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Bridging technical and social dimensions in critical infrastructure accessibility assessment: A case study from Chile

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ABSTRACT

Assessing accessibility to critical infrastructure (CI), e.g., drinking water supply and transportation network, during extreme natural events is fundamental for improving the resilience of urban and rural systems. This study introduces a novel methodology to evaluate the criticality of road network links for accessing CI, integrating both technical assessments and societal preferences. A Critical Accessibility Index (CAI) was developed and applied to a case study in the Metropolitan Region of Chile, using a goal programming framework to quantify the relative importance of seven CI types as perceived by 750 survey respondents. Drinking water supply was assigned the highest weight (59.7 %), followed by healthcare (15.9 %) and electricity (8.5 %), reflecting priorities during an earthquake scenario. The CAI was estimated under two scenarios: one assuming equal CI importance and another incorporating community preferences. Results showed that in scenario (a), 69.3 % of links had very low criticality, while in scenario (b), this decreased to 47.5 %, with a notable increase in medium and high criticality links. Spatial analysis underscored the heightened criticality of drinking water access, especially in rural areas with low redundancy. Policy implications emphasize the need for dual-focused investment planning that balances technical criticality with social priorities. This approach supports inclusive and robust disaster risk management, offering a replicable framework for diverse regional applications.

1. Introduction

Critical infrastructure (CI) comprises the systems and assets that deliver essential services to a nation and whose disruption would significantly affect national security and societal functioning [8,9,37]. The specific types of infrastructure considered critical vary between countries; however, common examples include power systems, telecommunications, transportation networks, drinking water supply systems, healthcare facilities, and educational institutions [5,9].

According to Disaster Risk Reduction Terminology, the main drivers for CI failure are geological and hydro-meteorological events. The first type of event can cause structural damage, affecting the services provided by the CI and disrupting the supply chains. At the same time, CI damage can introduce cascading effects which demand a detailed knowledge base to estimate the impacts on the population which not always are available [35]. The United Nations Office for Disaster Risk Reduction (UNDRR) provides a broader taxonomy of hazards that can trigger CI failure, categorising them into environmental, societal, geological, extraterrestrial, technological, meteorological, and hydrological hazards. The UNDRR [47] highlights that the interactions between these hazards should be assessed case-by-case under a multihazard framework.

Given the central role of CI in sustaining economic and social development, it is imperative to evaluate the risk of CI failure to inform the design and implementation of policies and measures aimed at enhancing resilience [4,20,30]. This need becomes particularly relevant during extreme natural events, where CI becomes even more essential for crisis response and recovery [14]. For instance, following a major earthquake, disruptions to drinking water and electricity services can severely impede rescue operations, potentially increasing the number of

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casualties. Moreover, the ability to access emergency services and healthcare facilities during such events—and throughout the recovery process—is critical [10,23].

Among all CI, road networks play a pivotal role by facilitating the movement of emergency response and repair teams to affected areas, thereby supporting the restoration of disrupted systems. Consequently, road networks constitute a CI for emergency management [19], enabling both the evacuation of populations from hazardous areas and access to other CI needed for recovery. Due to their connective function, road networks are intrinsically linked to the operation and accessibility of other CI systems [2]. However, their widespread geographical distribution renders them particularly vulnerable to various natural hazards [14,16,19,24].

Previous research on the effects of severe natural events on CI accessibility has often focused on a single type of CI or has overlooked the heterogeneity in the perceived importance of services provided by different CI systems [15,17,19]. For instance, Chamorro et al. [53] proposed a methodology to evaluate access to various CI types but did not consider the differing values that the population assigns to these services. The perceived importance of CI types varies based on social, economic, and geographical factors. While some studies have examined interdependencies among CI types—often relying on expert opinions to prioritize these relationships [22,52]—the perspective of the population regarding the importance of critical services remains underexplored.

To address this research gap, the primary objective of this study is to assess the accessibility to a set of diverse CI by developing and applying a synthetic index, called the Critical Accessibility Index (CAI). It identifies the most critical links within a road network based on the accessibility they provide to critical infrastructure. The CAI is applied in two distinct scenarios: (a) assuming that all types of critical infrastructure are equally important, and (b) incorporating the population's preferences for the services provided by critical infrastructure during the occurrence of an extreme event, such as an earthquake. Estimating the CAI for the two defined scenarios is crucial to comprehensively assess the criticality of road network links in terms of accessibility to CI. Scenario a) offers a baseline assessment grounded in technical and operational considerations. In contrast, Scenario b) incorporates integrates a social perspective that reflects the perceived importance of different CI types which might be relevant for decision-making to improve resilience.

The main novelties of this study lie in the development and application of the CAI, which represents a synthetic measure for identifying the most critical links within road networks based on their role in ensuring accessibility to CI. Unlike previous studies that either considered CI accessibility in isolation or relied solely on expert evaluations, this research integrates the population's preferences for CI services during extreme events to complement purely technical assessments. This dual-scenario approach, encompassing both uniform CI importance and community-specific priorities, provides a more comprehensive and socially attuned framework for evaluating road network vulnerabilities. Consequently, the proposed methodology enhances the capacity of decision-makers to prioritize interventions that reflect both systemic interdependencies and community resilience needs.

The structure of the article is as follows. Following this introduction, the methodology is presented. Subsequently, this methodology is applied to a case study of the surroundings of the upper basin of the Maipo River, in central Chile. Finally, the results are analyzed, and the conclusions and recommendations are presented.

2. Literature review

CI accessibility has emerged as a central concern in resilience research, urban planning, and disaster risk management [43]. Accessibility refers to the ease with which services and amenities can be reached through the road network [42]. Assessing accessibility necessitates identifying the most critical elements within a network [19]. For example, Han and Zio [20] employed topological analysis to identify critical network components, while Ghavami [19] identified essential links based on their accessibility, vulnerability, capacity, and strategic importance for emergency services. Garbut et al [17] underscored the impact of natural events on accessibility by comparing travel times and access to hospital infrastructure under normal conditions and during extreme events, thus identifying potentially isolated areas.

A foundational shift in CI accessibility research is the move from purely physical proximity to a more nuanced understanding incorporating space-time dynamics, user behavior, and service functionality [32]. Chen et al [6] introduced the STH-G2SFCA model (Space-Time Heterogeneous Gaussian Two-Step Floating Catchment Area), a novel methodology that evaluates service accessibility not only by distance but also by supply-demand mismatches, temporal availability, and users' queuing resistance. Genc et al [18] proposed a comprehensive fragility-criticality-equity framework for CI access in disaster-prone regions, using Louisiana as a case study. Their transportation network analysis incorporates drive-time to primary and secondary service facilities, alternative access points, and demographic equity. This reveals that fragility in access is not exclusive to rural regions—urban zones with rapid growth can also suffer from limited service alternatives. The study highlights Native American populations as disproportionately vulnerable, reinforcing the call for equitable access planning.

Tariverdi et al [41] further expand on user-centric accessibility by integrating population preferences, congestion effects, and road criticality under various disaster scenarios in Lima and Manila. Their model simulates accessibility under flood and seismic conditions, identifying not only isolated populations but also road segments whose disruption would have the greatest systemic impact. This whole-of-system approach bridges population needs with infrastructure topology, enhancing cross-sectoral planning. Takyi et al [40] employed machine learning and high-resolution satellite imagery to assess roadway accessibility following hurricanes in Florida. By detecting road closures and classifying open, partially closed, and fully closed roads, their model supports rapid emergency response and long-term infrastructure resilience planning.

Understanding the resilience of CI systems under extreme events necessitates a comprehensive grasp of cascading and rippling effects. These concepts capture how disruptions in one infrastructure element can propagate across systems, amplifying societal and economic impacts [45]. Cascading effects refer to interdependent failures—where a failure in one CI leads to sequential failures in others. Rippling effects, by contrast, involve broader systemic disturbances, often across social and spatial domains, without direct interdependency [48]. Recent literature reflects a growing emphasis on modeling interdependencies among CI systems to evaluate these effects. El-Maissi et al [12] present an integrated framework combining seismic fragility functions and accessibility indices to assess the impact of earthquakes on road networks and access to emergency services. While their model does not simulate cascading failures explicitly, it identifies infrastructure bottlenecks that could trigger broader accessibility losses under disaster scenarios.

Mossoux et al [34] propose two innovative metrics—"road accessibility risk" and "users' path vulnerability—to assess how hazard-induced road segment failures affect access to services. Although not formally modeling cascading effects, this work highlights how local disruptions in road networks can ripple through accessibility systems, isolating entire communities and thereby compromising resilience.

The application of advanced technologies, such as remote sensing and deep learning, offers new ways to detect and analyze ripple effects post-disaster. Cha et al. [54] utilize satellite imagery and semantic segmentation models to identify damaged roads after natural disasters. Although their model focuses on physical damage detection, it indirectly supports CI resilience by enabling faster response and prioritization, potentially limiting cascading delays in emergency logistics.

Furthermore, rippling effects are increasingly understood not only in physical terms but also in their socioeconomic dimensions. For example, Ji et al [26], developed a risk-based resilience concentration framework that integrates seismic risk assessments with resilience indices for infrastructure and socioeconomic systems. Their method reveals how inequities in community resilience and physical vulnerability can compound disaster impacts—representing a form of cascading inequality that emerges from spatially concentrated risks and limited recovery capacity. Alternatively, Wei et al [50] conducts a benefit-cost analysis of seismic risk mitigation strategies. Using damage probabilities and retrofitting costs, it evaluates economic feasibility for different building types, highlighting the importance of proactive investment in regions with moderate seismic risk to reduce future losses and enhance community resilience.Overall, the literature evidence that CI accessibility research has evolved into a multidisciplinary field, integrating geospatial science, transportation modeling, urban informatics, and social equity.

3. Methodology

The development of the CAI relies on two sequential stages, with the second one focused on Scenario b) assessment to incorporate the relative importance of each CI assessed (Fig. 1). In the first stage, a synthetic CAI is constructed based on the location and influence zones of each CI, as well as the length and influence zones of links. The second stage aims to determine people's accessibility preferences to a set of CIs in the event of an extreme natural event. It is based on a goal programming approach and the weights allocated to each CI reflect their relative importance in such scenario.

3.1. Estimation of the critical accessibility index

The proposed CAI was inspired by the methodological approach developed by Chamorro et al. [53]. According to it, the interurban road network is considered the central infrastructure, acting as a connector for the various services provided by different CI types. To understand this methodology, it is essential to define what constitutes a road link. It refers to any section of road between two intersections or between an intersection and either the starting or ending point of the road.

An area of influence of two kilometers around each CI facility in the study area was delineated. This distance is based on the Rural Access Index [44], which defines the maximum walkable distance for a person in a worst-case scenario. This area of influence captures all road links that provide access to a given CI. Therefore, both road links that intersect with this area and those that lie entirely within it were selected. These links warrant special attention in terms of managing and maintaining their level of service and trafficability.

Once these road links were identified, two key attributes were collected: their average annual daily traffic (AADT), expressed in vehicles/day-year, and their length expressed in km. These two variables were selected as proxies for road hierarchy, since official street classification was not consistently available for all road segments in the study area, particularly in rural municipalities. AADT, in particular, reflects the relative importance and functional role of links in the network, thereby serving as a robust alternative to direct classification. These attributes enable consideration of the hierarchy of links that provide access to each CI type. Based on these variables, the CAI for the access of each link was calculated:

$$\mathrm{CAI_i} = 1 + \sum_{j}^{m} \frac{W_j \cdot \mathrm{L_i} \cdot \mathrm{AADT_i}}{\mathrm{L_{T_{IC_j}}} \cdot \mathrm{AADT_{TICj}}} \tag{1}$$

where $\mathrm{CAI_i}$ is the Critical Accessibility Index score of the i-*th* link, j is the CI accessed by link i, m is the total number of infrastructure types link i accesses, T_{IC} refers to the total number of links that give access to infrastructure j, $\mathrm{W_j}$ is the weight associated with infrastructure j, L is the length of the road link (in km), and $AADT_i$ is the traffic on each link.

Each link has an associated CAI score, which depends on the number of CI types it provides access to and the number of road links that provide access to those CI types. The fewer the links providing access to a given CI type, the higher the CAI score for those particular links. Likewise, if a link provides access to many CIs, this also raises its final CAI score.

Based on the definition of CI provided by the European Union (Directive 2008/114/EC) and the availability of spatial data in the study area, we selected seven types of CI for this study: (i) drinking water

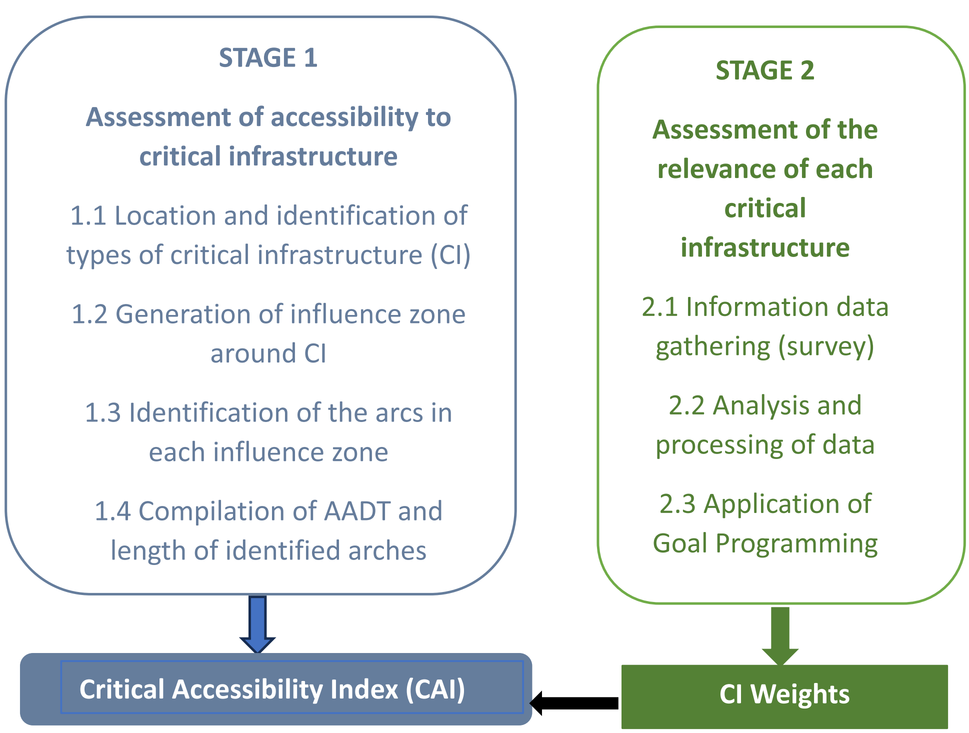

Fig. 1. Conceptual framework of the proposed methodology.

supply (W), (ii) electricity supply (EN), (iii) healthcare facilities (H), (iv) educational institutions (ED), (v) emergency and security services (EM), (vi) gas supply facilities (G), and (vii) fuel supply facilities (F). These categories represent essential services that are commonly prioritized in disaster resilience planning and are consistent with the CI types highlighted in previous studies (e.g., [7,21]).For better understanding the CAI meaning it is classified into five categories, ranging from "very low" for links with the lowest scores to "very high" for those offering greater accessibility. The intervals for these categories are defined using the natural breaks [25], a data grouping method, which minimizes within-class variance and maximizes between-class variance [1,38]. This method is particularly suited for skewed distributions like CAI scores, as it reveals statistically significant breaks in the data without relying on arbitrary thresholds. It has been widely applied in accessibility and network vulnerability studies [28,36,49]. Consequently, the numerical thresholds for these categories vary depending on the values and distribution of the calculated dataset and therefore are different for Scenarios a) and b) (see results section for more details).

3.2. Preference for each type of critical infrastructure

As illustrated in Eq. (1), the estimation of the CAI incorporates the weights allocated to each CI type, reflecting public preferences and priorities. Consequently, CI types with higher weights are considered to provide more essential services and should be prioritized in terms of accessibility. To identify and quantify societal preferences regarding CI during extreme natural events, a survey was conducted. As this survey serves as the primary data source for the case study, several key aspects were carefully considered: i) a clearly defined study area, both for survey administration and for the subsequent case study, ensuring comparability in terms of population, territory, and infrastructure conditions; ii) selection of a representative sample, including socioeconomic diversity; iii) formulation of questions that capture the necessary data in both quality and format; and iv) clear definition of the CI types included in the study, supported by the availability of spatial data to georeference each facility with the required attributes.

The weights for CI types were derived from a societal preference survey. This approach was chosen to capture community priorities during extreme seismic events, rather than relying exclusively on expert opinion. While a Delphi study with experts could provide technical insights, it would not adequately reflect the social dimension of resilience, which is central to our research objective.

In this study, to estimate population preferences, the selected CI types (see Case Study section) were evaluated through pairwise comparisons. These comparisons were processed using goal programming to convert qualitative preferences into quantitative weights, facilitating interpretation [27]. This multi-criteria decision analysis technique was used as it does not require consistency across responses [33]. This feature is particularly advantageous, as the respondents were not necessarily experts and a wide range of CI types were assessed.

Model (2) describes the goal programming model used in this study. The first equation is associated with the achievement function, which minimizes the total sum of the errors n_i and p_i (called unwanted variables). This is subject to three restrictions, which ensure that all weights W_j are greater than zero and their sum must be one. The third restriction reflects the goal that the weights obtained are as close as possible to the information obtained by the survey.

$$\textit{Minimize } n + p \tag{2}$$

Subject to

$$\begin{aligned} W_A > 0 \textit{ and } W_B > 0 \\ W_A + W_B = 1 \\ xW_A - yW_B + n - p = 0 \end{aligned}$$

where W_A and W_B are the weights of the pair of CIs compared. W_A and W_B are the parameters to be estimated, and x and y are the information obtained in the survey regarding people's preferences for CI *"B"* and *"A"*, respectively. The variables n and p are the possible errors, the unwanted deviational variable for the goal.

Considering that our case study embraces 7 types of CI (see Case study section), the specific goal programming model applied is shown in Model (3).

$$\textit{Minimize } \left(\sum n_j + \sum p_j \right) \tag{3}$$

Subject to:

$$\begin{aligned} \mathrm{W_w}; \mathrm{W_{EN}}; \mathrm{W_H}; \mathrm{W_{ED}}; \mathrm{W_{EM}}; \mathrm{W_G}; \mathrm{W_F} > 0 \\ \mathrm{W_w} + \mathrm{W_{EN}} + \mathrm{W_H} + \mathrm{W_{ED}} + \mathrm{W_{EM}} + \mathrm{W_G} + \mathrm{W_F} = 1 \\ x_j \mathrm{W_{OP1_j}} - y_j \mathrm{W_{OP2_j}} + n_j - p_j = 0 \end{aligned}$$

where $\mathrm{W_{OP1j}}$ and $\mathrm{W_{OP2j}}$, refer to the weights corresponding to the infrastructure pair comparison. In this case, $\mathrm{W_{OP1j}}$ and $\mathrm{W_{OP2j}}$ are the parameters to be estimated, while x_j and y_j represent people's preferences between infrastructure *OP*1 and *OP*2, respectively. n_j and p_j are the possible errors, the unwanted deviational variables for the goal. $\mathrm{W_w}; \mathrm{W_{EN}}; \mathrm{W_H}; \mathrm{W_{ED}}; \mathrm{W_{EM}}; \mathrm{W_G}; \mathrm{W_F}$ represent the weights allocated for the seven CI considered in this study, i.e., $\mathrm{W_w}$ is water system; $\mathrm{W_{EN}}$ is electricity system; $\mathrm{W_H}$ is health infrastructure; $\mathrm{W_{ED}}$ is educational infrastructure; $\mathrm{W_{EM}}$ is public safety and emergency infrastructure; $\mathrm{W_G}$ is gas service and; $\mathrm{W_F}$ is fuel supply infrastructure.

4. Case study

The proposed CAI for both scenarios was applied in the Metropolitan Region of Santiago, Chile, focusing on three municipalities in its southeastern sector: Puente Alto, Pirque, and San José de Maipo (Fig. 2). These areas were intentionally selected for their relevance to the study's goals. First, they represent a diverse urban–rural continuum with varying levels of road and CI density: Puente Alto is a densely urbanized area; Pirque is peri-urban; and San José de Maipo is predominantly rural with low redundancy in its road network. Second, all three municipalities lie within the upper Maipo River basin, a region of strategic hydrological and infrastructural importance. Third, these areas are highly susceptible to seismic and landslide hazards, which makes them relevan for analyzing accessibility during extreme events such as earthquakes. This combination of factors offers a unique opportunity to evaluate how spatial, functional, and social variability influence access to CI and to test the robustness of the CAI under contrasting territorial conditions. San José de Maipo is a mountainous region near the border with Argentina, through which the Maipo River flows (Fig. 2b). Its mountainous morphology hinders the existence of a dense and redundant road network and therefore limits the mobility and accessibility to CIs of the population. In contrast, Puente Alto, as an urban area, has a greater density of both road infrastructure and other CI (see Fig. 2c). Finally, Pirque is a *peri* urban area, but, unlike San José de Maipo, it has better access and proximity to critical services thanks to its proximity and connection to urban areas (see Fig. 2b).

Based on the definition of CI established by the European Union in Directive 2008/114/EC, the existing infrastructure in the area of study and the availability of databases, seven types of critical services and its associate infrastructure were considered. The acronym and the number of facilities for each type of CI is indicated in parentheses: (i) drinking water supply facilities (W, 5); (ii) electricity supply facilities (EN, 11); (iii) healthcare facilities (H, 24); (iv) educational institutions (ED, 67); (v) emergency and security services (EM, 24); (vi) gas supply facilities (G, 17); and (vii) fuel facilities (F, 43). Fig. 2c gives an overview of the 61 road links that comprise the study network. For the case study, the road network was georeferenced and includes length data in kilometers and traffic data in terms of AADT.

The pairwise comparison to quantify the relevance of CI types for the society in case of an extreme event was focused on the occurrence of an

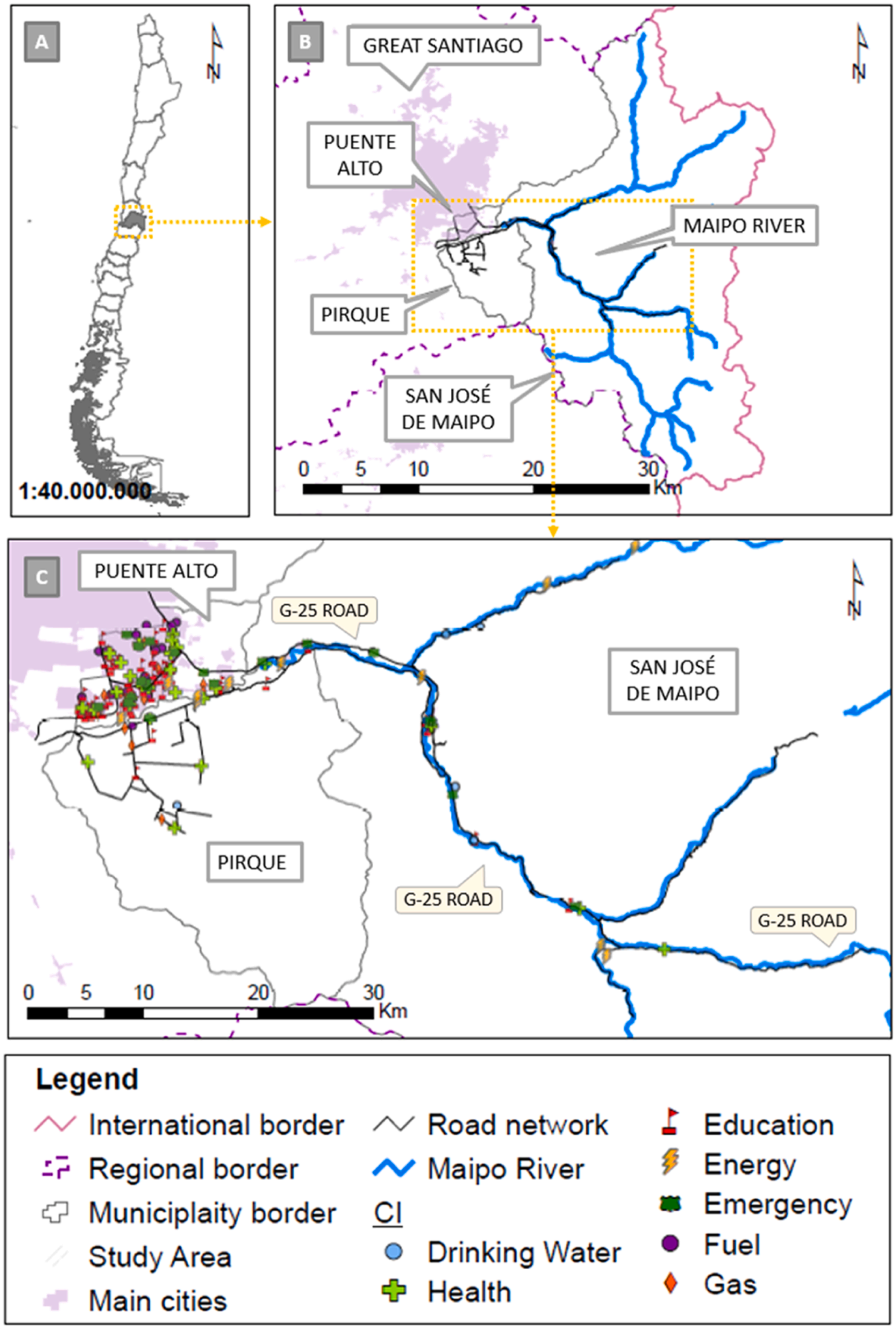

Fig. 2. Description of the case study area.

earthquake, as this represents a common natural hazard across Chilean municipalities [11,39]. Participants were asked the following question: *"In the event of an earthquake, which critical service do you consider most important to restore quickly, A or B?"* This question was posed for each possible pair of CI types (see Table 1), resulting in a total of 21 pairwise comparisons among the seven CI categories included in the study.

5. Results and discussion

5.1. Relevance assessment for each critical infrastructure type

To determine people's preferences relative to CI types, a survey was conducted in the Metropolitan Region of Chile, with a total of 750 responses collected. The survey was administered using in-person fieldwork conducted in selected municipalities to ensure coverage of both urban and rural respondents. The sampling strategy followed a non-probabilistic convenience sampling design, with no snowballing techniques used. While not random, the sample included a broad range of socioeconomic profiles and territorial contexts.

To ensure representation across diverse socioeconomic conditions and both rural and urban contexts—factors that critically influence access to essential services, as well as the impact and recovery from natural hazards—the survey was administered in five Chilean municipalities, including Puente Alto and San José de Maipo (Fig. 3). The objective was

Table 1
Results of the comparison of pairs showing respondents' preferences.

#	PAIRS	A (y_i)	B (x_i)	#	PAIRS	A (y_i)	B (x_i)
1	W-EN	674	76	12	H-ED	694	56
2	W—H	592	158	13	H-EM	537	213
3	W-ED	715	35	14	H-G	592	158
4	W-EM	655	95	15	H-F	634	116
5	W-G	707	43	16	ED-EM	130	620
6	W-F	711	39	17	ED-G	219	531
7	EN—H	268	482	18	ED-F	263	487
8	EN-ED	616	134	19	EM-G	490	260
9	EN-EM	397	353	20	EM-F	541	209
10	EN-G	555	195	21	G-F	503	247
11	EN-F	588	162				

(1) W: water, EN: energy, H: health, ED: education, EM: emergency, G: gas, F: fuel.

to derive the most representative weighting factors possible for each CI, enabling their application in other case studies (municipalities) without the need to conduct new location-specific surveys.

The sum of the total responses for each preference is represented by the variables x_i and y_i (see Table 1), which were used to solve the goal programming model 3. Table 1 lists the results of the pairwise comparison for the 750 responses collected. Because this study compares seven types of CI, 21 pairwise comparisons and therefore, goals were obtained.

Goal programming models were solved using LINGO software. The weights obtained for each of the analyzed CI are shown in Table 2. The results indicate that, according to respondents' preferences, access to drinking water supply is considered the most critical CI in the context of an earthquake, accounting for 60 % of the total prioritization score. In contrast, access to educational services was perceived as the least critical, with a relative weight of only 1.58 %.

These findings align with well-established disaster response frameworks, which emphasize the prioritization of life-sustaining services immediately following a hazardous event [46]. Access to safe drinking water is essential for preserving public health, supporting emergency response activities, and preventing waterborne disease outbreaks, particularly in the aftermath of infrastructure damage caused by seismic activity [51]. The high prioritization of water services likely reflects both their fundamental role in survival and their vulnerability to disruption during earthquakes [13]. In contrast, access to educational services, though vital for long-term recovery and community resilience, is typically not considered an immediate priority in the emergency response phase. This lower prioritization is consistent with Maslow's hierarchy of needs, wherein educational and developmental services are secondary to basic physiological and safety needs during crises [3,31]. These preferences may also be shaped by local disaster experiences, levels of infrastructure dependency, and the socio-demographic characteristics of respondents, which influence risk perception and prioritization behavior [29].

5.2. Assessment of accessibility to critical infrastructure

Once the weights for each CI were defined, the CAI scores were estimated for the two scenarios assessed. Scenario a) considers that all CIs are equally important, and scenario b) incorporates people's preferences in terms of CI relevance. Fig. 4 shows the CAI scores estimated for both scenarios. Before analyzing and comparing the CAI scores for both scenarios, it is important to highlight their numerical variability.

Table 2
Estimated weights for each analyzed critical infrastructure.

CI	Weight
Drinking water supply	0.5970
Electricity supply	0.0849
Healthcare facilities	0.1593
Educational institutions	0.0158
Emergency and security services	0.0755
Gas supply at home	0.0384
Access to fuel	0.0291

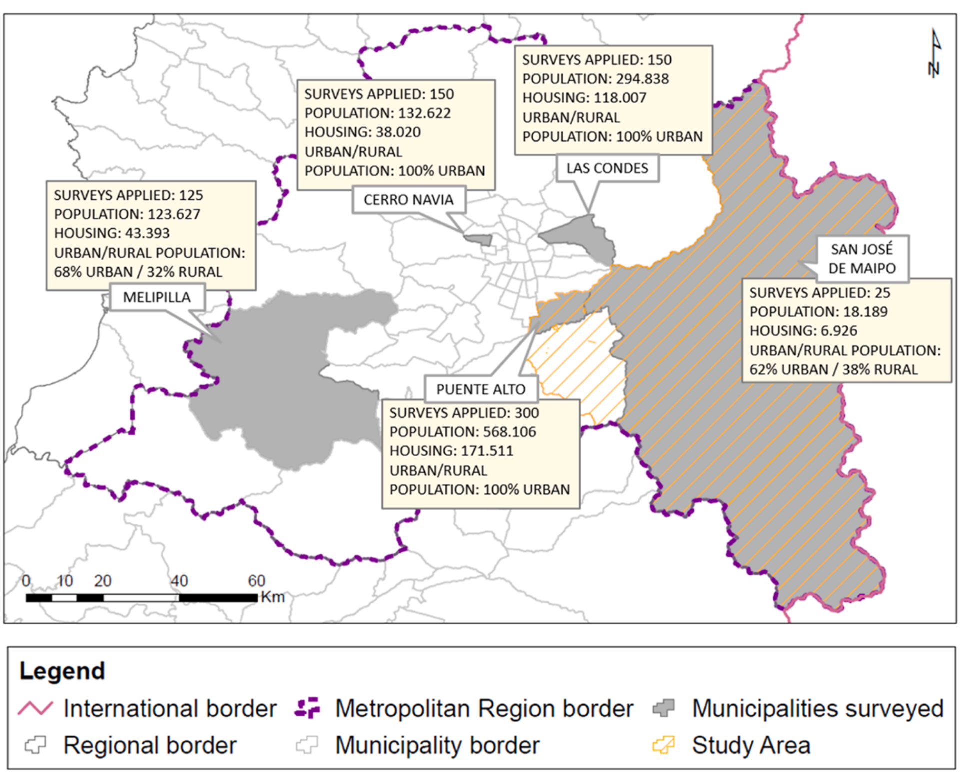

Fig. 3. Location and characterization of the municipalities involved in the survey.

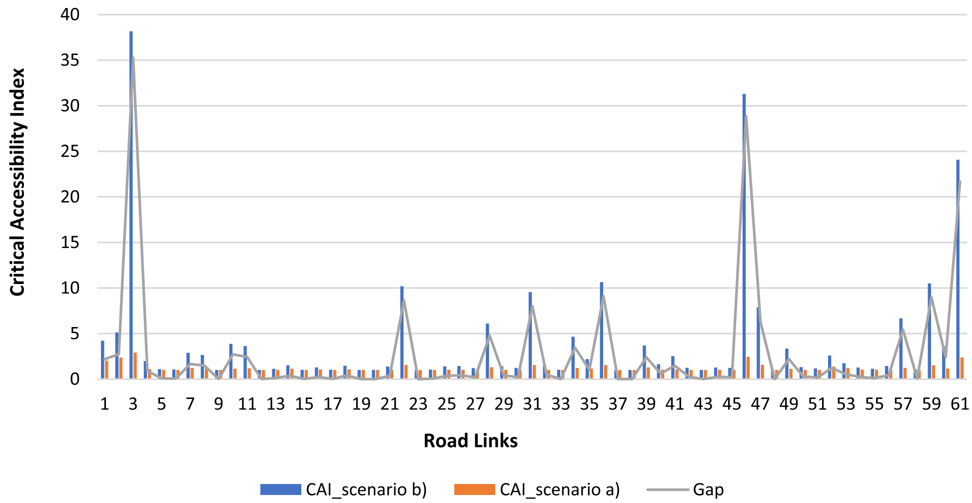

Fig. 4. CAI estimation for the two scenarios evaluated.

The CAI scores show notable differences between the two scenarios. Although the minimum CAI value is 1 in both scenarios, the maximum value varies significantly: from 2.91 in scenario b) to 38.17 in scenario a). An absolute comparison of CAI scores can therefore be misleading. As noted, the thresholds for defining CAI categories depend on the distribution of their values. Table 3 presents the threshold definitions for the qualitative CAI, allowing a direct comparison between both scenarios.

Based on the CAI classification (Table 3) and the estimated CAI scores for each scenario (Fig. 4), Table 4 presents the total number and percentage of road links distributed across the different CAI categories. The results show that in both scenarios, most road links are classified as having very low accessibility, with this trend being more pronounced in the scenario that considers all CIs equally relevant (69.3 %) compared to 47.5 % when people's preferences are included in the assessment. In both scenarios, the number of road links with very high accessibility is quite limited, representing 4.9 % and 6.6 % of links for scenarios (a) and (b), respectively. The very low category also includes those links that fall outside the two-kilometer influence zone of any CI type and are therefore not critical for accessibility. In this case study, which considers a small and linear road network, the number of such links is minimal, and their impact on the very low category is limited.

Spatially, the results of the CAI estimation for both scenarios are presented in Fig. 5, which categorizes the road network links based on their CAI scores. Fig. 5a depicts scenario a), while Fig. 5b illustrates scenario b). A comparison of the two scenarios highlights the predominant influence of drinking water infrastructure (represented by blue dots on the maps). Consequently, the road links that provide access to these water systems hold greater relevance, a significance that is consistent in both urban and rural areas. For example, the San José de Maipo area, which has a notably lower road density than the rest of the subnetwork, was already identified as a critical access area due to its near-zero redundancy. However, only medium CAI levels are reached in scenario a) because of the strong weighting of urban areas. When people's preferences are incorporated, this situation becomes more critical in San José de Maipo. Given the importance of drinking water infrastructure, high and very high levels of access are achieved for certain links that provide access to this service—specifically on the G-345 highway and parts of the G-25 highway.

Table 3
Thresholds of CAI for its categorical classification for scenarios a) and b).

Categorical classification of CAI	Scenario a)	Scenario b)
Very Low	≤4.7	≤1.1
Low	(4.7–7.9]	(1.1–1.4]
Medium	(7.9–10.5]	(1.4–2.1]
High	(10.5–38.2]	(2.1–2.9]
Very High	>38.2	>2.9

Table 4
Compilation of results according to CAI intervals, percentage is shown in brackets.

Classification of CAI	Scenario a)	Scenario b)
Very low	39 (69.3 %)	29 (47.5 %)
Low	11 (18.0 %)	8 (13.1 %)
Medium	4 (6.6 %)	14 (23.0 %)
High	4 (6.6 %)	6 (9.8 %)
Very high	3 (4.9 %)	4 (6.6 %)

5.3. *Discussion of results*

The findings of this study align with, and in some aspects expand upon, recent advances in literature that highlight multidimensional approaches to CI resilience under disaster scenarios. A central advancement in the literature is the shift from static proximity-based measures toward frameworks that incorporate user preferences. For example, Tariverdi et al [41] integrated congestion and user preferences under disaster conditions. Our CAI similarly emphasizes a user-centric perspective by explicitly incorporating societal preferences into CI weighting. This complements these studies by demonstrating that community perceptions provide valuable insights into which infrastructures are most critical during extreme seismic events—something often overlooked when relying solely on technical or expert-based evaluations Fig. 6.

Our results also resonate with equity-oriented frameworks. Genc et al [18] demonstrated that fragile access is not restricted to rural settings but also affects rapidly urbanizing areas, with vulnerable groups such as Native American populations disproportionately impacted. Likewise, our case study revealed significant inequalities in CI accessibility across urban, peri-urban, and rural municipalities of Santiago, Chile. In particular, residents in San José de Maipo were found to face extended travel times and limited redundancy.

From a network-criticality perspective, Mossoux et al [34] and El-Maissi et al [12] showed how bottlenecks in transport systems can ripple across accessibility networks, isolating communities and compromising service delivery. Our results corroborate this, as certain road segments in Puente Alto and Pirque were identified as disproportionately influential for access to multiple CI types. By applying goal programming, our approach not only highlighted these critical links but also revealed how prioritization shifts when community preferences (e.

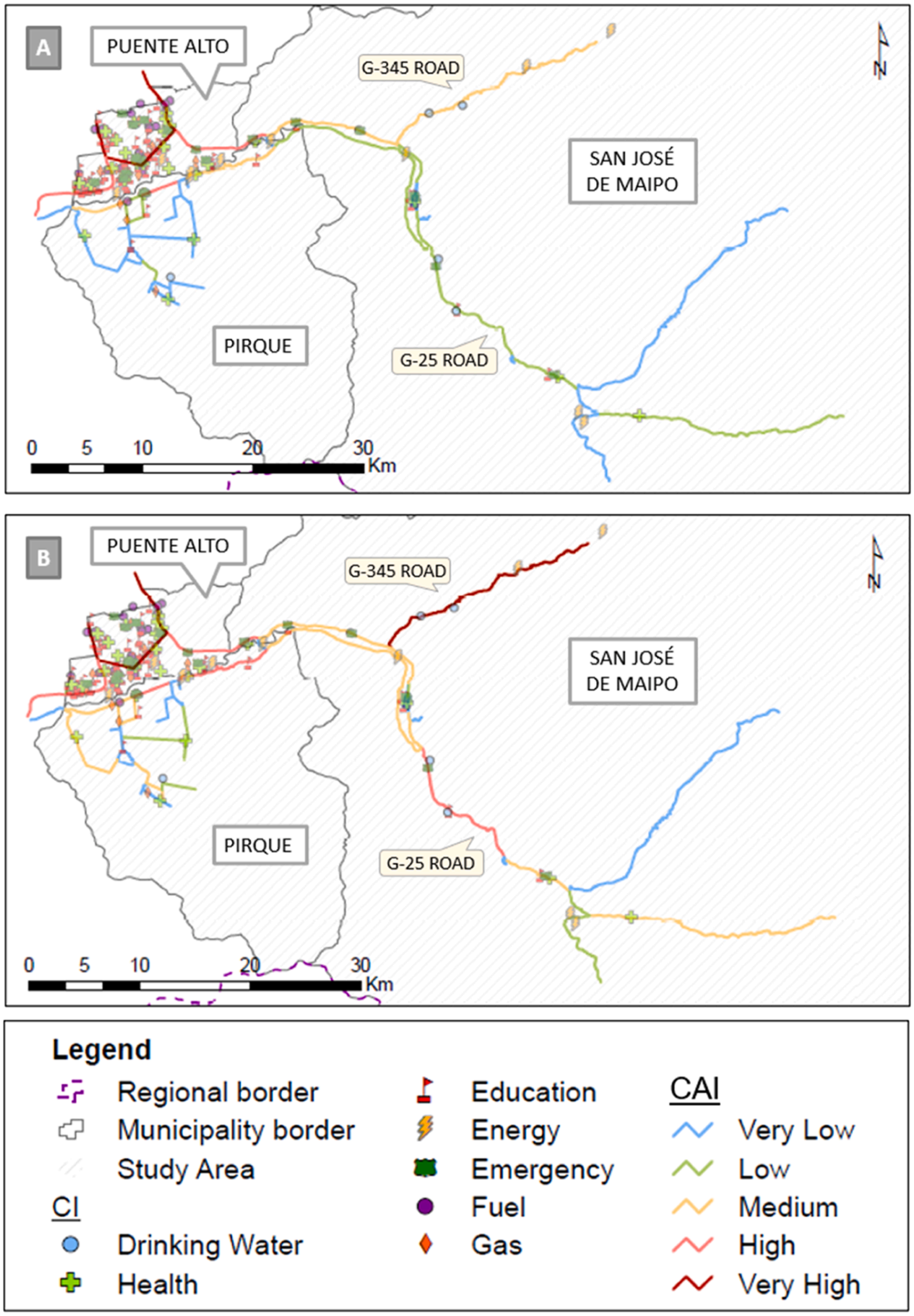

Fig. 5. Application of the CAI to the study area. A) Scenario a); B) Scenario b).

g., water supply and healthcare) are incorporated—adding a novel social dimension to criticality analysis.

Overall, our study reinforces the trajectory of CI accessibility research toward integrated, multidimensional frameworks. It extends existing approaches by embedding societal perception into criticality weighting, thereby linking technical assessments with community-informed resilience planning—an essential step toward equitable and context-sensitive disaster preparedness.

5.4. Policy implications

The comparative analysis of the CAI under the two evaluated scenarios provides valuable policy implications for decision-making and investment planning aimed at strengthening the resilience of CI in the face of extreme natural events. The substantial differences observed in CAI values and categorical distributions underscore the critical importance of integrating both technical assessments of infrastructure interdependencies and community-informed preferences in the planning process. In scenario a), where all CI types are treated as equally important, road network interventions could be guided by a purely technical understanding of accessibility. However, the results from scenario b), which incorporates people's preferences, demonstrate that such an approach may not fully reflect the accessibility priorities that are most relevant for communities during disaster events.

Notably, the results indicate a significant increase in the number of road links categorized as medium to very high accessibility in scenario

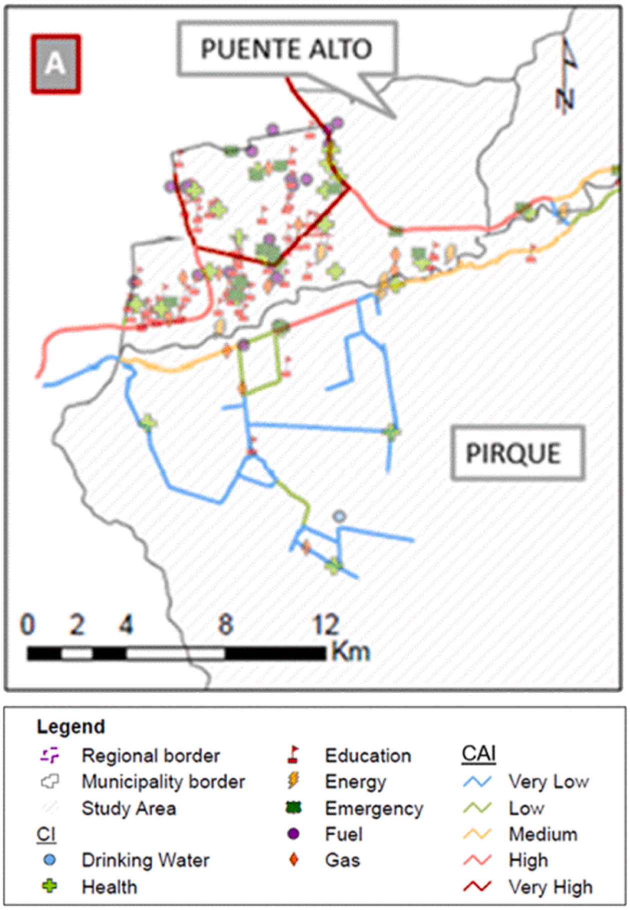

Fig. 6. Zoom of the application of the CAI to Puente Alto. A) Scenario a); B) Scenario b). Legend is the same as in Fig. 5.

b), suggesting a more nuanced understanding of accessibility criticality when social preferences are considered. This highlights the need for policy frameworks that integrate participatory processes, ensuring that infrastructure investment priorities align with the population's perceived importance of CI services. In particular, the consistent prominence of drinking water infrastructure as a critical service—highlighted in both urban and rural contexts—suggests that investments should prioritize improving the resilience of road links providing access to these facilities. Moreover, spatial analysis reveals areas with heightened criticality, such as San José de Maipo, characterized by low road density and minimal redundancy. These findings underscore the necessity of targeted investments in such regions to enhance system robustness and ensure continuity of critical services during and after extreme events. Addressing these vulnerabilities will not only mitigate risks associated with geographical isolation but will also enhance the overall adaptability and redundancy of the CI network.

In practical terms, decision-makers should adopt a dual-pronged approach. First, investments should focus on upgrading and maintaining road network segments identified as highly critical under both scenarios, ensuring that these links remain functional during disaster events. Second, strategic planning should explicitly consider community-based preferences for CI services, thereby fostering greater public acceptance and trust in resilience initiatives. This inclusive approach will strengthen the social dimension of resilience, complementing the technical measures traditionally emphasized in emergency management and infrastructure planning. By incorporating the CAI's scenario-based insights into policy and investment planning, governments and local authorities can develop more effective, equitable, and socially attuned strategies for emergency preparedness and long-term infrastructure resilience. Such integrated planning will be vital to safeguard populations, especially in the most vulnerable areas, and to promote a more robust and adaptive urban and rural infrastructure system.

6. Conclusions

Assessing accessibility to CI is of paramount importance for understanding and improving its resilience against natural extreme events. This study presents a novel approach to assessing road network accessibility to CI during extreme natural events by introducing the CAI. By applying the CAI under two scenarios—one assuming equal CI importance and another incorporating societal preferences—we demonstrated how integrating technical and social dimensions provides a more comprehensive understanding of criticality. The use of goal programming to quantify public preferences adds methodological value, especially in contexts with diverse territorial and social conditions.

The results highlight the central role of drinking water access and the importance of tailoring infrastructure planning to community needs. Findings from this study underscore the need for inclusive, data-driven approaches in disaster resilience planning, with particular attention to under-connected areas. The proposed framework can be adapted to other regions and hazard types, supporting more equitable and robust infrastructure investment decisions.

The incorporation of community preferences into CAI estimation not only enhanced the granularity of the analysis but also provided a socially attuned framework for prioritizing infrastructure interventions. This approach bridges the gap between technical infrastructure assessments and the lived experiences of communities, thereby supporting more inclusive and equitable disaster risk management strategies. In terms of policy implications, the results call for a dual focus in investment planning: technical upgrades of road links identified as critical under both scenarios and prioritization of links that serve the most essential CI as defined by community preferences. Such an approach will strengthen the resilience of urban and rural areas by enhancing both physical and social dimensions of disaster preparedness.

While this study provides a novel methodological framework to assess accessibility to CI under extreme natural events, some limitations must be acknowledged. First, the analysis relies on available spatial and traffic data, which may vary in quality or granularity across different regions. Second, the survey used to derive societal preferences employed a non-random, convenience sampling method, which, despite efforts to ensure diversity, may not fully capture the views of all population groups. Third, the case study is limited to a specific geographical and seismic context in Chile, which may affect the generalizability of the results. Future research should aim to apply the CAI methodology in different hazard contexts (e.g., flooding, wildfires) and regions to test its adaptability. Moreover, integrating real-time data on service disruptions could further enhance the comprehensiveness of the approach. Longitudinal studies that explore changes in accessibility and societal preferences over time would also provide valuable insights for adaptive infrastructure planning. Moreover, this study does not consider cascading effects between CI systems. Instead, it focuses on the role of road network links in ensuring direct access to CI facilities. Future research should explore integrating such effects to capture a more complete picture of infrastructure vulnerability.

CRediT authorship contribution statement

Marta Contreras: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Alondra Chamorro:** Writing – review & editing, Validation, Funding acquisition, Conceptualization. **Trinidad Gómez:** Writing – review & editing, Methodology. **Tomás Echaveguren:** Writing – review & editing, Supervision, Methodology, Conceptualization. **María Molinos-Senante:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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