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A multi-objective optimization model for planning emergency shelters after a tsunami

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ABSTRACT

Vertical evacuation helps people escape tsunami risks by elevating them above the level of tsunami inundation, usually by moving to higher ground or taking refuge in tall buildings or other elevated structures. Unlike horizontal evacuation, which involves moving away from the coast to higher ground, vertical evacuation reduces the demand for horizontal evacuation routes that can become congested and impede evacuation efforts. Therefore, investing in critical infrastructure that enables vertical evacuation is crucial in tsunami-prone areas. This study proposes a multi-objective optimization model to help decision-makers assign critical infrastructure for vertical evacuation in tsunami-prone areas. Critical infrastructure includes buildings that can provide shelter during a tsunami and road networks for rapid access to shelter points. The proposed model balances three objectives: (1) minimizing investment costs in critical infrastructure, (2) maximizing the population covered by shelters, and (3) minimizing the evacuation time for evacuees to reach the shelters. This model is tested on real-world data from the Coquimbo-La Serena coastal conurbation in the Coquimbo region of Chile. The study contributes to the literature on tsunami evacuation modeling and provides valuable information for decision-makers to plan and invest in critical infrastructure for vertical evacuation during tsunamis. A sensitivity analysis of various parameters is conducted, and managerial insights are provided.

1. Introduction

Historically, tsunamis have posed a latent risk for coastal cities, resulting in thousands of deaths and extensive damage to public and private infrastructure. For example, the May 22, 1960 earthquake in Chile with a magnitude of 9.4 on the Richter scale triggered a tsunami that struck the country's southern coasts within 20 to 30 min, reaching up to 10 meters above mean sea level [1]. This tsunami caused 1600 fatalities, 3000 injuries, and two million homeless. Similarly, the August 16, 1976 earthquake in the Philippines with a magnitude of 7.9 produced a tsunami that left at least 90,000 homeless, 5000 dead, and 9500 injured [2]. On December 26, 2004, an earthquake hit the coast of Indonesia with a magnitude of 9.3, producing a tsunami that impacted several countries and left an estimated 130,000 deaths and 30,000 missing people [3,4]. More recently, in 2011, another earthquake occurred in Japan, whose waves caused 15,893 deaths, 6152 wounded, and 2556 missing [5]. These historical events highlight the multifaceted hazards that tsunamis pose to coastal populations, including the risk of survival, investment, residence, work, and mobility. While accurate forecasting of natural disasters, such as tsunamis, remains a challenge for researchers. Taking timely and appropriate actions can help mitigate the impacts of disasters [6].

In this context, Humanitarian Logistics (HL) and disaster management are fields of study that mainly focus on planning, implementing, and controlling the flow of goods, materials, and information from donors-individuals and organizations to people affected by this type of events [7]. Most studies have developed Operations Research and Management Sciences (OR/MS) methodologies and frameworks to minimize the effects of natural disasters [8–10]. HL and disaster relief operations take place in challenging, high-stress environments and usually require rapid responses, as is the case for tsunamis worldwide [11]. This is why OR/MS has been employed to take on the complex decision-making process within HL and disaster relief contexts [12], where a quick and effective response is essential. Authors have also defined a four-step cycle framework composed of *mitigation, preparedness, response* and

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recovery [13]. With the *mitigation* step relating to activities included in the design of a network and localization of early systems and relief facilities, which allows for minimizing collateral effects [14]. Nikbakhsh and Zanjirani Farahani [15] highlights mitigation as the most critical stage because the decisions considered in the mitigation stage will have the most significant impact on minimizing the collateral effects of a disaster situation. Hence, planning tsunami vertical evacuations falls within the mitigation step, as the network design seeks to minimize the detrimental effects of tsunamis.

Before a tsunami hits the shore, quick evacuation is crucial as tsunamis can strike without warning, leaving little time for people to react [16]. Previous authors have identified key activities that allow for a smoother evacuation in the event of a tsunami, among them: (1) carrying out drills, (2) clearing garbage on critical roads, and (3) extending the width of the same roads to avoid vehicular and pedestrian congestion [17]. A rigorous plan is necessary to select and facilitate a fast evacuation and suitable infrastructure (i.e., evacuation routes and shelters). In addition, several criteria must be considered when planning tsunami evacuations, such as coverage, evacuation time, and investment level. Vertical evacuation is a recommended solution in urban areas unable to reach pedestrian evacuation before the estimated arrival of the waves [18]. For vertical evacuations, it is essential to accessible shelters. An earthen mound or building intended as a haven of safety in the event of a tsunami is known as a *vertical shelter*. The shelter is built to withstand an earthquake and resist the effects of a tsunami and is intended for short-term (12–24 h) protection. It is tall enough to lift refugees above the level of a tsunami inundation [19]. Vertical evacuation is preferred to horizontal evacuations for tsunamis due to their ability to provide elevation and refuge above the inundation zone, reducing the risk of flooding and offering a safer haven for individuals during a tsunami event [16]. In terms of mathematical modeling, the decision variables involved in crafting vertical evacuation plans diverge significantly from those employed in horizontal evacuations. Horizontal evacuation strategies primarily focus on determining the optimal routes for the at-risk population to reach safety in a timely manner. In contrast, vertical evacuation introduces a heightened level of complexity to the model. The challenge extends beyond route selection, encompassing the identification of suitable shelter locations and the allocation of specific population groups to these designated havens. A vertical evacuation model requires additional decision variables to account for the capacity of the shelters, the height of the shelters, as well as the proximity to the coast. This added layer makes mathematical models for vertical evacuation more complex due to the number of decision variables and constraints. Hence, a vertical evacuation model can be adapted to account for horizontal evacuations by selecting potential shelter all outside the tsunami-prone area. However, adapting a horizontal model for vertical evacuation entails more modification (e.g., extra variables, extra constraints) and may require more computational resources. Although studies have addressed tsunami response, such as the 2009 South Pacific tsunami [20] or the tsunami that occurred in 2011 in Tohoku after an earthquake [21,22], there is a dearth of literature pertaining to evacuation modeling for a tsunami event. Moreover, there are few studies related to the response after a tsunami caused by a previous earthquake [5,23]. Most of the studies proposing logistical evacuation by routes, destinations, and accommodations are related to hurricanes [24–26]. Furthermore, León and March [27] identified that there is scarce literature on critical infrastructure in the context of an earthquake situation followed by a tsunami.

This study aims to fill in the gaps in the literature on tsunami evacuation plans that consider the infrastructure as well as the evacuation routes using OR/MS techniques.

To the best of our knowledge, this study is the first to present a Multi-Objective (MO) formulation for investing in tsunami evacuation plans that simultaneously considers coverage risk, evacuation times, and total costs. The model employs a constrained shortest-path formulation to design evacuation routes between districts and vertical shelters. This formulation allocates the budget between two categories: routes and shelters. Dedicating resources to enhancing routes results in reduced travel times, facilitating quicker evacuations. This can be achieved through measures such as increasing route capacity, alleviating congestion, or optimizing the configuration of evacuation zones. In contrast, directing funds toward shelters extends coverage to a larger population while enhancing safety levels. This is accomplished by increasing the capacity and height of individual shelters. By balancing the allocation of the budget between these two categories, our approach aims to achieve broader coverage and shorter evacuation times. Notably, our model not only determines budget allocation but also optimizes the selection of vertical shelter locations and routes. It also takes into account critical factors such as government-imposed restrictions regarding evacuation times and coverage guidelines. The proposed decision support framework simultaneously considers vertical shelter locations and the mobility facilitated by evacuation routes. Also, the proposed modeling approach provides a comprehensive tsunami evacuation planning tool that encompasses the capacity of vertical shelters, the configuration of routes between population centers and shelters, and even the height specifications of vertical shelters.

This paper is organized as follows. Section 2 provides a brief literature review. Section 3 shows the problem statement, the estimation procedure of relevant parameters, and the assumptions. Sections 4 and 5 describe the proposed mathematical model. Section 6 shows basic definitions of MO optimization. Then, Sections 7 and 8 show a study case and computational results, respectively. Section 9 presents the main managerial insights. Finally, conclusions and future work are given in Section 10.

2. Literature review

Disaster management is a complex socio-technical process that involves the organization of an interconnected set of activities and stakeholders [13]. It encompasses multiple dimensions, including social and behavioral aspects, the convergence of materials and resources, structural frameworks for response and coordination, as well as considerations for uncertainties [13]. According to Holguín-Veras et al. [9], OR/MS solutions for humanitarian relief and disaster management must consider social costs. For example, objective functions should aim to minimize the total human suffering and also employ constraints such as the highest allowable delivery time, minimum quantities of commodities, and multiple routes to satisfy demand. Holguín-Veras et al. [9] also asserted that most of the models designed to support decision-making were formulated to explicitly consider logistics costs and social impacts of the delivery. They also underscored that social costs should include opportunity costs and inter-temporal benefits of deprivation and suffering caused by delays in the relief delivery.

In post-emergency logistics, hundreds or even thousands of formal or informal/improvised supply chains interact; they overlap, cooperate, or even compete for limited resources and try to help [28]. Gralla et al. [29] suggests authors conduct an exhaustive analysis of experts' preferences to define an appropriate objective function. However, it is not an easy feat to explicitly incorporate expert preferences, and this introduces deprivation costs, as explained by Pérez-Rodríguez and Holguín-Veras [30] and Yáñez-Sandivari et al. [13]. Additionally, second disasters, also known as convergence, must also be considered when deciding on materials, network structure, response planning, and coordination for relief [13]. Another phenomenon that is a direct consequence of the convergence effect is traffic congestion, which can obstruct the relief efforts of police, firefighters, and emergency medical technicians, among others [28,31]. Thus, effective tsunami evacuation planning must take into account various stakeholders, such as policymakers, affected individuals, and neighboring communities, as well as multiple dimensions of the problem. These dimensions include budget allocation, evacuation time, potential shelter locations, risk assessment, and coverage area. To address these complexities, we introduce a multi-objective model that optimizes the distribution of funds between two main categories: routes and shelters. Our model aims to maximize coverage, minimize evacuation, and minimize the budget.

In this section, we discuss a set of selected papers that cover two main aspects related to our research. First, in Section 2.1, we present recent literature on the MO approach to solve HL problems. Then, in Section 2.2, we discuss contributions that have tackled tsunami evacuation.

2.1. Multi objective optimization

Ma et al. [10] proposed a tri-level programming model for the disaster preparedness planning phase. The top level of the model addressed the pre-determined location of facilities and inventory through decision variables. The second level represented the damage caused by the disaster, while the third level determined response and recovery decisions. The solution approach for the MO models, in this case, was similar to the third method mentioned by Yáñez-Sandivari et al. [13]. In general terms, Irohara et al. [32] used a hierarchical model in which he first planned the restoration of damaged routes, structures, and networks to distribute aid. In contrast, Ma et al. [10] presented a MO supplemental location–allocation optimization model for emergency shelters during earthquake-related natural disasters. This model offered several objective functions, providing greater robustness to decision-makers. Although this paper presented a location–allocation optimization model for emergency shelters, it needs to be adapted to a tsunami situation due to the typical conditions that occur during such events in an area. One of the measures we propose is assessing the risk of approaching the coast in the face of an impending tsunami, which is often triggered by an earthquake.

Rodríguez-Espíndola and Gaytán [33] introduced a method that simultaneously defines the location of shelters and distribution centers, allocating pre-positioned goods and decisions required to satisfy flood victims. The tool combines a geographical information system (GIS) tracking system and an optimization model. The GIS determines the flood risk in areas of a city to assess the flood situation and rule out flood-prone facilities. The multi-commodity multimodal optimization model is solved to obtain the Pareto frontier under two criteria: distance and cost. Although what Rodríguez-Espíndola and Gaytán [33] proposed is similar to what we propose, we include an improvement to the objective functions by measuring the critical infrastructure necessary to protect the population from the estimated risk in the mitigation stage. This measure not only takes into account the costs and distances but also awards risk coverage.

According to Esposito Amideo et al. [34], more attention has been given recently to the combined problems of shelter location and evacuation routes. Most models integrate (1) shelter location and car-based evacuation decisions, (2) shelter location and bus-based evacuation decisions, or (3) shelter location and evacuation issues by both car and bus. However, these models are usually adapted to the context of hurricanes or other types of emergencies, with tsunamis being one of the least reviewed with OR techniques. The model we propose is specifically adapted to tsunamis in the mitigation stage, where the most significant safety benefits to the community can be observed. In addition, evacuation strategies have been shown to effectively reduce casualties during major disasters, including tsunamis [35]. However, evacuation planning is a complex problem that involves many behavioral and management facets [36]. For tsunamis, warnings can be issued within two to three minutes of a large earthquake [37].

Xu et al. [38] highlighted the importance of accurate location and allocation of disaster emergency shelters for effective urban planning and emergency management. However, existing models for location–allocation problems still have gaps concerning their realism and applicability. To address these issues, the authors propose a scenario-based hybrid bi-level model that incorporates uncertainties of population dynamics and considers various scenarios within location–allocation problems for earthquake emergency shelters. The proposed model uses a combination of particle swarm optimization and simulated annealing algorithms for solving.

Similarly, Alçada-Almeida et al. [39] proposed a web-based decision support system to aid fire departments and emergency medical services in designing evacuation plans for urban areas. Their MO extension of the p-median model determines the number and location of rescue facilities. In contrast, our proposed model not only decides the capacities of vertical shelters but also identifies critical routes for efficient evacuation.

Haghi et al. [40] proposed an MO programming model for the location of relief goods and medical centers in the pre/post-disaster phases. The model incorporates uncertainties of demand, supply, and cost parameters and includes facility failures. Doerner et al. [41] presented a MO decision analysis for the location of facilities at risk of tsunami inundation, such as schools in near-shore areas. The model has three objective functions, including potential risk of a tsunami event, cost, and coverage criteria. Our proposed model is different, focusing on determining locations of vertical shelters and routes of evacuation for people, which must take into account the specific challenges posed by a tsunami. Cao et al. [42] proposed a MO mixed-integer programming model for aid distribution strategies in earthquake situations. The model aims to minimize victims' suffering and maximize their satisfaction while considering various demand points and sub-phases. In contrast, our proposed model focuses on the location of vertical shelters and evacuation routes specifically for a tsunami. Rath and Gutjahr [43] proposed a three-objective optimization model with medium-term economic, short-term economic, and humanitarian objective functions. They solved the single-objective constrained optimization problem using an exact method and a math-heuristic technique based on a Mixed-Integer Linear Programming (MILP) formulation.

Recently, Shaw et al. [44] proposed a closed problem, a robust and multi-objective model for the location–allocation problem in the distribution of resources in disaster relief operations. Three objective functions are included cost, time, and coverage area. A methodology based on fuzzy numbers is applied to deal with uncertainty on some parameters. Numerical experiments are conducted using small instances with up to four relief camps and two temporary distribution centers for distributing relief materials. Geng et al. [45] highlighted the need for location models of refugee facilities to consider shelter detours, pre-storage of relief materials, and different types of shelters. They propose a multi-standard constrained site selection model to optimize pre-disaster shelter site allocation. Our proposed model focuses on determining the locations of vertical shelters and evacuation routes for a tsunami rather than optimizing the allocation of shelter sites.

The existing body of research on multi-objective models for disaster preparedness largely neglects tsunami-specific scenarios that incorporate investment considerations. Current models focus predominantly on earthquakes and floods but often overlook the challenges posed by tsunamis, such as rapid onset and large-scale impact. Additionally, these models rarely integrate cost-benefit analyses or investment optimization, leaving a crucial gap in planning for an effective tsunami response.

2.2. Tsunami evacuation

Evacuation planning is part of the response planning phase of disaster management, i.e., it is part of the preparedness stage according to the four phases of HL [46] and evacuation in the event of a tsunami is part of the response phase since it must be carried out before the tsunami reaches the coast. This problem has been studied and some models have been proposed to assist in the response planning of tsunami evacuations.

Makinoshima et al. [35] proposed a simulation tool for tsunami evacuations in an urban setting and tested their tool with instances based on Kesennuma and Tohuko, cities in Japan. They found that bottlenecks in building corridors and roads delay the population's evacuation time. León et al. [47] developed an agent-based simulation to assess evacuation strategies using a case study in the Great Valparaíso Metropolitan Area and the city of Viña del Mar, Chile. León et al. [47] highlight the impact of evacuation times on the effectiveness of mitigation and emergency policies in the face of a tsunami. Also, underscore that vertical evacuation must consider morphological characteristics: (1) the siting of the sites for the construction of the vertical evacuation buildings; (2) the minimum quantity of surface that each person must have: 0.93 m^2; (3) an adequate number of access with appropriate characteristics; (4) internal system of traffic able to work [48]. Moreover, they found that vertical evacuation improves population coverage significantly, minimizing general damages (i.e., lives, and economic damages, among others).

Park et al. [49] presented a mathematical formulation for vertical tsunami evacuations that seeks to minimize the evacuation time while maximizing the population's survival probability. Due to the complexity of the problem, they resorted to developing a genetic algorithm to obtain solutions. The potential of the tool using an instance derived from Cannon Beach, Oregon, in the USA was illustrated. Through their experiments, they found that the probability of survival increased as the number of shelters increased and underscored the importance of considering the evacuation time and existing high points (i.e., structures or topology above the tsunami waves) when designing an evacuation plan.

Li et al. [50] proposed a three-stage stochastic strategy for designing emergency response networks, addressing both primary and secondary disasters. Their model initially focuses on determining the locations and capacities of distribution centers (DCs) and shelters. Furthermore, the model optimizes two types of flow decisions: (i) moving victims from affected areas to shelters and (ii) transporting goods from DCs to shelters. According to the objective function, this model is designed to minimize costs, which include: (i) the initial investment needed to establish DCs and shelters, (ii) transportation expenses, and (iii) penalties associated with unevacuated victims. The algorithmic approach here requires historical data, which can be non-possible in some contexts. Li et al. [50] recommended paying more attention to traffic problems in this context. In this sense, our model incorporates a sub-problem to define routes with constraints focused on saving the evacuation process.

To ensure the safety of communities affected by a tsunami, specific minimum parameters for critical infrastructure investment are necessary for effective preventive measures, which can enable the survival of the safeguarded people. Despite existing models providing valuable insights into tsunami evacuation planning, they often fall short in addressing the need for critical infrastructure investment as an integral part of effective preventive measures. This gap is particularly salient given that proper investment in infrastructure can significantly enhance the survival rates and overall safety of communities at risk. Our model fills this void by incorporating a sub-problem focused on optimizing evacuation routes with specific constraints, thus ensuring a more efficient use of resources and better outcomes during the crucial moments of tsunami evacuation. By doing so, we contribute a more holistic approach to tsunami preparedness that balances immediate needs with long-term investment considerations.

To sum up, the previously reviewed literature has some gaps that need to be addressed in future research. Firstly, there is a need to explore more diverse MO functions. Secondly, complex models that are difficult to solve need to be developed to address the practicality and applicability of the models. Thirdly, there is a need to compare the computed solutions on the Pareto frontier to provide a comprehensive analysis of the location–allocation problem. Fourthly, critical connections between evacuation zones and destinations need to be improved in addition to location–allocation of shelters. Lastly, more research is needed to understand the relationship between investment in road improvement and its positive impact on evacuation times in tsunami situations, which should be addressed with various techniques to prepare the community.

3. Problem statement: a Multi-objective Location–Allocation Problem with investment

The proposed Multi-Objective Location–Allocation Problem (MOLAP) in this study considers a coastal zone divided into a set of districts, denoted as D, which are previously identified. The problem is defined to support a decision process related to fortifying critical infrastructure (*i.e.*, shelters and evacuation routes) for evacuation during tsunamis. Each district $d \in D$ is associated with two fundamental parameters: one that indicates the population ψ_d, and another that reflects the potential impact of a tsunami r_d.

Our research aims to determine a plan for critical infrastructure investment to improve the evacuation time and coverage of the population during the event of a tsunami. The proposed formulation seeks to locate shelters within a set of potential shelters I and increase the capacity of the available routes to evacuate from the districts to possible shelters. Potential shelters are defined according to the building permits of the area under study. Moreover, each potential shelter must possess a minimum height dictated by governmental safety legislation. Each vertical shelter that is selected must possess a minimum capacity, which is determined based on the estimated number of people per district. In sum, the investment plan must consider three important aspects: the estimated impact by district, the monetary resources necessary for construction, and the evacuation times, where these factors affect the characteristics that these vertical shelters must possess.

In addition to relevant decisions like defining where the vertical shelter will be located, which districts will it cover, what capacity and height it will have, times of evacuation or transfer, and distances to reach a shelter must reflect reality. This study assumes that the time required to travel from the district d to the shelter i is directly proportional to the distance it takes to travel along the concerning routes. A parameter T_{id}, which represents the total time required to travel from district d to the vertical shelter i, can be decreased by δ_{id} if an investment is made in the road that connects the district d and the shelter i, respectively. For this study, investments in roads are made to either widen the width of the road or clean of debris or obstacles that could obstruct the evacuation.

Given the above, the mathematical formulation considers multiple decision variables. The location decision for each shelter $i \in I$ is denoted by $y_i \in \{0,1\}$. While, the investment decisions that consider a potential "increase" in the flow of people within the area are denoted by p_{id} and represent an estimated total investment percentage to the route connection between the vertical shelter i and the district d, denoted by ϱ_{id}. Finally, decisions linked to capacity $q_i \in \mathbb{R}^{\geq 0}$ and height of each shelter $h_i \in \mathbb{R}^{\geq 0}$.

The objectives considered through the investment plan on critical infrastructure seek to decrease the total evacuation time of the population through the objective f_3, together with the maximization of f_2 that represents the impact covered by the investment decisions, and the minimization of the investment required for better performance of future contingency plans, f_1. Then, the problem has the following MO function:

$$f = (f_1, -f_2, f_3). \tag{1}$$

With this, the MOLAP aids in the development of a contingency plan that will address in detail the different types of decisions, within which are preparation and immediate response, where the first of them: seeks to estimate the areas of high impact in case of a possible natural disaster-related to a tsunami and thus use such information to establish intelligent decisions of a preventive nature. In contrast, the second type of decision: immediate response, is related to what to do when the eventuality occurs so that the affected person can stay out of hazard. The parameters defined above, such as the population quantity or density indicator plus the impact indicator, are estimated and, therefore, correspond to the mitigation stage into HL, *i.e.*, based on the information available, the aim is to create and optimize a contingency plan.

The MOLAP considers the following assumptions:

1. A district can only be served by a shelter within the cluster assigned.
2. The district demand is indivisible.
3. The shelter capacity has no physical limitation.
4. The population taking shelter is exclusively pedestrian, *i.e., they arrive by running or walking*.
5. There is a maximum number of shelters that can be built or utilized.
6. Shelters maximum capacity is a user-defined parameter in the model.
7. Travel times between districts and shelters are known and constant.
8. Investment costs for infrastructure improvements are deterministic.
9. Mandatory districts must be served regardless of other considerations.
10. Each shelter must meet a minimum height requirement.
11. Investments in route improvements linearly decrease travel time.

Regarding assumption 1, it is important to remark that these clusters C_k are disjoint sets of districts, i.e., $\bigcup_{k=1}^{K} C_k = D$ and $\bigcap_{k=1}^{K} C_k = \emptyset$, where K is the number of clusters. Let v_i be the set of districts that can be served from shelter i. Then, $d' \in v_i$ iff $\exists l$ such that $i \in C_l$ and $d' \in C_l$. Note that the higher the number of clusters, the more permissive solutions are provided for the installation of vertical shelters closer to each other. These clusters are spherical subsets of districts grouped by means of the k-means algorithm. This assumption focuses on providing suitable solutions for the evacuation plan, i.e., well-defined macro-zones. Moreover, these assumptions ensure that we capture the decision maker's desired attributes of emergency evacuation plans. For example, assumption 1 seeks to avoid chaos caused by pedestrians trying to reach other clusters.

This problem seeks a solution to answer the following questions: How much should the government investment be to build shelters and improve evacuation times?; Is there a relationship between investment in critical infrastructure and coverage?; Does the total evacuation time influence a government's coverage and investment in building vertical shelters and improving evacuation routes?; In addition to the above, vertical shelters must-have features indicating height and capacity as several people harbored. Thus, it can be explained in the following way:

1. If there is a high flow of population near a coastal area and it exists a minimum standard of H_d meters above mean sea level to be safe in the tsunami's event, then will be necessary a building that has enough height and capacity and the associated investment will be higher.
2. If a district or area is far from the coastal area but has a high density, then the expected depth of that district is less than a district near the coastal area. However, it is essential, too, due to the high population in that zone, and if an unexpected event happens there, the consequences will be greater. It is not seeking with this objective function's model.

Considering that the social order as a response given eventual catastrophe can be a crucial factor in mitigating the impact is essential. Thus, while we have fewer routes to follow, and in another way, less flow of people for each course increases the efficiency of implementing the contingency plan. As a final objective, the model seeks to identify what route to follow and what to select for each district. Furthermore, the MOLAP can be explained in the following way: If we choose to evacuate people from district d to shelter i, then there is a maximum time available of T_{id}. The model is flexible with investments related to improvements in routes that allow shorter times to arrive at a secure location, and that is limited by p_{id} representing a proportion of investment ϱ_{id} respectively. On the other hand, it seeks to maximize the coverage of all impact related to the indicator defined above, which is the product between k_d, a parameter associated with the depth of the wave at a particular district d, and the parameter ψ_d which represents the population in the district d. These parameters, k_d and ψ_d, are directly proportional indicators with r_d, suggesting that their relationship could serve as a method to estimate the impact of the wave's arrival in district d based on population density conditions. For practical purposes, in this article, the function used to relate these indicators and estimate the impact is the product of the two parameters. Thus, the risk indicator r_d is defined, encapsulating the considerations of both the wave's depth and the population's density in district d. In addition to the latter, we must consider the third component that measures the total travel time between district d and vertical shelter i. Moreover, it is necessary to consider that if a vertical evacuation shelter is built on a particular district d, then another vertical shelter will not be allocated to the district. If a standing shelter i is built on district d, then all other districts contented by the set v_i will evacuate to that vertical shelter.

3.1. Sub problem: constrained shortest path problem (CSPP)

The estimation of the evacuation times T_{id}, which were stored in a matrix mentioned by assumption 7, was performed through a sub-problem of the shortest route considering a tsunami threat. This implies that while we seek to minimize evacuation times between origin–destination, a penalty is incurred for approaching a higher risk area (*i.e.*, a route closer to the coast). We capture this by having the T_{id} parameter increase as you approach the coast, causing evacuation times to be penalized in the proposed primary model.

4. Formulation for the MOLAP

The MOLAP is formulated as a Multi-Objective Mixed Integer Quadratic Problem (MOMIQP) as follows:

4.1. Sets

D:	Set of districts of the zone under study (indexed by d)
E:	Subset of mandatory districts that must have a vertical shelter at the zone under study (indexed by e)
I:	Set of potential vertical evacuation shelters (indexed by i)
v_i:	Set of districts that can be served from shelter i. To obtain this subset, we generate clusters to identify which district $d \in D$ is near (in the same cluster) to another district $d' \in D$ and included in the same subset (indexed by i).

4.2. Parameters

T_{id}:	Minimum traveling time between district $d \in D$ and shelter $i \in I$
r_d:	Indicator that measures the total impact when a tsunami hits a community, it is disaggregated by district $d \in D$
ψ_d:	Floating population estimated according to district $d \in D$
H_d:	Minimum height necessary (in meters) to build shelter $i \in I$ on district $d \in D$
k_d:	Depth associated to district $d \in D$
S:	Total vertical shelters that are allowed to be installed in the city
δ_{id}:	Reduced evacuation time on the connection between district $d \in D$ and vertical shelter $i \in I$ due to investment whose objective is to improve the capacity of the road.
CF :	Fixed cost of building a vertical shelter
ι, κ:	Unit costs related to the number of people assigned to a particular vertical shelter and meters above mean sea level, respectively.
ξ:	Maximum time to evacuate, previously established by authorities.
γ:	Parameter associated with displacement between districts. It is the maximum value in meters that a person travels to relocate in a more dangerous zone.
ϱ_{id}:	Total investment to improve the connection with roads between district $d \in D$ and vertical shelter $i \in I$
λ:	Maximum travel time due to connection between vertical districts $i \in I$ and districts $d \in D$ by, $max\{T_{id}\}$.

4.3. Decision variables

$y_i = \begin{cases} 1, \text{if vertical shelter } i \in I \text{ is selected} \\ 0, \text{otherwise.} \end{cases}$

$z_{id} = \begin{cases} 1, \text{if district } d \in D \text{ is attended by vertical shelter } i \in I \\ 0, \text{otherwise.} \end{cases}$

p_{id}: Proportion of investment (ϱ_{id}) between the connection of route which connects district $d \in D$ until vertical shelter $i \in I$, thus, the model decides the level of investment on the connection for the reduction of evacuation times which can be obtained by, δ_{id}.

q_i: Capacity of the vertical shelter $i \in I$

h_i: Height of the vertical shelter $i \in I$ given in meters.

τ_{id}: Time of evacuation between district $d \in D$ to vertical shelter $i \in I$, after a proportion of investment (p_{id}), is made on this route.

4.4. Optimization model

$$\text{Min Z} = (f_1, -f_2, f_3) \tag{2}$$

$$f_1 = CF \sum_{i\in I} y_i + \sum_{i\in I} \iota q_i + \sum_{i\in I} \kappa h_i + \sum_{d\in D}\sum_{i\in I} \varrho_{id} p_{id} \tag{3}$$

$$f_2 = \sum_{i\in I}\sum_{d\in D} r_d z_{id} \tag{4}$$

$$f_3 = \sum_{i\in I}\sum_{d\in D} \tau_{id} z_{id} + \sum_{i\in I}\sum_{d\in D} (1 - z_{id})\lambda \tag{5}$$

$$\sum_{i\in I} z_{id} = 1 \qquad \forall d \in E \tag{6}$$

$$\sum_{d\in v_i} y_d \le 1 \qquad \forall i \in I \tag{7}$$

$$z_{id} \le y_i \qquad \forall i \in I, d \in v_i \tag{8}$$

$$p_{id} \le z_{id} \qquad \forall i \in I, d \in D \tag{9}$$

$$T_{id} - p_{id}\delta_{id} \le \tau_{id} \qquad \forall i \in I, d \in D \tag{10}$$

$$\sum_{i\in I} y_i \le S \tag{11}$$

$$\sum_{d\in D} z_{id}\Psi_d = q_i \qquad \forall i \in I \tag{12}$$

$$h_i - H_i y_i \ge 0 \qquad \forall i \in I \tag{13}$$

$$\tau_{id} z_{id} \le \xi \qquad \forall i \in I, d \in D \tag{14}$$

$$(k_i - k_d) z_{id} \le \gamma \qquad \forall i \in I, d \in D \tag{15}$$

$$y_i + y_d = z_{id} \qquad \forall i \in I, d \in D \tag{16}$$

$$\sum_{i\in I} z_{id} \le 1 \qquad \forall d \in D \tag{17}$$

$$q_i > \epsilon - M(1 - y_i) \qquad \forall i \in I \tag{18}$$

$$q_i \le M y_i \qquad \forall i \in I \tag{19}$$

$$p_{id} \le 1 \qquad \forall i \in I, d \in D \tag{20}$$

$$y_i \in \{0, 1\} \qquad \forall i \in I \tag{21}$$

$$z_{id} \in \{0, 1\} \qquad \forall i \in I, d \in D \tag{22}$$

$$\tau_{id}, p_{id} \ge 0 \qquad \forall i \in I, d \in D \tag{23}$$

$$q_i, h_i \ge 0 \qquad \forall i \in I \tag{24}$$

Note that $D = I$, due to elements $\forall d \in D$ belonging to I too, that is $D \subseteq I$ and $D \supseteq I$. Furthermore, Eq. (2) is related to multiple objectives that seek to be minimized by three components or dimensions: $f_1, -f_2, f_3$, where each of them is represented on Eqs. (3), (4), (5), which Eq. (3) is the first component associated to budget used for investment on critical infrastructure, second objective in Eq. (4) is associated with total prize due to coverage offered to the population in the zone, and the first component in Eq. (5) is associated with minimum time for evacuation between a district $d \in D$ and vertical shelter $i \in I$. Eq. (3) has three components; the first is related to the set-up and installation of vertical shelters, for example, building permits and contracts, among others. Eq. (4) is related to maximizing coverage per district served $d \in D$. Then Eq. (5) has two components: the first component refers to the total evacuation times after a reversal between the various connections between districts and vertical shelters, and the second component is a penalty for not evacuating to a particular district. In conjunction, the components of Eq. (5) force the model to search for the most convenient connection for compulsory evacuation.

The set of constraints in Eq. (6) is related to a district that is mandatory to cover, defined by the set E. This district must be attended by any vertical shelter $i \in I$ due to characteristics such as the proximity to the coast, the height of the terrain, or geographical features that may intensify the impact of the tsunami wave. Eqs. (7) and (8) address the proximity between vertical shelters and the facility in case a potential shelter serves a district. In addition, Eq. (7) ensures that if a vertical shelter is located and constructed in district $d \in D$, then every other district $d \in v_i$ cannot have a vertical shelter, Eq. (8) assure that if a vertical shelter is located in district $d \in D$, every other district must be attended by this particular vertical shelter. Then Eq. (9) represents the investment in an improvement of a route between districts and vertical shelters. The investment in improving the connection between district $d \in D$ and vertical shelter $i \in I$ is represented by Eq. (10). Also, suppose the proportion of investment is more than zero. In that case, there is a decrease in time of traveling, with the difference represented by δ_{id}, and the final result of improvement is represented by τ_{id}, receiving quadratic constraints related to the investment connection between vertical shelters and districts.

Eq. (11) ensures that there cannot be more vertical shelters than S, which is an input parameter provided by decision-makers. Then, Eq. (12), ensures quantity population that is attended and covered by a particular shelter $i \in I$. Eq. (13) makes sure that if a vertical shelter is constructed in district $d \in D$, it must have more than H_d of height. Eq. (14) imposes a restriction on the traveling time as it cannot be more than ξ, which is another input parameter provided by decision-makers. Moreover, Eq. (15) is associated with the tolerance of depth and distance between district $d \in D$ and the coast, given as a parameter. Eq. (16) imposes that if a vertical shelter $i \in I$ attends a district $d \in D$, a vertical shelter cannot be built in district $d \in D$. Eq. (17) makes sure that each district $d \in D$ is attended only once. Eqs. (18) and (19) are indicator constraints. In other words, these equations ensure that when $y_i = 1$ then $q_i \ge \epsilon$, where ϵ is a number very close to zero and captures when it a vertical shelter is selected on $i \in I$. However, when $y_i = 0$, it ensures that district $i \in I$ cannot house people, so $q_i = 0$. Note that the M Parameter is a considerable number. Eq. (20) imposes the proportion of investment on a connection between district $d \in D$ and vertical shelter $i \in I$. Finally, Eqs. (21), (22), (23) and (24) are related with natural definition.

5. Formulation for the CSPP

As mentioned in Section 3.1, we propose a sub-problem, which is solved for each district and vertical shelter, that allows identifying the shortest route adapted given the threat of a tsunami. Each evacuation time for each district and potential vertical shelter is stored in a matrix. This problem is defined on a graph $G = (V, E)$ where V is the set of nodes and E is the set of edges, with $|V| = n$ and $|E| = m$. The source node (a shelter) is represented by i, and d is the target node (a district). A distance l_{gh} is considered for each edge $(g, h) \in E$ on G.

5.1. Parameters

l_{gh}: Distance in meters from node g to node h

c_g, c_h: Distance from node $g, h \in V$ to the coast.

β: Penalty factor due to moving people to a zone nearer to the coast

5.2. Decision variables

$$f_{gh} = \begin{cases} 1, \text{if the edge is in the shortest path from node } g \in V \text{ to node } h \in V \\ 0, \text{otherwise.} \end{cases}$$

k_{gh} : Meters that people can bring near to coast from node $g \in V$, to node $h \in V$

5.3. Optimization model

$$T_{id} = \min \left\{ \sum_{(g,h)\in E} l_{gh} f_{gh} + \beta \sum_{(g,h)\in E} k_{gh} \right\} \quad \forall i \in I, d \in D \tag{25}$$

$$\sum_{h:(g,h)\in E} (f_{gh} - f_{hg}) = 0 \quad \text{if} \quad g \neq i, d \tag{26}$$

$$\sum_{h:(g,h)\in E} (f_{gh} - f_{hg}) = 1 \quad \text{if} \quad g = i \tag{27}$$

$$\sum_{h:(g,h)\in E} (f_{gh} - f_{hg}) = -1 \quad \text{if} \quad g = d \tag{28}$$

$$(c_h - c_g) f_{gh} \geq -k_{gh} \quad (g,h) \in V^2 \tag{29}$$

$$f_{gh} \in \{0,1\} \quad \forall g \in V, h \in V \tag{30}$$

$$k_{gh} \geq 0 \quad \forall g \in V, h \in V \tag{31}$$

The objective function represented by Eq. (25) minimizes the total traveling time between district $d \in D$ and vertical shelter $i \in I$, gathering the edges which union generates the optimal time path in tsunami's situation. This objective has two essential components. The first component is the total meters people must traverse in terms of travel time. The second is the total penalty due to moving people to a zone closer to the coast so that decision-makers can select the importance of the β as a function of the total evacuation time between the district and the vertical shelter. Eqs. (26)–(28) ensure that the path $g - h$ structure uses the traditional flow formulation. Eq. (29) are associated with the tolerance of the movement that approaches the coast. Finally, Eqs. (30) and (31) define the nature of the decision variables.

6. Basic definitions of multi-objective optimization

Before showing the solution method, it is necessary to consider the following definitions related to the Multi-objective Optimization Problem (MOP).

Definition 1 (*Pareto Optimal Solution*). A feasible solution $\hat{x} \in X$ is called efficient or Pareto Optimal if there is no other $x \in X$ that dominates it, such that $f(x) \leq f(\hat{x})$. If $\hat{x}$ is efficient, $f(\hat{x})$ is called non-dominated point. If $x^1, x^2 \in X$ and $f(x^1) \leq f(x^2)$ we say x^1 dominates x^2 and $f(x^1)$ dominates $f(x^2)$. The set of all efficient solutions $\hat{x} \in X$ is denoted X_E and called the efficient set. The set of all non-dominated points $\hat{y} = f(\hat{x}) \in Y$, where $\hat{x} \in X_E$, is denoted Y_N and called the non-dominated set [51].

In the case of MO optimization, we optimize a set of functions,

$$\min_{x\in X}(f_1(x), \dots, f_p(x)), \tag{32}$$

of the Pareto class,

$$(X, f, \mathbb{R}^P)/id/(\mathbb{R}^p, \leq),$$

when these criteria have opposite behaviors considering the search for a solution, we necessarily have to degrade at least one criterion to improve another. Hence, it is necessary to assess all these objectives to define the non-dominated solutions as follows:

– A solution x dominates a subset x_2 ($x_2 \prec x$) iff $\forall i f_i(x) \leq f_i(x_2)$ and $\exists i$ such that $f_i(x) < f_i(x_2)$.

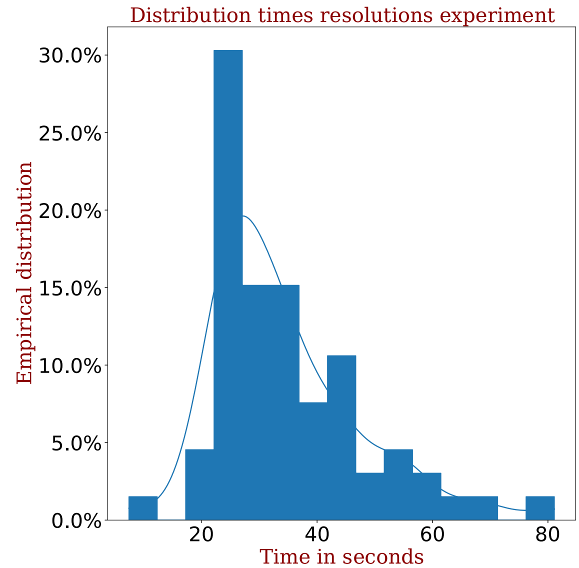


Fig. 1. Distribution times experiment per instance.

– A subset x is not dominated if $\nexists x_2 | x \prec x_2$.
– The set of all non-dominated subsets is called the Pareto set.

Definition 2 (*Nadir Point*).

1. The point $y^I = (y_1^I, \dots, y_p^I)$ given by
$$y_k^I := \min_{x\in X} f_k(x) = \min_{y\in Y} y_k \tag{33}$$
is called the ideal point of the multi-criteria optimization problem $\min_{x\in X}(f_1(x), \dots, f_p(x))$.
2. The point $y^N = (y_1^N, \dots, y_p^N)$ given by
$$y_k^N := \max_{x\in X_E} f_k(x) = \max_{y\in Y_N} y_k \tag{34}$$
is called the nadir point of the multi-criteria optimization problem [51].

Theorem 1 (*Geoffrion (1968)*). *Let $\lambda_k > 0, k = 1, \dots, p$ with $\sum_{k=1}^p \lambda_k = 1$ be positive weights. If $\hat{x}$ is an optimal solution of*

$$\min_{x\in X} \sum_{k=1}^p \lambda_k f_k^*(x)$$

then $\hat{x}$ is a properly efficient solution of (32), where $f_k^*(x)$ represents normalized function objectives.

This approach is known as the weighted sum method. Our model was solved by applying this strategy. This simple approach allows us to obtain Pareto frontiers very fast, and these frontiers show the expected trade-off among objectives; in other words, it offers a reasonable set of alternatives for decision-makers. We appreciate the simplicity, scalability, and interactivity that the weighted sum method provides. Hence, we refrain from resorting to other advanced MO approaches. Fig. 1 shows the running time distribution. On average, the execution time was 34.5 s, with a standard deviation of 13.2 s, implying that this method can solve the model efficiently. The maximum running time was 100 s, respectively.

Objective functions f_1, f_2, and f_3 were normalized or standardized with known methods. It generated a large sample, so f_1 and f_3 obtained the average and standard deviation ($\mu_i, \sigma_i \; \forall i \in \{1,3\}$), and then it implemented Eq. (35). This measure was taken to make competitive on the same scale objectives functions y because extracting a $min f_1$ and $\min f_3$ directly from the model constraints is impossible. To give an idea of how Eq. (35) normalizes. First, the objective function is shifted to zero by subtracting the mean of a previously obtained large sample. It was standardized that the dispersion of these zero-centered values is divided by the standard deviation, thus obtaining values ranging between −2 and 2, respectively. Also, in the normalization method, the minimizing function is marked positive, while the maximizing function is marked negative. To provide a sense of fairness between each objective function, it is necessary to normalize using root mean square [52]. Also, V_i is variance of $f_i, \forall i \in \{1,3\}$.

$$f_i^* = \frac{f_i - E(f_i)}{\sqrt{E(V_i)}} \forall i \in \{1,3\} \tag{35}$$

Finally, for the component related to the hedge risk premium, each value obtained from the initial untransformed sample, the maximum and minimum values (f_2^N, f_2^I) were obtained, respectively. Then, we implemented the obtained values of the objective function f_2 into Eq. (36), where the range of values goes from zero to one.

$$f_2^* = \frac{f_2 - y_2^I}{y_2^N - y_2^I} \tag{36}$$

7. Case study and data collection

On December 26, 2004, a devastating earthquake struck off the coast of Indonesia with a magnitude of 9.3. This event, one of the most significant in recent history, generated a catastrophic tsunami that impacted several countries around the Indian Ocean, resulting in an estimated 130,000 deaths and 30,000 missing people [3,4]. This tragedy highlights the intense seismic and volcanic activities associated with the Pacific Ring of Fire, a region discussed by Hinga [53]. Located along the coasts of the Pacific Ocean, the Ring of Fire is characterized by some of the most critical subduction zones in the world. Spanning over 40,000 km (25,000 miles) and shaped like a horseshoe, it is home to more than 75% of the world's active and inactive volcanoes. The Ring of Fire encompasses numerous countries, including Chile, Argentina, Bolivia, Peru, Ecuador, Colombia, Panama, Costa Rica, Nicaragua, El Salvador, Honduras, Guatemala, Mexico, the United States, and Canada, as illustrated in Fig. 2. The region's geological activity, particularly frequent and significant earthquakes, often occurring under or near the ocean, poses a substantial risk for triggering tsunamis. This aspect of the Ring of Fire's seismic activity is vital for risk assessment and disaster preparedness. The chapter 'History and Seismology in the Ring of Fire: Punctuating the Indonesian Past' in 'Environment, Trade, and Society in Southeast Asia: A Longue Durée Perspective' offers a historical and seismological perspective on these phenomena [54]. Specifically, the connection of Indonesia to the Ring of Fire has resulted in numerous significant seismic and volcanic events, illustrating the magnitude, location, and immediate fatal consequences of these natural disasters. This underscores the critical importance of disaster preparedness and response in geologically active areas.

Some of the consequences listed are as follows [53]:

- Alaska suffered three major earthquakes in less than eight years. On March 9, 1957, a 9.1 magnitude earthquake struck the Andreanof Islands, while in 1964 and 1965, earthquakes of 9.1 and 8.7 magnitudes generated a tsunami of 10-meter high waves.
- December 26, 2004, a 9.0 earthquake in Indonesia and Sumatra triggered a tsunami that killed over 250,000 people.
- On March 11, 2011, Japan suffered a 9.0 earthquake, followed by a tsunami with 10-meter-high waves, which swept away entire villages and caused a nuclear disaster.
- On May 22, 1960, Chile suffered the most intense earthquake ever recorded; it measured 9.5 on the Richter scale and shook the cities of Santiago and Concepción. Five thousand people died, and two million were left homeless.

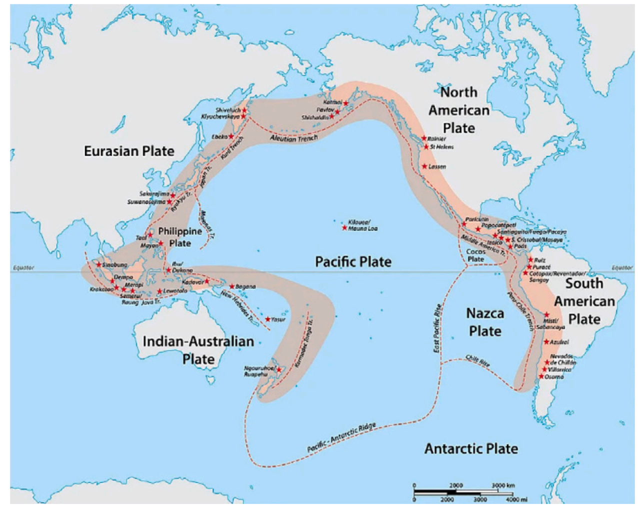


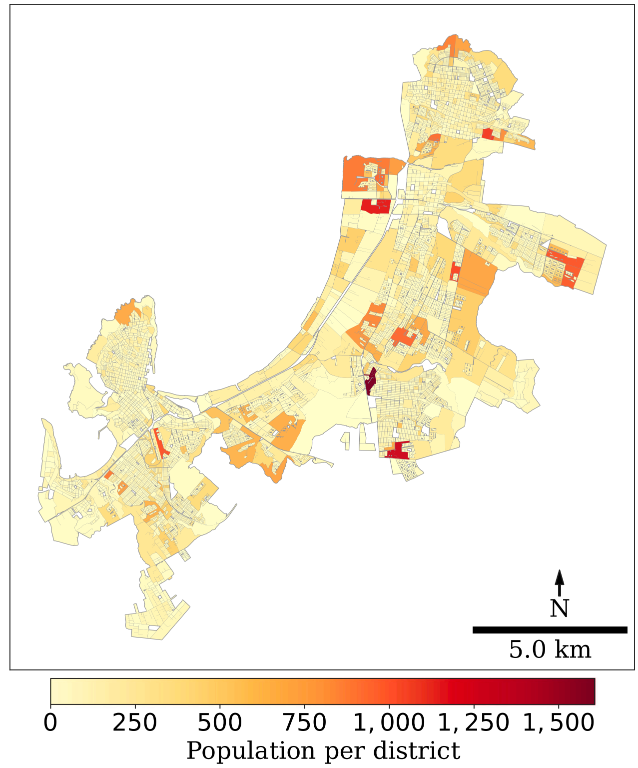
Fig. 2. Map showing the extent of the Pacific Ring of Fire (area shaded in brown) [55].

On the other hand, in the historical seismic distribution that Chile has had, there is a higher concentration of these events in the north of the country after the great earthquake that occurred in 1960 in Valdivia. The regions with the highest historical frequency of solid seismic events (leading to a subsequent coastal tsunami) are the regions of Antofagasta and Coquimbo, with a total of 476 and 311, respectively. In Addition to the above, the maximum magnitudes on the Richter scale for these regions have been 7.5 and 8.4, according to Lara Belmar and Barrenechea Riveros [56]. Furthermore, the Oficina Nacional de Emergencia del Ministerio del Interior (ONEMI) declared a red alert for a significant earthquake and tsunami warning on September 16, 2015, in the region of Coquimbo [57]. This seismic event had a magnitude of 8.4 on the Richter scale. After the seismic event, the region's residents were alerted of a potential tsunami that resulted in 15 deaths, two injuries, 10 people in shelters, 27,272 people affected, 2442 houses destroyed, and 2712 with significant non-habitable damage. After the tsunami in Coquimbo on September 16th, 2015, Paulik et al. [58] collected information about depth and physical and non-physical attributes for damaged and undamaged buildings. Some important conclusions were obtained within the gathered database as 655 watermarks, whose measured depth range from 0.1 to 4.7 m, with an average of 1.47 m and 1.02 m standard deviation. It also mentioned that more than 3000 damage samples were recorded for tsunami-exposed buildings and infrastructure components. In addition, he states that the Coquimbo Region, in its geological and infrastructure structure, is related to a resonance effect, implying that the impact of a tsunami is significantly amplified in several areas of the region.

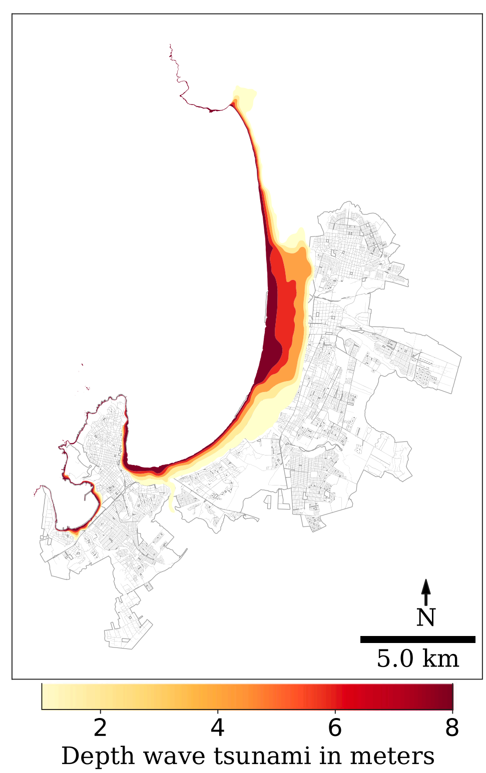
Moreover, it is mandatory to mention the importance of this topic; also, the proposed model is flexible enough to be adapted for any country or zone that is prone to tsunamis and has populations that live near the coast. However, to get a better approximation of evacuation times or travel time between different districts, we need to compute all the combinations where we suppose that the shortest route is taken if district $d \in D$ is attended by vertical shelter $i \in I$. A route collects different roads or paths $p \in P$ that connect inwardly. This study considers the case of the zone located in the Coquimbo Region, Chile. The total data is gathered and extracted by Biblioteca del Congreso Nacional (BCN) [59], Chile. This data collects different features inserted into this particular zone. For example, the region, province, and municipality names shaped areas with latitude and longitude coordinates based on GIS. On the other hand, depth information was estimated by Servicio Hidrográfico y Oceanográfico de la Armada de Chile (SHOA), and it is represented by Fig. 3. The dark red zones have more estimated depth in meters, so these are more affected by a tsunami due to a natural disaster after an earthquake. Those colors can vary due to this zone's height, deviations, and shapes. Also, it is essential to have at least one estimation of depths where decision-makers need to apply vertical shelter to mitigate effects during a disaster.

We only need to focus on the zone that can be affected by a tsunami. Furthermore, it is important to estimate time connections between vertical shelters $i \in I$ and districts $d \in D$ as the minimum travel time connection, in which each route connection is constituted by a set of the small paths that belong to La Serena-Coquimbo. In addition, those route connections that represent T_{id} have a source and target node. Those nodes are represented by Fig. 4. We also intersected all paths as a via of space and established this zone as the official zone we are interested in studying. Each road has a target node point expressed by latitude and longitude, so to record intersections, we needed to examine each point to construct a transportation network. This network is shown in Fig. 4 where each node intersects between them and conforms to the conurbation of La Serena-Coquimbo.

On the other hand, the estimation of the r_d parameter was considered by the product between the height of the wave due to tsunami (k_d), and the total population registered (ψ_d) according to the Census (2017), Chile. The r_d parameter obeys the following logic: "If we are observing higher levels of wave's height due to tsunami and higher values of the population on a district $d \in D$, then r_d takes values higher, and our modeling considers those cases with more priority and vice versa". Regarding CF, ϱ_{id} parameters were estimated using similar values costs that Vergara-Perucich and Aguirre-Nuñez [60] have studied to build different types of buildings in Santiago, Chile.



(a)



(b)

Fig. 3. (a) Total population per district in the Coquimbo Region: the colored bar as it reddens indicates a higher population density in a district. (b) Depth of wave due to tsunami estimation: the color bar indicates that as it gets redder, a higher depth wave is observed for the tsunami estimate.

8. Results and sensitivity analysis

This section provides experimental results and managerial insights. The implementation details are given in Section 8.1, Pareto frontiers are presented in Section 8.2, and finally, the sensitivity analysis is performed in Section 8.3.

8.1. Implementation

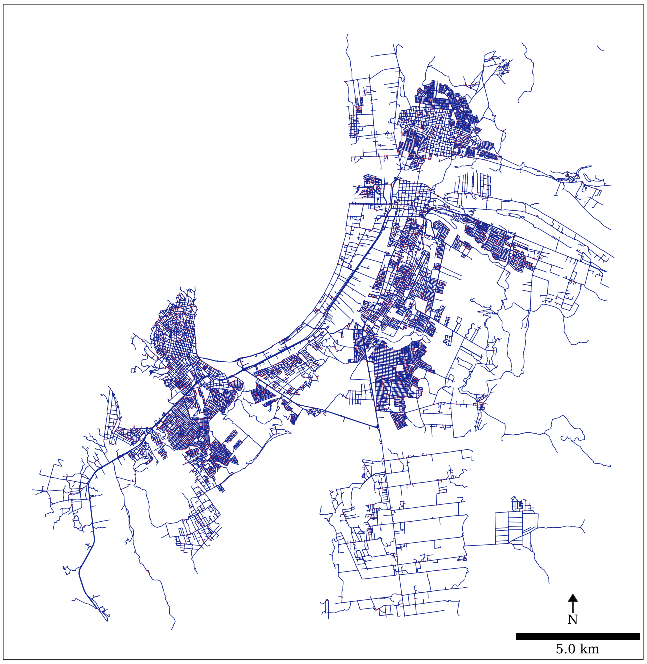
The mathematical model was implemented on Python 3.7 and solved with Gurobi 9.1.2. All tests were performed on a -Windows 10 computer with an Intel(R) Core(TM) i7-10510U CPU@1.80 GHz 2.30 GHz and 16 GB of RAM. For a test about a toy model, check https://github.com/ChristianSotelo/Logistic_Humanitarian.

8.2. Pareto frontiers

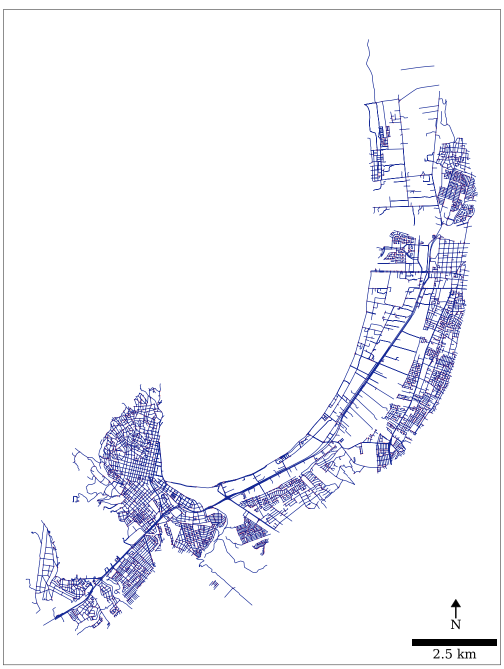
To improve the visual interpretation of the Pareto solutions in our experiments, we represent the three objectives in 2D projections, such as $(f_1, f_2), (f_1, f_3), (f_2, f_3)$. These Pareto frontiers were obtained by performing 120 instances, i.e., an instance for each $w_i \in \{0.00, 0.25, 0.50, 0.75, 1.00\}, \forall i = \{1, 2, 3\}$, number of clusters $\in \{30, 80\}$ and $S \in \{10, 15, 20, 25\}$ with $\sum_{i \in \{1,2,3\}} w_i = 1$. Figs. 5, 6, and 7 considers 30 clusters. To define the clusters, and consequently v_i, we use k-means [61], in which GIS coordinates were transformed into vector units to obtain distances for each combination of districts $(d, d') \in D^2$.

From Fig. 5, we can observe upward trends; whereas the award for care over risk increases, so does the budget needed to invest. This trend makes sense, given that the number of people served when the budget is high, the number of vertical shelters, and their capacity is much higher compared to when the award for risk coverage is prioritized. On the other hand, it is observed that as f_3 is prioritized, given that w_3 is increased, the trend between f_2 and f_1 is shifted to the right and down, implying a larger budget needed and more challenging to maximize coverage awards.

In Fig. 6, we can observe downward trends, whereas the budget required for critical infrastructure investment increases implies lower



(a)



(b)

Fig. 4. (a) Full Network IV Region, Coquimbo, the full network has 23,975 paths and 17,933 individual nodes. (b) Network model due to tsunami estimation, the tsunami network only has 10,773 paths and 7,556 unique nodes. Note that each node can connect with various paths simultaneously.

total travel times. It is to be expected that as the number of vertical shelters increases and these, in turn, are distributed within the study area given the non-proximity constraint defined in the mathematical model presented in Section 4, the total travel time will be lower. However, this does not necessarily ensure that the complexity of the routes is straightforward. On the other hand, when f_2 is prioritized since w_2 is increasing, it implies a shift of the trend to the right and up, implying more costly infrastructure investment plans and higher total attention times.

From Fig. 7, we can observe upward trends: whereas the premium for risk coverage increases, the total transfer times are also affected upward. This is because as more people are required to move from one district to another (due to the location of the vertical shelter), these movements add to the traveled distance but not necessarily to the actual average transfer times. On the other hand, as f_1 is prioritized, given that w_1 is increasing, the curve is shifted to the left and upwards, implying higher total transfer times and lower total risk coverage.

8.3. Sensitivity analysis

In this section, we want to address different analyses that can help the decision-makers. Suppose the proposed model is to be used as a reference for the critical infrastructure investment plan. In that case, the authorities should pay special attention to the priorities of the objective function and the normalization method (standardization or feature scaling), as this may significantly influence the quality of the solution required for a specific area. In addition to the above, evaluating such an investment plan in a different city can be totally distinct from our case study. For example, the estimation of the depth of a tsunami after an earthquake depends on the study area.

8.3.1. Coverage of risk's population

The total population at risk considered in the model is 39,977 people. In addition, from Figs. 8(a) and 8(b), it can be seen that as w_1 increases, the coverage of individuals decreases at different rates. When w_1 weights are in the interval [5–35]%, there is a significant decrease from the point of view of the population coverage at risk according to the SHOA estimation, reaching coverage levels between 70%–97%. On the other hand, as w_2 increases, it is clear that there is a higher population coverage, an effect not necessarily reflected in w_3 (which can be influenced by w_1). When w_2 has levels of 80%–100% and w_1 at 5%–35%, the coverage mentioned above is achieved; however, coverage decreases when w_1 increases, even though w_2 is the second most crucial relationship objective function. Recall that f_2 is associated with the risk coverage premium, while f_3 only focuses on decreasing the travel time (*i.e.,* distance) between districts and vertical shelters.

In addition, as w_1 increases, the difference in coverage obtained, given by the combinations (w_2, w_3), becomes smaller, and this can be explained by the fact that $w_2 + w_3$ loses importance compared to w_1, as seen on Fig. 8(c). On the other hand, from Fig. 8(d), it can be inferred that although in almost all combinations w_3, adequate population coverage is achieved, it is found that w_3 levels are between 70%–100%, representing a much higher coverage that is easily achieved compared to the rest of the combinations. When w_2 has low levels of importance, the coverage curve of the population at risk increases more smoothly, so it implies higher levels of demand to w_3 to improve coverage; this can be seen in Fig. 8(e). Furthermore, as studied in Section 6, due to the different normalization approaches among the objective functions, it can be concluded that population coverage is affected mainly by higher values of budget prioritization for critical infrastructure investment.

Finally, coverage is influenced mainly by the weight in the budget for investment in critical infrastructure and the risk coverage premium. In contrast, evacuation times only influence population coverage a little.

8.3.2. Height of vertical shelters

In contrast to the population coverage, according to Fig. 9(a), it is found that as w_1 grows, so does the average height required to install a vertical shelter. This is because, in the model, there is a restriction associated with the set of districts that must be served, given the proximity to the coast and the danger it represents, according to the SHOA estimation. Moreover, it is explained that since f_1 is related to the maximum budget to be occupied, as the latter is prioritized,

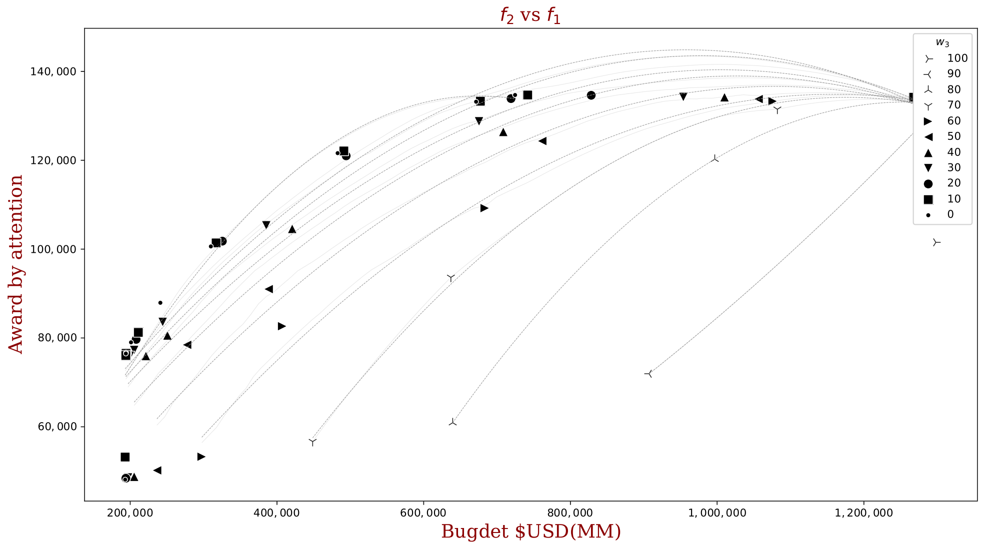


Fig. 5. Pareto frontier f_2 vs f_1. The figures show the weight of the objective function f_3, while the curves show the ratio for each isocurve confirmed by each type of figure.

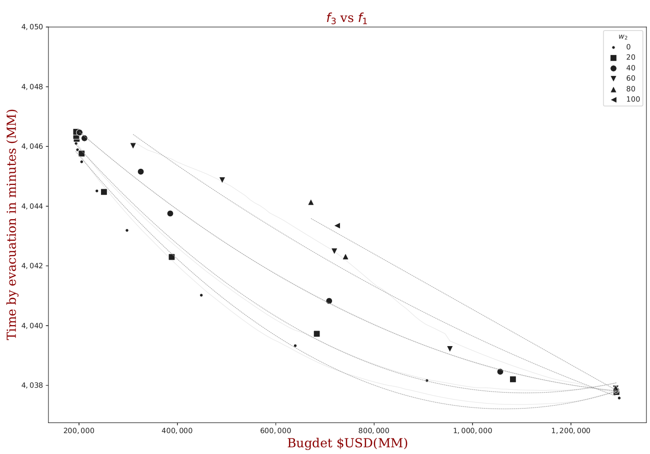


Fig. 6. Pareto frontier f_3 vs f_1. The figures show the weight of the objective function f_2, while the curves show the ratio of each isocurve confirmed by each type of figure.

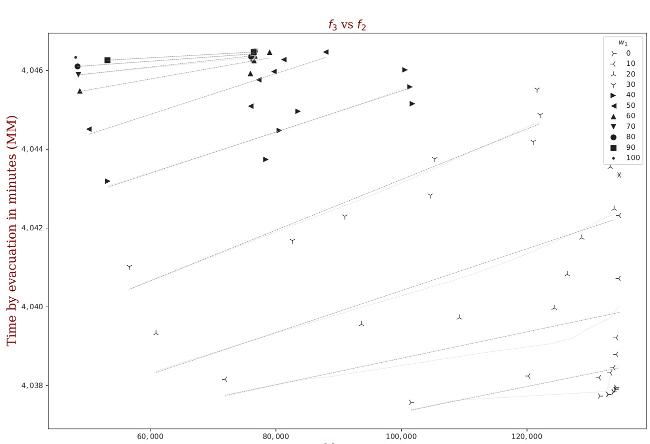


Fig. 7. Pareto frontier f_3 vs f_2. The figures show the weight of the objective function f_1, while the curves show the ratio of each isocurve confirmed by each type of figure.

it is expected to focus on the highest risk areas, given the previously mentioned restriction. However, when w_1 is at very high levels, it implies a lower population coverage and usually the one that is isolated in the higher risk of the natural catastrophe. When w_1 is at levels of 5%–40%, the average height of vertical shelters is 14 or 15 m. After that range, a growth slope on the average height of vertical shelters is observed until it reaches 17 meters when w_1 is at levels of 40%–80%.

Interestingly, when w_2 has lower levels of importance concerning $w_1 + w_3$, the curve of average vertical lodge height is affected and shifted downward, implying less need to have high average vertical lodge heights. When w_2 is at 0%, the average height starts from 11 meters and slowly increases as opposed to other higher levels of w_2. There is a difference of at least three meters when $w_2 = 0\%$ and $w_2 > 0\%$. Additionally, according to Fig. 9(b), as w_3 becomes less critical compared to $w_1 + w_2$, it implies higher average heights compared to lower w_3. That is to say that, when $w_3 > 80\%$, the average is between 14 and 11 m, while $w_3 \in [40 - 70]\%$, the average heights are between 15 and 17 m. Moreover, there is a non-linear trend between w_1 and w_3 since there is a monotonic average height growth at initial points of w_1 versus w_3. However, when we prioritize w_1 at the expense of w_3, there will always be a final decrease concerning those averages.

On the other hand, according to Fig. 9(c), although when w_2 is increasing, it implies higher average heights for vertical shelters, this also means a decreasing growth rate until reaching 18 m. Furthermore, according to Fig. 9(d), when w_3 is at lower levels on the order of [0–10]%, it implies higher vertical shelter heights curves versus the importance it possesses when $w_1 + w_2$.

Finally, there is a positive relationship as the weight values of the objective functions f_1, f_2 increase, concluding that vertical shelters tend to move closer to the coast, given the tsunami estimate according to SHOA.

8.3.3. Route time final improvement between vertical shelters and districts

In Fig. 10(a), we have that in terms of the percentage of improvement concerning the maximum connection times achieved per instance, it was obtained that as these improvements tend to decrease as w_1 grows. It is essential to mention that at high levels of w_2, maximum route improvement is reached with more stability, getting a level between 9%–11%. As w_1 grows, a point is reached where such maximum decreases abruptly, reaching levels of 0.5%–2%. Furthermore, as w_2 decreases, this curve (route improvement) remains stable until the abrupt drop is gone.

Regarding w_3, it is interesting to know that when $w_3 = 0\%$ in Fig. 10(b), the percentage change over the percentage improvement is significant, implying that the variable associated with the final connection times between vertical shelters and districts loses significance in the model. However, when $w_3 > 0\%$, the maximum improvement tends

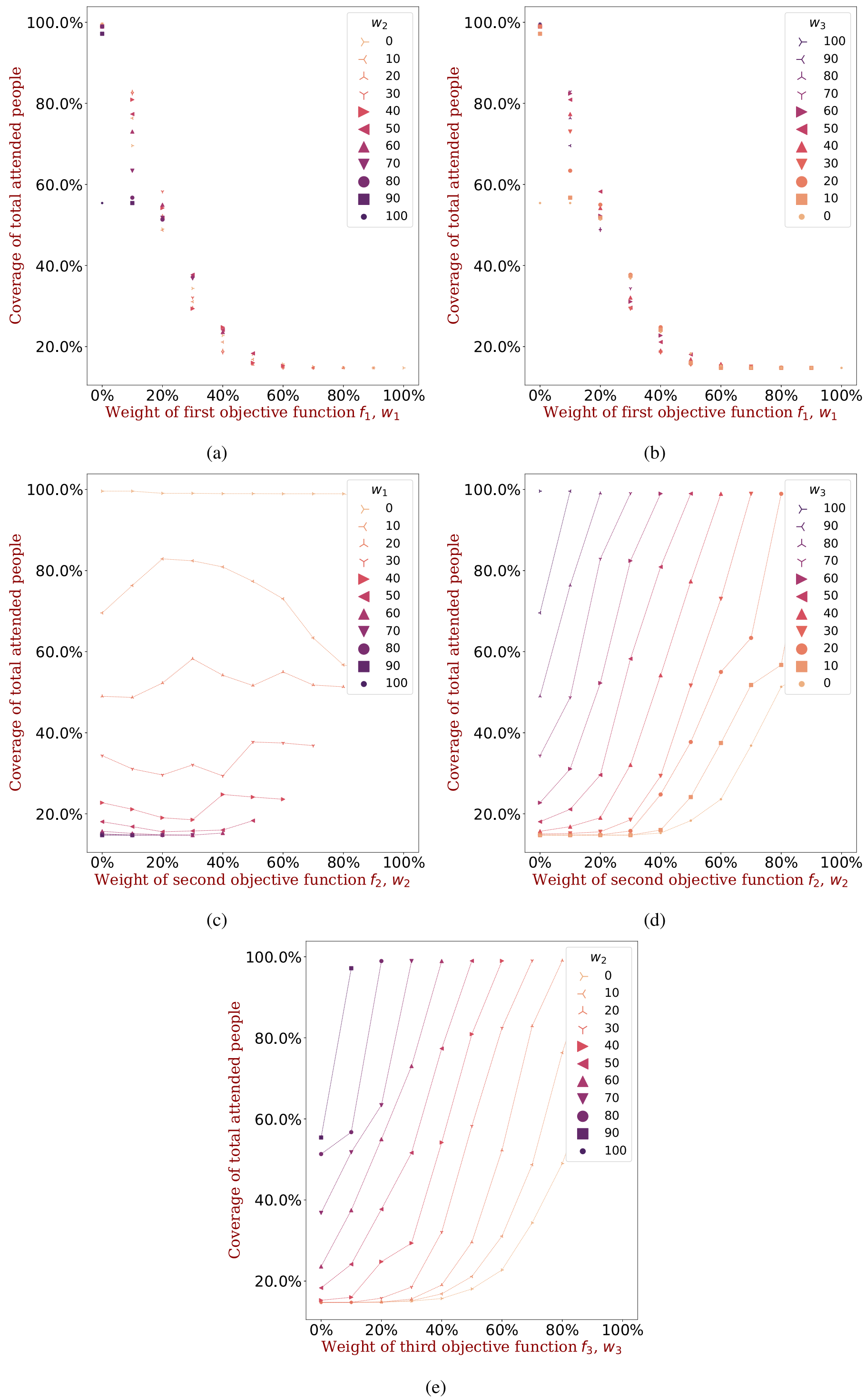


Fig. 8. Coverage total attended population.

to remain stable at around 10 percent. In addition, it was observed that when w_3 increases, the maximum improvement of the routes tends to be stable and higher than the rest of the combinations $w_1 + w_2$.

At the average percentage improvement over the route connections between vertical shelters and districts in Fig. 10(c). As w_1 grows, the improvement tends to decrease more smoothly. In addition, as w_2 increases, the decrease becomes more accentuated. From an average of 0.025%, it reaches levels of 0.005% in percentage route improvement.

In addition to the above and unlike w_2, when w_3 is high, the improvement averages tend to decrease much more smoothly when w_1 increases. It starts from 0.025% down to 0.017%. On the other hand, when w_1 grows, besides noticing a decrease in the average percentage improvement en route, these curves also get closer to each other, decreasing the dispersion. Furthermore, when w_3 is at [0–20]% levels, a change can be observed in the average improvement over the connections more smoothly, see Fig. 10(d). Finally, the investment in the connection between the vertical shelters is strongly influenced by the weights given to the objective functions f_1, f_3 because they are the metrics related to evacuation times and the associated budget. At the same time, the risk coverage premium does not generate a solid relationship to such improvements.

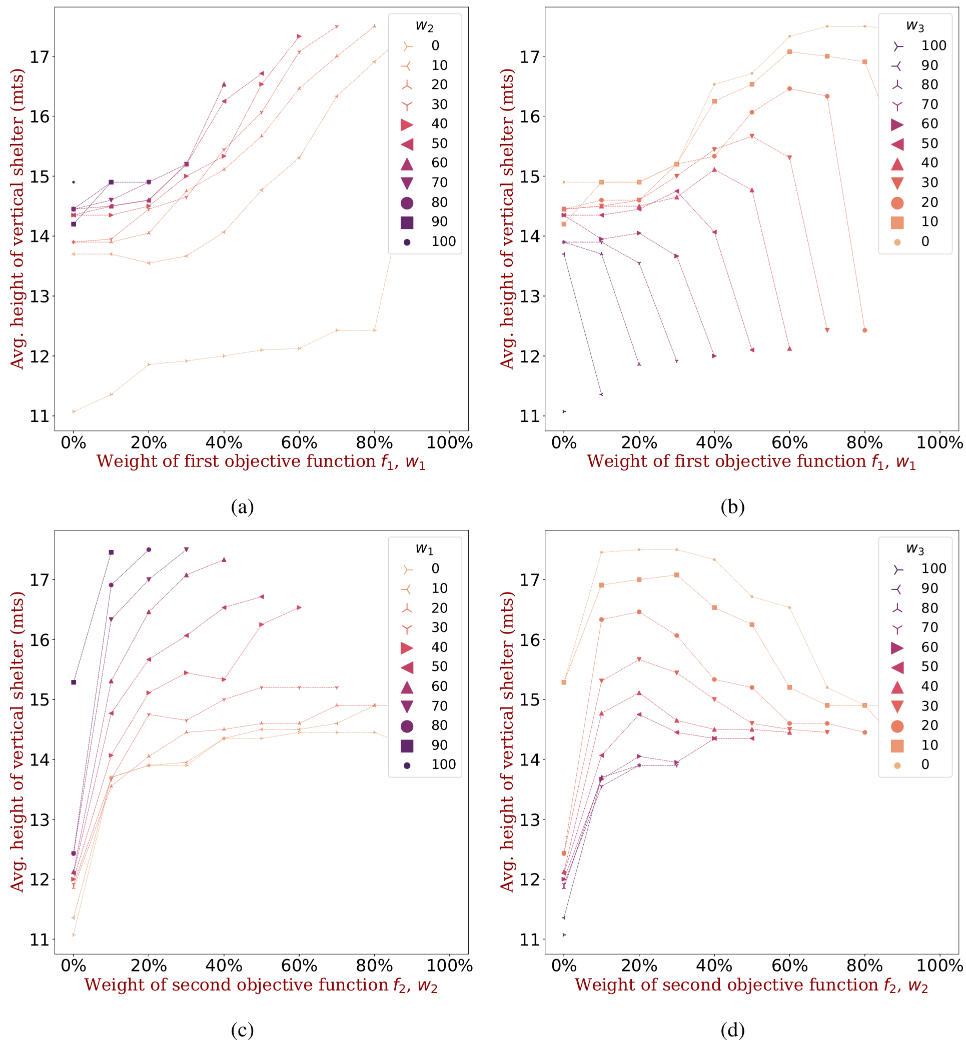


Fig. 9. Height of Vertical Shelters due to tsunami's depth.

8.3.4. Total installed vertical shelters

Within the model, 407 possible locations for vertical shelters were obtained. In addition, as for the number of vertical shelters selected, as expected and according to Fig. 11(a), they tend to decrease as w_1 increases. This implies that as w_1 increases in importance, the vertical shelters that are installed tend to move closer to the coast, where there is a greater risk of collateral damage to nearby districts, given the search to minimize the budget, reaching in some cases the seven vertical shelters mentioned above. We have an upper bound of 20 shelters, by restriction, and a lower bound of seven shelters as a minimum feasible given the mandatory constraint of attention to districts near the coast.

Furthermore, in Fig. 11(a), we have that as w_2 is relaxed, it implies smoother decay curves. That is, when $w_2 = 0\%$, at most 14 facilities are needed within the risk zone, while when $w_2 > 80\%$, at least 18 facilities are required. This can occur for several reasons that the model and its constraints can explain. One is the set of districts in which they must be served and restrictions related to the maximum transfer times between districts to the respective vertical shelters.

In addition to the above and according to Fig. 11(b) when w_3 is in the [80–100]% range, the number of vertical shelters needed to be installed tends to decrease abruptly, starting from 20 to 14 installations. In addition to the above, it is interesting that w_3, when it relaxes or becomes less important compared to the $w_1 + w_2$ combination, has a smoother and longer installation curve until it reaches seven installations. This implies that indirectly, as the values of w_3 decrease, the combination of $w_1 + w_2$ increases. Additionally, as previously observed, as w_1 increases, the decrease of total installed vertical shelters can be more abrupt, thus implying that as w_2 grows within the same combination of $w_1 + w_2$, the model allows the selection of more vertical shelters, which explains a longer curve to the right, as seen in Figs. 11(a) and 11(b) together.

8.3.5. Count of attended districts per vertical shelter

The maximum number of districts served per vertical shelter obtained was around 94 locations. That is, one standing shelter served 94 districts located within the risk zone. This number steadily decreases as w_1 increases to six locations. In addition to the above, as w_2 is in the [5–30]% levels, the decrease is much more smoothed concerning the rest of the $w_1 + w_3$ combinations, reaching a maximum of seven locations, reflected in Fig. 12(a).

Furthermore, according to Fig. 12(b), when w_3 grows, it is natural to expect the maximum number of locations served per vertical shelter to be monotonically increasing. However, when w_1 is on the order of [80–100]%, the growth of the curve on the number of districts served per shelter grows much less as opposed to other combinations $w_2 + w_3$, reaching less than 20 districts.

When we look at the trend of the averages of the number of districts per vertical shelter in Fig. 12(c), they tend to decrease steadily as in the maximums of attention. When w_1 is on the order of [0–25]%, cases of 29 average districts served per vertical shelter are observed. In addition to the above, as w_2 tends to approach 0, it implies a smoother curve, starting from 29 average districts served per shelter to eight locations.

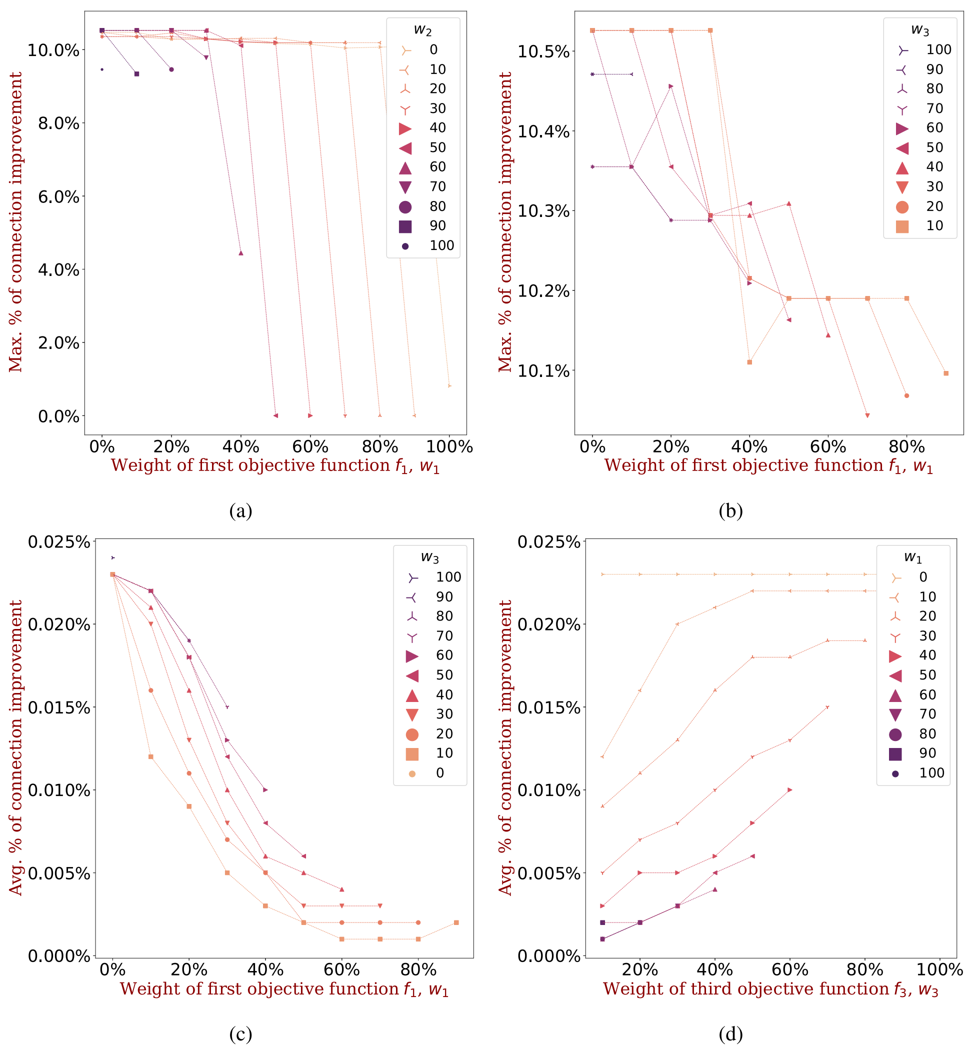


Fig. 10. Final improvement Connection between vertical districts $i \in I$ and districts $d \in D$.

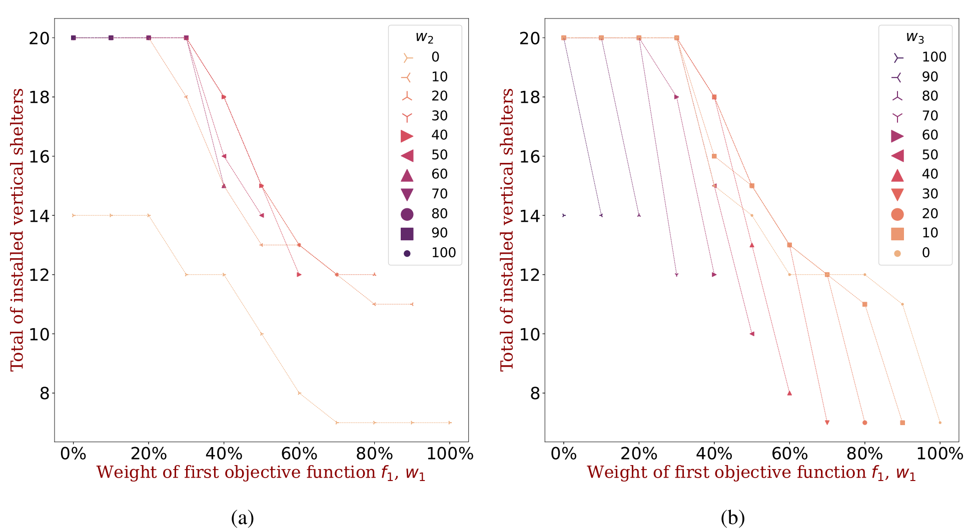


Fig. 11. Total installed vertical shelters.

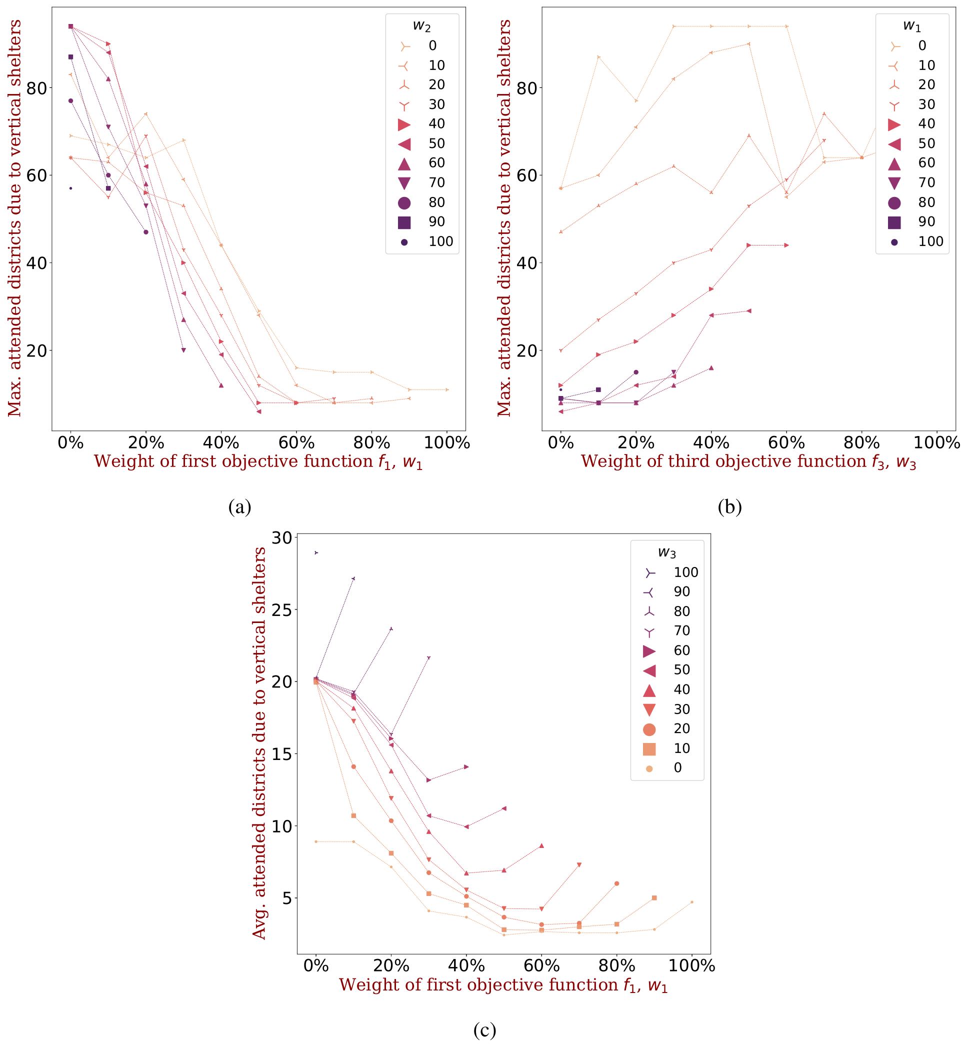


Fig. 12. Attended districts $d \in D$ per vertical shelter $i \in I$.

On the other hand, in Fig. 12(c), it is concluded that when w_3, is in the order of 0%–25%, there is an average number of districts served per vertical shelter of eight or nine locations, whose number decreases slowly as w_1 grows. In addition, when $w_3 > 70\%$, there is a more pronounced growth in the average number of districts served per vertical shelter, reaching 27–29 locations in some cases.

8.3.6. The complexity of network connections between vertical shelters and served districts

The complexity of the solution is defined as the number of total connected routes between vertical shelters and districts. This is similar to the average number of districts served per standing shelter, even though the coefficient of variation detected is high. This suggests a "linear" behavior between the complexity of the solution and the average number of districts served per vertical shelter. Moreover, according to Fig. 13, as w_1 tends to grow, the dispersion between the solution complexity curves tends to decrease. When w_1 is in the [70–90]% levels, the complexity of the solution reaches at most 50 different connections.

8.3.7. A representative case

In Fig. 14, we can observe solutions where the objective functions were defined for the network on the left, implying a maximum priority to investment in critical infrastructure. In contrast, the network on the right is related to a solution whose weights of the objective function possess another type of weighting, where the total evacuation times between the district and a vertical shelter are prioritized. In addition, we can see the type of solution that can be found given the prioritization characteristics in the objective function initially given to the non-linear MO mathematical programming model. From there, a solution with fewer vertical shelters and closer to the coast is expected when there is an increased prioritization of the component related to the investment of critical infrastructure, prioritizing only those districts that, by the rule of proximity to the coast, must be served.

Furthermore, in Fig. 14, notice that the prioritization is concentrated on some of the components that are not related to the investment in critical infrastructure, but, instead, the search for the minimization of the total evacuation times or the premium for risk coverage, it is observed that there is a much more complex attention network, which could cause certain inconveniences in the face of events declared by Yücel et al. [62], in which there could be variation in a connection between a district and a vertical shelter, given that the initial route selected may not be usable after an earthquake.

Regarding the vertical assessment decision, the non-linear MO mathematical programming model states that the average meters required to safeguard the community's safety within the Coquimbo region tend to grow as we give more importance to the component of the objective function related to the investment of critical infrastructure. In this case, it is concluded that vertical shelters tend to move closer to

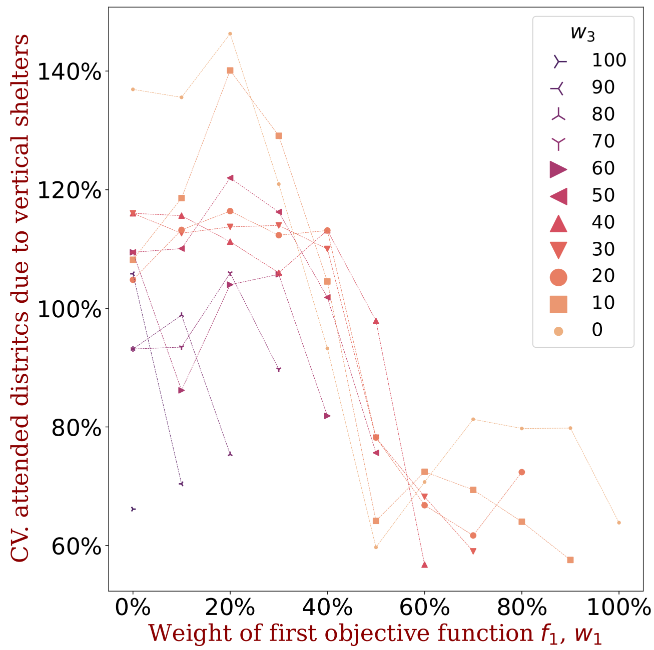
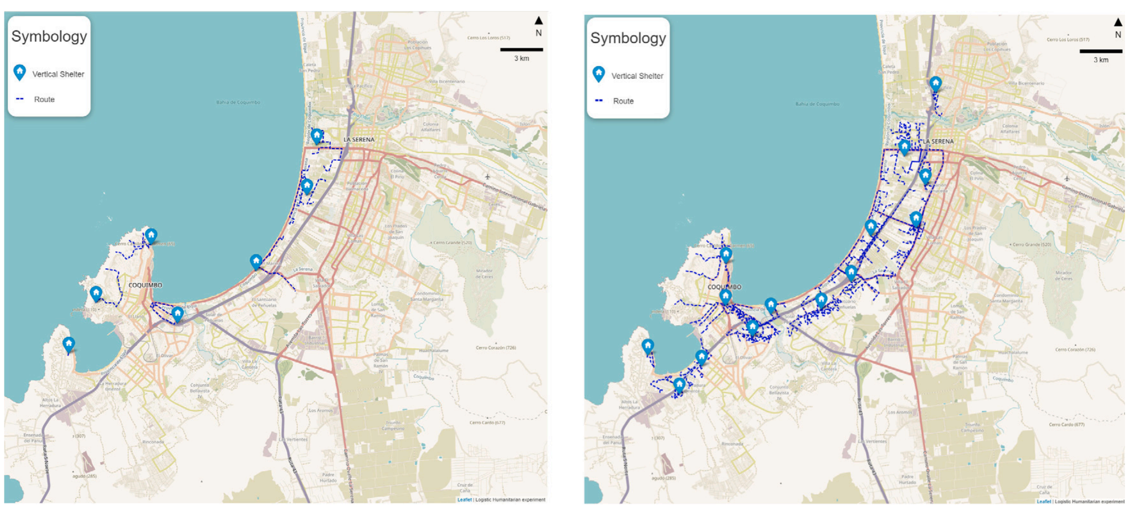


Fig. 13. Complexity of network connections.



(a) (b)

Fig. 14. (a) Network solution when the budget is prioritized. (b) Network solution when evacuation time is prioritized.

the coast, privileging a vertical evacuation. However, the latter implies a higher opportunity cost regarding coverage of the total population, which is not advisable in risk situations. The proposed model also depends exclusively on the distribution of certain districts' coasts, slopes, and heights and the potential set of vertical shelters defined by the authorities. In addition to the above, the model will react differently if the authorities decree that the evacuation and sheltering time for a potential tsunami will change.

9. Managerial insights

The interpretation of our results has brought forth several crucial aspects that must be taken into consideration before the implementation of our proposed modeling approach. One of the foremost considerations is the dangerous distance to the coast. In tsunami-prone areas, the proximity of districts to the coast presents a substantial risk. Decision-makers must recognize this distance as a pivotal parameter during the planning process, as it holds direct sway over the risk level and the formulation of effective evacuation strategies. Ensuring a safe distance from high-risk coastal zones emerges as an imperative measure for both risk mitigation and the safety of residents. Another critical factor is the travel time to a vertical shelter. The duration it takes to reach shelters plays a decisive role in the success of evacuation plans. Policymakers should prioritize the minimization of this travel time, ensuring swift and secure access to shelters for all individuals. This involves a careful evaluation of factors like traffic conditions, road accessibility, and the strategic placement of shelters relative to densely populated areas. Investments in critical connections and routes are equally indispensable to facilitate efficient evacuations. Identifying and enhancing these crucial pathways can significantly reduce travel times to shelters, thereby enhancing the overall efficacy and success of evacuation strategies. Also, the analysis revealed an intriguing insight into the impact of critical infrastructure investment. A downward trend observed indicates that increased investment in critical infrastructure correlates with reduced total travel times, see Fig. 6. This insight holds substantial implications for enhancing the effectiveness of evacuation plans. It is important to acknowledge that minimizing travel times and optimizing infrastructure investment are opposing objectives. Hence, decision-makers are advised to define intervals within the Pareto frontier and selectively choose solutions that align best with their specific needs within these intervals. This approach streamlines the decision-making process and eliminates the need to evaluate all possible solutions on the Pareto frontier. Furthermore, understanding the risk coverage and transfer times relationship is pivotal when developing strategies that effectively balance risk coverage and evacuation efficiency. Our analysis shows an upward trend, wherein higher premiums for risk coverage lead to extended total transfer times, see Fig. 7. Striking the right balance between these two factors is essential for crafting effective evacuation plans. To enhance analytical clarity for stakeholders, we advocate for the implementation of our model through a Decision Support System (DSS). This system employs visual tools that adeptly transform complex data into easily interpretable formats, providing stakeholders with clear and insightful analytical data. These tools prove invaluable for informed strategic decision-making, especially in areas pertaining to infrastructure investment and risk management. Additionally, the dynamic nature of these visualizations allows for adjustments and recalibrations in response to varying scenarios and requirements, offering stakeholders a flexible and adaptable analytical framework. Moreover, our model efficiently provides coverage for an at-risk population of approximately 40,000 inhabitants, achieving optimal protection levels ranging between 70%–97%. This optimal coverage is primarily driven by factors such as infrastructure investment and the degree of risk coverage, with evacuation times playing a secondary, yet significant, role in influencing the overall coverage effectiveness. Lastly, the model incorporates a critical parameter for "Mandatory Districts as Required Coverage", with a specific emphasis on key districts deemed essential for coverage. It is imperative for decision-makers to allocate focused attention to these pivotal areas, as they constitute integral components of the model's successful delivery of optimal risk coverage and the efficiency of evacuation planning. The careful definition and prioritization of these districts are indispensable elements of robust and effective strategies for disaster preparedness and response.

10. Conclusions

This article presents a non-linear MO mixed-integer programming model that combines coverage risk, evacuation times, and total costs to improve critical infrastructure. The model also incorporates vertical evacuation decisions, using mobility established by routes in a matrix to select the capacity of vertical shelters, determine which routes should be accessible for such shelters, and calculate the required height for an eventual tsunami. Additionally, this model identifies the critical routes that require investment to improve their capacity, reducing overall evacuation times for a specific district assigned to a vertical shelter. The proposed model integrates essential decision-making criteria and incorporates ad-hoc geological parameters, including slopes, depths, and terrain heights, to estimate the depth of an eventual tsunami in a particular area. Moreover, the model allows for specific conditions to be included, such as the desired evacuation type (horizontal or vertical), and incorporates parameters to help decision-makers narrow down their options, such as the total evacuation time. By combining these factors, our model provides a comprehensive tool for optimizing evacuation planning and infrastructure improvement in disaster-prone areas. Furthermore, the model presented proposes a plan for investing in critical infrastructure to improve connections between the vertical shelters and districts. This approach enhances horizontal evacuations and promotes community preparedness by increasing efficiency and generating robustness. Although the model is located in the mitigation phase within the four main stages of hazard management, it has significant implications for all phases of disaster management, contributing to a more comprehensive and effective approach to disaster preparedness and response.

While the model presents an investment plan for critical infrastructure that considers multiple factors, such as the coverage risk for a given population in a district and minimum travel times, there is room for future work to incorporate uncertainty into crucial parameters such as r_d and T_{id}. For example, seasonal changes in population distribution could affect these parameters, as well as changes in the dynamics of routes connecting vertical shelters to districts. Despite these potential challenges, the model's resolution efficiency using the weighted resolution method provides fast solutions, averaging 34.5 s per model. This efficiency enables various investment scenarios for critical infrastructure to be evaluated and weighted in a two-stage stochastic resolution situation.

This study does have limitations that must be acknowledged. Firstly, even though we have considered the worst-case scenario for the impact of a tsunami wave, our model does not account for the variability in the population at coastal zones during peak seasons, such as the influx of visitors during the summer. Secondly, we have not factored in the possibility of facilities being compromised due to earthquakes occurring prior to a tsunami event. To address these limitations and enhance the effectiveness of our decision support tool, a promising avenue for future research would be to incorporate uncertainty into the model. This could be achieved through the implementation of either a robust or stochastic formulation, although it is essential to note that this would necessitate the collection of additional data and may introduce computational challenges due to the increased complexity of the model. Nonetheless, this enhancement would further strengthen the applicability and resilience of our approach in real-world disaster management scenarios.

CRediT authorship contribution statement

Christian Sotelo-Salas: Data curation, Formal analysis, Software, Visualization, Writing – original draft. **Carlos A. Monardes-Concha:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing. **Francisco Pérez-Galarce:** Conceptualization, Formal analysis, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Rosemarie Santa González:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

Data availability

Data will be made available on request.

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Appendix

A.1. Data

See Tables 1–4.

Table 1
Population coverage and height average per vertical shelter.

Weight f_1 (%)	Weight f_2 (%)	Weight f_3 (%)	Pop. coverage (%)	Avg. height v. shelter (mts.)
0	0	100	100	11
0	40	60	99	14
0	80	20	99	14
10	0	90	70	11
10	40	50	81	14
10	80	10	57	15
20	0	80	49	12
20	40	40	54	14
20	80	0	51	15
30	0	70	34	12
30	40	30	29	15
40	0	60	23	12
40	40	20	25	15
50	0	50	18	12
50	40	10	16	17
60	0	40	16	12
60	40	0	15	17
70	0	30	15	12
80	0	20	15	12
90	0	10	15	15
100	0	0	15	15

Table 2
Improvement connection percent between vertical shelters and districts.

Weight f_1 (%)	Weight f_2 (%)	Weight f_3 (%)	Max. improvement connection (%)	Avg. improvement connection (%)
0	0	100	10.5	0.024
0	40	60	10.5	0.023
0	80	20	10.5	0.023
10	0	90	10.5	0.022
10	40	50	10.5	0.022
10	80	10	10.5	0.012
20	0	80	10.3	0.019
20	40	40	10.5	0.016
30	0	70	10.3	0.015
30	40	30	10.3	0.008
40	0	60	10.2	0.010
40	40	20	10.2	0.005
50	0	50	10.2	0.006
50	40	10	10.2	0.002
60	0	40	10.1	0.004
70	0	30	10.0	0.003
80	0	20	10.1	0.002
90	0	10	10.1	0.002

Table 3
Total installed vertical shelters & Attended districts avg. per vertical shelter.

Weight f_1 (%)	Weight f_2 (%)	Weight f_3 (%)	Total installed vertical shelters (Units)	Total avg. attended districts (Units)
0	0	100	14.0	28.93
0	40	60	20.0	20.15
0	80	20	20.0	20.00
10	0	90	14.0	27.14
10	40	50	20.0	18.85
10	80	10	20.0	10.70
20	0	80	14.0	23.64
20	40	40	20.0	13.80
20	80	0	20.0	7.15
30	0	70	12.0	21.67
30	40	30	20.0	7.65
40	0	60	12.0	14.08
40	40	20	18.0	5.11
50	0	50	10.0	11.20
50	40	10	15.0	2.80
60	0	40	8.0	8.62
60	40	0	12.0	2.67
70	0	30	7.0	7.29
80	0	20	7.0	6.00
90	0	10	7.0	5.00
100	0	0	7.0	4.71

Table 4
Complexity solution.

Weight f_1 (%)	Weight f_2 (%)	Weight f_3 (%)	Complexity solution (Units)
0	0	100	405
0	40	60	403
0	80	20	400
10	0	90	380
10	40	50	377
10	80	10	214
20	0	80	331
20	40	40	276
20	80	0	143
30	0	70	260
30	40	30	153
40	0	60	169
40	40	20	92
50	0	50	112
50	40	10	42
60	0	40	69
60	40	0	32
70	0	30	51
80	0	20	42
90	0	10	35
100	0	0	33

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