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Multi-level assessment of flood risk perception and flood behaviour

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Abstract. Understanding the relationships between flood risk perception and flood behaviour is crucial for adequate risk management and risk communication strategies, but quantitative approaches are still challenging research. Based on a survey of 1007 residents in four different localities of Chile exposed to river floods, this study builds and applies a framework for assessment of flood risk perception and flood behaviour at the individual, household, neighbourhood and municipality levels. Results show that almost all respondents were aware of flood risk. Economic and personal resources highly control worry and preparedness: households with better economic situation were less worried about floods, while minor economic resources at the municipal and neighbourhood levels triggered the adoption of cautionary measures at the household level. Experiences where the flood passed outside the household increased worry and preparedness. Worry decreased with trust in the neighbours. Overall, worry and preparedness in the study area were intermediate, with an increasing dispersion in the lower levels. Increasing worry did not necessarily translate into higher preparedness. Municipalities exhibited different flood behaviours, and some neighbourhoods exhibited flood behaviours different to those of their municipalities, evidencing important differences across the analysed levels. Obtained results suggest that risk communication and risk management strategies should be adapted to focus on the needs of specific neighbourhoods exposed to floods.

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1 Introduction

Floods are well recognized as one of the most damaging natural hazards worldwide, and the damage they cause is increasing (Adikari & Yoshitani, 2009; Blöschl, 2022). Absolute flood prevention or protection is unattainable and flood risk management is the only practicable way forward (Birkholz et al., 2014). Important drivers for an adequate flood risk management are related to the flood risk perception, adaption and resilience of exposed communities (Rufat et al., 2020). However, relationships between flood risk perception and flood behaviour remain poorly explored, even when these relationships are crucial for risk management (Kuhlicke et al., 2020; Bin-Husayn, 2024).

The flood risk is the product of hazard, vulnerability and value of the goods exposed (Kron, 2005). For a given discharge, the hazard is the product of the probability of occurrence by the hazardousness magnitude. The probability of occurrence of a given flood, is assumed to be the same as that of its peak discharge and is commonly determined through a frequency analysis. The corresponding hazardousness magnitude varies over the territory and is computed locally as the flow depth by the flow velocity (Martín-Vide, 2009; Díez-Herrero, Laín-Huerta, and Llorente-Isidro, 2009; Bodoque et al., 2016; Link et al., 2019). The vulnerability distinguishes between physical vulnerability, such as the vulnerability of buildings (e.g.: Mazzorana et al., 2014; Stephenson et al., 2014), vehicles (Xia et al., 2011) and people (Jonkman & Penning-Rowsell, 2008), and the social vulnerability, which is a much more complex concept, and is commonly evaluated in a simplified way through so called social vulnerability indices, SVIs (e.g., Kocks et al., 2015).

Flood risk perception is shaped by the social, political, cultural, religious, and historical contexts (Lechowska, 2022), and is relevant for flood risk management, as it determines the attitude, i.e. the level of preparation for a flood, and the possible behaviour of the residents when facing a flood (Bradford et al., 2012; Lechowska, 2018). Raaijmakers et al. (2008) identified three specific elements of flood risk perception, namely: awareness, worry and preparedness, and later Lechowska (2018) identified a so-called 'clear relation' between worry and awareness with flood risk perception, while relations between flood risk perception and preparedness was identified as an 'unclear relation', as well as the relation between worry and awareness with preparedness and between awareness and worry. Remarkably, Scolobig et al. (2012) showed that the link between awareness and preparedness is not at all straightforward, as in the Italian Alps, residents felt both slightly worried about flood risk and slightly prepared to face an event. There was also a clear discrepancy between the actual adoption of household preparatory measures and the willingness to take self-protection actions among the studied localities.

The long-term interactions between the human and social systems have been studied in a socio-hydrology context (Sivapalan et al., 2012; Sivapalan & Blöschl, 2015). Socio-hydrological systems are complex systems and thus, exhibit emergent properties due to the interactions between elements of the lower levels (Damper, 2000; Giorgiu, 2003; Reuter et al., 2005). Such interactions have been studied through three different methods: surveys and interviews, differential equations, and agent-based models (di Baldasarre et al., 2015). In particular, the socio-hydrology of floods recognized already different flood behaviour types that emerge from the interactions between the social and the hydrological system during floods, such as the so-called "forgetting or levee effect" and the "learning or adaptation effects" (di Baldasarre 2017). Moreover, Barendrecht et al. (2017) reviewed long-term feedbacks between humans and floods that may lead to complex phenomena such as coping strategies, levee effects, call effects, adaptation effects, and poverty traps. Notably, in addition to the well-known adaption effect and levee effect, Leong (2018) proposed the existence of the status quo or path dependency effect (see e.g. Mendoza Leal et al., 2024) and a fourth, unnamed effect when communities undertake adaptive measures against floods even when they do not experience floods frequently, i.e. mainly motivated by external information, which will called here the "proactive effect". Further, Leong (2018) proposed the four mentioned effects to be dependent on two dimensions, namely the flood magnitude and the adaptive capacity of the communities. Similarly,

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Mazzoleni et al. (2024) considered four stylized types of attitudes towards risk to characterize a society or social groups: risk neglecting, risk controlling, risk downplaying and risk monitoring societies. An operationalization of Leong's (2018) diagram with the typologies of flood behaviours is still pending, as a clear distinction between "small" and "large" floods, as well as a proxy of flood resilience, distinguishing between "status quo" and "adaption" have not been proposed.

Clearly, flood risk perception and flood behaviour are interlinked, but the intuitive progression from awareness to worry to preparedness is not realistic in many cases (see e.g. Wachinger et al., 2013; Lechowska, 2022), as elements such as trust in the institutions (e.g. in some Alpine areas of Italy reported by Scolobig et al., 2012), previous flood experiences (see e.g. Veloso et al., 2022), social networks (Haer et al., 2016; Karunarathne & Lee, 2020), and minor economic and personal resources can generate situations without worry but with preparedness, or with high worry but without preparedness. Moreover, the urban and neighbourhood scales –and, more specifically, the characteristics of the built environment– play a decisive role in shaping both community life and the perception of risk. A growing body of evidence shows that spatial configurations affect social interaction, cohesion, and the capacity for collective action, generating differentiated forms of community (Blokland, 2017; Krellenberg et al., 2014) and, therefore, unequal vulnerabilities to hazards. In this study, variables such as housing quality, hazard proximity, neighbourhood socioeconomic composition, and the territorial socio-material index (ISMT) illustrate how material conditions of the habitat are directly linked to subjective worry and preparedness. Following Bourdieu (1999), the relationship between habitat and habitus highlights how the physical and social environment moulds dispositions, shaping not only everyday sociability but also the capacity to anticipate, interpret, and respond to flood risk. Thus, the built environment is not a neutral background but an active determinant that conditions the articulation between worry and preparedness, reinforcing the need to analyse risk perception and behaviour from a spatially sensitive perspective. Particularly in contexts of significant historical urban and territorial inequalities such as in Latin America.

Spatial scale is crucial for understanding the relationship between risk and behaviour, as both worry and preparedness vary significantly across territories, while flood hazardousness is strongly conditioned by local factors. Previous research has examined flood risk and behaviours mainly at the local scale, such as neighbourhoods or municipalities. This article goes further by incorporating individual and household characteristics, allowing us to capture the multilevel complexity of space and its consequences for flood risk perception and adaptive behaviours.

In this article, the dimensions and variables that explain worry and preparedness at the different levels: individual, household, neighbourhood and municipality, and the relationships between worry and preparedness as well as the flood behaviour are analysed in four municipalities located along Chile, that represent different forms of urban agglomeration, ranging from small localities to intermediate cities within the national context. The aim of the study is to answer the following questions: What are the variables explaining the elements of flood risk perception: worry and preparedness? How correlated are worry and preparedness at the different levels? What are the different flood behaviours that emerge from the interaction between the social and hydrological systems along the studied localities? The next section describes the study area, and statistical analysis. Section 3 present the obtained results on variables explaining worry and preparedness, their correlations and distribution among the neighbourhoods and municipalities. The advantages of our analysis combining different statistical methods is discussed, and local findings such as the explaining variables of flood risk perception are discussed in relation to those observed in other cases around the world. The applicability of the results on flood behaviour is discussed for enhanced flood risk communication and management. The paper concludes with final remarks on the obtained results, regarding the role of space and the social conditions in the formation of local preparedness and worry.

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2 Materials and methods

2.1 Study area

The study area corresponds to four Chilean municipalities that have experienced floodings in recent years: San Pedro de Atacama, located in Antofagasta Region, San Fernando in the O'Higgins Region, and Hualqui and Arauco in the Biobío Region. Fig. 1 shows the location of the study area, including surveyed households.

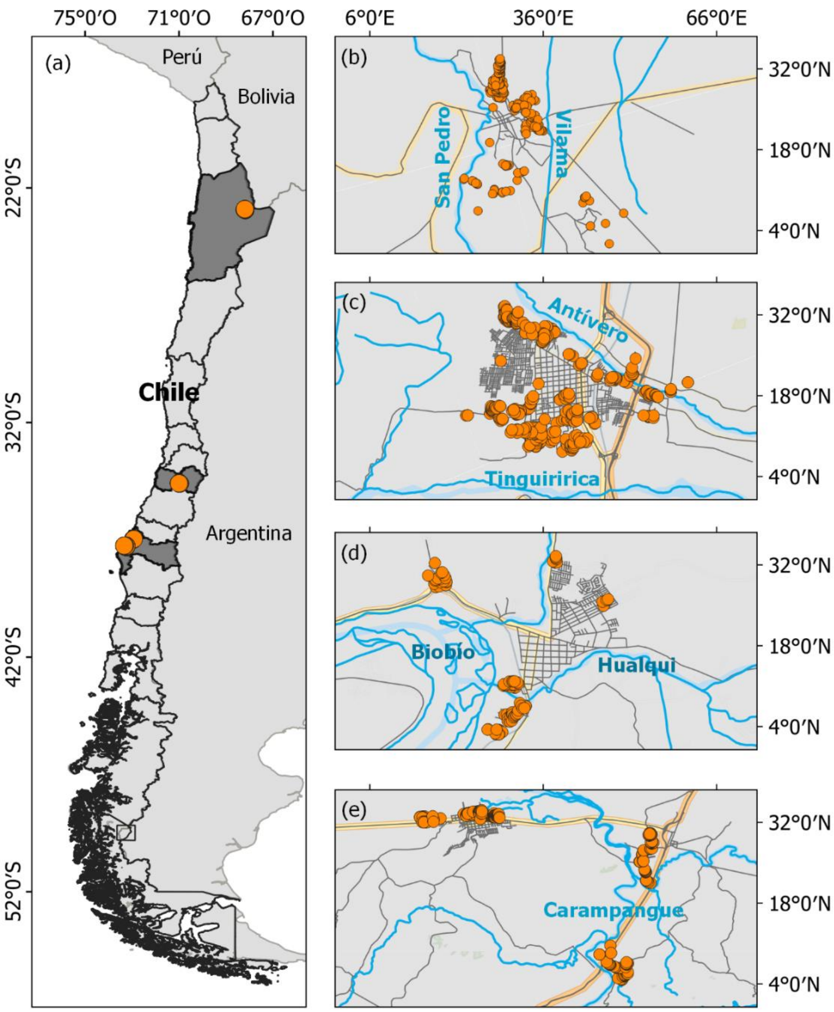

Figure 1. Location of the study area: a) the four municipalities in Chile, and surveyed households in (b) San Pedro de Atacama, (c) San Fernando, (d) Hualqui, and (e) Arauco.

According to the modified Köppen-Geiger climate classification by Sarricolea et al. (2017), the predominant climate in San Pedro de Atacama is a cold desert climate with dry winters (BWk(w)) where the "w" indicates a precipitation regime dominated by summer rainfall, influenced by the South American monsoon system and locally known as the "invierno boliviano" (Houston, 2006; Sarricolea et al., 2017), in San Fernando and Hualqui the climate is mediterranean with winter rainfall (Csb), characterized by dry summers and moderate precipitation concentrated in the colder months. In Arauco the climate is mediterranean with winter

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rainfall (Csb(i)) where "i" denotes the effect of costal influence, which reduces temperature extremes and increases atmospheric humidity due to the proximity to the Pacific Ocean.

According to the available hydrometeorological records from stations administered by the National Water Agency, DGA, the average annual precipitation in San Pedro de Atacama, San Fernando, Hualqui, and Arauco is 42.41 mm ranging between 11.90 and 112.30 mm, 670.49 mm ranging between 146.80 and 1229.80 mm, 1019 mm, ranging between 268.50 and 1664.40 mm, and is 1,143 mm ranging between 704.30 mm and 1643. San Pedro de Atacama is affected by river floods due to the overflow of the San Pedro River (933.0 km^2, average annual flow 0.83 m^3/s) and the Vilama River (379.04 km^2, average annual flow 0.15 m3/s), San Fernando is affected by river floods due to the overflow of the Antivero River (443.11 km^2, average annual flow 7.63 m^3/s) and Tinguiririca River (4730 km^2, average annual flow 50.2 m^3/s), Hualqui is affected by river floods due to the overflow of the Biobío River (24,264 km^2, average annual flow 955 m^3/s) and Hualqui River (65.0 km^2, average annual flow 0.48 m^3/s), and Arauco is affected by, river floods due to the overflow of the Carampangue River (1,262 km^2, average annual flow 61.5 m^3/s).

According to Census data the population of San Pedro de Atacama has experienced significant growth, since the late 1990s. From year 2002 to 2024 it shows a transformation from a village of 1,938 inhabitants to a town with 9,843 inhabitants, and 5,071 housing units. In San Fernando, the population increased from 63,732 in 2002 to 75,585 in 2024, with an increase of 11,853 people or 18.5%. The number of housing units grew from 24,695 in 2017 to 31,420 in 2024. In Hualqui, the population rose from 18,768 in 2002 to 24,333 in 2017, representing a growth of 29.7%. By 2024, the population reached 26,746, showing a continuous but slower growth of 9.9%. The number of housing units also increased, from 7,754 in 2017 to 10,881 in 2024. In Arauco, the population grew from 34,873 in 2002 to 36,257 in 2017, a modest increase of 4%. However, between 2017 and 2024, it grew more notably to 38,941, with an increase of 7.4%. Housing units rose from 11,663 in 2017 to 13,185 in 2024, with an increase of 13% over the period.

2.2 Survey

The survey consisted of both open- and closed-ended questions and was structured around nine thematic dimensions: respondent characteristics, household characteristics, housing characteristics, location of the social network, experience during the most recent flood event, perception and knowledge of flood risk, collaboration networks, flood preparedness, and head-of-household characteristics.

The questionnaire was administered in 2024 using Pen and Paper Personal Interviews (PAPI). A total of 1,015 surveys, each comprising 80 questions, were conducted across four flood-prone municipalities in Chile. After data cleaning and validation, 1,007 responses were retained for analysis. The final sample distribution was as follows: 252 households in San Pedro de Atacama, 380 in San Fernando, 100 in Hualqui, and 275 in Arauco. Considering the population size and the homogeneity of residents aged 18 and over in each municipality, the sample design ensured a 95% confidence level with a maximum margin of error of 5%.

2.3 Other data sources

In addition to survey-based data, external sources were incorporated to complement the analysis, including: the distance from the household to the water, the territorial socio-material index ISMT, the multidimensional poverty index MPI, the income poverty rate IPR and the municipal common fund dependency MCFD. Each of these indicators makes it possible to integrate socio-economic and socio-spatial variables to interpret the results derived from primary data. As mentioned, both the structural

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characteristics of Latin American societies and territorial inequalities contribute to understanding the complexity of the relationship between flooding, preparedness, and worry. The operationalization of each indicator is presented below.

The distance from each household to the nearest overflowing river, was computed from GIS georeferenced location of the household, as the shortest straight distance to the nearest perennial water body.

The territorial socio-material index (ISMT), which considers the education level of the head of household, overcrowding (people per bedroom), cohabitation (number of households sharing a dwelling) and housing material quality (walls, roof, and flood conditions).

Each variable is normalized, and the final ISMT score is derived through principal component analysis (PCA), where the first principal component captures the main axis of variance across the four indicators. The resulting score reflects the relative socio-material vulnerability of each zone. The ISMT was computed using data from the 2017 Chilean population and housing Census (INE, 2017), following the methodology implemented in the “ismtchile” R package (Rosas, 2025), which operationalizes the approach developed by the Observatorio de Ciudades UC (2019).

The ISMT used in this study was obtained as a GIS layer from the data platform of the Observatorio de Ciudades UC. The index is provided at the block level (manzana) across the national territory. To assign an ISMT value to each household in the survey, the coordinates of the surveyed homes were spatially joined with the ISMT block-level layer using a point-in-polygon operation. This spatial matching allowed us to attribute the corresponding ISMT score to each surveyed household based on its location.

The multidimensional poverty index (MPI) considers five dimensions: education, health, employment and social security, housing and environment, and social networks and cohesion. Each dimension consists of one or more indicators with specific weights.

The calculation follows the Alkire and Foster (2007) methodology, which involves building a binary deprivation matrix, applying indicator weights. The MPI considers the incidence (H) and intensity (A) of poverty according to the Eq. (1).

$$\mathrm{MPI} = \mathrm{H} \cdot \mathrm{A}\,, \tag{1}$$

The multidimensional poverty index (MPI) ranges from 0 to 1. Higher values mean that households face more disadvantages in areas such as education, health, work, housing, and social support. A value of 0 means the household has no disadvantages in any of the indicators, while a value close to 1 means the household is doing poorly in almost all of them. Higher MPI values indicate worse living conditions and greater poverty.

The income poverty rate (IPR) is based on the comparison between the per capita disposable income of a household and the official national poverty line. A household is classified as income-poor if its per capita income falls below this threshold, which is calculated based on the cost of a basic basket of food and essential services, adjusted by household size and geographic location. Formally, the IPR is defined according to the Eq. (2) and Eq. (3).

$$\mathrm{IPR}_i = \begin{cases} \frac{\text{Total income}_i}{\text{Houlshold size}_i} < \text{Poverty line}_i \rightarrow 1 \\ \text{Otherwise} \rightarrow 0 \end{cases} \tag{2}$$

$$\mathrm{IPR} = \frac{1}{N} \sum_{i=1}^{N} \mathrm{IPR}_i \tag{3}$$

The income poverty rate (IPR) ranges from 0 to 1. At the household level, it takes value 1 if the household’s per capita income is below the poverty line, and 0 otherwise. At the municipal or national level, the IPR represents the proportion of households

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classified as income-poor. Higher values indicate a greater share of households living below the minimum income required to meet basic needs.

The multidimensional poverty index (MPI) and the income poverty rate (IPR) used in this study were obtained from the 2022 CASEN Survey (Ministry of Social Development, 2023), which provides disaggregated estimates at the municipality level.

The municipal common fund dependency (MCFD) measures what proportion of a municipality's funding comes from the Municipal Common Fund (FCM), i.e., how much the municipality depends on nationally redistributed resources rather than generating its own revenue. MCFD considers the number of transfers received from the common fund and the total municipal revenue, according to Eq. (4).

$$\text{MCFD}=\frac{\text{Trasfers from common found}}{\text{Total municipal revenue}} \tag{4}$$

Higher MCFD values indicate greater financial dependence on the FCM, while lower values suggest greater self-financing capacity. The MCFD was computed using data from the Chilean sub-secretariat for regional and administrative development (SUBDERE, 2022).

Table 1 shows the ISMT, MPI, IPR and MDFD for each municipality and for the whole sample.

Table 1. ISMT, MPI, IPR and MDFD for each municipality and for the whole sample.

Municipality	ISMT (average)	MPI	IPR	MCFD
San Pedro de Atacama	0.582	0.225	0.049	0.515
San Fernando	0.504	0.136	0.068	0.470
Hualqui	0.497	0.209	0.103	0.840
Arauco	0.487	0.171	0.092	0.727
Total sample (average)	0.534	0.175	0.068	0.588
Min	0.412	0.171	0.049	0.47
Max	0.725	0.255	0.103	0.840
Standard Deviation	0.076	0.036	0.019	0.135

In addition, to estimate the recurrence of flood events in each municipality, a review of national and regional news reports was conducted for the period 2000–2025. This search aimed to identify significant flooding over the last 25 years and to calculate the frequency of occurrence of a damaging flood, i.e. a flood reported in the news. Additionally, the dates of the floods detected in the literature were verified with the available discharge measured at gauge stations.

2.4 Statical analysis

The survey answers and complementary data were analysed through complementary methods, namely the univariate analysis, regressions by level, a multilevel regression, principal coordinates and cluster analysis, and contingency tables. All statistical analyses and visualizations were conducted in R-4.4.3. A value of $p < 0.05$ was interpreted as statistically significant.

Variables were organised into four hierarchical levels, namely individual, household, neighbourhood and municipality. Table 2 shows the variables characterizing each level.

Table 2. Variables characterizing individuals, households, neighbourhoods and municipalities.

Level	Variables
Individual	- Gender

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	- Occupation - Residence 5 years ago - Age respondent - Location of social ties - Trust in neighbours - Knowledge of flooding areas - Socioeconomic group
Household	- Housing quality - Socioeconomic group - Time living in the neighbourhood - Number of age-dependent people - Flooding outside their home - Hazard proximity
Neighbourhood	- Neighbourhood interaction - High socioeconomic portion - Low socioeconomic portion - Perceived closeness to neighbourhood - Territorial socio-material index
Municipality	- Territorial socio-material index SD - Satisfaction with the commune - Municipal Common Fund dependency - Multidimensional Poverty Index - Income Poverty Rate

The logic of the hierarchical multilevel analysis lies in explicitly recognizing the nested structure of the data: individuals are embedded in households, households in neighbourhoods, and neighbourhoods in municipalities. This implies that responses regarding flood risk perception and preparedness are not independent observations but are influenced by contextual conditions operating at higher levels of aggregation. Multilevel modelling allows separating the variance attributable to each level, while simultaneously estimating the effects of explanatory variables at the individual, household, neighbourhood, and municipal scales. In this way, it becomes possible to distinguish, for example, whether worry is mainly explained by individual attributes (such as age or trust in neighbours), by household conditions (housing quality, direct exposure), or by broader spatial contexts (socioeconomic composition of the neighbourhood, municipal financial autonomy). This hierarchical logic is essential for analysing risk perception, since, as Bourdieu's notions suggests, spatial and social structures exert systematic influences that shape dispositions, experiences and behaviours across scales. In this sense, space across different scales operates as a structuring force of social relations and emerges as a distinctive analytical dimension, enabling a deeper understanding of the socio-spatial configuration within socio-hydrological dynamics.

2.4.1. Univariate analysis

A univariate analysis was conducted to describe the characteristics of the sample, using derived variables from the survey and complementary external data sources. Descriptive statistics were calculated, including frequencies for categorical variables and means with standard deviations for continuous variables. The analysis was performed for the full sample and disaggregated by municipality, allowing for a comparison of the characteristics of each municipality.

The analysis was based on a set of variables obtained from both the household survey and complementary external sources. The survey data analysed included variables representing dimensions such as socio-demographic characteristics, housing conditions and social networks. As well as variables related to experience during the most recent flood, perception and knowledge of flood risk, flood preparedness, and flood risk awareness. Some of these variables were taken directly from individual survey questions (e.g., gender, occupation, age group), while others were constructed as composite indicators (e.g., housing quality, perceived

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closeness to the neighbourhood, and social vulnerability, preparedness level). Table 3 shows the list of variables used in the univariate analysis, including their scale and a brief description.

Table 3. List of variables used in the univariate analysis.

Variable	Type	Description
Gender	Binary (1/0)	Gender of the respondent
Occupation	Categorical (1–3)	Employment status categorized by current activity
Residence 5 years ago	Categorical (1–3)	Place of residence five years prior
Age respondent	Categorical (1–4)	Age range of the respondent
Location of social ties	Ordinal (1–3)	Location of nearby social connections (e.g. within the neighbourhood, within the commune, etc.)
Trust in neighbours	Ordinal (1–3)	Level of trust in neighbours
Knowledge of flooding areas	Binary (0/1)	Knowledge of flood-prone areas within their locality
Socioeconomic group	Ordinal (1–3)	Grouping based on education, occupation, household income and household size
Housing quality	Ordinal (1–3)	Index based on type of dwelling and materials of walls, floor, and roof
Time living in the neighbourhood	Ordinal (1–3)	Number of years that the household has been residing in the current dwelling
Number of age-dependent people	Binary (0/1)	Presence of at least three dependent people in the household, considering individuals under 15 and over 65 years old as "age-dependent people."
Flooding outside their home	Binary (0/1)	Whether floodwaters passed outside the respondent's home during the last flood event
Neighbourhood interaction	Ordinal (1–3)	Frequency of interaction with neighbours
Perceived closeness to neighbourhood	Ordinal (1–3)	Respondents evaluate their sense of belonging and connection to their neighbourhood
Satisfaction with the commune	Ordinal (1–3)	Degree of satisfaction with living in the commune
High socioeconomic portion	Continuous 0-1	Proportion of households in the neighbourhood classified within high socioeconomic groups (A, B, C1a, C1b)
Low socioeconomic portion	Continuous 0-1	Proportion of households in the neighbourhood classified in lowest socioeconomic group (E.)
Worry	Ordinal (1–3)	Reflects the respondent's subjective perception of flood risk at their home
Preparedness	Ordinal (0–3)	Composite index based on actions taken during the last flood and the perceived effectiveness of those actions
Hazard proximity	Ordinal (1–4)	Distance between the house and the river causing flooding in the area
Territorial socio-material index	Continuous 0-1	Index capturing socio-material vulnerability based on census data
Territorial socio-material index SD	Continuous 0-1	Standard deviation of the socio-material index across households within the municipality, reflecting the degree of internal inequality in socio-material conditions
Municipal Common Fund dependency	Continuous 0-1	Proportion of municipal revenue dependent on the Common Municipal Fund
Multidimensional Poverty Index	Continuous 0-1	Index that assesses poverty considering household income, education, health and living conditions
Income Poverty Rate	Continuous 0-1	Proportion of the population living below the income poverty line in each commune

2.4.2 Ordinal regression by level

Ordinal regression models were conducted to examine the relationship between the explanatory variables and the dependent variables: worry and preparedness. To assess the contribution of variables operating at different contextual scales, separate models were estimated for each level of analysis. This stepwise approach allowed for an independent evaluation of the effects associated with each level, without conflating them with broader contextual influences. A backward selection procedure based on p-values was applied to retain only those variables with a statistically significant contribution to each model.

2.4.3 Multi-level ordinal regression

A multilevel ordinal regression model was estimated to assess the combined effects of explanatory variables from different contextual levels (individual, household, neighbourhood, and municipality) on flood risk worry and preparedness. This modelling approach accounts for the hierarchical structure of the data, with individuals nested within households, households within neighbourhoods, and neighbourhoods within municipalities. Unlike the regression models by level, which analysed each context separately, the multilevel model incorporates all levels simultaneously. Variable selection was performed using a backward

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stepwise procedure based on p-values. In addition, the models were evaluated to obtain the predicted average level of worry and preparedness in each locality, based on the explanatory variables considered.

2.4.4 Multilevel analysis

To explore similarities between neighbourhoods and municipalities based on the explanatory variables of worry and preparedness according to the multi-level regression., a Principal Coordinates Analysis (PCO) was computed using Gower distance, which allows for the combination of ordinal and continuous data types. This method enabled the projection of multivariate dissimilarities into a reduced two-dimensional space while preserving the pairwise distances between observations as accurately as possible (Abdi and Williams, 2010). Subsequently, hierarchical clustering using Ward's method was conducted on the same distance matrix to identify groups of similar neighbourhoods and municipalities. For both spatial levels, the input data were aggregated by either neighbourhood or municipality, averaging the relevant variables obtained in the multilevel regressions. The resulting clusters were visualised through dendrograms and biplots, with shapes distinguishing administrative levels and colours denoting cluster membership.

2.4.5 Contingency tables

The relationship between worry and preparedness was explored using contingency tables and ordinal correlation analysis. Contingency tables were used to visualize the joint distribution and applied Pearson's c^2 test to assess the null hypothesis of independence between variables. Direction and magnitude of the association were quantified through the Spearman's rank correlation (r) which is appropriate for ordinal data and ranges from −1 to 1 (positive values indicate a direct relationship). Analyses were conducted for the full sample separately by municipality and at neighbourhood level.

3. Results

3.1 Sociodemographic, social networks and flood experience characteristics

Appendix A presents the univariate analysis at the municipality level. Table 4 summarizes the main findings of the univariate analysis of the study municipalities, highlighting aspects related to sociodemographic aspects, social networks and flood experience.

Table 4. Characteristics of the municipalities included in this study.

Municipality	Population in 2024 (thousands)	Region	Sociodemographic	Social Networks	Flood experience
San Pedro de Atacama	10	Antofagasta	Young and active population New residents	Lowest level of trust in the neighbourhood	Low level of worry and preparedness
San Fernando	78	O'Higgins	Old population High presence of dependent people	High trust in the neighbourhood Social ties outside the municipality	Moderate to low level of worry and medium high preparedness
Hualqui	26	Biobío	Old population High presence of dependent people	High trust in the neighbourhood Social ties local	High level of worry and medium to high level of preparedness
Arauco	37	Biobío	Old population Medium presence of dependent people	High trust in the neighbourhood Social ties local	High level of worry and medium to high level preparedness

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Interestingly, almost all respondents (96.2%) live closer than 750 m from the river (57.9%), declares to know the flooding areas (84.7%), or experienced the flood passing outside the home (55.4%), and thus in the present study people were assumed to be aware of flood risk.

3.2 Variables and dimensions explaining flood risk perception

3.2.1 Worry

The multilevel ordinal regression model predicts the probability that an individual i, living in neighbourhood j and municipality k, reports a level of worry equal to or below a given ordinal category. The linear predictor reveals the hierarchical structure of the data in Eq. (5).

$$\eta_{ijk}=-0.151\cdot X_1-1.134\cdot X_2-0.496\cdot X_3-0.368\cdot X_4+1.548\cdot X_5-4.450\cdot X_6+u_k+v_{jk} \quad (5)$$

where η_{ijk} estimate the probability that the person belongs to a category of worry. X_1 is the age range of the respondent, X_2 is trust in the neighbourhood, X_3 is the knowledge of flooding areas, X_4 is housing quality, X_5 is flooding outside their home, and X_6 is the high socioeconomic portion in the neighbourhood. The terms u_k and v_{kj} are random effects that capture differences between municipalities and between neighbourhoods that are not explained by the variables in the model. specifically, u_k represents the deviation of municipality *k* from the overall average, while v_{kj} captures the deviation of neighbourhood *j* within municipality *k*. These random effects are assumed to follow a normal distribution with mean zero and variances estimated by the model, allowing it to account for unobserved contextual influences that affect the level of worry across geographic units. Table 5 shows the explanatory variables of worry according to the multi-level regression, indicating the regression parameters.

Table 5. Explanatory variables of worry according to the multi-level regression.

Variable	Level	Estimate	Std. Error	z-value	p-value	Interpretation
Age respondent	Individual	-0.151	0.155	-0.975	0.009	Older age → Less worry
Trust in neighbours	Individual	-1.134	0.496	-2.287	0.022	Greater trust in neighbours → Less worry
Knowledge of flooding areas	Individual	-0.496	0.188	-2.631	0.009	Awareness of flood-prone areas → Less worry
Housing quality	Household	-0.368	0.144	-2.556	0.011	Better housing quality → Less worry
Flooding outside their home	Household	1.548	0.144	10.731	0.000	Flooding outside the home → Increased worry
High socioeconomic portion	Neighbourhood	-4.450	1.974	-2.254	0.024	Higher share of ABC1 households → Less worry

At the individual level, older respondents, those with greater trust in neighbours, and those aware of flood-prone areas consistently reported lower levels of worry. At the household level, better housing quality was associated with reduced worry, while having experienced flooding outside the home remained a strong predictor of elevated worry. At the neighbourhood level, living in areas with a higher proportion of high socioeconomic households was linked to less worry about flooding. Noteworthy, no variables at the municipal level were found to be statistically significant. The most important variables where those associated with the higher levels, neighbourhood and household.

Ordinal regression models for each level are included in Appendix B. A comparison between the ordinal regression by level and the multi-level regression reveals that at the individual level, three variables: age, trust in neighbours, and knowledge of flooding areas are significant in both models, i.e. the key dimensions of demographic characteristics (age), social cohesion (trust), and awareness of risk (flood-prone areas) are robust predictors of worry. In contrast, gender, occupation, and socioeconomic group were only significant in the regression by level. Their exclusion from the multilevel model, thus their effects are either moderated

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or better captured by other variables when all levels are analysed simultaneously. At the household level, the variable flooding outside the home was significant in both models, highlighting the importance of direct exposure to flood events to explain increased worry. This variable reflects experience with the past flooding dimension. Housing quality appeared as significant only in the multilevel regression, suggesting that better physical living conditions are associated with lower worry. At the neighbourhood level, the proportion of households classified within high socioeconomic groups was significant in both models. This variable represents the socioeconomic composition of the neighbourhood and is associated with lower levels of worry, i.e.: residents of higher income neighbourhoods are less worry about floods. In contrast, variables such as the low socioeconomic portion, neighbourhood interaction, perceived closeness to the neighbourhood, and the territorial socio-material index were only significant in the regression by level. At the municipal level, the income poverty rate was significant in the ordinal regression, and none of the variables were statistically significant in the multilevel regression. Overall, according to Eq. 5 worry in the study area was 1.874 (intermediate), with an increasing dispersion in the lower levels, varying from 1.817 (intermediate) to 2.338 (high) across municipalities and between 1.040 (low) and 2.520 (high) across neighbourhoods.

Figure 2 presents the Principal Coordinate Analysis (PCO) based on the variables significantly associated with worry according to the multilevel regression for the neighbourhood and municipality levels.

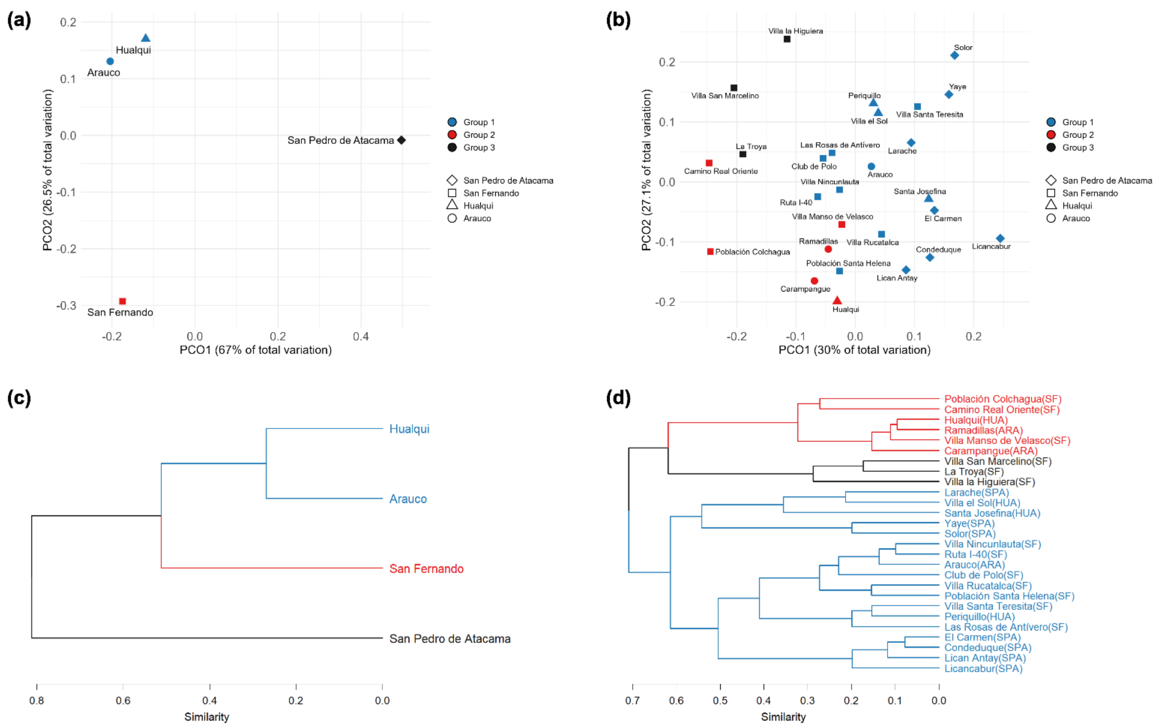

Figure 2. Principal coordinate analysis (PCO) of worry at (a) the municipal level and at (b) the neighbourhood level. Dendrogram showing clusters based on similarity for (c) the municipal level and (d) the neighbourhood level.

The PCO at the municipal level shows that both axes capture 67.0% and 26.5% of the total variation of worry, explaining more than 93.5% of the variability in the data. The hierarchical clustering dendrogram supports the three groups resulting from the PCO. Interestingly, Hualqui and Arauco group together, showing similar characteristics of worry. San Fernando appears moderately

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similar to Hualqui and Arauco, and San Pedro de Atacama is the most dissimilar, forming its own branch. At the neighbourhood level, the PCO shows that both axes capture 30.0% and 27.1% of the total variation of worry, explaining more than 57.1% of the variability in the data. Three main clusters of neighbourhoods are identified, which broadly align with the municipalities they belong to. Interestingly, Group 1 includes a mix of neighbourhoods of all municipalities, showing that areas from different municipalities can share similar worry-related characteristics. Group 2 is composed of neighbourhoods from San Fernando, Hualqui, and Arauco. Group 3 contains a smaller set of neighbourhoods exclusively from San Fernando, indicating more homogeneous variables related with worry within this locality.

3.2.2 Preparedness

The multilevel ordinal regression model predicts the probability that an individual *i*, living in neighbourhood *j* and municipality *k*, reports a level of preparedness. The multilevel, reveals the hierarchical structure of the data in Eq. (6).

$$\eta_{ijk}=0.312\cdot X_1+0.366\cdot X_2+0.331\cdot X_3+0.439\cdot X_4+0.314\cdot X_5+0.918\cdot X_6+2.976\cdot X_7-2.337\cdot X_8+u_k+v_{jk} \quad (6)$$

where η_{ijk} estimate the probability that the person belongs to a category of preparedness. X_1 is the gender of the respondent, X_2 is the knowledge of flooding areas, X_3 is the socio-economic group, X_4 is the housing quality, X_5 is the time living in the neighbourhood, X_6 is flooding outside their home, X_7 is the low socioeconomic portion, and X_8 is the municipal common found dependency. The terms u_k and v_{jk} are random effects that capture differences between municipalities and between neighbourhoods that are not explained by the variables in the model. specifically, u_k represents the deviation of municipality *k* from the overall average, while v_{jk} captures the deviation of neighbourhood *j* within municipality *k*. Table 6 shows the explanatory variables of preparedness according to the multi-level regression, indicating the regression parameters.

Table 6. Explanatory variables of preparedness according to the multi-level regression

Variable	Level	Estimate	Std. Error	z-value	p-value	Interpretation
Gender	Individual	0.312	0.124	2.521	0.012	Male → Higher preparedness
Knowledge of flooding areas	Individual	0.366	0.180	2.038	0.042	Awareness of flood-prone areas → Higher preparedness
Socioeconomic group	Individual	0.311	0.307	1.014	0.002	Belonging to a higher socioeconomic group → Higher preparedness
Housing quality	Household	0.439	0.132	3.325	0.001	Better housing quality → Higher preparedness
Time living in the neighbourhood	Household	0.314	0.150	2.097	0.036	Longer residence in the neighbourhood → Higher preparedness
Flooding outside their home	Household	0.918	0.131	7.019	0.000	Flooding outside the home → Higher preparedness
Low socioeconomic portion	Neighbourhood	2.976	1.095	2.718	0.007	Higher share of Group E households → Higher preparedness
Municipal Common Fund dependency	Municipality	-2.337	0.712	-3.280	0.001	Lower dependence on Municipal Fund → Higher preparedness

At the individual level, being male, having knowledge of flood-prone areas, and belonging to a higher socioeconomic group were positively associated with greater preparedness. At the household level, living in a higher-quality dwelling, having resided longer in the same home, and experiencing flooding outside the home were all linked to higher levels of preparedness. At the neighbourhood level, a greater proportion of households classified within low socioeconomic groups was associated with increased preparedness. At the municipal level, lower dependence on the Municipal Common Fund was positively related to preparedness, suggesting that residents in less financially dependent municipalities tend to report higher levels of readiness for future flood events. Noteworthy, the most important variables explaining preparedness where those associated with the higher levels, municipality and neighbourhood.

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Ordinal regression models for each level are included in Appendix B. A comparison between the ordinal regression by level and the multi-level regression reveals that the knowledge of flood-prone areas and the socioeconomic group were significant in both models, highlighting the relevance of the dimensions risk awareness and socioeconomic status on preparedness. Preparedness increased with the knowledge of flood-prone areas and when belonging to a higher socio-economic level. Age and place of residence five years ago, were significant in the regression by level but were not in the multilevel model. At the household level, the housing quality, the time living in the neighbourhood, and the occurrence of flooding directly outside the home were significant in both models, i.e.: preparedness at the household level depends on the quality of housing and past experiences with flooding. The socioeconomic group and number of age-dependent people in the household were significant only in the regression by level. Only belonging to the lower socioeconomic portion was significant at the neighbourhood level, i.e.: more vulnerable neighbourhoods exhibit greater preparedness. Neighbourhood interaction was only significant in the regression by level. Only one variable at the municipal level was significant in both regression models, namely Municipal Common Fund dependency. This suggests that living in economically more autonomous municipalities is associated with greater preparedness among residents. Overall, according to Eq. 6 preparedness in the study area was 1.920 (intermediate), with an increasing dispersion in the lower levels, varying from 1.088 (intermediate) to 2.356 (high) across municipalities and between 0.605 (low) and 2.745 (high) across neighbourhoods.

Figure 3 presents the Principal Coordinate Analysis (PCO) based on the variables significantly associated with worry according to the multilevel regression for the neighbourhood and municipality levels.

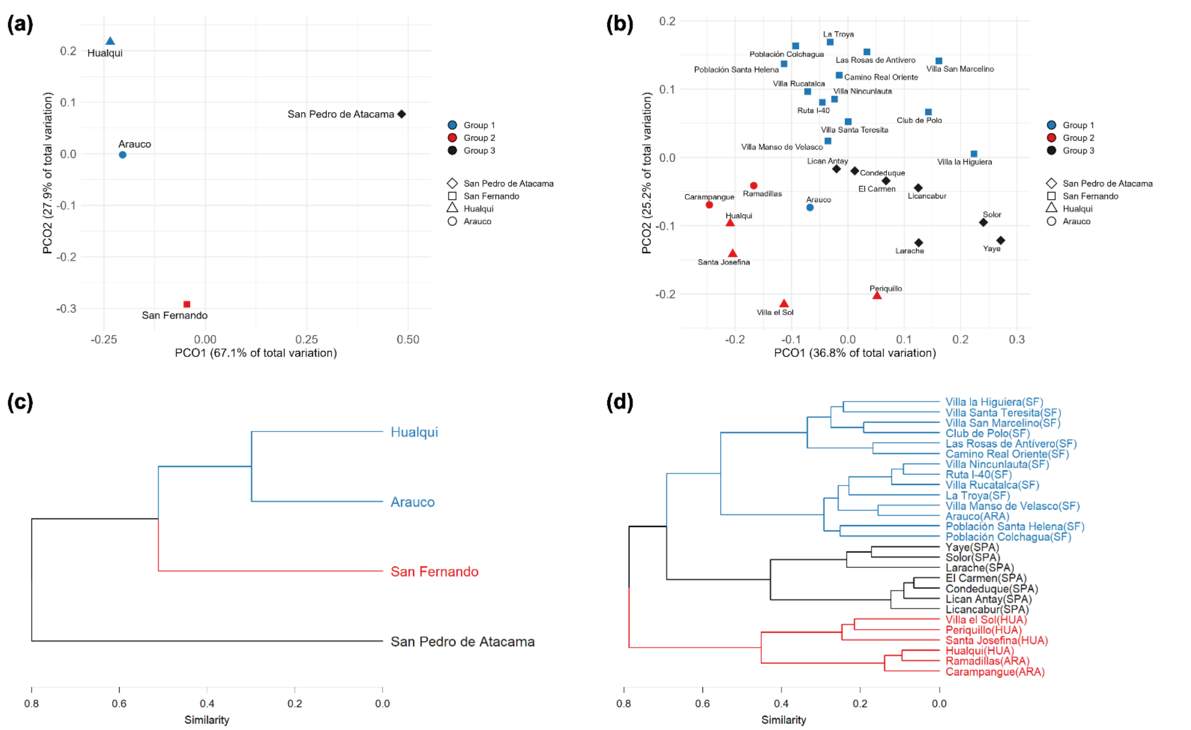

Figure 3. Principal coordinate analysis (PCO) of preparedness at (a) the municipal level and at (b) the neighbourhood level. Dendrogram showing clusters based on similarity for (c) the municipal level and (d) the neighbourhood level.

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The first and second PCO axis explain 67.1 and 27.9% of 95.0% of the total explained variation at the municipal level (Fig 3a), indicating that the analysis captures a large proportion of the differences in preparedness across municipalities. The PCO plot at the municipal level reveals three distinct groups. Group 1 includes Hualqui and Arauco, positioned close to each other on the plot, indicating high similarity in their preparedness-related profiles. Group 2, composed solely of San Fernando, displays a distinct preparedness pattern, largely separated along the second PCO axis. San Fernando shares some similarities with Group 1 on the first axis, suggesting overlap in certain preparedness related characteristics, but it differs markedly on other dimensions, leading to its separation as an independent cluster. Group 3 consists of San Pedro de Atacama, positioned furthest from the other groups along PCO1, reflecting a markedly different preparedness profile. The dendrogram (Fig 3c) supports these distinctions, showing strong similarity between Hualqui and Arauco, and clearer separation from San Fernando and San Pedro de Atacama. This analysis showed that preparedness is not uniform across municipalities, and while some localities, like Hualqui and Arauco, share similar preparedness levels, others present unique patterns.

At the neighbourhood level, the first and second PCO axis explain 36.8 and 25.2% of the 62.0% explained variation. The PCO plot at the neighbourhood level (Fig 3b) reveals three main groups, which align with the clustering patterns observed in the dendrogram (Fig 3d). Group 1 includes neighbourhoods from San Fernando and one from Arauco, which cluster closely together. Group 2 is composed of neighbourhoods from Hualqui and Arauco, showing homogeneity within these municipalities. Group 3 contains neighbourhoods from San Pedro de Atacama, which, although they form a distinct conglomerate, confirms that the preparedness is homogeneous at the neighbourhood or municipality level. The dendrogram shows similar preparedness in most neighbourhoods of Hualqui and Arauco, and a clearer separation of San Fernando.

3.3 Correlation between worry and preparedness

Figure 4 shows the heatmaps, derived from contingency tables between worry and preparedness, which visualize the joint distribution of both variables at the municipality and neighbourhood levels. Table 7 presents the results of the Spearman coefficient analysis and Pearson's χ^2 test.

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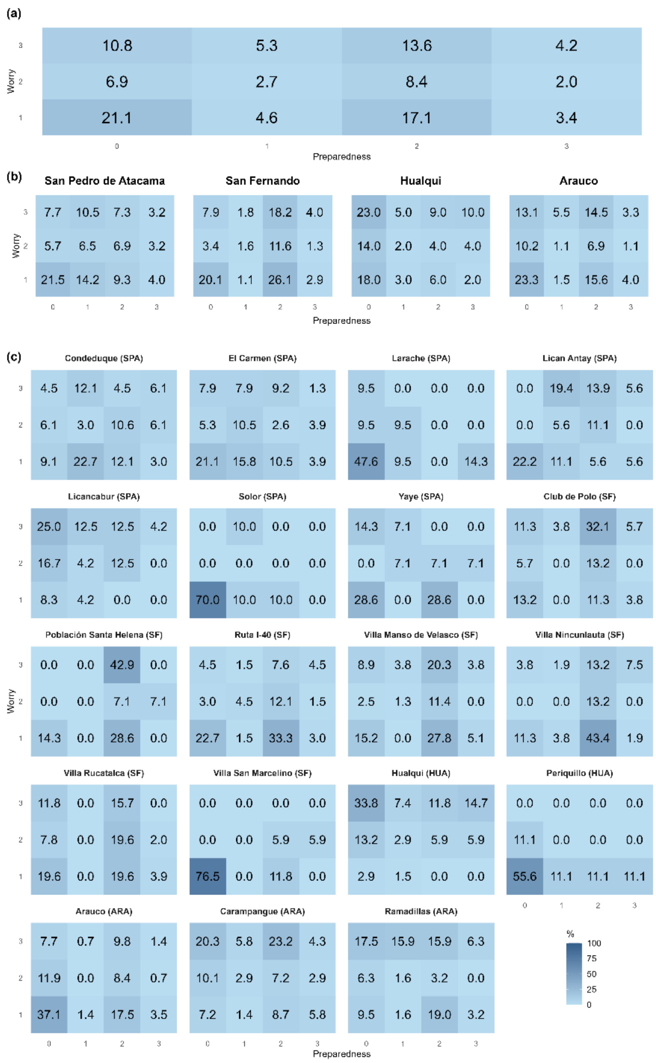

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Figure 4. Heatmaps with the joint distribution of worry and preparedness for (a) the whole sample, (b) the municipality level, and (c) neighbourhood level.

Table 7. Correlation and independence test of worry and preparedness at different levels.

Place	N	ρ	p value	χ^2	p value
Level: Whole sample	1001	0.116	<0.001	22.200	<0.001
Level: Municipality					
San Pedro de Atacama	247	0.159	0.013	10.400	0.110
San Fernando	379	0.154	0.003	20.600	0.002
Hualqui	100	0.142	0.158	3.160	0.803
Arauco	275	0.089	0.142	14.600	0.027
Level: Neighborhood					
Condeduque (SPA)	66	0.129	0.302	9.284	0.157
El Carmen (SPA)	76	0.120	0.303	6.396	0.393

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Larache (SPA)	21	-0.097	0.675	4.350	0.387
Licancabur (SPA)	36	0.132	0.538	2.844	0.897
Solor (SPA)	24	0.430	0.214	4.444	0.302
Yaye (SPA)	10	-0.068	0.816	9.644	0.150
Lican Antay (SPA)	14	0.394	0.018	16.519	0.008
Club de Polo (SF)	53	0.153	0.275	6.212	0.397
Población Santa Helena (SF)	14	0.347	0.224	9.333	0.087
Ruta I-40 (SF)	66	0.163	0.019	11.398	0.070
Villa Manso de Velasco (SF)	79	0.004	0.970	6.488	0.381
Villa Rucatalca (SF)	51	0.005	0.973	2.841	0.646
Villa San Marcelino (SF)	17	0.704	0.002	10.578	0.044
Villa Nincunlauta (SF)	53	0.235	0.009	10.982	0.009
Hualqui centro (HUA)	68	0.035	0.078	2.741	0.883
Periquillo (HUA)	18	-0.244	0.329	1.125	1.000
Arauco Centro (ARA)	143	0.154	0.007	6.034	0.424
Carampangue (ARA)	69	-0.099	0.419	3.548	0.761
Ramadillas (ARA)	63	-0.103	0.423	9.171	0.163

In the whole sample, the highest frequencies are concentrated in the combinations of low worry with non-preparedness and medium-high worry with medium-high preparedness indicating that preparedness increase with worry. However, mixed results are observed at the municipality level, without consistent patterns to conclude meaningful correlations between worry and preparedness. Moreover, the relation between worry and preparedness was analysed only in 19 out of the 27 neighbourhoods, as the remaining eight had insufficient variation in responses or a very small number of cases. Most neighbourhoods of San Pedro de Atacama showed weak and non-significant correlations between worry and preparedness, with the exception of Lican Antay that had a statistically significant relation of preparedness increasing with worry. In San Fernando, Villa San Marcelino is the only neighbourhood with a statistically significant and strong positive correlation, indicating increasing preparedness with worry. However. the sample size in this neighbourhood is small, which warrants cautious interpretation. Villa Nincunlauta stands out for having a high proportion of respondents with medium preparedness who are not worried. In Hualqui and Arauco, neighbourhoods showed weak and non-significant correlations between worry and preparedness, with no cases reaching statistical significance.

3.4 Flood behaviour

The review of news reports between 2000 and 2025 revealed that San Pedro de Atacama experienced seven significant flood events, in years 2001, 2012, 2013, 2015, 2017, 2019, and 2023, with an average flooding frequency of 3.7 years; San Fernando experienced four major flood events in years 2000, 2006, 2015, and 2023, with an average flood frequency of 7.7 years; Hualqui experienced five floods in years 2001, 2003, 2006, 2023, and 2024, with an average flood frequency of 5.8 years, and Arauco experienced eight flood events in years 2001 (twice), 2003, 2006, 2008, 2019, 2023, and 2024, with an average flooding frequency of 3.3 years. Figure 5 shows the maximum instantaneous discharges for each month between years 2000 and 2025 measured at gauge stations in rivers San Pedro@San Pedro de Atacama, Vilama@San Pedro de Atacama, Tinguiririca@San Fernando, Biobío@Hualqui, Hualqui@Hualqui, and Carampangue@Arauco. Red circles indicate the maximum discharge in the years when floods were reported in the news.

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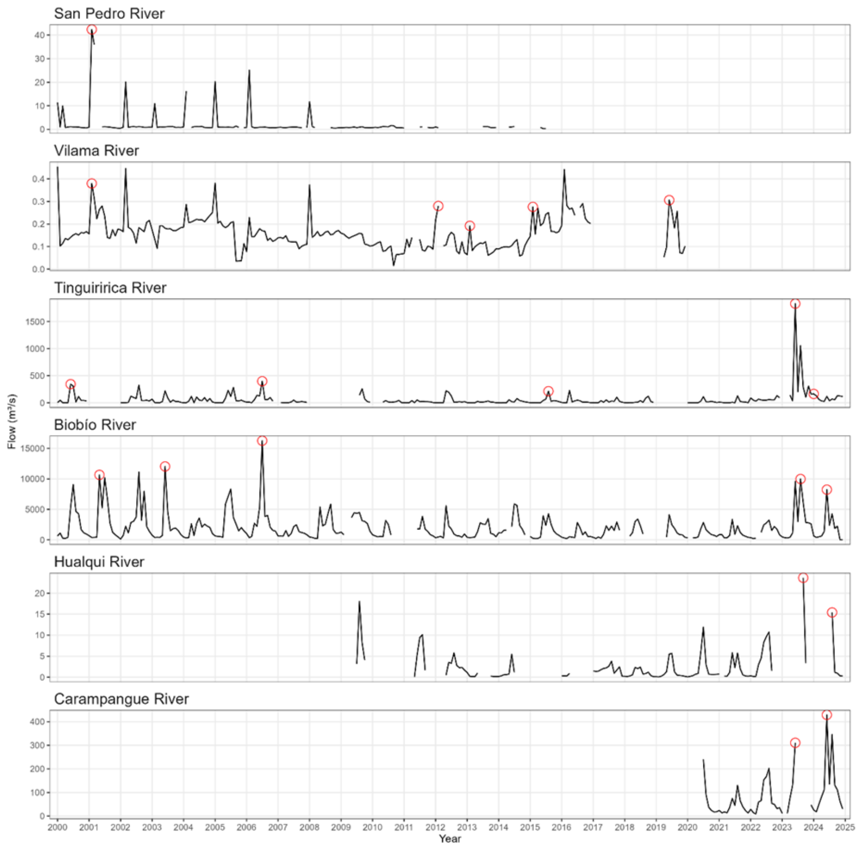

Figure 5. Maximum instantaneous discharges for each month between years 2000 and 2025 measured at gauge stations San Pedro@San Pedro de Atacama, Vilama@San Pedro de Atacama, Tinguiririca@San Fernando, Biobío@Hualqui, Hualqui@Hualqui, and Carampangue@Arauco.

Even when the discharge series have important data gaps, a very good consistency between the measured maximum discharges and the reported floods in the news is observed. The preparedness was different in the different localities and neighbourhoods as revealed by the clusters in Fig. 4. Table 8 presents the average predicted level of preparedness for each municipality, as estimated by the multi-level ordinal regression model. The outcome variable is measured on an ordinal scale from 0 (non-preparedness) to 3 (high preparedness).

Table 8. Explanatory variables of preparedness.

Municipality	Level of preparedness with Eq. 6
San Pedro de Atacama	1.088
San Fernando	2.356
Hualqui	1.793
Arauco	1.977

San Fernando exhibits the highest level of preparedness, followed by Arauco, Hualqui and San Pedro de Atacama. Obtained results on the flood recurrence and preparedness allow a quantitative classification of the characteristics flood behaviour in the different municipalities and neighbourhoods. Figure 9 shows the flood behaviour according to flood recurrence and preparedness in Leong's

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(2018) diagram, for which we assumed a threshold of 7 years for the time needed to forget a flood (see e.g. Lechowska, 2018; Barendrecht et al., 2019).

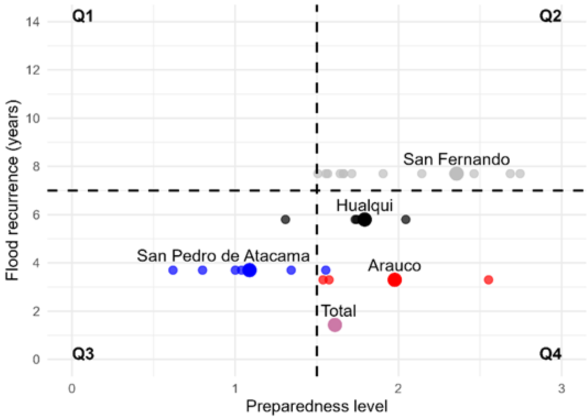

Figure 6. Flood behaviour according to flood recurrence and preparedness, adapted from Leong (2018). Q1: forgetting effect; Q2: proactive effect; Q3: status quo effect; Q4: learning effect.

Overall, the studied area exhibited an intermediate preparedness level, with a high flood recurrence and, consequently, a learning effect. At the municipality level, Hualqui and Arauco grouped as municipalities exhibiting a learning effect. Interestingly, Hualqui and Arauco share similarities in terms of the municipality size and socioeconomic level, which at the same time are different to the other localities studied. San Pedro de Atacama presented a status quo effect. San Fernando has a proactive effect. Even when there are insufficient available data to evaluate the flooding recurrence at lower scales, i.e. neighbourhoods and households, the flood behaviour at the different neighbourhoods was evaluated assuming that flood recurrence in a neighbourhood is the same as that of the corresponding municipality. Interestingly, two neighbourhoods: Solor at San Pedro de Atacama and Hualqui center exhibited a flood behaviour different to that of the corresponding municipality.

4 Discussion

4.1 Variables and dimensions explaining flood risk perception

In the present study people were assumed to be aware of flood risk, as almost all respondents live close to the river, declares to know the flooding areas, or experienced the flood outside their home. Indeed, knowledge of flood-prone areas is widely accepted as a direct indicator of awareness (Mondino et al., 2020; Bradford et al., 2012), and proximity to rivers is associated with increased awareness due to the visibility of hazards (Gray-Scholz et al., 2019; Ali et al., 2022). Moreover, Bradford et al. (2012) highlighted that even where there was no damage to a household, experiencing flooding in the neighbourhood or seeing others affected was enough to raise awareness of flood risk.

Our results show that economic and personal resources highly control worry and preparedness: households with better economic situation are less worried about floods, while minor economic resources at the municipal and neighbourghood levels trigger the adoption of cautionary measures at the household level. This finding is in line with Bronfman et al. (2019) who link socioeconomic advantage to increased resources and perceived control and with Działek et al. (2019) who showed that low-income groups may

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express higher worry but lower preparedness due to structural constraints. Similarly, Takao et al. (2004) and Shah et al. (2017) found that poor housing conditions can increase both perceived risk and urgency to act.

The knowledge of flooding areas decreased worry and increased preparedness in line with previous findings by Scolobig et al. (2012), Ashenefe et al. (2017), Cao et al. (2020) and Veloso et al. (2022). However, experiences where the flood passed outside the household increased both worry and preparedness, suggesting that similarly to awareness, worry is linked to experiencing flooding in the neighbourhood or seeing others affected.

Higher trust in neighbors was associated with lower levels of worry in line with Scolobig et al. (2012) and Kerstholt et al. (2017), who suggest that stronger social trust or neighbourhood networks may reduce risk perception, possibly because individuals feel they can rely on their community in the event of a flood.

Older individuals reported both higher preparedness and lower worry. Prior studies offer mixed findings: while some associate older age with vulnerability, others link it to accumulated knowledge or more proactive behavior (Shah et al., 2017; Bronfman et al., 2019). Similarly, extended residence in the same location has been associated with increased preparedness, possibly due to stronger place attachment or accumulated local knowledge (Poussin et al., 2014; Mavhura et al., 2022). A further possibility in our case is related to better housing belonging to older people.

4.2 Correlation between worry and preparedness

Four variables partly explained worry and preparedness: the knowledge of flooding areas, housing quality, flooding outside their home, and the socioeconomic class of the neighbourhood. Contingency tables and ordinal correlation analysis showed that in general worry and preparedness are positively correlated. However, patterns were heterogeneous within municipalities, and in many cases, the distribution of responses across categories was balanced or dispersed, without a clear alignment between the two variables. Moreover, most neighbourhoods showed weak and non-significant correlations between worry and preparedness, indicating that higher worry does not necessarily translate into higher preparedness at the neighbourhood level. This is in line with findings from Poussin et al. (2014) and Cao et al. (2020), who, although not measuring this correlation directly, emphasize that emotional and cognitive components such as worry, awareness, or perceived risk do not automatically lead to preparatory actions.

4.3 Flood behaviour

The classification of flood behaviors proposed by Leong (2018) allowed us to develop a quantitative assessment of the flood behavior observed in the study area. A critical issue was to determine the threshold to distinguish between the small and large floods. Terpstra (2011) suggests that the positive influence of experiences on private mitigating behaviours may disappear several years after the flood. Lechowska (2018) found that according to The International Commission for the Protection of the Rhine ICPR (ICPR 2002), flood risk perception decreases 7 years after flooding while catastrophic disasters are remembered much longer. flood risk perception usually decreases 7 years after flooding while catastrophic disasters are remembered much longer. Consequently, Barendrecht et al. (2019) assumed the half time of awareness, i.e.: the time after which awareness is halved, is 7 to 10 years after a flood. A threshold of 7 years was adopted in the present study to distinguish between "small" and "large" floods. Noteworthy, floods in San Fernando have a recurrency of 7.7 years, and thus this municipality could also fall beyond the threshold value. Overall, the studied area exhibited a learning effect with intermediate preapredness and high flood recurrency. At the municipal level, obtained flood behavior for Arauco was consistent with findings by Veloso et al. (2022), who studied the relations between preparedness and psycho-social attributes of people and communities exposed to river floods in a nearly pristine socio-

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hydrological system, applying a hydrologicalhydraulic analysis of flood risk in combination with results from a survey, social cartography, semistructured non-participant observation, and semi-structured interviews. The flood behaviour for San Pedro de Atacama was consistent with findings by Mendoza Leal et al. (2024), who conducted fieldwork to reconstruct a flood event, hydrological analysis and semistructured interviews with key informants to characterize people's responses to floods and showed evidence that the so-called status quo effect, i.e. when communities do not learn and adapt to prevent damage even when exposed to frequent floods was present at the riparian community scale. A possible reason partly explaining such behaviour is related to the particular convective storms occurring in Atacama (Alcayaga et al., 2025). San Fernando exhibited a proactive effect, which might be related to housing quality and time living in the neghbourhood. Two neighbourghoods -Solor at San Pedro de Atacama and Hualqui center- exhibited a flood behavior different to that of the corresponding municipality. Obtained results clearly show an increasing dispersion when lowering the level of analysis of flood behavior. It is relevant to notice that Fig. 6 shows only a picture of the surveyed neighbourhoods in 2024. But flood risk perception changes after a flood experience, and thus dynamic flood behaviours are expected at the different levels, which merits further investigation.

5 Conclusion

A multi-level assessment of flood risk perception (worry and preparedness) and flood behaviour at the individual, household, neighborhood and municipality levels was proposed and applied to a survey of 1007 residents in four different localities of Chile exposed to river floods.

Almost all respondents were aware of flood risk. Economic and personal resources highly controlled worry and preparedness: households with better economic situations were less worried about floods, while minor economic resources at the municipal and neighborhood levels triggered the adoption of cautionary measures at the household level. Experiences where the flood passed outside the household increased worry and preparedness. Worry decreased with trust in the neighbors. Overall, worry and preparedness in the study area were intermediate, with an increasing dispersion in the lower levels.

The correlation patterns between worry and preparedness were heterogeneous without a clear alignment between the two variables. In many cases correlations were statistically non-significant, and thus, higher worry did not necessarily translate into higher preparedness.

Municipalities exhibited different flood behaviors, and some neighborhoods exhibited flood behaviors different to those of their municipalities, evidencing important differences across the analyzed levels, according to several urban scales. Obtained results suggest that flood risk perception and flood behaviour should be analyzed at the neighborhood level. Consequently, risk communication and risk management strategies should be adapted to focus on the needs of specific neighbourhoods exposed to floods.

This study provides an innovative multilevel perspective on flood risk perception and behaviour, yet some aspects should be noted. The cross-sectional survey offers a solid snapshot of the situation but does not capture how perceptions and preparedness may change over time. Social dimensions such as trust or cohesion were addressed through simplified indicators, which future research could complement with more nuanced or qualitative approaches. Moreover, preparedness was examined mainly at the household scale, leaving room to further explore community and institutional responses. These considerations suggest directions for extending this work rather than limitations of its current scope.

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Appendix A: Univariate analysis for each municipality

Figures A1, A2 and A3 show the socio-economic characteristics, social networks and flood experience characteristics for each municipality and the whole sample.

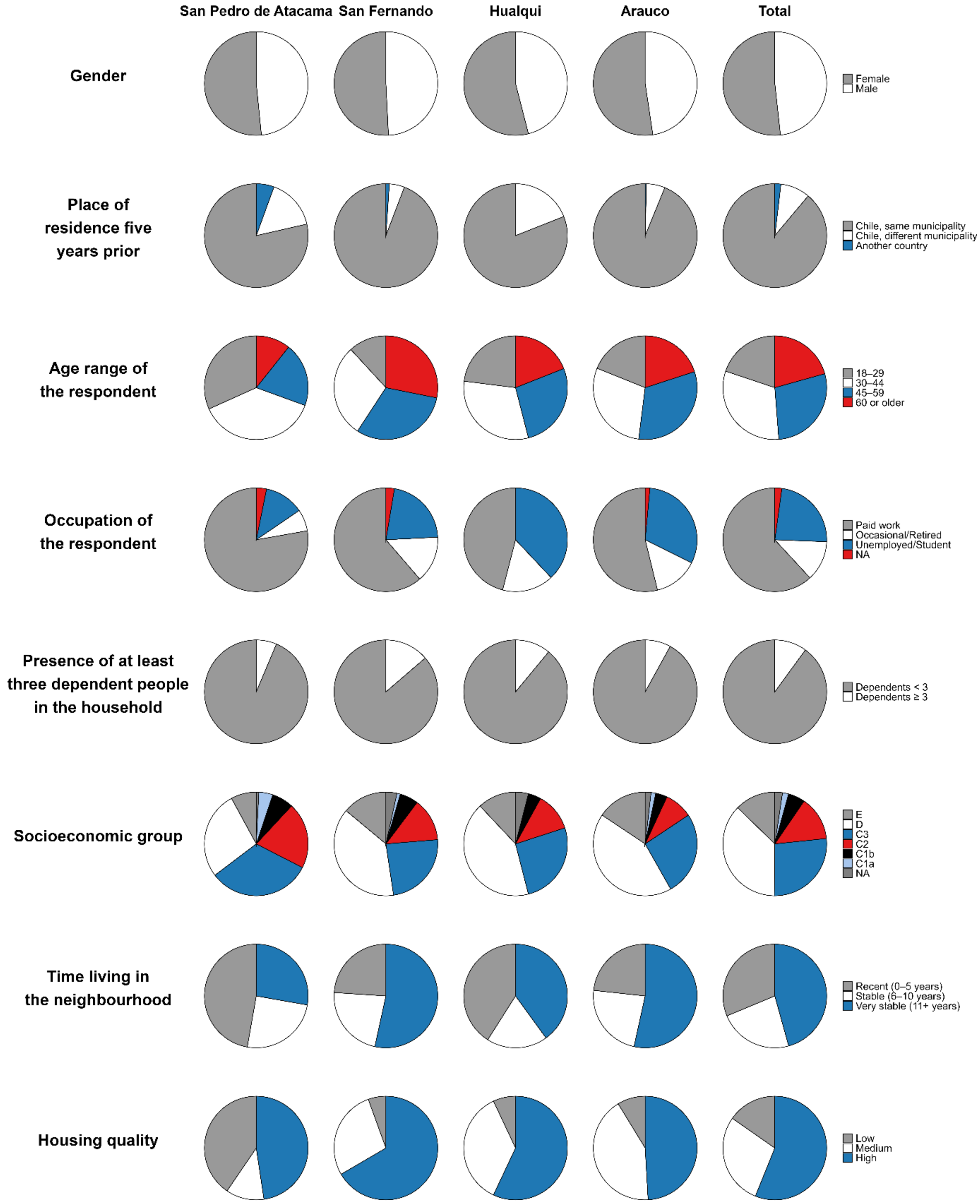

Figure A1. Gender, place of residence five years prior, respondent age range, and occupation, together with dependent people in the household, socioeconomic group, time living in the neighbourhood and housing quality for each municipality and for the whole study area.

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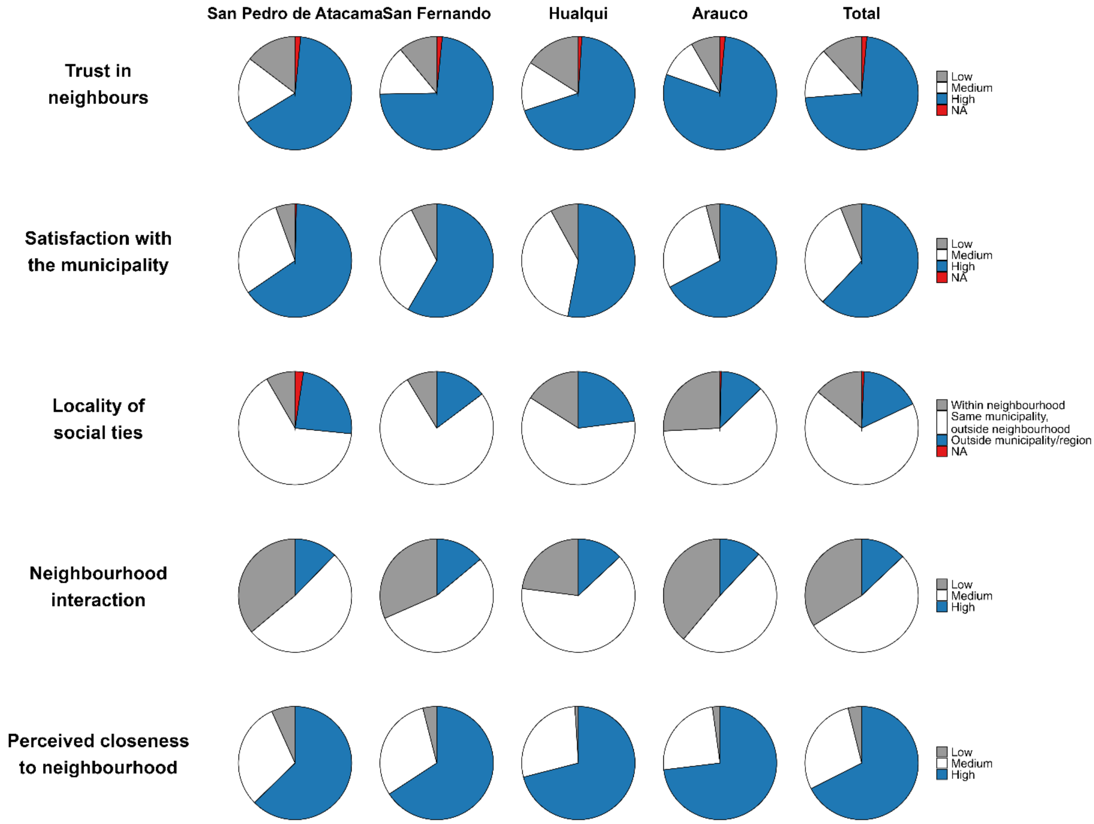

Figure A2. Trust in neighbours, satisfaction with the municipality, location of social ties, neighbourhood interactions and perceived closeness to neighbours.

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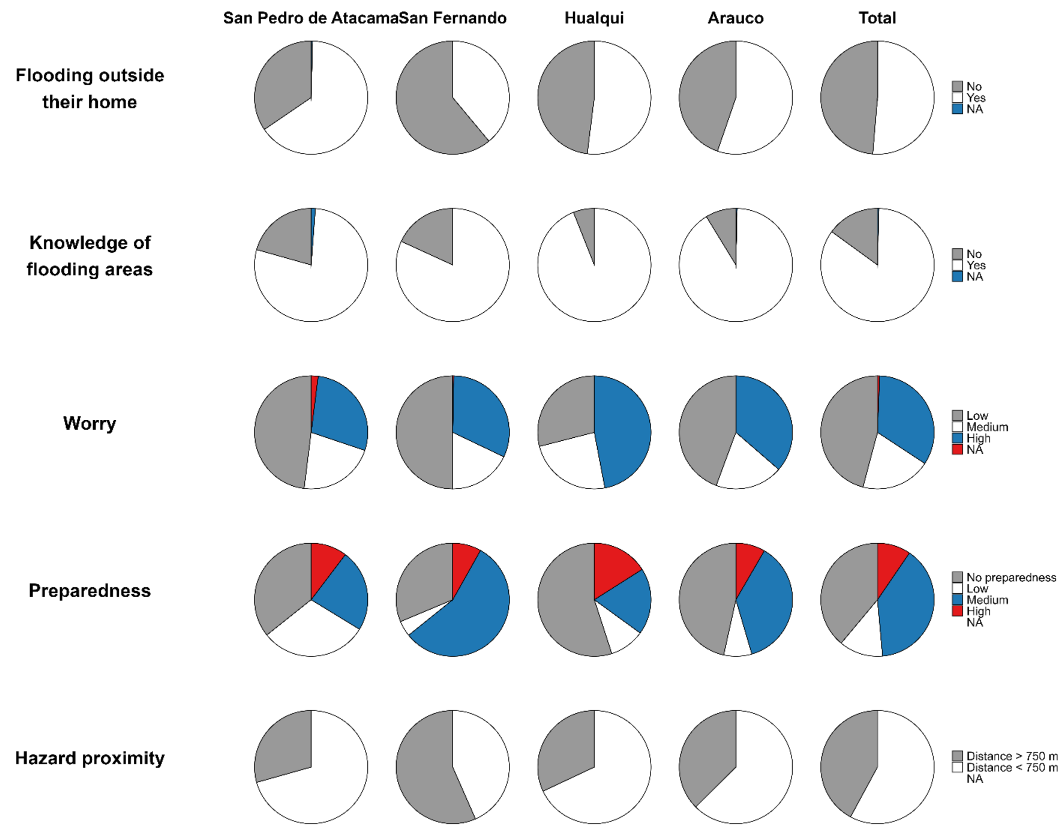

Figure A3. Flooding outside their homes, knowledge of flooding areas, worry about flood risk, flood preparedness and hazard proximity.

In terms of respondent and household characteristics, gender distribution was balanced across all localities. The proportion of individuals not living in the same residence was higher and similar in San Pedro de Atacama and Hualqui. San Pedro de Atacama also had the youngest respondents, while the other localities concentrated older populations.

The dominate occupation in all localities is paid work, with San Pedro de Atacama having the largest proportion. A similar proportion of dependent people was observed across all localities. San Fernando, Arauco and Hualqui displayed similar socioeconomic group distribution, where lower-income groups predominated, in contrast, the middle-income groups predominate in San Pedro de Atacama.

The time living in the neighbourhood was highest in San Fernando and Arauco, while the largest proportion of recent arrivals was in San Pedro de Atacama. Housing quality was highest in San Fernando, intermediate in Hualqui and Arauco, and lowest in San Pedro de Atacama.

High levels of trust in neighbours were observed across all localities, and satisfaction with the municipality was also predominantly high in every case, with slightly lowest level in Hualqui. In all localities, social ties were predominantly located in the municipality, but in another neighbourhood.

The predominant level of interaction between neighbours is medium in every case, with slightly highest values of low interaction in San Pedro de Atacama and Arauco. The perception of closeness to the neighbourhood was predominantly high across all localities.

In San Pedro de Atacama, most of the respondents experienced flooding outside their home. Less than the half of the people in San Fernando reported flood outside their home. Close to the half of the people experienced flooding outside their home in Arauco and Hualqui.

The knowledge of flooding areas is high across all municipalities, above 78% in every case. Low levels of worry are observed present in San Pedro de Atacama and San Fernando, while medium to high levels are more prevalent in Hualqui and Arauco.

Preparedness varies considerably between localities. In San Pedro de Atacama, no preparedness and low preparedness predominates. In San Fernando, medium levels of preparedness prevail. In Hualqui and Arauco, a significant portion report medium to high preparedness.

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Appendix B: Ordinal regression models for each level

Worry

Equations (B1) to Eq. (B4) include the significant predictors of worry for the different levels:

$$\eta(1)=-0.059\cdot X_1+0.484\cdot X_2-0.022\cdot X_3-1.120\cdot X_4-0.029\cdot X_5-0.190\cdot X_6 \quad \text{(B1)}$$

where η(1) is the level of worry for the individual level. X_1 is gender, X_2 is occupation of the householder, X_3 is age of the responder, X_4 is the level of trust in neighbours, X_5 is the knowledge of flooding areas and X_6 is the socioeconomic group of the respondent.

$$\eta(2)=1.668\cdot X_7-0.367\cdot X_8 \quad \text{(B2)}$$

where η(2) is the level of worry for the household level. X_7 is the occurrence of flooding outside their home and X_8 is the distance between the household to the nearest water body.

$$\eta(3)=-4.622\cdot X_9+4.180\cdot X_{10}-5.236\cdot X_{11} \quad \text{(B3)}$$

where η(3) is the level of worry for the neighbourhood level. X_9 is the proportion of ABC1 (high socioeconomic status) households in the neighbourhood, X_{10} is the low socioeconomic portion in the neighbourhood, and X_{11} is the territorial socio-material index ISMT.

$$\eta(4)=9.472\cdot X_{12} \quad \text{(B4)}$$

where η(4) is the level of worry for municipality level, X_{12} indicates the proportion of people living in poverty.

At the individual level, being unemployed or retired was associated with greater worry, while older age, greater trust in neighbours and knowledge of flood-prone areas were associated with lower levels of worry. In addition, individuals from higher socio-economic groups tended to perceive less worry.

At the household level, having experienced flooding outside the home during the most recent event emerged as the strongest predictor of increased worry. Greater distance from the river was also associated with reduced concern.

At the neighbourhood level, residing in areas with a higher proportion of low-income households was positively associated with worry. Conversely, living in areas with a greater share of high-income residents or a higher territorial socio-material index was related to lower levels of worry.

At the municipal level, only the income poverty rate was a statistically significant predictor of worry, suggesting that residents in economically poorer municipalities have higher worry about flood risk perception.

Preparedness

The ordinal regression model revealed the variables explaining preparedness. Eq. (B5) to Eq. (B8) include the significant predictors of preparedness for the different levels.

$$\eta(1)=-0.427\cdot X_1+0.260\cdot X_2+0.480\cdot X_3+0.191\cdot X_4 \quad \text{(B5)}$$

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where h(1) is the level of preparedness for the individual level, X_1 is had living outside of the municipality five year ago, X_2 is age of the responder, X_3 is the knowledge of flooding areas, X_4 socioeconomic group of the responder.

$$\eta(2)=0.507\cdot X_5+0.331\cdot X_6+0.385\cdot X_7+0.332\cdot X_8+0.894\cdot X_9 \tag{B6}$$

where η(2) is the level of preparedness for the household level, X_5 is housing quality, X_6 is the socioeconomic group, X_7 is time living in the neighbourhood, X_8 is the presence of at least three dependent people in the household and X_9 is flooding outside their home.

$$\eta(3)=0.252\cdot X_{10}+3.775\cdot X_{11} \tag{B7}$$

where η(3) is the level of preparedness for the neighbourhood level, X_{10} represents neighbourhood interaction and X_{11} indicates the proportion low socioeconomic portion in the neighbourhood.

$$\eta(4)=6.588\cdot X_{12}-1.372\cdot X_{13} \tag{B8}$$

where η(4) is the level of preparedness for the municipality level, X_{12} indicates the Territorial socio-material index and X_{13} indicates municipal common fund dependency.

At the individual level, older respondents, those who reported knowledge of flood-prone areas, and individuals from higher socioeconomic groups demonstrated greater preparedness. These variables reflect the dimensions of demographic characteristics (age), risk awareness (knowledge of flooding areas), and socioeconomic status (socioeconomic group). In contrast, having lived in a different municipality five years prior was associated with lower levels of preparedness, suggesting that recent movers may have lower familiarity with flooding risk in the locality.

At the household level, improved housing quality, longer time living in the neighbourhood, and the presence of dependent individuals were all positively associated with preparedness. Additionally, experiencing flooding outside the home during the most recent event emerged as a strong predictor of higher preparedness, indicating that experience with floodings is an important variable that increase preparedness in the householders.

At the neighbourhood level, greater interaction with neighbours and a higher proportion of households classified in the lowest socio-economic group (GSE E) were associated with greater preparedness. These results suggest that social cohesion and economic vulnerability may foster greater action at the community level.

At the municipal level, two variables were significant: greater heterogeneity in socio-material conditions (as measured by the standard deviation of the ISMT) and lower dependence on the Municipal Common Fund. The first may reflect how internal inequality increases risk perception and motivation, while the second points to the role of local economic autonomy in fostering better preparedness infrastructure or support.

At the municipality level, greater heterogeneity in socio-material conditions (as measured by the ISMT standard deviation) was associated with higher preparedness. Additionally, lower dependence on the Municipal Common Fund was linked to increased preparedness among residents.

Data availability

All data can be provided by the corresponding author upon request.

Author contributions

RC and VS analyzed the data; FL and OL conceptualization of the MS; OL and RC wrote the MS draft; VS and FL reviewed and edited the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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