two estimates for the replacement cost for a building destroyed by the 2017 fires in California. The first estimate, \$300,000, is an HCD-estimated average, whereas the second is an SBA-estimate at \$314,968. Considering the 1,855 buildings in Santa Rosa in the case study, losses should be in the order of \$556.5 million to \$584.3 million. Data collected from the OpenFEMA portal indicate Sonoma County (where Santa Rosa is located) received \$2.13 million in FEMA housing repair assistance [29]. Note that only single-family, owner-occupied buildings are eligible for FEMA housing repair assistance. According to the Action Plan, 3,044 single-family buildings were destroyed in Santa Rosa, out of which 2,061 were owner-occupied buildings. The case study data comprised 965 single-family, owner-occupied buildings. Hence, if the FEMA assistance is evenly distributed among buildings and corrected by the under-representation of owner-occupied buildings in our sample, the FEMA IHP received should be in the order of \$1 million (i.e., $(965/2,061) \times 2.13$). Data from the OpenSBA portal indicate Sonoma County received \$99.3 million. If evenly split among all buildings in the case study, Santa Rosa should have received close to \$60.5 million (i.e., $(1,855/3,403) \times 99.3$). Lastly, the action plan allocates \$21.47 million CDBG-DR dollars to housing repair and reconstruction of owner-occupied housing. Sonoma County accounted for 67% of the total disaster losses in California in 2017 [7]. Thus, we estimate the CDBG-DR going to Sonoma County at \$6.7 million ($(965/2,061) \times 0.67 \times 21.4$)

The benchmark values for the Camp Fire case are estimated similarly. As per Figure 58 in the HCS 2018 Action Plan [8], the cost of replacement per square foot in Butte County was \$153.25 and on average, each building has 1,574 square feet. According to Figure 59 in the 2018 Action Plan, the average replacement cost per building in Butte County was \$356,549. Thus, losses across the 1,524 buildings in our dataset are estimated to be in the range of \$367.61 million to \$543.39 million. Data collected from the OpenFEMA portal indicate Butte County received \$34 million in FEMA housing repair assistance. According to the Action Plan, 7,133 single-family, owner-occupied buildings were destroyed in Butte County. The case study data comprised 702 single-family, owner-occupied buildings. Hence, if the FEMA assistance is evenly distributed among buildings, the simulated results should be in the order of \$3.34 million ($(702/7133) \times 34$. Data from the OpenSBA portal indicate Butte County received \$291 million. If evenly split among all buildings in the case study, Santa Rosa should have received close to \$37.3 million (i.e., $(1,524/11,888) \times 291$). According to Figure 60 in the Action Plan, all disasters in California in 2018 caused \$11.9 billion in housing-related losses, of which \$7.56 billion were experienced in Butte County. California received \$205.1 million in CDBG-DR assistance for the reconstruction of single-family, owner-occupied homes. Assuming even distribution, Butte County should receive \$130.3 million. Since our data set represents 6% of these buildings, the estimated CDBG-DR funding should be in the order of \$12.78 million (i.e., $(702/7133) \times 130.3$).

9 Supplementary Materials - Overview, Design concepts and Details Structure for RAAbIT

9.1 Overview

9.1.1 Purpose

The RAAbIT (Recovery Assessments with Agent-based Tools) model simulates post-disaster housing recovery to understand the dynamics of rebuilding processes, including inequalities in access to financing and resources, labor market dynamics, and the impact of community-level factors on recovery timelines. It aims to inform disaster planning and policy by modeling interactions among households, finance providers, and contractors following disasters such as hurricanes or earthquakes.

9.1.2 Entities, State Variables, and Scales

The model includes the following entities and their state variables:

Scales:

- **Spatial Scale**: Community level, with households located in specific neighborhoods, enabling density-based analyses.

- **Temporal Scale**: Post-disaster recovery period, with discrete time steps representing days or weeks, covering months to years.

9.1.3 Process Overview and Scheduling

The main processes in RAAbIT are:

1. **Decision to Rebuild**: Assumed instantaneous ($T_{\text{decision}} = 0$) unless the user specifies a fixed value or probability distribution.

2. **Securing Financing**: Households interact sequentially with finance providers (Insurance $\rightarrow$ FEMA $\rightarrow$ SBA $\rightarrow$ Bank $\rightarrow$ HUD) until sufficient funds are obtained or all options are exhausted.

3. **Obtaining Building Permit**: Households apply to the Permit Assessor Agent, incurring a delay (D_{permit}).

4. **Procuring Materials**: Not modeled explicitly; assumed no delay ($D_{\text{materials}} = 0$) unless the user inputs a distribution.

5. **Hiring Contractors**: Households hire Local or Out-of-town Contractors, with delays ($D_{\text{workforce}}$) due to availability and prioritization.

Entity	State Variables
Household Agents	- Socioeconomic Status: Income (H_{inc}), homeownership status (owner-occupied or landlord) - Losses: Damage level (none, minor, moderate, severe, complete) based on Hazus MH 4.2 methodology - Financing Status: Funds secured from each finance provider (e.g., $F_{\text{stocks}}, F_{\text{retirement}}, F_{\text{home}}$) - Reconstruction Status: Current stage in recovery (e.g., decision, financing, permitting, repair) - Location: Spatial coordinates for density calculations
Finance Provider Agents	- Type: Insurance, FEMA, SBA, Bank, HUD - Approval Criteria: Specific to each type (e.g., logistic regression for FEMA, debt-to-income ratio for Bank) - Maximum Amounts: Caps on funding (e.g., $41,000 for FEMA HA in 2023) - Disbursal Times: Time to provide funds (e.g., lognormal for Insurance)
Service Provider Agents (Contractors)	- Type: Local Contractor or Out-of-town Contractor - Availability: Number of contractors available - Prioritization Behavior: Density-based (using Gaussian kernel density estimator) or other user-defined behaviors - Response Ratio (R): For Out-of-town Contractors, willingness to enter the community (0 to 1)
Permit Assessor Agent	- Permit Delay (D_{permit}): User-defined (constant, probability distribution, or time series)
Environment	- Community Features: Spatial distribution of households, infrastructure availability - Replacement Costs: Calculated using Hazus methodology (e.g., $B_{\text{rc}} = A_{\text{main}} \cdot C_{\text{main}}(f, ir) + A_{\text{bsm}} \cdot C_{\text{bsm}}(f, ir) + 1_g \cdot C_g(f, \text{cars}, \text{ir})$)

Table 9: Entities and their state variables in the RAAbIT model.

6. **Conducting Repairs or Reconstruction**: Repair time (T_{repair}) depends on damage level, using Hazus or Census data.

The total recovery time (T) for each household is modeled as:

$$T = T_{\text{decision}} + T_{\text{finance}} + D_{\text{permit}} + D_{\text{materials}} + D_{\text{contractor}} + T_{\text{repair}} \tag{24}$$

Processes are executed in discrete time steps, with durations and delays calculated dynamically based on agent interactions and system state.

9.2 Design Concepts

9.2.1 Basic Principles

RAAbIT is grounded in agent-based modeling principles, simulating heterogeneous agents (households, finance providers, contractors) with distinct behaviors and decision-making processes. It emphasizes resource competition, socio-economic disparities, and spatial dynamics in post-disaster recovery.

9.2.2 Emergence

Community-wide recovery patterns, such as overall recovery timelines and inequalities (e.g., by income or location), emerge from the individual decisions and interactions of Household, Finance Provider, and Service Provider Agents.

9.2.3 Adaptation

- Households adapt by selecting finance providers based on approval likelihood and seeking contractors based on availability.
- Contractors adapt by prioritizing households (e.g., in denser areas) to optimize their workload.

9.2.4 Objectives

- **Households**: Minimize recovery time by securing funds and hiring contractors efficiently.
- **Finance Providers**: Disburse funds according to their criteria (e.g., FEMA prioritizes need-based grants).
- **Contractors**: Maximize benefit by prioritizing households based on density or other strategies.

9.2.5 Learning

Learning is not explicitly modeled, but households may implicitly adjust strategies (e.g., applying to alternative finance providers after denials).

9.2.6 Prediction

Households predict their ability to secure funds and hire contractors based on their attributes (e.g., income, losses) and system state (e.g., contractor availability).

9.2.7 Sensing

- Households sense the availability of funds from finance providers and contractors in the community.

- Contractors sense demand (e.g., unmet demand triggers Out-of-town Contractor entry).
- Finance Providers sense household attributes (e.g., income, losses) to determine approval.

9.2.8 Interaction

- **Direct Interactions**: Households apply for funds from Finance Providers, hire Contractors, and apply for permits from the Permit Assessor.
- **Indirect Interactions**: Competition for limited resources (e.g., contractors) creates market dynamics; density-based prioritization influences recovery patterns.

9.2.9 Stochasticity

- Financing approval probabilities (e.g., FEMA, SBA) are stochastic, based on logistic regression models.
- Disbursal times (e.g., Insurance) follow lognormal distributions.
- Repair times for complete damage use a multinomial distribution.
- User-defined delays (e.g., permits) may involve random draws from distributions.

9.2.10 Collectives

While not explicitly modeled, spatial density effects (e.g., contractor prioritization using Gaussian kernel density estimation) create collective behaviors, as households in denser areas recover faster.

9.2.11 Observation

Model outputs include:

- Recovery times for individual households and the community.
- Inequalities in recovery (e.g., by income, location).
- Resource utilization (e.g., total funds disbursed, contractors employed).
- Spatial patterns of recovery (e.g., density-based recovery rates).

9.3 Details

9.3.1 Initialization

- **Households**: Initialized with attributes from census data, including income (H_{inc}), home value, and damage level (based on Hazus MH 4.2). Assigned probabilities for accessing savings or equity (e.g., F_{stocks}, F_{home}).
- **Finance Providers**: Initialized with type-specific parameters:
  - Insurance: Deductible (d_{ins}), coverage (c_{ins}), lognormal disbursal time.
  - FEMA: Logistic regression model for approval ($P(O_{\text{FEMA},h} = \text{yes})$), maximum grant (e.g., $41,000 in 2023).
  - SBA: Approval model ($P(O_{\text{SBA},h} = \text{yes}|L)$), loan characteristics.
  - Bank: Loan limits based on debt-to-income ratio and collateral.
  - HUD: Grant limits avoiding duplication of benefits.
- **Contractors**: Local Contractors initialized based on pre-disaster workforce availability; Out-of-town Contractors initialized with zero presence, activated by unmet demand with response ratio R.
- **Permit Assessor**: Initialized with user-defined permit delay parameters (constant, distribution, or time series).

9.3.2 Input Data

- **Census Data**: Household attributes (e.g., income, homeownership) from sources like the 2020 Census Wealth and Asset Ownership tables.
- **Hazus Data**: Replacement costs and repair times from the 2021 Hazus Inventory Manual and Hazus MH 4.2.
- **Historical Data**: Financing approval models (e.g., FEMA, SBA) from OpenFEMA Portal.
- **Construction Data**: Repair times for complete damage from U.S. Census Bureau residential construction data.
- **User-Defined Data**: Permit delays, material shortage distributions, contractor behaviors.

9.3.3 Submodels

- **Decision Submodel**: $T_{\text{decision}} = 0$ by default, assuming instantaneous decision to rebuild. Users can specify a fixed value or probability distribution.
- **Financing Submodels**:

  - **Insurance**: Covers losses above deductible (d_{ins}, 5–25%) up to coverage (c_{ins}, typically pre-disaster replacement cost). Disbursal time follows a lognormal distribution.
  - **FEMA**: Approval probability: $P(O_{\text{FEMA},h} = \text{yes}) = \text{logit}^{-1}(\beta_0 + \beta_1 X_1 + \cdots)$, based on historical data. Maximum grant adjusted for inflation (e.g., \$41,000 in 2023).
  - **SBA**: Approval probability: $P(O_{\text{SBA},h} = \text{yes}|L)$, based on losses and historical data (2008–2019). Low-interest loans with specific disbursal times.
  - **Bank**: Loans limited by gross debt-to-income ratio and collateral (e.g., new mortgage calculation).
  - **HUD**: Grants up to $F_{\text{CDBGDR}} = \max(0, \text{total loss} - \text{other funds})$, avoiding duplication.
  - **Funding Calculation**: Total funds at time t:

$$F(t) = F_{\text{stocks}} \cdot 1_{\text{stocks}}(H_{\text{inc}}) \cdot m_{\text{us}\to r}^{\text{stocks}} + F_{\text{retirement}} \cdot 1_{\text{retirement}}(H_{\text{inc}}) \cdot m_{\text{us}\to r}^{\text{retirement}} + \cdots \tag{25}$$

- **Permit Delay Submodel**: User-defined options:
  - Constant value.
  - Probability distribution for random assignment.
  - Time series of delays ($\{t : D_{\text{permit}}(T = t)\}$).
- **Material Delay Submodel**: Default: $D_{\text{materials}} = 0$. Optional: User-defined probability distribution for shortages.
- **Contractor Submodel**:
  - **Local Contractors**: Prioritize households based on density (Gaussian kernel density estimator):

$$\text{Density}(\boldsymbol{z}) = \text{KDE}(\text{damaged buildings at } \boldsymbol{z}) \tag{26}$$

    Alternative user-defined behaviors possible.
  - **Out-of-town Contractors**: Attracted by unmet demand, with number proportional to response ratio R:

$$N_{\text{out-of-town}} = R \cdot \text{unmet demand} \tag{27}$$

    Prioritize households using same behaviors as Local Contractors if $R < 1$.
- **Repair Time Submodel**: For none to severe damage: Hazus MH 4.2 repair times. For complete damage: Multinomial distribution based on U.S. Census Bureau data (average 180+ days).

9.4 Verification and Validation

- **Verification**:
  - **Code Debugging**: Ensures logical consistency and error-free implementation.
  - **Sensitivity Analysis**: Tests model robustness by varying parameters (e.g., approval rates, contractor availability) and analyzing output variance.
  - **Statistical Methods**: Variance and range of outputs to assess stability; Analysis of Variance (ANOVA) to evaluate parameter significance.
- **Validation**:
  - **Empirical Validation**: Comparison with historical disaster recovery data (e.g., FEMA, SBA approval rates from OpenFEMA).
  - **Spatial Validation**: Density-based recovery patterns compared to empirical studies showing faster recovery in denser areas.
  - **Statistical Methods**: Logistic regression to validate financing approval probabilities; correlation analysis for recovery times; descriptive statistics for outcomes.
- **Limitations**: Assumption of $T_{\text{decision}} = 0$ may underestimate recovery times; lack of material shortage modeling limits realism; validation depends on historical data availability.

9.5 Visualization

9.5.1 Conceptual Diagram of Agents and Interactions

- **Description**:
  - **Nodes**: Household Agent, Finance Provider Agents (Insurance, FEMA, SBA, Bank, HUD), Service Provider Agents (Local Contractor, Out-of-town Contractor), Permit Assessor Agent.
  - **Links**: Household applies for funds, permits, hires contractors; Finance Providers approve/deny funds; Contractors perform work; unmet demand triggers Out-of-town Contractor entry.

9.6 Flowchart for Household Recovery Process

- **Description**: Steps from decision to rebuild (T_{decision}) to completing repair (T_{repair}), with annotations for durations/delays.

Agent Type	Key Attributes	Interactions	Behaviors
Household	Income, damage level, financing status, location	Apply for funds, permits, hire contractors	Seek funds sequentially, hire available contractors
Finance Provider	Approval criteria, max amounts, disbursal times	Approve/deny funds	Type-specific approval models (e.g., logistic regression)
Local Contractor	Availability, prioritization behavior	Perform repairs, prioritize households	Density-based prioritization (KDE)
Out-of-town Contractor	Availability, response ratio R	Perform repairs, enter based on demand	Same as Local Contractors if $R < 1$
Permit Assessor	Permit delay parameters	Issue permits	User-defined delay models

Table 10: Summary of RAAbIT agents and their interactions.

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