Collecting and Prioritizing Building Information via Online Microtasks for Tsunami Evacuation Shelter Selection

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ABSTRACT

Securing sufficient tsunami evacuation shelters is essential for reducing tsunami casualties, but designating new facilities is costly for local governments. An alternative is to use existing private buildings, though potential candidates reach tens of thousands. While crowdsourcing is promising, its practical quality remains unclear. We set two research questions and conducted crowdsourcing experiments: (1) How feasible is it to collect reliable building information through online micro-tasks in crowdsourcing? (2) Are there any batch strategies to choose candidate buildings in order to maximize evacuation population coverage while accounting for possible refusals under the uncertainty? To answer the questions, we evaluated the quality of crowd-collected building information. Then, we formulated the task as a Maximum Coverage Problem with domain-specific constraints and analyzed an approximation algorithm with theoretical guarantees. Results show that crowdsourcing yields usable data quality and that the proposed prioritization approach is effective, demonstrating the feasibility of crowdsourcing-based evacuation shelter planning.

Keywords

Crowdsourcing, Tsunami Evacuation, Shelter Selection, Maximum Coverage, Spatial Optimization

INTRODUCTION

Securing adequate tsunami evacuation shelters is essential for reducing human casualties, yet many coastal municipalities still face a shortage of suitable sites (Zhang et al. 2019; Liu and Hao 2025; Inoguchi and Tamura 2024). Providing a sufficient number of shelters is constrained by evacuation time (Zhang et al. 2019). Table 1 summarizes the time to start evacuation in different settings. Since Kuji City, Iwate Prefecture, reports that the first tsunami wave may arrive in as little as 30 minutes after an earthquake (River Division, Maintenance Department, Kuji City, Iwate Prefecture 2022), we have only eight effective minutes for movement on winter nights.

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Table 1. Time from earthquake occurrence to beginning evacuation (Kuji, Iwate Prefecture 2022)

	Immediate Evacuation	*Evacuation after preparation*
Daytime	5 min (7 min in winter)	10 min (12 min in winter)
Nighttime	15 min (17 min in winter)	20 min (22 min in winter)

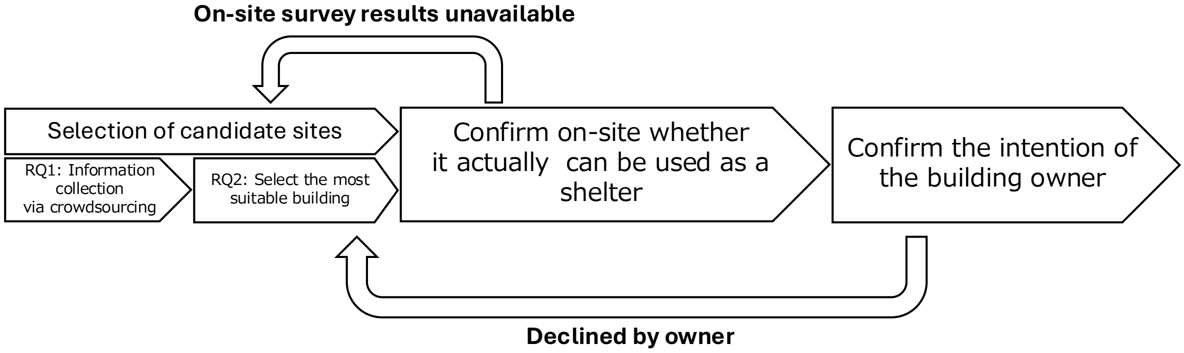


Figure 1. Overall workflow for tsunami shelter designation. The phase *Information Collection via Crowdsourcing* addresses RQ1, while *Select the most suitable building* addresses RQ2.

Traditionally, shelters have been selected from a narrow pool of public buildings such as schools or community centers after costly on-site surveys to assess structural soundness and capacity (Inoguchi and Tamura 2024).

Recent studies highlight the promise of re-purposing existing private buildings as temporary vertical-evacuation sites (Inoguchi and Tamura 2024). Through expert-led on-site inspections, they surveyed 66 non-wooden buildings (three or more stories), with experts physically visiting each location. This labor-intensive process identified 12 suitable sites that could reduce tsunami-inaccessible areas by 3.76 km^2, potentially enabling roughly 199 additional residents to reach safety based on Kuji City's population density of 53 people/km^2. These figures illustrate both the impact and the resource intensity of current practice. The problem of this approach, however, is that the evaluation was conducted by a small number of experts; the sheer scale of potential candidates (often tens of thousands) renders conventional field inspection impractical. The effects of utilizing more scalable human resources, such as the crowd, would be interesting but not addressed.

In this study, we propose a three-phase approach to designate existing buildings as evacuation shelters: (1) select candidate buildings based on on-hand information, (2) visit each building to verify requirements, and (3) ask owners to confirm that their buildings can be used as shelters (see Figure 1).

Due to limited resources, we cannot apply a brute-force method that checks every building through all phases. Instead, we must pick a small number N of buildings while considering how many people we can cover. If we are allowed to physically visit N buildings within the given budget, the ideal strategy (ignoring time efficiency) is a building-at-a-time iterative process: select the most valuable building, verify it on-site, obtain permission, and then repeat under the updated shelter set. If a candidate is rejected, the process backtracks and selects the next-best option. In reality, such an iterative strategy is not realistic in terms of time and cost efficiency. We therefore explore a non-iterative three-phase batch method that uses micro-task-based crowdsourcing to streamline early screening of candidate buildings in the first phase. Beyond technical scalability, we position this workflow as a citizen-science information system for disaster management, with primary empirical focus on preparedness: online crowdworkers contribute structured building observations through microtasks, while municipalities retain accountability for final on-site verification and designation. This role-sharing aligns with whole-of-society and participatory-governance principles by combining broad public participation with institutional decision authority (Goodchild et al. 2010; Ramchurn et al. 2013; Groß et al. 2023).

While attractive, two challenges must be addressed. First, incomplete imagery or local constraints may cause unsuitable buildings to be accepted in screening. Second, the batch-style non-iterative approach requires us to prioritize candidates under uncertainty because the workflow does not allow backtracking to earlier phases in the flow chart.

Accordingly, we investigate the following research questions:

(RQ1) How feasible is it to collect *reliable* building information through online micro-tasks?

(RQ2) Are there any batch strategies to choose candidate buildings in order to maximize evacuation population coverage while accounting for possible refusals under the uncertainty?

To address RQ1, we evaluate whether the checklist proposed by Inoguchi and Tamura (2024) can be accurately completed through crowdsourcing. For RQ2, we translate the shelter selection problem into a tractable expected-coverage maximization formulation.

Our contributions are twofold. First, a crowdsourcing experiment demonstrates that practically usable data quality can be achieved online (RQ1). Second, our prioritization method matches the accuracy of exhaustive search while remaining computationally tractable (RQ2).

This paper follows a workflow-oriented structure aligned with the three-phase shelter designation process. After reviewing related work, we first evaluate the feasibility of crowdsourced screening for building attributes (RQ1), and then formalize and validate candidate prioritization under uncertainty (RQ2). This ordering mirrors the two distinct decision phases in practice: scalable pre-screening and budget-limited site-visit prioritization. The problem formulation appears in RQ2 because it corresponds to the second decision phase. We then summarize this three-phase workflow and position RQ1 and RQ2 within it.

RELATED WORK

We review four strands of prior work that jointly define our contribution: quality-controlled crowd-based mapping for risk analysis, community-centered participation across the disaster life cycle, and optimization-based shelter planning.

Crowdsourced building assessment

Street-view audits show that non-experts can label accessibility or structural attributes with useful accuracy (Hara, Le, et al. 2012; Hara, Sun, et al. 2014). Large-scale systems such as *Project Sidewalk* (Saha et al. 2019), *Polygon Consensus* (Budig et al. 2016), and global OpenStreetMap quality analysis (Biljecki et al. 2023) demonstrate scalable volunteer mapping of building-related attributes. Disaster-focused microtask frameworks, including Thakur et al. (2021) and MapSwipe (Groß et al. 2023), show that imagery-based labeling can be performed quickly. Although these findings support the feasibility of crowdsourcing for candidate screening at scale, they do not provide specific frameworks to the problem of collecting and prioritizing building information for Tsunami evaluation shelter selection. Recent work also highlights two additional points relevant to our setting: remote mapping quality must be explicitly assessed before operational use (Eckle and de 2015), and participatory mapping can capture local risk knowledge that is useful for preparedness-oriented planning (Klonner et al. 2016; Schelhorn et al. 2014).

Crowdsourcing for disaster coordination and response

CollabMap shows how simple online tasks can assemble evacuation routes for civil defense (Ramchurn et al. 2013). Mobile-phone anomaly detection reveals spontaneous shelters after earthquakes (Ochiai et al. 2022), complementing our goal of selecting sites before an event. Hybrid ML-and-crowdsourcing methods speed geolocation of disaster imagery (Firmansyah et al. 2024), while the vision of volunteered geographic information (Goodchild et al. 2010) and social-media integration for rescue scheduling (Kabir and Madria 2019) underline the growing role of citizen data. Open academic crowdsourcing infrastructures such as Crowd4U have also been supporting disaster-related microtask workflows (Morishima et al. 2014). ISCRAM studies on volunteer coordination and recovery processes also show that citizen participation remains central across later disaster phases (Reuter et al. 2013; Rogstadius et al. 2013; Neef et al. 2013).

Co-production, resilience, and critical perspectives

Recent disaster studies argue that communities should be treated as co-producers of risk knowledge rather than passive data providers (Lejano et al. 2021). Coastal resilience frameworks also stress that governance, infrastructure, and social capacity must be considered together (Almutairi et al. 2020). In parallel, critical crisis-informatics work warns that crisis data are partial and that information systems can shape which risks and groups become visible in decision processes (Crawford and Finn 2015; Soden and Palen 2018). These perspectives motivate our design choice to use crowdsourcing as a decision-support layer with explicit quality checks and municipal accountability, rather than as an automated replacement for institutional judgment.

Table 2. Experiment Details

Item	*Value*
Reward per person	110 JPY = 0.77 USD (5 Jun 2025)
Number of tasks per person	3
Number of participants	30

Shelter location and maximum coverage optimization

The Maximum Coverage Location Problem (Church and ReVelle 1974) and its greedy $(1 - 1/e)$ approximation (Khuller et al. 1999) underpin shelter placement. Tsunami-specific coverage analysis (Zhang et al. 2019) and evacuation simulation platforms such as EURASIM (Chondrogiannis et al. 2021) extend this foundation. Recent models optimize emergency facility placement or evacuation time (Matinrad and Granberg 2024; Liu and Hao 2025) but assume a predefined candidate set and do not address large-scale screening or acceptance uncertainty. Our RQ2 model integrates expected-coverage optimization with crowdsourced screening and preserves the submodularity guarantee while weighting gains by acceptance probability.

Across the four strands above, our paper extends prior work to preparedness-oriented municipal planning by converting crowdworker-generated building observations into a transparent prioritization workflow for tsunami shelter candidate selection, while keeping the outputs usable for downstream response and recovery updates (Shackleton 2018; Jayasiri and Prasanna 2022; Reuter et al. 2013; Rogstadius et al. 2013; Neef et al. 2013).

METHOD OVERVIEW

The workflow (Figure 1) proceeds in three phases: (1) online screening of candidate buildings, (2) on-site verification of structural requirements, and (3) owner confirmation. If resources were unlimited, the ideal strategy would be an iterative, building-at-a-time process: select the most valuable building, verify it on-site, obtain owner permission, and then re-optimize the next choice given the updated shelter set. If a candidate is rejected, the process backtracks and selects the next-best option. In practice, however, this sequential strategy is too costly and slow to repeat N times. Because the number of site visits is limited, candidates must be selected in advance to maximize expected evacuation coverage while accounting for potential refusal. We therefore combine scalable online screening (RQ1) with expected-coverage optimization and greedy selection (RQ2).

RQ1: CROWDSOURCING BUILDING INFORMATION QUALITY

In this section, we evaluate whether crowdsourcing can provide building information of sufficient quality for selecting tsunami evacuation shelters, addressing RQ1.

Inoguchi and Tamura (2024) developed a comprehensive checklist for identifying suitable evacuation buildings through expert-led field surveys. While this method ensures high accuracy, it requires significant time and expertise. Their approach relies on trained experts visiting each candidate building to assess structural materials, deterioration levels, floor counts, rooftop accessibility, and available evacuation space. We adapt this checklist to online microtasks using Google Street View, enabling screening at scale (2,279 buildings) while assessing the quality tradeoff.

Task design and platform setup

We submitted microtasks to a crowdsourcing platform and verified the quality of the results. The workers were recruited via Lancers, a major crowdsourcing platform in Japan. In the experiment, workers were asked to annotate buildings for which we already had ground truth data, and the annotations were evaluated by comparing them with the correct answers. Details of the task request on Lancers are shown in Table 2.

The task consists of a Google Street View window and a structured questionnaire. Figure 2 shows an example task. In this setup, workers complete the task by referring to the Google Map on the right and entering information into the form on the left.

Figure 3 shows how to operate the map section. A tsunami icon marks the target building, and workers can drag the orange figure in the bottom-right corner of the screen to a nearby street to enter Street View mode and observe the surroundings. Workers inspect multiple viewpoints and enter observations in the form. If the building is not visible, they may skip the task.

Table 3. List of Building Attributes

Attribute	*Choices*
Material	Wood, Reinforced Concrete, Not sure
Deterioration	Old, Not old, Not sure
Number of Floors	1, 2, ..., 20, 21 or more, Not sure
Accessibility to Rooftop (Multiple choice)	External stairs, Ladder, Internal stairs
Evacuation Space	Yes, No, Not sure
Usage	Commercial building, Office building, Apartment, Private residence, Not sure

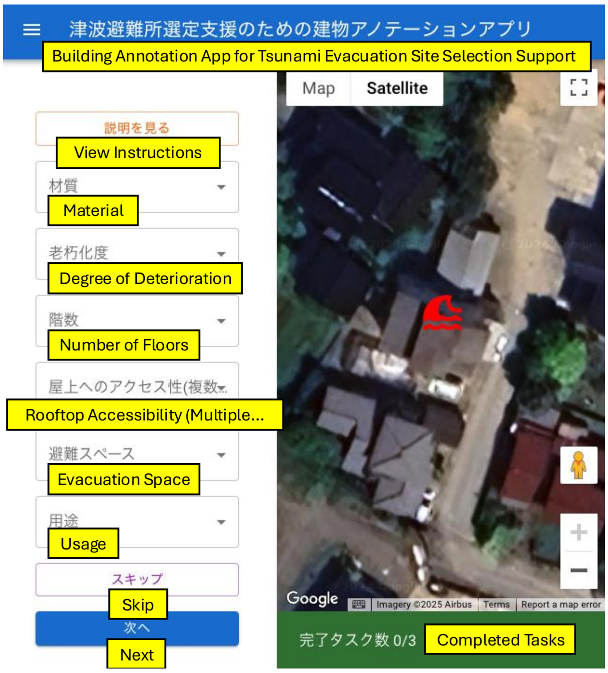


Figure 2. Example task

Table 3 shows the questions developed by Inoguchi and Tamura (2024). We consulted one of the authors and replaced the free-text form with a set of choices. As a result, all items except for 'Accessibility to Rooftop' became single-choice questions. Since some building features may not be visible in Street View, a 'Not sure' option is included for the single-choice items. For rooftop accessibility, workers selected from external stairs, ladder, and internal stairs using a multiple-choice format (no explicit 'Not sure' option). This judgment was based on visible exterior evidence from street-level views and map/aerial imagery; no indoor inspection was used in this RQ1 validation. If rooftop access could not be inferred from observable cues (e.g., potential internal access not visible from outside), workers could leave the rooftop-access options unselected.

For 'Material,' we limited the options to wooden structures and reinforced concrete. Although there are steel-framed buildings that resemble wooden structures, they are generally not robust and thus unsuitable as shelters. Additionally, workers may not have detailed architectural knowledge, so we simplified the choices for practicality.

Data sources and gold-standard construction

To conduct the experiment, coordinates and ground truth data of the target buildings were needed. We considered three data sources: the Google Maps API, the Overpass API, and ZENRIN Building Point Data. Since scraping is prohibited by the Google Maps API and detailed building data is often unavailable in Japan through the Overpass API, we used ZENRIN Building Point Data for Takaoka City, Toyama Prefecture.

The building point data provides coordinates and basic attributes for each building. However, ZENRIN does not include all the attribute types required for our experiment (such as building material, deterioration status, rooftop accessibility, and evacuation space availability). Therefore, while we utilized ZENRIN's coordinate data to lo-

Figure 3. Operation flow of the Google Map section

Table 4. Accuracy of the gold-standard creators' adjudicated consensus against the author's annotations on 10 sampled buildings (Kuji City). The overall accuracy is computed using Usage (Res. vs. Non-res.), Material, Evacuation Space, Deterioration, Accessibility to Rooftop, and Number of Floors (allowing one-floor underestimation).

Attribute	*Accuracy*
Usage	90.0%
Usage (Res. vs. Non-res.)	100.0%
Material	30.0%
Evacuation Space	100.0%
Deterioration	90.0%
Accessibility to Rooftop	100.0%
Number of Floors	80.0%
Number of Floors (allowing one-floor underestimation)	90.0%
Overall (all attributes)	85.0% (51/60)

cate target buildings, we created ground-truth data for these additional attributes through manual annotation and adjudication.

In this experiment, we first constructed gold-standard answers for the dataset. Two annotators were recruited and given a guideline describing how to determine the correct values. The guideline addressed ambiguous cases, such as buildings presenting different floor counts from various viewing angles. To ensure consistency, the guideline instructed annotators to report the minimum visible floor count when such discrepancies occurred. They independently labeled all items, then adjudicated any discrepancies to produce a single agreed set of answers. The initial inter-annotator agreement (before adjudication) was 83.3% across all attributes. Because official datasets rarely provide fine-grained attributes such as rooftop accessibility, we intentionally constructed the gold standard from the same Street View evidence available to crowdworkers, enabling a fair and conservative feasibility evaluation.

To assess the reliability of the gold-standard creators, we conducted a 10-question test using Kuji City data. We shuffled the dataset and sampled 10 buildings, then compared their adjudicated consensus against the author's answers. Accuracy was computed per attribute, and overall accuracy was computed across all 6 attributes for 10 buildings (60 attribute matches). Results are summarized in Table 4. Although we see low accuracy for building material, this is caused by the misclassification of wooden construction to reinforced concrete. Therefore, we can recover the error in the second verification phase. All other attributes have perfect and good accuracy. For number of floors, exact estimation from appearance can be difficult, so we report both exact matching and one-floor underestimation tolerance, since overestimation could be critical in evacuation planning.

Evaluation metrics and results

We evaluated crowdworker attributes against the adjudicated gold standard. For each attribute, we calculated accuracy across all responses including 'Not sure'. For all attributes except 'Number of Floors' (which has many potential values), we computed precision, recall, and F1-score. For 'Number of Floors,' we also report accuracy with one-floor underestimation tolerance. For 'Usage,' since the acceptance probability α may vary by usage, we also aggregated results by broader usage, grouping them into 'residence' and 'non-residence' to see if workers

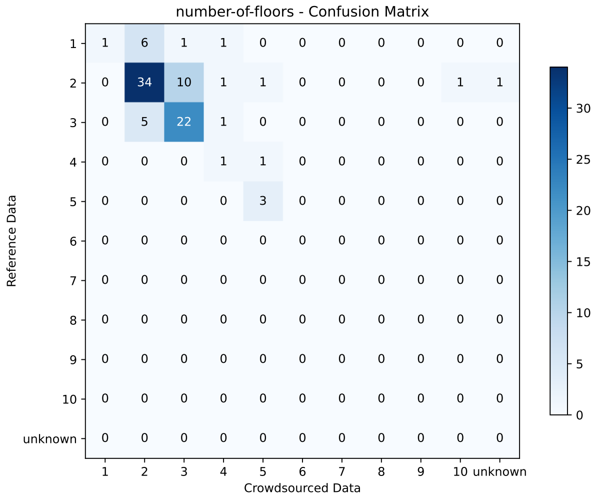


Figure 4. Confusion matrix showing the distribution of floor count estimation errors by crowdworkers

could distinguish at that level. For rooftop accessibility, because the task was multiple choice without an explicit 'Not sure' option, no-selection cases were treated as 'Not sure' during evaluation.

Due to a technical issue with the platform, data from one participant (out of 90 total) could not be retrieved. To maintain consistency in the dataset size, this participant's responses were filled with 'Not sure' for all attributes.

The results are shown in Table 5. Usage accuracy was 68.9%, rising to 82.2% when grouped into residential versus non-residential. Exact floor count accuracy was 67.8%, improving to 87.8% with one-floor underestimation. Figure 4 shows that most errors are one-floor underestimates. Material accuracy was 61.1%. Evacuation space and deterioration achieved 61.1% and 67.8% accuracy, while rooftop access was the most challenging at 53.3%.

Discussion

Crowdsourcing provides usable screening signals for attributes tied to height and broad usage categories, which are central for filtering candidates. Material identification shows modest accuracy but high precision for reinforced concrete, meaning positives are reliable even if some true cases are missed; rooftop access remains harder to assess reliably and should be confirmed during on-site verification. Since approximate heights are sufficient for screening, grouping floors into broader ranges (e.g., 1–3, 4–6, 7+) can further stabilize classifications.

RQ2: CANDIDATE PRIORITIZATION UNDER UNCERTAINTY

RQ1 establishes which building attributes can be screened reliably and provides the data quality estimates used to weight candidate reliability. These filtered candidates and reliability rates become the inputs to the prioritization model. We now formalize the selection problem and present the optimization approach.

We investigate a batch strategy to choose candidate buildings that considers the possibility of rejection. Table 6 summarizes the notations.

Problem Formulation

Due to budgetary constraints for shelter selection, the number of candidate sites that can be visited for on-site inspection is limited to $M \in \mathbb{N}$. Let $\mathcal{B}$ be a set of all buildings, and each building i has acceptance probability α_i as a shelter when visited for on-site inspection. $\mathcal{S} = \{s_1, ..., s_N\} \subseteq \mathcal{B}$ be a set of existing shelters, and let $C = \{c_1, ..., c_M\} \subseteq \mathcal{B} \backslash \mathcal{S}$ be a set of candidate shelters. To note, for simplicity of description, we define acceptance probability $\alpha_j = 1$ for each existing shelter $s_j \in \mathcal{S}$.

The problem is to find a set of candidate shelters $C \subseteq \mathcal{B}$ which contains M elements that maximizes an objective function $F : 2^{\mathcal{B}} \to \mathbb{R}$. Formally, the problem is defined as follows:

$$\max_{C \subseteq \mathcal{B}, |C|=M} F(\mathcal{S} \cup C). \tag{1}$$

Table 5. Results of Crowdsourcing Experiment (N/A indicates cases where precision/recall were undefined due to zero division. The overall accuracy is computed using Usage (Res. vs. Non-res.), Material, Evacuation Space, Deterioration, Accessibility to Rooftop, and Number of Floors (allowing one-floor underestimation).)

Attribute	*Label*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Usage	Apartment	68.9%	97.7%	87.5%	92.3%
	Private residence		40.0%	54.5%	46.2%
	Commercial building		66.7%	44.4%	53.3%
	Office building		36.4%	40.0%	38.1%
	Not sure		22.2%	66.7%	33.3%
Usage (Res. vs. Non-res.)	**Residential**	**82.2%**	**89.7%**	**88.1%**	**88.9%**
	Non-residential		**87.0%**	**71.4%**	**78.4%**
	Not Sure		**22.2%**	**66.7%**	**33.3%**
Material	Reinforced Concrete	61.1%	96.4%	62.8%	76.1%
	Wood		0.0%	N/A	N/A
	Not sure		10.0%	25.0%	14.3%
Evacuation Space	Yes	61.1%	63.6%	53.8%	58.3%
	No		69.4%	72.3%	70.8%
	Not sure		0.0%	0.0%	N/A
Deterioration	Not old	67.8%	98.0%	65.8%	78.7%
	Old		27.8%	90.9%	42.6%
	Not sure		33.3%	33.3%	33.3%
Accessibility to Rooftop	Inside Stairs	53.3%	3.4%	50.0%	6.5%
	Ladder		33.3%	20.0%	25.0%
	Outside Stairs		12.5%	25.0%	16.7%
	Not Sure		0.0%	N/A	N/A
Number of Floors	-	67.8%	-	-	-
Number of Floors (allowing one-floor under-estimation)	**-**	**87.8%**	**-**	**-**	**-**
Overall	All attributes	68.9%	-	-	-

The objective function F evaluates the desirability of a selected set of candidate shelters. In this study, the objective function is defined as *the number of additional people who become able to evacuate as a result of the selected shelters*.

This maximization can be cast as a Maximum Coverage problem, for which a greedy algorithm provides a $(1-1/e)$-approximation guarantee (Khuller et al. 1999). To handle uncertainty in feasibility, we weight each candidate by

Table 6. Parameters and Definitions

Parameter	*Definition*
Basic Sets and Constraints	
$\mathcal{B}$	Set of buildings
$\mathcal{S}$	Set of currently designated evacuation shelters
$\mathcal{C}$	Set of candidate buildings for new shelters
$\mathcal{H}$	Set of hexagonal cells for spatial discretization
M	Maximum number of site inspections and owner negotiations that can be conducted
Coverage and Capacity	
Cap_j	Maximum evacuees shelter/candidate j can accommodate
H_j	H3 cells within evacuation range of shelter/candidate j
$\mathcal{J}_h$	Shelters/candidates covering cell h
A_h	Area of H3 cell h in km^2
ρ_h	Population density of region containing cell h
Cap_h	Evacuable population allocated to cell h
Probabilistic Elements	
α_j	Probability that candidate j passes inspection and receives owner consent
Planning and Evaluation	
$\text{Prioritize}_{\mathcal{S},\mathcal{C}}$	Function returning candidates sorted by priority
F	Function computing expected evacuation population
$\Delta(c)$	Marginal gain when adding candidate c
Simulation Parameters	
R	Number of simulation runs (set to 10,000)
r	Index of simulation trial, where $r \in \{1, 2, \ldots, R\}$
P_{existing}	Evacuation population covered by existing shelters only
ΔP_r	Increase in evacuation population in simulation trial r
$\mathcal{X}$	Set of candidates selected by greedy algorithm
$\mathcal{T}$	In simulations: $\mathcal{T} = \mathcal{S} \cup \{\text{accepted candidates}\}$

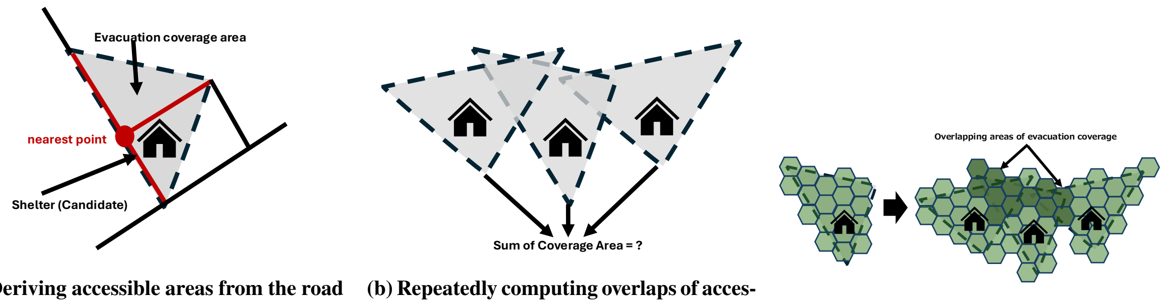
its acceptance probability times its incremental coverage population, approximating expected covered population while preserving submodularity. We next define the objective function.

Objective function and discretization

To compute the objective, we derive accessible evacuation areas from the road network. Using the Python library ‘osmnx‘ and OpenStreetMap data, we compute an accessible polygon for each shelter/candidate via the following steps (Figure 5a):

1. Find the nearest road network node from each shelter or candidate site.
2. From that node, traverse the edges within a walkable distance before the tsunami arrives.
3. Construct a convex hull from the nodes along the traversed edges to define the area covered by the shelter or candidate site.

Because overlap across shelters and candidates must be computed repeatedly (Figure 5b), direct polygon operations are costly. We discretize the area into H3 hexagons (Uber 2018) to streamline computation. H3 provides uniform distances to adjacent cells, making them more suitable for approximating human movement toward shelters (Figure 6); we use $resolution = 10$, corresponding to an average hexagon area of 0.015047502 km^2.



(a) Deriving accessible areas from the road network. **(b) Repeatedly computing overlaps of accessible areas is computationally intensive.** **(c) Overlap of accessible areas.**

Figure 5. Road network analysis and accessible area computation.

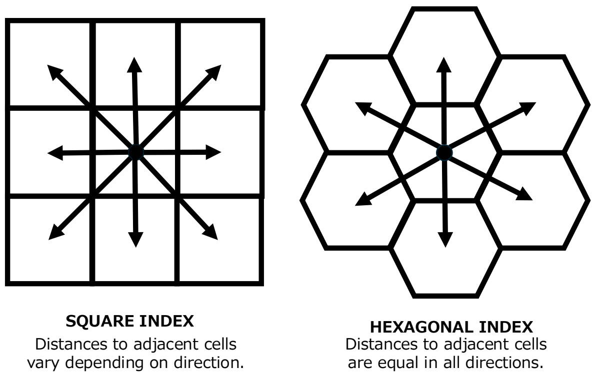


Figure 6. Comparison of hexagonal and square grid indices.

Evacuable population in a H3 cell h can be calculated as:

$$Cap_h = \sum_{j \in \mathcal{J}_h} \frac{Cap_j}{|H_j|} \tag{2}$$

where Cap_j be the capacity of each shelter j, H_j is a set of H3 cells within evacuation range of shelter j, and $\mathcal{J}_h$ is existing shelters covering cell h. However, allocating more shelter capacity than the local population is not cost-effective. Therefore, it is desirable to estimate capacity while considering population density.

We use the population census data published by e-Stat (National Statistics Center 2025), collected at the level of town units and updated every five years.

The method for determining the population density of each cell is illustrated in Figure 7. The cell may overlap multiple regions; we use the region containing the cell center. Let A_h be the area of the H3 cell (h) and ρ_h be the

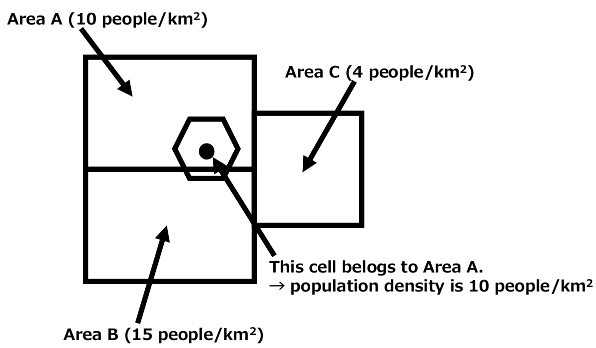


Figure 7. Population density is determined based on the region to which the center of a cell belongs.

Algorithm 1 Prioritization Function Prioritize

Require: Existing shelter set $\mathcal{S}$, candidate shelter set C

1: $P_{\text{base}} \leftarrow F(\mathcal{S})$
2: **for all** $c \in C$ **do**
3: $\quad \Delta(c) \leftarrow F\big(\mathcal{S} \cup \{c\}\big) - P_{\text{base}}$
4: **end for**
5: **return** $\text{sort\_desc}\Big(\{(c, \Delta(c)) : c \in C\}, \text{key} = \Delta(c)\Big)$

population density of the corresponding area. The evacuable population in a H3 cell h is calculated as follows:

$$Cap_h = \min\left(\sum_{j \in \mathcal{J}_h} \frac{Cap_j}{|H_j|},\ \rho_h \cdot A_h\right) \tag{3}$$

Hence, given a set of shelters $\mathcal{X} \subset \mathcal{B}$ the total evacuable population is calculated as:

$$\sum_{h \in \mathcal{H}} Cap_h = \sum_{h \in \mathcal{H}} \min\left(\sum_{j \in \mathcal{J}_h} \frac{Cap_j}{|H_j|},\ \rho_h \cdot A_h\right) \tag{4}$$

where $\mathcal{H} = \bigcup_{j \in \mathcal{X}} H_j$ is the union of sets of H3 cells provided by all shelters.

This study accounts for the uncertainty that candidate sites may not always be available as shelters. Therefore, we assign an acceptance probability α_j to each candidate shelter c_j(We assign $\alpha_i = 1$ for each existing shelter $s_i \in S$.) and calculate the weighted contribution as the expected number of evacuees.

The final objective function, based on expectation, is as follows:

$$F(\mathcal{X}) = \mathbb{E}[\sum_{h \in \mathcal{H}} Cap_h] = \sum_{h \in \mathcal{H}} \min\left(\sum_{j \in \mathcal{J}_h} \alpha_j \cdot \frac{Cap_j}{|H_j|},\ \rho_h \cdot A_h\right) \tag{5}$$

Greedy algorithm and approximation guarantee

The expected evacuation population maximization problem has an objective function $F(\mathcal{X})$ that is monotone (adding sites never decreases coverage) and submodular (marginal gains decrease due to the min operator). Therefore, the greedy algorithm achieves a $(1 - 1/e)$-approximation (Nemhauser et al. 1978). We iteratively select the candidate that provides the maximum marginal gain until the budget M is exhausted, using the prioritization function in Algorithm 1.

Computational complexity

We preprocess and cache the mapping from each shelter/candidate to its reachable H3 cells, which makes road network computations $O(1)$ lookups. With cached H3 coverage, computing $F(\mathcal{S})$ is $O(|\mathcal{S}| \cdot |\mathcal{H}_s|)$. For the prioritization step:

- Computing $F(\mathcal{S})$: $O(|\mathcal{S}| \cdot |\mathcal{H}_s|)$, where $s \in \mathcal{S}$ denotes an individual shelter and $|\mathcal{H}_s|$ is the number of H3 cells covered by shelter s
- Computing marginal gains for all candidates: $O(|C| \cdot |\mathcal{H}_c|)$, where $c \in C$ denotes an individual candidate and $|\mathcal{H}_c|$ is the number of H3 cells covered by candidate c
- Sorting candidates: $O(|C| \log |C|)$

Under a fixed evacuation radius, this simplifies to $O(|\mathcal{S}| + |C| \log |C|)$. Exhaustive search is intractable (e.g., $|C|$=1000, budget M=30 yields $\binom{1000}{30} \approx 10^{57}$ subsets), while the greedy method runs M iterations and is practical at scale.

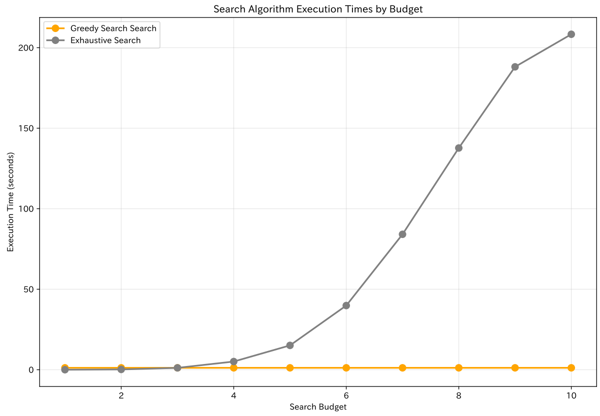


Figure 8. Runtime comparison between Greedy and Exhaustive Search (oracle upper bound)

Runtime comparison

We measured runtime on a filtered set of 20 candidate sites obtained through crowdsourcing-based building filtering (five or more stories, non-wooden, not deteriorated, with evacuation space). Experiments were run on a MacBook Pro (2021 model with Apple M1 Pro chip, 16 GB memory, macOS Sequoia 15.4.1.), with results in Figure 8. For budgets 1–3, the greedy algorithm requires more computation time than exhaustive search because it must calculate the accessible area polygons for all candidate sites when executing the prioritization function. However, since polygon calculations are cached, exhaustive search becomes more time-consuming for larger budgets. Additionally, as the budget increases, exhaustive search benefits from an increased probability of cache hits for previously computed accessible areas, resulting in a slightly slower growth in computation time for budgets 9–10. Accordingly, we use exhaustive search only as a reference upper bound on small filtered candidate sets, and rely on greedy selection for scalability.

Validation: Synthetic Data

We use exhaustive search as an oracle upper bound to assess the performance of the greedy approximation under the same objective function (Eq. 5). While exhaustive enumeration is infeasible at scale, it provides a reference for the best achievable expected coverage in small instances.

This section verifies the performance of the greedy approximation for the maximum coverage problem by comparing it with an exhaustive search.

Synthetic data generation

To evaluate the performance of the algorithms under controlled conditions, we generated synthetic datasets with varying candidate densities around a reference point (40.1874°N, 141.7756°E). Each dataset contains 3 clusters with 5 candidates each (capacity: 500 people, acceptance probability: 0.3), with density controlled by spatial dispersion.

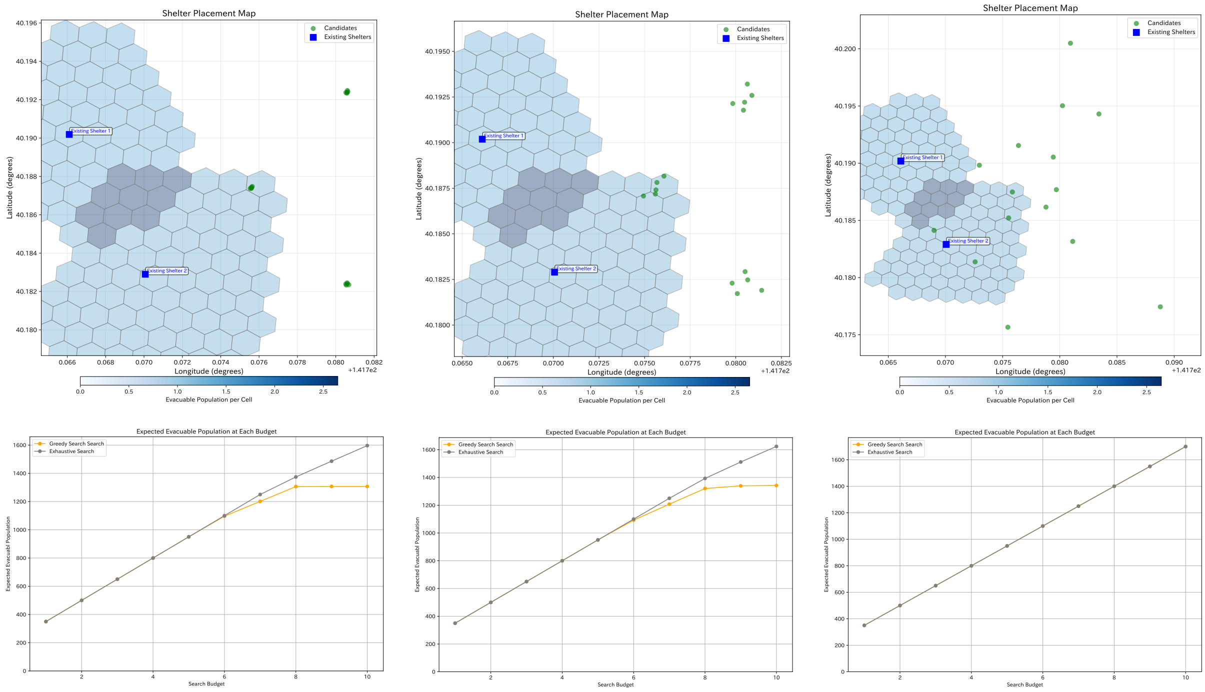
Evaluation method

We evaluate the performance of the algorithms by computing the expected evacuation population using Equation 5 for each method. For budgets $M \in \{1, \ldots, 10\}$, both greedy and exhaustive search select M candidates from 15 available sites. Tests are conducted across three density scenarios to assess spatial clustering effects.

Results

Figure 9 shows that performance degradation is most pronounced under high-density and medium-density conditions, where the greedy algorithm achieves 80–95% of optimal (5–20% gap) in the budget range 7–10. Under low-density conditions, the greedy algorithm matches the exhaustive search results.

This density-dependent performance can be explained by the interaction between spatial clustering and the greedy selection strategy. In high-density scenarios, candidates are tightly clustered, creating significant coverage overlap. The greedy algorithm selects candidates based on immediate marginal gain and can therefore lock in overlapping coverage that is locally attractive but globally suboptimal. In contrast, when candidates are spatially dispersed (low



(a) High density: 35.05candidates/km^2 **(b) Med. density: 23.25 candidates/km²** **(c) Low density: 3.43 candidates/km²**

Figure 9. Algorithm performance under varying candidate densities (Top: spatial distribution, Bottom: expected evacuation population covered by budget; exhaustive search shown as an oracle upper bound)

density), each selection provides more independent coverage with minimal overlap, making the greedy choice align more closely with the global optimum. This explains why the algorithm performs near-optimally in low-density conditions: local decisions avoid the coverage redundancy that characterizes suboptimal solutions.

Across all scenarios, performance exceeds the theoretical $(1 - 1/e) \approx 63.2\%$ guarantee with substantial runtime savings.

Validation: Real-World Data

In this section, we examine the efficiency of the algorithm by considering the selection of shelters for actual tsunami inundation locations.

Shelter data sources

We used the 'Designated Emergency Evacuation Sites' dataset provided by the Geospatial Information Authority of Japan for existing shelters.

Candidate shelters were sourced from different data providers depending on the availability and quality of building information in each city. For Kuji City, Iwate Prefecture, we retrieved buildings within a 5 km radius centered at (40.1874°N, 141.7756°E) using the Overpass API. For Takaoka and Imizu cities in Toyama Prefecture, we used ZENRIN Building Point Data, which provides comprehensive building attributes including floor counts and building categories that are typically unavailable through open data sources.

For candidate-site attribute information, most buildings retrieved via the Overpass API lack annotations such as the number of floors or building usage. Therefore, we collected attribute data for candidate sites in Kuji City using the crowdsourcing task presented earlier. Unlike the RQ1 validation experiment, we removed the 'Unknown' option for individual items and instead allowed workers to skip entire buildings, as having 'Unknown' for specific attributes would make it difficult to assign properties to candidates. The task details are shown in Table 7, resulting in 1,724 annotated candidate sites.

For Takaoka and Imizu cities, building categories were directly obtained from ZENRIN Building Point Data by converting the detailed ZENRIN building codes to our experimental categories. ZENRIN provides overly detailed building categories as shown in Appendix Table 10, which we grouped into simplified categories used in the experiment using the mapping shown in Appendix Table 11. This automated conversion eliminated the need for crowdsourcing in these cities, as ZENRIN data already contained the necessary building type information.

Table 7. Experiment Details

Item	*Value*
Location	Kuji City
Reward per person	124 JPY = 0.87 USD (5 Jun 2025)
Number of tasks per person	10
Number of participants	228
Skip	Allowed

Table 8. Capacity by Building Category

Use	*Capacity (people)*
Commercial Building	442
Apartment Building	187
Office Building	421
Private Residence	163
Others	386

Filtering candidate sites

To filter candidate sites and identify buildings located in tsunami risk areas, we applied different filtering criteria based on available hazard data for each city. For Kuji City, we first overlaid the Overpass API building data with evacuation-difficult zones (Provided by Toyama University) and identified 2,279 buildings located within those zones. We then applied additional filters using the crowdsourcing data, selecting only buildings that met all of the following criteria: (1) three or more floors, (2) not deteriorated, and (3) available evacuation space. This rigorous filtering reduced the candidate set to 47 buildings. For Imizu City, we similarly filtered the ZENRIN building data using evacuation-difficult zones. For Takaoka City, we utilized the tsunami inundation assumption data from the National Land Numerical Information Service (The National Land Numerical Information Service 2025) to identify buildings within potential tsunami hazard areas.

Shelter capacity

Existing shelter capacity was determined using actual data from municipal sources (Iwate Prefecture 2025, Imizu-shi 2025, Takaoka-shi, Toyama 2025). For existing shelters that could not be identified in the municipal data, the capacity was set to 100 people.

Candidate capacity was estimated using the Building Construction Statistics Survey (Ministry of Land, Infrastructure, Transport and Tourism 2023). We mapped builder categories to our usage categories (Appendix Table 12), derived floor area per building type, and divided by the per-person evacuation area (1 m^2) defined with expert input to obtain capacities (Table 8). In other words, candidate capacity is modeled as a category-level prior:

$$Cap_j = \frac{\overline{A}_{u(j)}}{a_{\text{pp}}} \tag{6}$$

where $\overline{A}_{u(j)}$ is the average floor area of usage category $u(j)$ from official statistics and $a_{\text{pp}} = 1$ m^2/person is the assumed emergency area per evacuee. Because the open statistics are aggregated at category level, this step does not model within-category size variance for each individual building. We therefore use this estimate for large-scale prioritization only, while final suitability and effective capacity are confirmed in the on-site verification phase. In addition, population-capped coverage in Eq. 4 limits over-allocation in sparsely populated cells.

Acceptance probability

Acceptance probability was defined as the probability that each site owner will grant approval for experimental candidate site selection. Following discussions within the collaborative research team, the base acceptance probabilities for each building category were set as shown in Table 9. We differentiate between rural and urban areas to reflect varying community characteristics. Kuji City, being a rural area with strong community ties, exhibits high acceptance probabilities even for private residences. In contrast, Takaoka and Imizu cities in Toyama Prefecture, which are more urbanized, show lower acceptance rates for private properties while maintaining similar rates for commercial buildings.

Table 9. Base Acceptance Probabilities by Building Category and Area Type

Building Category	*Rural Areas (Kuji)*	*Urban Areas (Takaoka, Imizu)*
Commercial Building	0.85	0.85
Apartment Building	0.30	0.50
Office Building	0.80	0.40
Private Residence	0.85	0.03

Algorithm 2 Algorithm Performance Evaluation via Monte Carlo Simulation

Require: selected candidates C, shelters $\mathcal{S}$, acceptance probabilities α, trials $R = 10{,}000$

```
P_existing ← ComputePopulation(S)
for r = 1 to R do
    T ← S
    for c ∈ C do
        if rand() ≤ α_c then
            T ← T ∪ {c}
        end if
    end for
    ΔP_r ← ComputePopulation(T) − P_existing
end for
return mean({ΔP_r}), std({ΔP_r})
```

However, acceptance probabilities also account for data reliability. For Kuji City, we multiply the base acceptance probability by the crowdsourcing reliability rate of 68.9% (overall accuracy from Section RQ1: Crowdsourcing Building Information Quality); for Takaoka and Imizu cities, ZENRIN data yields a reliability rate of 100%. Therefore, the effective acceptance probability α_j for candidate j is:

$$\alpha_j = \alpha_{base,j} \times r_{data} \tag{7}$$

where $\alpha_{base,j}$ is the base acceptance probability for the building category of candidate j, and r_{data} is the data reliability rate (0.689 for Kuji City, 1.0 for Takaoka and Imizu cities).

This formulation reflects the compounded uncertainty from both owner acceptance and data quality, ensuring that our optimization accounts for the practical limitations of crowdsourced building assessment.

Evaluation method

We evaluate selected candidates $C = (c_1, \ldots, c_M)$ using Monte Carlo simulation with $R = 10{,}000$ trials, as detailed in Algorithm 2.

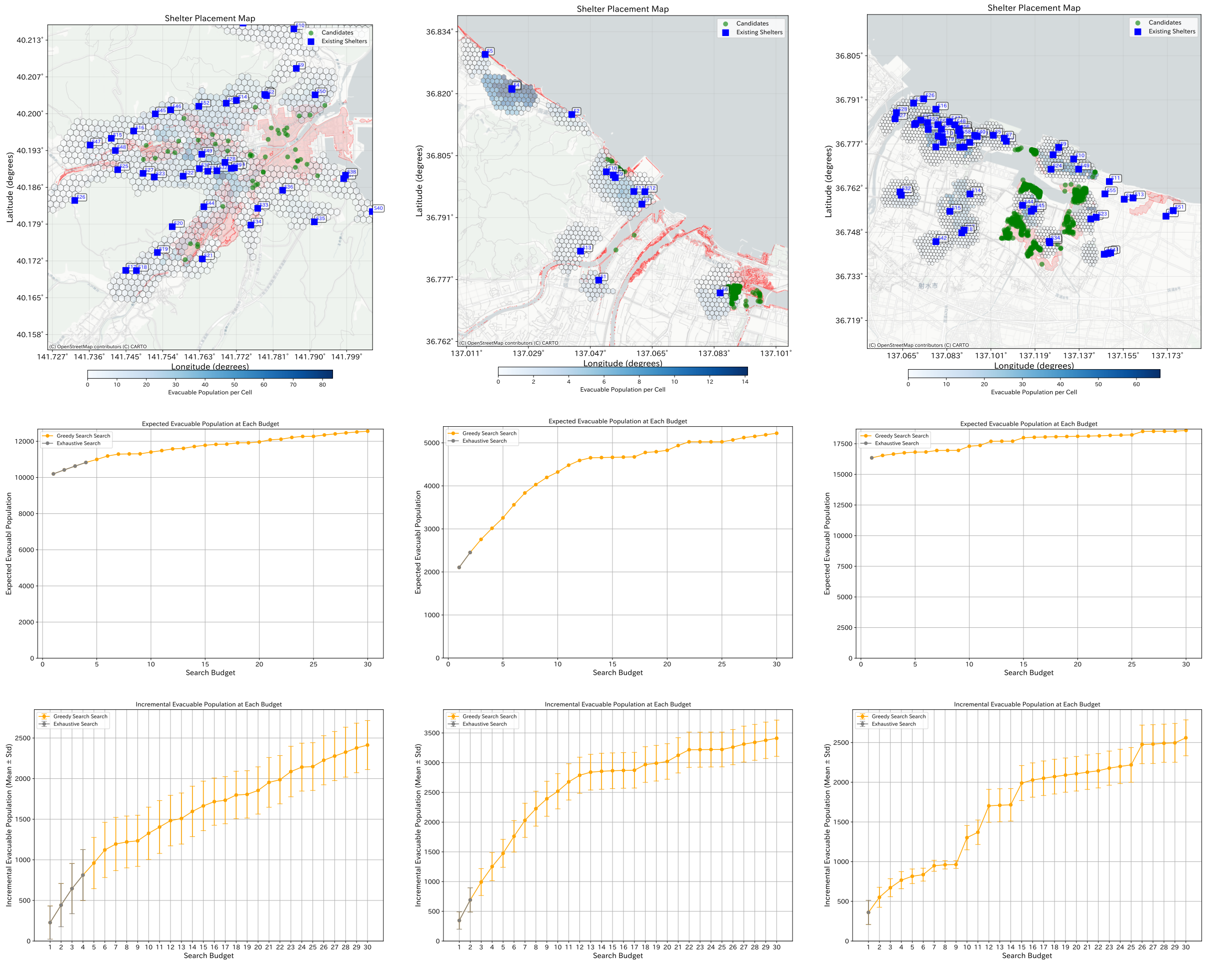
The simulation models owner acceptance stochastically: each candidate $c \in E$ is accepted with probability α_c. We compute the population increase ΔP_r for each trial and report the mean and standard deviation. The ComputePopulation function calculates evacuation capacity within 800 m walking distance (10 minutes) of each shelter, accounting for overlapping coverage areas, and is computed according to Equation 4.

Because exhaustive search must enumerate $\binom{|C|}{M}$ subsets, its computational cost explodes combinatorially (for example, $|C|$=1000 and M=30 yields $\sim 10^{57}$ combinations). We therefore increased the inspection budget step-by-step ($M = 1, 2, \ldots$) but, at each budget level, allowed exhaustive search to run for at most **10 minutes** of wall-clock time; if it had not completed by then, the exploration was halted altogether and no further budgets were attempted. This time limit further emphasizes that exhaustive search serves as an oracle reference rather than a scalable baseline.

Results

Figure 10 presents results for three Japanese coastal cities: Kuji (Iwate), Takaoka (Toyama), and Imizu (Toyama), each with distinct shelter distributions and evacuation requirements.

At budget $M = 30$, the greedy algorithm enables shelter access for an additional 2,400 people in Kuji City, 3,400 people in Takaoka City, and 2,550 people in Imizu City, with the largest absolute gain observed in Takaoka and particularly efficient early-stage coverage in Imizu. Across all three cities, the greedy algorithm consistently achieves 90–95% of exhaustive-search performance, significantly exceeding the theoretical $(1 - 1/e) \approx 63.2\%$ guarantee.



(a) Kuji
(Density: 3.58 candidates/km^2)

(b) Takaoka
(Dens.: 21.76 candidates/km^2)

(c) Imizu
(Dens.: 43.31 candidates/km^2)

Figure 10. Spatial distribution of shelters (top), expected evacuation population covered by budget (middle), and incremental evacuation gains from Monte Carlo simulation (bottom) for three coastal cities in Japan, with exhaustive search shown as an oracle upper bound in the plots

All cities also show diminishing returns after roughly 10–15 selections, suggesting a practical budget range for deployment. The remaining performance gaps correlate with spatial distribution: dispersed shelter patterns such as Kuji show slightly larger gaps than more concentrated layouts such as Takaoka and Imizu. These results validate the approach's effectiveness across diverse urban contexts, from rural areas to densely developed coastal cities, with computational efficiency enabling real-time planning decisions.

INTEGRATED DISCUSSION

Taken together, the findings provide a connected answer to both RQs. We showed that online microtasks can provide building information of sufficient quality for initial filtering (RQ1), and that a greedy algorithm based on expected coverage effectively prioritizes candidate sites under uncertainty (RQ2). Experiments with real-world and synthetic data confirmed that this approach achieves near-optimal performance with significantly reduced computational cost.

From a practical perspective, these findings support a two-layer operational design: crowdworker-generated screening for scale, followed by municipal and expert verification for accountability. This role-sharing aligns with institution-supporting citizen science and co-production perspectives, where broad public participation strengthens rather than replaces formal decision authority (Jayasiri and Prasanna 2022; Lejano et al. 2021; Shackleton 2018). From an organizational perspective, this means municipalities can use crowdworker-generated screening results to triage scarce site-visit capacity, while disaster-management agencies retain final designation authority and responsibility for approval decisions.

From a theoretical perspective, the results confirm prior work that crowd-based geospatial data can support preparedness oriented disaster planning when quality is explicitly assessed (Eckle and de 2015; Klonner et al. 2016;

Schelhorn et al. 2014). They also supplement ISCRAM studies that have emphasized response and recovery by providing a concrete preparedness-phase integration of crowdsourced screening and coverage optimization (Reuter et al. 2013; Rogstadius et al. 2013; Neef et al. 2013). In this study, we do not claim direct falsification of prior work; rather, we extend it by showing how these strands can be operationally combined under municipal planning constraints.

This study has limitations that should be addressed before deployment. The crowdsourcing step depends on Street View visibility and imagery recency, which can obscure key building attributes and affect screening quality. The acceptance probabilities are modeled at the category level and do not capture all social, legal, or organizational factors that influence owner decisions. Candidate capacity is also estimated from category-level average floor area and does not fully capture within-category building-size variance. In addition, our expected-coverage model assumes independent acceptance events and fixed evacuation-demand conditions within each evaluation setting. Human-centered issues such as informed consent, equitable coverage across neighborhoods, and potential bias from uneven data availability remain important considerations for future work. Following critical crisis-data literature, these limitations include representational bias, privacy concerns, and the risk that algorithmic prioritization makes some needs less visible in practice (Crawford and Finn 2015; Soden and Palen 2018).

Another limitation is that our evaluation was conducted in a Japanese context. In principle, the workflow can be transferred to resource-constrained municipalities in other countries, because both computational resources and online crowd labor can be sourced beyond the target region. However, such transfer requires local calibration, particularly with respect to differences in building styles, cultural practices, and the availability of remotely observable evidence.

Future work includes extending the model to account for resident sentiment and social acceptance, conducting scenario-specific sensitivity analysis with local stakeholders, and adding explicit fairness and accountability audits for municipal use. A concrete next step for capacity estimation is to estimate evacuee capacity while explicitly modeling within-category variance, for example by introducing uncertainty ranges rather than single deterministic values.

CONCLUSION

This paper explored practicability of the approach of selecting tsunami evacuation shelters by combining online crowdsourcing and spatial optimization. We showed that online microtasks can provide building information of sufficient quality for initial filtering (RQ1), and that a greedy algorithm based on expected coverage effectively prioritizes candidate sites under uncertainty (RQ2). Experiments with real-world and synthetic data confirmed that this approach achieves near-optimal performance with significantly reduced computational cost. Our findings demonstrate the practical value of integrating crowdsourcing with algorithmic planning for disaster preparedness.

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APPENDIX

Table 10. ZENRIN Building Category List

Category	*Contents (Building Codes)*
Residential	Private residence (1001), Condominium (1002), Apartment (1003), Housing complex (1004), Dormitory/company housing (1005), Residential (1006), Residential/office combined (1008)
Business	Restaurants (2001), Retail (food) (2002), Retail (clothing) (2003), Retail (daily goods) (2004), Services (rental) (2005), Ceremonial services (2006), Personal services (2007), Auto services (2008), Other services (2009), Discount stores (2010), Finance/insurance (2011), Real estate (2012), Infrastructure (2013), Professions (2014), Sports (2015), Entertainment (2016), Hotel/Inn (2017), Medical/Welfare (2018), Public (2019), Education (2020), Delivery/post (2021), Transport (2022), Construction/facilities (2023), Automotive (2024), Cooperatives (2025), Religion (2026), General business (2027)
Commercial	Mixed-use commercial (3001), Commercial (3002), Mixed-use office (3003), Office (3004)
Other	Other (9999)

Table 11. Conversion to Experimental Categories

Converted Category	*Original Building Codes*
Private Residence	1001
Apartment	1002, 1003, 1004, 1005, 1006, 1007, 1008
Office Building	3003, 3004
Commercial Building	2001...2027, 3001, 3002
Other	All others

Table 12. Usage to Category Mapping for Candidate Shelters

Original Usage Category	*Mapped Category*
A Residential Buildings	Private Residence
B Semi-residential Buildings	Apartment
C Residential-industrial Mixed Use	Office Building
J Wholesale/Retail Buildings	Commercial Building
M Hotel/Restaurant Buildings	Commercial Building
F Manufacturing Buildings	Office Building
H Information/Communication Buildings	Office Building
K Finance/Insurance Buildings	Office Building
L Real Estate Buildings	Office Building
Q Government Buildings	Office Building
N Educational Buildings	Other
O Medical/Welfare Buildings	Other
P Other Service Buildings	Other