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A spatial fuzzy logic approach to urban multi-hazard impact assessment in Concepción, Chile

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Abstract

Even though most cities are exposed to more than one hazard, local planners and decision-makers still have a limited understanding of the exposure and sensitivity to and the spatial distribution of hazards. We examine the impact of multiple hazards in the Concepción Metropolitan Area (CMA), Chile. A flexible methodology based on spatial fuzzy logic modelling was developed to explore the impact of weather-related hazards, including coastal flooding, fluvial flooding, water scarcity, heat stress, and wildfire. 32 indicators were standardised and then aggregated through a stepwise approach into a multi-hazard impact index. We find that all the municipalities in the CMA increased their level of impact between 1992 and 2002, due to a larger increase in the exposure rather than the modest decrease in sensitivity. Municipal sensitivity was driven mostly by changes in the population's age structure. Wildfires and water scarcity appeared to have the largest impact on all municipalities. Fuzzy modelling offered high flexibility in the standardization and aggregation of indicators with diverse characteristics, while also providing a means to explore how the interaction of numerous indicators influenced the index. The resulting maps can help identify indicators, components, and hazards or combinations of hazards that most influence the impact on municipalities. The results can be used to improve and promote dialogue amongst policy-makers and stakeholders regarding prioritisation of resources for urban development in ways that can also reduce exposure and sensitivity and lower vulnerability to climate change. The methods presented can be adapted to other cities.

Keywords: developing countries, bottom-up evaluation, fuzzy modelling, geographical information system (GIS), vulnerability

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1. Introduction

The spatial assessment of recent past exposure and sensitivity to multiple hazards can serve as a first step to strengthening the understanding of the base conditions of a city, which is a fundamental element in urban planning (Mastrandrea et al., 2010). Even though most cities are exposed to more than one hazard (Dilley et al., 2005), and there is substantial evidence to indicate that the impact of hazards will increase (IPCC, 2012), there is still limited knowledge among local planners and policy-makers of exposure and sensitivity to hazards and their spatial distribution (Funfgeld, 2010). Thus, there is a pressing demand for suitable methods to analyse urban exposure and sensitivity to hazards, which can be combined with adaptive capacity to assess a city's overall vulnerability.

Many attempts have been made to explore the specific impacts of droughts, floods, heat waves, sea level rise, and wildfires (Fischer and Schär, 2010; Fried et al., 2004; Hinkel et al., 2010; Lehner et al., 2006), and a growing number of hazard-specific studies focus on urban areas (Birkmann et al., 2012; Taubenböck et al., 2011). However, few studies explore combined multi-hazard impacts (Forzieri et al., 2016; Lung et al., 2013; McCubbin et al., 2015; Preston et al., 2008), and even fewer the multi-hazard impact in urban areas (Rosenzweig and Solecki, 2001; Swart et al., 2012). This is due in part to the complexity of these kinds of assessments, which justifies the ongoing discussion regarding the definition of the concepts of exposure and sensitivity and the interrelations between the two. Multi-hazard impact assessments also involve difficulties in accessing hazard of diverse nature, intensity, and scale (Kappes et al., 2012) and in accessing and managing multiple databases (Greiving et al., 2006). In the case of future impact, there is also the challenge of projecting the socio-economic factors underlying sensitivity (Schauser et al., 2010). Finally, the connections that can exist among hazards, as with heat stress and wildfires, and different scales of analysis are additional challenge (Forzieri et al., 2016).

Despite these challenges, there are important advantages to taking a multi-hazard approach (UN, 2002), which provides a more realistic assessment of the complexity of an urban area and an integrated view of the total impact related to weather-related hazards (IPCC, 2012). It favours the identification of the factors affecting multiple hazards, particularly in relation to socio-economic factors of social sensitivity, such as the connection between the elderly population, and heat stress and fluvial flooding. Additionally, the multi-hazard approach permits the identification of possible links among hazards in an area, as with droughts and increases in vector-borne diseases (Greiving et al., 2006). Since the intensity of pre-existing impacts provides some insight about the degree of harm that climate change can cause in the near future this approach offers a basis for understanding current impact (Dessai and Hulme, 2004; Miller and Bowen, 2013). Furthermore, they increase knowledge and awareness of the impact assessment, since they allow for testing the selection of indicators, their aggregation, and the comparison of different hazards (Gallina et al., 2016; Kappes et al., 2012).

In the present study, the temporal and spatial distribution of exposure and sensitivity to multiple hazards was tracked for the nine municipalities in the Concepción Metropolitan Area (CMA) in Chile through a multi-hazard impact (MHI) index, based on the work done by Lung et al. (2013) and Swart et al. (2012) who assessed the impact of multiples hazards in Europe and employed a set of urban indicators to assess vulnerability to climate change. We used indicators to track related hazards, exposure, and sensitivity in 1992 and 2002, through a fuzzy overlay approach using geographic information systems (GIS). The use of biophysical and socio-economic indicators is based on the access to reliable data set, see (Cutter and Finch, 2008). Fuzzy Logic (Zadeh, 1965) is a multi-valued logic approach which involves the assignment of partial or intermediate values over a well-defined range (0 to 1). Therefore, it favours the identification of different degrees of impact rather than overly crude, binary understandings like 'vulnerable' or 'not vulnerable'. Fuzzy logic offers a flexible and straightforward standardization of spatial objects of different values favouring comparison (Espada et. al, 2013), enabling the comparison of differences in exposure and sensitivity levels between municipalities over time. Furthermore, it facilitates addressing the data variability and vagueness as well as imprecision of interpretations (Acosta et al., 2013; Mazzorana and Fuchs, 2010). (Pradhan, 2011) notes that analysis using fuzzy logic in GIS i) allows researchers to evaluate complex problems in a practical way, ii) is understandable and easy to implement, iii) allows flexibility in the combination of maps and iv) is easily implemented in the GIS language.

This research is framed around the following questions: a) Which were the most exposed and most sensitive municipalities of the CMA in 1992 and 2002?; b) How did exposure and sensitivity change across CMA municipalities between 1992 and 2002?; and c) Which hazards have the greatest influence on the calculation of the MHI index developed for the municipalities? Our results are intended to help stakeholders and policy-makers in the municipalities to understand the baseline conditions of the area, and thus support the first stage in the process of planning for climate change in cities; the situation analysis (Grafakos et al., 2015).

2 Study Area and Methods

2.1 The Concepción Metropolitan Area

The CMA is located in the coastal area of the Bío-Bío Region in southern-central Chile (Figure 1); it covers 2,077 km^2 with 220 km of coastline. It is Chile's second most important city after the capital of Santiago, and comprises ten municipalities (listed in Fig. 1). The CMA has a warm-temperate coastal Mediterranean climate, with winter rainfall and high atmospheric humidity, and a dry season lasting from four to five months (Errázuriz et al. 1998).

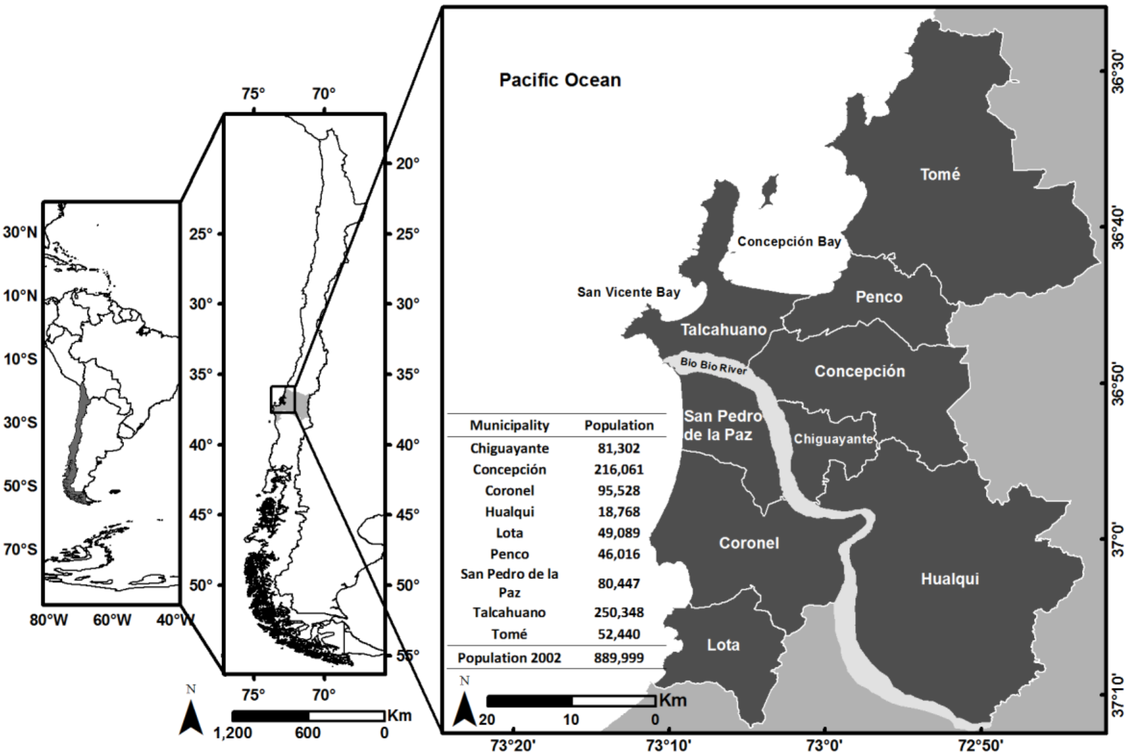

Figure 1. CMA location and table of population projections of CMA municipalities for 2002 (NIS, 2011).

As in many developing countries, the CMA's urban expansion has been rapid and uncontrolled, with the population more than doubling in the last 50 years. The varied terrain of the region has directed expansion, which has occurred predominantly around the municipalities of Concepción and Talcahuano, forming two axes of influence of urban dynamics (Almuna et al. 2012). An inadequate land use policy has resulted in strong spatial socio-economic segregation (Azócar et al. 2010; Sabatini et al. 2001), resulting in land use conflicts, environmental and ecological problems, and particularly compromising the proper functioning of watersheds

(Mardones and Vidal 2001; Pauchard et al. 2006). More than 50% of the metropolitan area is exposed to varying degrees of risk from flooding, waterlogging, tsunamis, and landslides (Mardones and Vidal, 2001).

2.2 Developing the multi-hazard impact index

The CMA's MHI index was developed in three stages (Figure 2). In the first stage, the overall indicator framework was determined through a critical review of the literature regarding exposure and sensitivity, from which an aggregation framework of selected indicators was established to calculate and create the MHI index (stage two). In the third and final stage, sensitivity and uncertainty analyses were carried out to test the robustness, relevance, and significance of the selected indicators to exposure and sensitivity for the model outputs. All analyses were carried out using the GIS software ArcGIS v10 (ESRI, 2012).

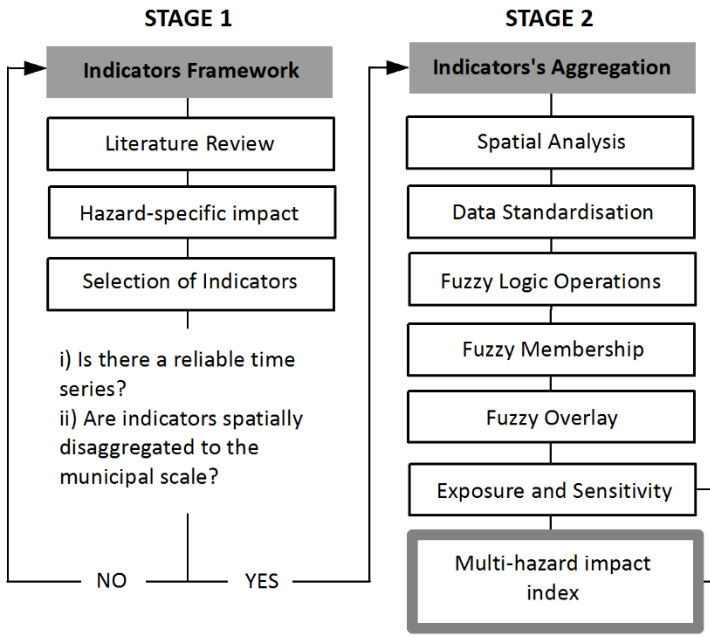

Figure 2. Stages in the development of the multi-hazard impact assessment in the CMA.

Stage 1: Conceptualisation of the indicator framework

Five natural hazards were analysed: coastal flooding, fluvial flooding, water scarcity, heat stress, and wildfire. As in Lung et al. (2013), the selection of hazards was based on i) those that impacted urban areas with social and economic consequences (Mardones and Vidal, 2001), ii) those that are expected to be a concern in the future (Boulanger et al., 2014; Klempa, 2009), and iii) those that for which reliable data is available for assessment. Table 1 presents the indicators that were selected based on the literature review, the experience of local stakeholders, and data availability. Further criteria for indicator selections included the availability of a reliable 20-year time series from 1982 to 2002 for each municipality. Supplementary Material S1 presents a detailed description of the CMA indicators. Schauser et al. (2010) and Swart et al. (2012) presented an extensive review of indicators that was used to study urban exposure and sensitivity.

Table 1. Details of selected indicators of exposure and sensitivity

Indicators used to assess changes in exposure and sensitivity to coastal flooding

Indicators/Proxies	Unit/description	Component	Source[b]
Area prone to coastal flooding	% of area in the coastal flooding area	Exposure	NSGM
Residents in the area	% of residents in the area at risk of coastal flooding	Sensitivity	NIS
Critical infrastructure	% of transport infrastructure in the area at risk of coastal flooding	Sensitivity	MPW
Elderly people	% of population > 65 years in the area at risk of coastal flooding	Sensitivity	NIS
Very young people	% of population < 5 years in the area at risk of coastal flooding	Sensitivity	NIS

Indicators used to assess changes in exposure and sensitivity to fluvial floods

Indicators/Proxies	Unit/description	Component	Source[b]
Area prone to fluvial flooding	% of flooded area, magnitude of a 50-year flood	Exposure	NSGM
Residents in the area	% of residents in the area at risk of fluvial flooding	Sensitivity	NIS
Critical infrastructure	% of transport infrastructure in the area at risk of fluvial flooding	Sensitivity	MPW
Elderly people	% of population > 65 years in the area at risk of fluvial flooding	Sensitivity	NIS
Very young people	% of population < 5 years in the area at risk of fluvial flooding	Sensitivity	NIS

Indicators used to assess changes in exposure and sensitivity to water scarcity

Indicators/Proxies	Unit/description	Component	Source[b]
Droughtiness	Standardised precipitation index (SPI)	Exposure	MA
Water exploitation	Water exploitation index (WEI)	Exposure	GDW
Water consumption	Water consumption per capita (litres/day)	Sensitivity	SISS
Growth of water demand	Variation in urban population served by drinking water	Sensitivity	NIS
Poverty	% of the population living in extreme poverty or poverty	Sensitivity	MSD
Elderly people	% of population > 65 years	Sensitivity	NIS
Very young people	% of population < 5 years	Sensitivity	NIS

Indicators used to assess changes in exposure and sensitivity to heat stress

Indicators/Proxies	Unit/description	Component	Source[b]
Very hot days	Frequency of very hot days, with maximum temperature > 95th percentile	Exposure	MSC
Very hot nights	Frequency of very hot nights, with minimum temperature > 95th percentile	Exposure	MSC
Heat wave	Number of consecutive days with maximum temperature > 95th percentile	Exposure	MSC
Population density	Population density, people/km^2	Exposure	NIS
Poverty	% of the population living in extreme poverty or poverty	Sensitivity	MSD
Elderly people	% of population > 65 years	Sensitivity	NIS
People 65+ Living Alone	% of households composed of one adult >65 years	Sensitivity	NIS
Very young people	% of population < 5 years	Sensitivity	NIS

Indicators used to assess changes in exposure and sensitivity to wildfires

Indicators/Proxies	Unit/description	Component	Source[b]
Wildfires events	Ratio of the total number of wildfire fires to the area at	Exposure	NFC

	risk of wildfire		
Total area burned	Ratio of total area burned to the area at risk of wildfire	Exposure	NFC
FWI	Forest fire weather index (FWI)	Exposure	MSC
Residents in the area	% of residents in the area at risk of wildfire	Sensitivity	NIS
Critical infrastructure	% of transport infrastructure in area at risk of wildfire	Sensitivity	MPW
Elderly people	% of population > 65 years	Sensitivity	NIS
Very young people	% of population < 5 years	Sensitivity	NIS

[b] Source: NIS—National Institute of Statistics, MSD—Ministry of Social Development, MH—Ministry of Health, MHUD—Ministry of Housing and Urban Development, GDW—General Directorate of Water, SISS—Superintendent of Sanitary Services, MSC—Meteorological Service of Chile, NFC—National Forest Corporation of Chile, MA—Minister of Agriculture, MPW—Ministry of Public Works.

Stage 2: Aggregation of indicators through fuzzy logic

Indicator standardization with fuzzy membership functions

The attribute values for indicators reflecting exposure and sensitivity were each transformed using linear or non-linear fuzzy membership functions to create standardised indicator values. According to the different ways that each indicator is understood to influence the impact on a municipality, four fuzzy membership functions were studied to standardise the actual ranges of each indicator's data into fuzzy membership values from 0 to 1. Membership values close to 1 reflect a greater exposure and sensitivity to weather-related hazards, whilst membership values approaching 0 indicate the contrary. Figure 3 graphically illustrates the fuzzy membership functions.

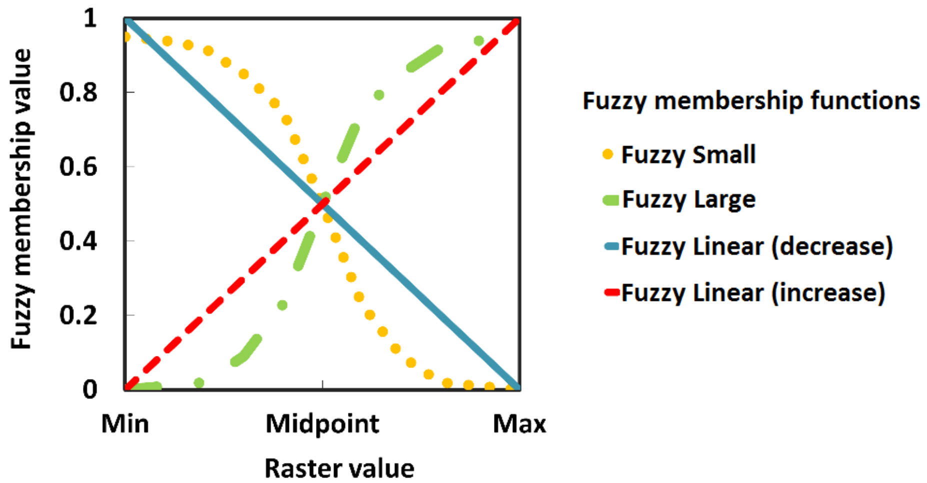

Figure 3. Fuzzy membership functions used for standardisation of the indicators. The horizontal axis shows the range of attribute values for each layer to be standardised, while the vertical axis indicates the corresponding membership values for each point.

In most cases, a positive linear membership function was selected to represent the positive linear relationships assumed between an indicator and exposure and sensitivity. This can be illustrated by indicators of sensitivity such as 'residents in the area' and 'critical infrastructure'. However, in some cases it was not appropriate to use a fuzzy linear function to characterise a relationship, as when there was not enough robust data available regarding minimum and maximum indicator values. In such cases, a midpoint value may be the best available data (see midpoint in Figure 3), so fuzzy large functions were selected instead for indicators such as 'total area burned' or 'wildfire events', as they have an increasing relationship with exposure.

Aggregation with fuzzy overlay functions

After the membership values were assigned to each indicator, fuzzy overlay functions were used to aggregate each of the various components. First, individual indicators of each hazard were aggregated into exposure and sensitivity. Second, the exposure and sensitivity of each hazard were combined into a hazard-specific impact. Third, the exposure and sensitivity of all hazards under study were aggregated to assess their combined effect. Finally, the overall MHI index was calculated by combining specific hazard impacts in a fourth level of aggregation (see Figure 4). To perform the process of aggregation, the fuzzy overlay functions available in ArcGIS were studied, and the GAMMA function selected to explore the relationships between the multiple input criteria by taking all the input values into consideration in the analysis. This is fundamental, since in impact assessment the combination of evidence is more important than any one input. Further discussion on the selection and use of the GAMMA function can be found in (Araya-Muñoz et al., in press.; Ki and Ray, 2014; Lewis et al., 2014; Malins and Metternicht, 2006; Vafai et al., 2013), while Supplementary Material S2 provides a list of the fuzzy overlay functions. To have a superior comparative representation of the differences in the level of exposure and sensitivity across the urban area, outputs were tested for values of (γ) in the range [0, 1] in increments of 0.1. For the aggregation process as a whole, $\gamma = 0.8$ was selected, since it produces the largest spread of values of the index.

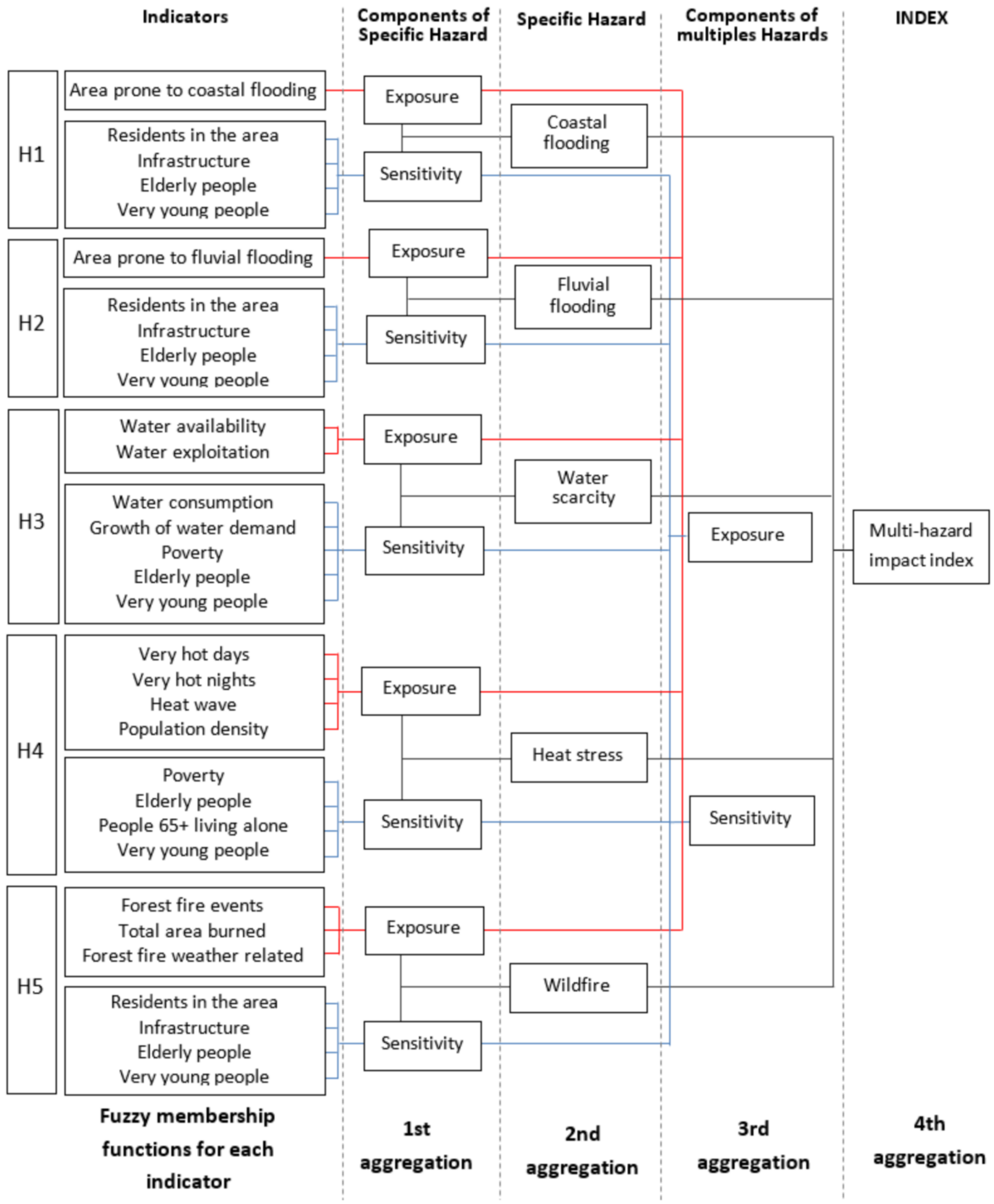

Figure 4. Stage of aggregation. Hazards included were coastal flooding (H1), fluvial flooding (H2), water scarcity (H3), heat stress (H4), and wildfires (H5).

3. Results

First level of aggregation: CMA exposure and sensitivity by hazard

At the first level of aggregation, Figure 5 shows radar charts for the exposure and sensitivity of each of the five hazards assessed per municipality. The values represented range from 0 (non-membership) to 1 (full membership). In the 1990s, two new municipalities were established in the CMA, San Pedro de la Paz in 1995 and Chiguayante in 1996; these two municipalities therefore have no values plotted for 1992.

The results show substantial contrasts between municipalities and overall from 1992 to 2002, with an increase in exposure and a smaller decrease in sensitivity. Wildfire, heat stress, and water scarcity were the hazards to which exposure and sensitivity were generally highest in all municipalities. Exposure and sensitivity to coastal flooding can be observed for those municipalities that have coasts, so Hualqui and Chiguayante do not have any such values. Exposure and sensitivity to fluvial flooding present the lowest values, since this hazard affects only specific areas of the different municipalities. Coastal and fluvial flooding displayed the largest variability of all hazards across municipalities. Exposure and sensitivity do not always coincide; there are cases in which sensitivity is higher than exposure, such as in heat stress in Hualqui, and exposure is higher than sensitivity, as with water scarcity in Coronel. The following paragraphs describe in detail the most important results by hazard.

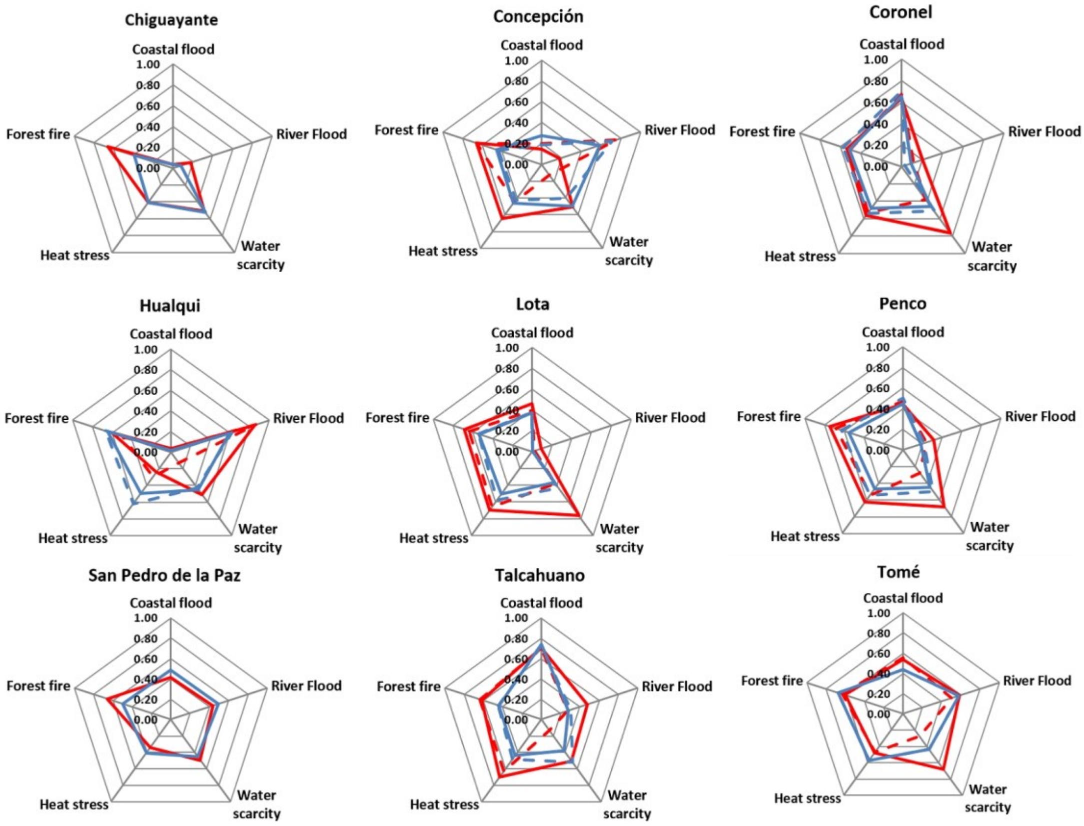

Figure 5. Hazards from the first fuzzy aggregation by municipality. Exposure is depicted in red, sensitivity in blue. Dashed lines represent 1992; solid lines represent 2002.

Second level of aggregation: Hazard-specific impacts on CMA municipalities

Figure 6 presents the impact by hazard for each municipality from the second level of aggregation. It shows that all municipalities were exposed to more than one hazard and that the impacts of these hazards varied across municipalities. While Chiguayante and Hualqui benefited from their limited exposure to coastal areas, the rest of the municipalities were exposed to all the studied hazards. It also shows that wildfires, which affect all municipalities, ranked above the other hazards in the years studied. Wildfires were a significant threat to Penco, Hualqui, and Tomé in both 1992 and 2002, while Hualqui and Lota had the largest increases in wildfire impact. Water scarcity and heat stress hazards followed wildfires in the ranking. Water scarcity was the hazard with the largest increase in the CMA during the study period (46.8%). Hualqui and Tomé saw the largest increases in water scarcity, due mainly to population growth. Heat stress varied between municipalities; Lota, Talcahuano, and Tomé had higher heat stress levels, while Penco, Concepción, and Talcahuano saw the highest increases between 1992 and 2002. Even though almost all CMA municipalities were exposed to coastal flooding, they were a major threat in Talcahuano, Coronel and Penco. Similarly, fluvial flooding affected nearly all the municipalities but ranked near the bottom of the list of hazards because it affected only specific areas of each municipality. In general, most municipalities saw increases in the impact of fluvial flooding because they expanded into areas of greater fluvial risk. Talcahuano, Lota, and Coronel had the highest increases in fluvial flooding.

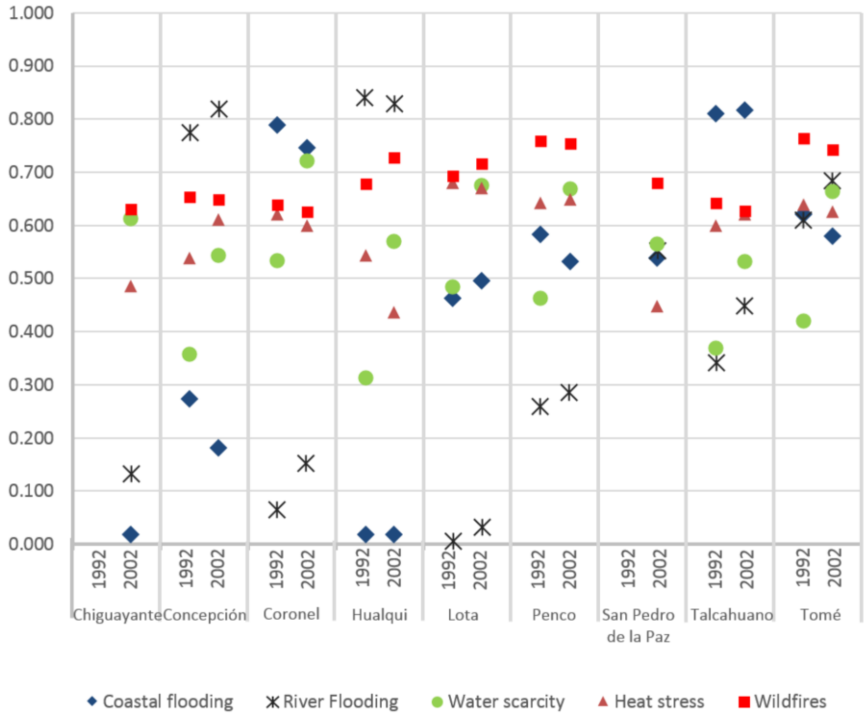

Figure 6. Impact of each hazard from the second fuzzy aggregation by municipality for 1992 and 2002.

Third level of aggregation: Overall CMA exposure and sensitivity

Figure 7 shows the third level of aggregation: fuzzy overlay values of exposure and sensitivity within the range of 0 to 1 for each municipality in 1992 and 2002. In general, exposure increased and sensitivity decreased, due mainly to sensitivity indicators that relate to socio-economic factors like poverty; these indicators declined as a reflection of the broad improvement in Chile's socio-economic condition. The increase in exposure (30.4%) was much larger than the decrease in sensitivity (-8.1%) between 1992 and 2002. In 2002, Lota and Penco had the highest gaps between exposure and sensitivity, with exposure higher in both cases. Only Hualqui and San Pedro presented similar levels of exposure and sensitivity; the difference between the two components was similar for all other municipalities.

Significant increases in exposure were observed in Talcahuano and Lota, while Coronel and Tomé showed lower increases in exposure. In 1992, Talcahuano, Tomé, and Penco presented the highest exposure; they remained the most exposed to 2002. Most municipalities showed a decrease in sensitivity between 1992 and 2002, though Coronel and Lota saw increases. Penco and Talcahuano showed the largest decreases. Tomé and Talcahuano were the most sensitive municipalities in both 1992 and 2002.

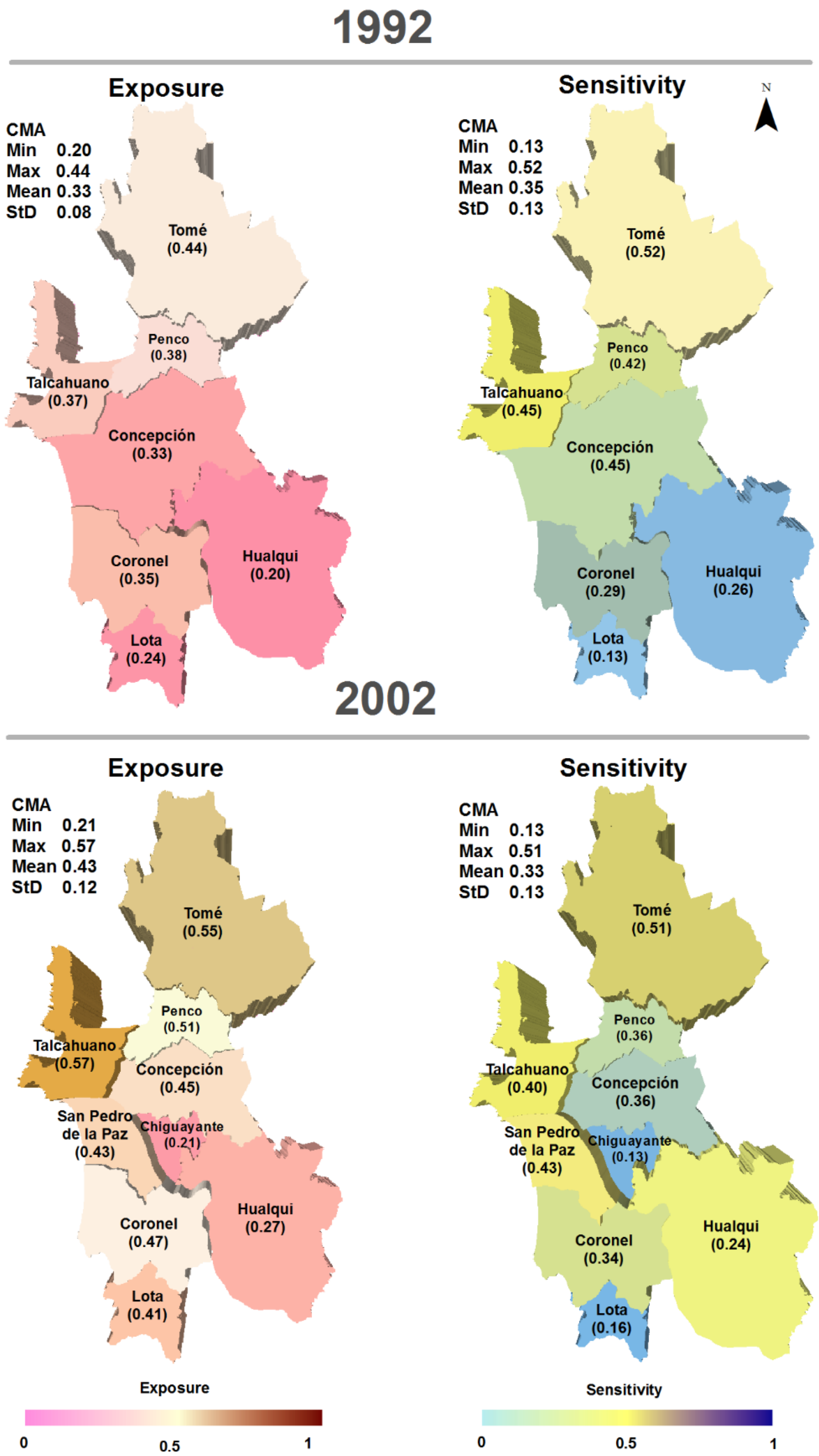

Figure 7. Exposure and sensitivity by municipality (1992–2002); red is exposure and blue is sensitivity.

Fourth level of aggregation: The CMA multi-hazard impact index

For the fourth and final level of aggregation, Figure 8 shows that during the study period all municipalities had increased MHI levels. The gap in 1992 between the municipalities with the highest and lowest index values was 173%; that widened to 234% in 2002. In 1992, Talcahuano, Tomé, and Penco showed the highest MHI index values, while Hualqui and Lota had the lowest values. In 2002, the ranking of the municipalities was nearly unchanged. Tomé, Talcahuano, and Penco had the highest index values, while Chiguayante, Hualqui, and Lota had the lowest values. The position of Chiguayante and Hualqui is due partly to the fact that, unlike all other municipalities, they are located far from the sea and therefore do not have exposure to coastal flooding. The position of Lota is explained largely due to its comparatively low exposure and sensitivity to fluvial floods in both 1992 and 2002. Relative change shows that the MHI index increased by an average 8.9% over the decade, with the municipalities with the lowest values on of the index experiencing the greatest increases. For instance, in Coronel the index increased by 24.8%, and in Lota by 55.9 %. Meanwhile, Penco and Hualqui presented smaller increases of 8.4% and 9.79% respectively.

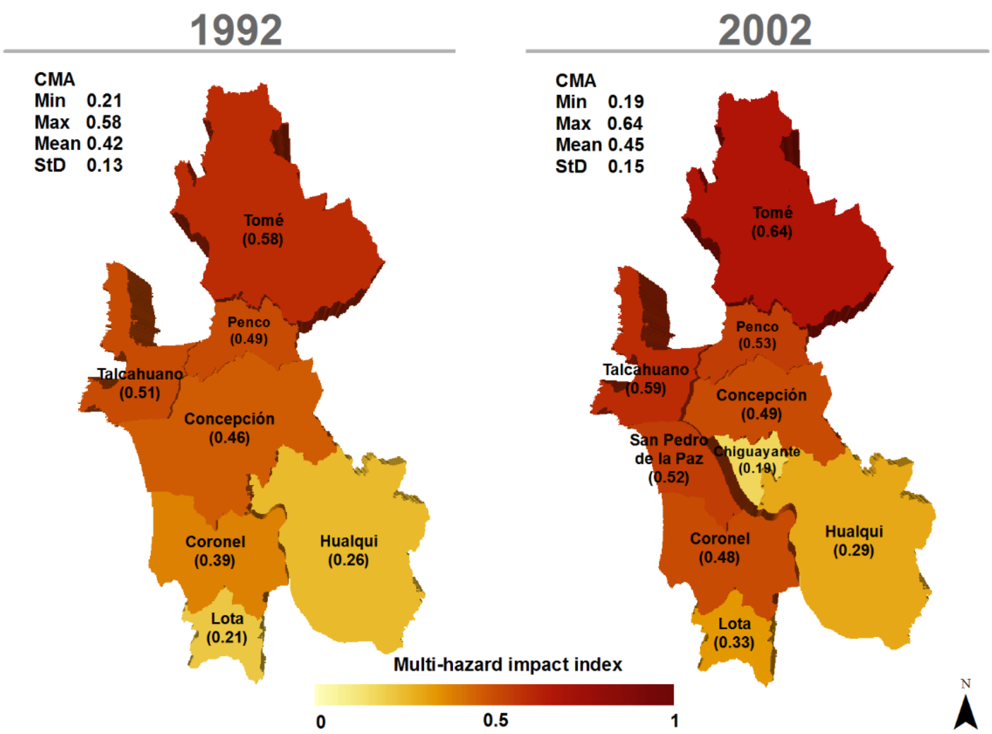

Figure 8. Absolute changes in the CMA multi-hazard impact index, 1992–2002.

4. Discussion

4.1 The multi-hazard impact index

The present study presents a novel framework for the evaluation of multiple hazards in the urban context that offers flexibility in the evaluation of hazards of different natures. The indicators that explain the index were normalised through membership functions to generate comparable values to enable the collective analysis of hazards. The structure of the index allows for consulting different levels of the various components of the index, including those for the impact of each hazard and those for the impact of aggregated hazards. This enables differentiation of and information about the socio-economic and biophysical factors that underlie and explain exposure and sensitivity.

The use of indicators to represent sensitivity and exposure to specific hazards at two time points permitted tracking their temporal and spatial changes. Monitoring helps to identify changes in the status of municipalities and reveal hotspots of exposure or sensitivity to a specific hazard or to multiple hazards. It is thus possible to emphasise the differences across CMA municipalities. A robust set of indicators to assess the impacts of different hazards has been proposed, which has the added benefit that it can be systematically built and refined over time. This study is the first to use fuzzy modelling for the standardisation, aggregation, and mapping of the impact of multiple hazards using ArcGIS. The fuzzy approach proved to be an efficient tool for the straightforward standardisation of multiple indicators, offering the possibility of assigning partial membership and thus incorporating realism into the analysis. It also demonstrated flexibility in the aggregation of indicators with differing attribute ranges and granularities along with components and hazards. This flexibility favours the assessment of hazards of different nature, which cannot be evaluated by direct comparison or simple addition (Kappes et al. 2012).

The GAMMA aggregation function proved to be optimal for carrying out this aggregation process, as it was able to take into consideration multiple input criteria. This function permitted an appropriate aggregation between inputs with high and low memberships from multiple eligibility criteria. Similar results were demonstrated by Lewis (2014), who noted that the GAMMA fuzzy overlay function best recognises trade-offs between combinations of multiple criteria. Sensitivity analysis showed that the best value of aggregation is $\gamma = 0.8$, since this value permits the maximum differentiation between CMA municipalities. Lower GAMMA values resulted in MHI index values that were lower than the input values of the indicators, while a GAMMA of 0.9 or higher resulted in higher MHI index values than input indicator values. It should also be noted that a larger number of indicators leads to a greater increase in the of GAMMA function, particularly when several indicators have values lower than 0.5; in the present study that resulted in very low MHI index values. It is striking but true to stipulate that the existence of just *one* indicator with very low values (i.e., a median near 0) may substantially reduce the value of the associated hazard. On the other hand, for a large number of indicators with values greater than a 0.5 increase the effect of SUM term of GAMMA function became more noticeable, which is particularly problematic when indicators have a median close to 1 and narrow ranges, as represented by low standard deviations. Finally, if the distribution of an indicator is complex by dint of being highly asymmetric or containing outliers, the resulting index can be very sensitive to that characteristics.

The model results stage proved to be very useful in discriminating input indicators with different levels of impact. Initially, 46 indicators were used as model inputs to study exposure and sensitivity to each hazard. After initial evaluation, only 32 indicators remained: five for coastal flooding, five for fluvial flooding, seven for water scarcity, eight for heat stress, and seven for wildfires. This procedure enabled the discarding of all indicators that had no major influence on the model, facilitating the analysis process, and reducing the data required.

The structure of the MHI index was designed and built in four stages, which can be analysed separately or together. Thus, it is simple to refer to the results and explain the origin of a specific end value in the index. It is also easy to identify exposure and sensitivity separately and specific hazards individually, emphasising their differences. The value of the MHI index and its structure resides not only in the fact that it permits the identification of municipalities and sectors that are more exposed and sensitive than others to specific hazards, but also in its ability to identify municipalities that are highly exposed and sensitive to more than one hazard, which is critical in terms of urban planning. A municipal scale was used to provide information that enabled understanding the base conditions of the city. This scale of work facilitates addressing processes and dynamics at the local level (Barnett et al., 2008), which in many cases determines the degree of impact, as these are more visible and palpable at the local scale rather than from national, let alone global, perspectives (Eriksen and Kelly, 2007).

The proposed method is highly transportable to other urban municipalities worldwide, with some refinement to respond to the specific urban context. This method is intended to be simple, accessible, practical, and operable by other scientists, stakeholders and planners. Consequently, the assessment was based on ArcGIS, a widely used tool that enables a flexible, transparent, and straightforward aggregation of the multiple criteria that explain the MHI index through fuzzy tools and facilitates their spatial representation in maps. This favours the implementation of the model in other urban areas globally. In addition, the model design permits integration with adaptive capacity models for vulnerability assessment. See (Araya-Muñoz et al. in press).

Limitations

Any selection of indicators can be executed arbitrarily (Hinkel, 2011; Luers et al., 2003). In this study, the selection of indicators was based on current knowledge of the studied hazards and the availability of reliable data for the studied period; it was assumed that these would explain the condition of sensitivity and exposure for each hazard. Thus, these results could change as knowledge on the subject expands and new data become available. They may also evolve if different indicators are selected; for example, if in this research 'very young population' had not been selected as a sensitivity indicator, sensitivity values would have increased because of the greater influence of the 'elderly people' indicator. They could also vary if a different set of hazards were studied. The selection of indicators was also limited by the availability of reliable data sets. As commonly occurs in developing countries, the Chilean databases for the evaluation of impacts have several shortcomings; data may i) not exist, ii) be very recent, or iii) not be comparable, because the methodologies for their calculation have changed.

This study began by considering each indicator as equally important in representing the MHI, and in fuzzy logic weighting does not apply. However, indicators and components may indirectly acquire different weights through the assessment: 1) given the structure of the index, with a different number of indicators for each hazard, hazards with a higher number of indicators tend to have lower results, because fuzzy GAMMA consists of SUM and PRODUCT terms, the latter of which is strongly influenced by the number of indicators: the higher the number of indicators, the lower the result. 2) Given the structure of the index, when an indicator is relevant to more than one hazard (e.g., 'elderly people'), it may be overrepresented in the aggregation of the hazards. The effect on the index of such indicators was reported through an uncertainty analysis. 3) With fuzzy membership functions, particularly with fuzzy LARGE, the higher spread increased differentiation between municipalities, which affected the average of the indicator. A large spread implied a higher differentiation between municipalities and a higher impact on the index, but also a lower average. 4) The fuzzy GAMMA function used in the aggregation process, which is composed by fuzzy SUM and fuzzy PRODUCT overlay functions, enables the balancing of multiple input criteria (Lewis et al. 2014). However, when a selected GAMMA value is close to 0, the PRODUCT term of GAMMA becomes more important, giving more weight to the lowest components of the index; for values above 0.7 GAMMA, this influence tends to decline.

In addition, some authors argue that in order to encourage transparency and credibility in a study of vulnerability, the approach must be based on stressors or specific hazards (Luers et al. 2003; Tol and Yohe 2007), because the aggregation of results can be considered an oversimplification that may hide information or situations of interest by incorporating uncertainties (Lung et al., 2013). To avoid this situation to some degree, the four stages involved in this assessment can each be consulted as a way to ensure transparency. Furthermore, the possible interdependences, such as the cascade effect, between hazards were not evaluated in this assessment (Gallina et al., 2016). Finally, this study focused on evaluating the impacts of multiple hazards at the urban scale and therefore did not directly assess the impact experienced by specific individuals; rather, it assessed the impacts on society as a whole in the different municipalities.

Improvements and recommendations

There remains work to do in the design of indicators for monitoring changes in exposure and sensitivity to various hazards in the CMA. There are other hazards that should be considered for future studies, such as hantavirus, storms, pluvial floods, landslides, and liquefaction. There is evidence of all of these having affected the area in the past, and each could be aggravated by future socio-economic and climatic change. In addition, since widely available information was used in this research so as to be easily replicated in other cities nationwide or worldwide, it would be useful to identify the exposure, sensitivity, and indicators that most influence the impact by hazard in other cities, shedding light on the socio-economic drivers of MHI and their spatial distribution in the broader urban context. These are likely to change depending on specific time and place.

In light of the rapid changes in developing-country urban areas like the CMA, regularly reviewing and updating the MHI socioeconomic indicators is clearly required. Census statistical data updates can provide the necessary information to identify spatial changes at the municipal level of exposure and sensitivity to each hazard. This information offers the possibility of tracking changes in the structure of exposure and sensitivity over time. It would also be advisable to present the proposed set of indicators, methods, and different results of the MHI assessment to stakeholders in the area under study in order to contrast this assessment with their knowledge (see Preston et al., 2008; Sperotto et al., 2016). This would allow researchers to learn from informed feedback regarding the set of indicators, the method developed in this study, and the most effective ways of presenting the results.

4.2 Multi-hazard impact index on the CMA

The results of this study highlight the increase in weather-related risks for municipalities in the CMA in the years studied. They also point to the differences between hazard-specific impacts and their relative importance in the magnitude of change of the MHI index. Hazards such as wildfires, water scarcity, and heat stress, to which all municipalities were exposed, are of great importance in defining the overall level of municipal impact. In this context, municipalities like Tomé, Penco, and Talcahuano require special attention because of the higher impact of their overall risk.

The higher importance of wildfires, water scarcity, and heat stress compared to fluvial and coastal flooding arises because, beyond the fact that they affect all municipalities, the change in exposure for these hazards was greater than the reduction in sensitivity to them. For fluvial flooding, even though both exposure and sensitivity increased, only specific parts of the city were affected. For coastal flooding, even though exposure was high in seven municipalities, in almost all municipalities both exposure and sensitivity have decreased due to the expansion of urban areas to areas outside the area of coastal flooding risk.

The CMA has one of the largest forest plantation areas in Chile (NFC, 2015), with a buffer zone at the wildland-urban interface of 100 metres (NFC, 2006). Despite this buffer zone, most fires occur in areas around cities (NFC , 2010). Between 1985 and 2002, over 13,295 fires affected the CMA, burning over 76,006 ha of wild land and 22.7% of the forest area. 20 fires affected more than 500 hectares, and are thus termed large fires, covering a total area of 50,162 hectares, nearly two thirds of the entire area burnt in the 1985–2002 period. Seven municipalities in the CMA (Tomé, Lota, Penco, Coronel, Concepción, San Pedro De La Paz, and Hualqui) appear on the nationwide list of critical municipalities in terms of the occurrence of forest fires (NFC, 2010). González et al. (2011) note that the summer water deficit and winter decrease in precipitation are among the causes of the lengthening the CMA fire season in recent years. Future reduction of precipitation combined with a temperature increase could favour the degradation of vegetation and thus the increased generation of fuel to spread fires (González et al., 2011).

Water scarcity is another hazard of interest, as the increase in its exposure was much greater than the reduction in its sensitivity. Currently, most superficial basins in the study area (the Bío-Bío and Itata Rivers and the coastal watersheds) have no resources to meet new water consumption demands (MPW, 2012). Regarding groundwater resources, MPW (2012) notes that no study has been completed on either recurrent or long-term availability. Despite the lack of additional water resources, it is expected that the demand for water will continue to grow in the near future (GDW, 2007; Partnership, 2000). Additionally, a sustained long-term reduction in rainfall and continued population growth are expected, which could increase pressure on water resources in the area.

Our findings also indicated that rapid changes in age structure and poverty reduction played an important role in sensitivity. Among social sensitivity indicators, an increase in the elderly population and a decrease in the very young population occurred in all municipalities. Nationally, the ratio of elderly people per hundred children is expected to be 170 by 2050 (NIS, 2005). The NIS estimates that the CMA population over 65 will grow by 180% between 1990 and 2020, while the population under five will decline by 30%. The total fertility rate decreased in the study period from 2.52 to 2.00, or below replacement level (NIS, 2011, 2007). Moreover, the poor population decreased during the study period in all municipalities, though the relative differences between municipalities remained largely unchanged. This implies that both the richest and the poorest municipalities maintained their 1992 positions in the 2002 ranking. This reduction of poverty at the municipal level did help to reduce sensitivity, but structural inequalities observed in the CMA are the cause of the rigid ranking of socio-environmental sensitivity.

In view of the increasingly older population, age structure should be considered carefully if we are to understand the current and future impacts of climate change on these municipalities. There is general agreement that the elderly population is particularly sensitive to climatic stresses such as heat events, floods, droughts, wildfire, sea level rise, and higher concentrations of pollutants and allergens in the air. Therefore, reducing the sensitivity of the elderly would have significant effects on the overall municipal level of climate change vulnerability. We observed, for instance, a comparatively higher proportion of elderly people in poor municipalities like Tomé and Hualqui. In 2020, it is expected that the elderly will comprise 14.3% of the population in Tomé and 10.4% in Hualqui. It is therefore necessary to introduce measures to buttress this group's resources and reduce its sensitivity, which in turn would reduce overall municipal levels of climate change vulnerability. Finally, tracking the changes in the level of sensitivity that policy measures might achieve for this group would help to inform future decisions and research.

5. Conclusions

The present study offers an assessment of the impact of multiple hazards in the CMA based on the aggregation of available indicators through a fuzzy-based model. This assessment enabled the successful spatial tracking of changes in exposure and sensitivity to various hazards across CMA municipalities and over time. Our findings showed that fuzzy modelling offers high flexibility in the standardisation and aggregation of indicators with diverse characteristics. Fuzzy membership, due to its partial membership feature, allows for a straightforward and realistic standardisation of the indicators. The fuzzy overlay function GAMMA provides a better balance between aggregations of multiple indicators, components, and hazards than other measures, because GAMMA recognises and considers the particularities of each input in the aggregation process. Special care must be taken in both the selection of the GAMMA value and in the membership functions used for indicator standardisation. ArcGIS software offered a straightforward model implementation and analysis of the results, showing the benefits of their use in the field of vulnerability to climate change. This research provides a procedure to assess the impact of diverse weather-related hazards in a realistic and consistent manner, which allows scientists, stakeholders, and decision-makers to improve their understanding of the base conditions of the city. It also provides a set of urban indicators that can be built upon systematically over time and thus used to monitor changes. The method proposed here i) encourages transparency and easy communication of results due to its staged structure, ii) favours comparative analysis among index components, iii) can easily be implemented together with an adaptive capacity model to evaluate a city's overall vulnerability, since it was designed for that purpose, and iv) presented a flexible method that can be implemented in other cities, taking into consideration differences in the urban context and any user-specific requirements to support decision-making processes.

The municipalities of Tomé, Talcahuano, and Penco should be most closely monitored, because they presented both a higher exposure and a higher sensitivity in 1992 and 2002. From 1992 to 2002 all municipalities in the CMA increased their MHI levels. This increase was mainly influenced by the relatively large increase in exposure, which was moderated by a smaller decrease in sensitivity. Changes in the age structure are driving the sensitivity of the municipalities, though to different degrees. However, the MHI index ranking of municipalities was maintained throughout the studied period, meaning that despite the economic progress and social change experienced by the CMA municipalities, they have not significantly changed their sensitivity. The hazards that were shown to be most relevant for all municipalities are wildfires and water scarcity, but all hazards should be taken seriously, since most municipalities were affected by multiple hazards.

6. References

Acosta, L., Klein, R.J.T., Reidsma, P., Metzger, M.J., Rounsevell, M.D. a., Leemans, R., Schröter, D., 2013. A spatially explicit scenario-driven model of adaptive capacity to global change in Europe. Glob. Environ. Chang. doi:10.1016/j.gloenvcha.2013.03.008

Araya-Muñoz, D., Metzger, M.J., Stuart, N., Wilson, A.M.W., Alvarez, L., in press. Assessing urban adaptive capacity to climate change. J. Environ. Manage.

Barnett, J., Lambert, S., Fry, I., 2008. The Hazards of Indicators: Insights from the Environmental Vulnerability Index. Ann. Assoc. Am. Geogr. 98, 102–119. doi:10.1080/00045600701734315

Birkmann, J., Bach, C., Vollmer, M., 2012. Tools for Resilience Building and Adaptive Spatial Governance. Raumforsch. Raumordn. 70, 293–308. doi:10.1007/s13147-012-0172-0

Boulanger, J.-P., Buckeridge, M.S., Castellanos, E., Poveda, G., Scarano, F.R., Vicuña, S., 2014. Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Five Assessment Report of the Intergovernmental Panel on Climate Change. Central and South America. Cambridge University Press, Cambridge, U.K.

Cutter, S.L., Finch, C., 2008. Temporal and spatial changes in social vulnerability to natural hazards 105, 2301–2306

Dessai, S., Hulme, M., 2004. Does climate adaptation policy need probabilities ? Clim. Policy 4, 107–128. doi:10.1080/14693062.2004.9685515

GDW, 2007. Estimaciones de demanda de agua y proyecciones futuras. Zona II. Regiones V a XII y región metropolitana.

Dilley, M., Chen, R.S., Deichmann, U., Lener-Lam, A.L., Arnold, M., Agwe, J., Buys, P., Kjekstad, O., Lyon, B., Yetman, G., Lerner-Lam, A.L., Arnold, M., Agwe, J., Buys, P., Kjekstad, O., Lyon, B., Yetman, G., 2005. Natural Disaster Hotspots A Global Risk Analysis, World Bank. The World Bank, Washington, D.C. doi:10.1080/01944360902967228

Eriksen, S.H., Kelly, P.M., 2007. Developing Credible Vulnerability Indicators for Climate Adaptation Policy Assessment. Mitig. Adapt. Strateg. Glob. Chang. 12, 495–524. doi:10.1007/s11027-006-3460-6

Espada, R., Apan, A., Mcdougall, K., 2013. Using spatial modelling to develop flood risk and climate adaptation capacity metrics for assessing urban community and critical electricity infrastructure vulnerability 1–6.

Fischer, E.M., Schär, C., 2010. Consistent geographical patterns of changes in high-impact European heatwaves. Nat. Geosci. 3, 398–403. doi:10.1038/ngeo866

Forzieri, G., Feyen, L., Russo, S., Vousdoukas, M., Alfieri, L., Outten, S., Migliavacca, M., 2016. Multi-hazard assessment in Europe under climate change. Clim. Change. doi:10.1007/s10584-016-1661-x

Fried, J.S., Torn, M.S., Mills, E., 2004. The impact of climate change on wildfire severity: A regional forecast for northern California. Clim. Change 64, 169–191. doi:10.1023/B:CLIM.0000024667.89579.ed

Funfgeld, H., 2010. Institutional challenges to climate risk management in cities. Curr. Opin. Environ. Sustain. 2, 156–160. doi:10.1016/j.cosust.2010.07.001

Gallina, V., Torresan, S., Critto, A., Sperotto, A., Glade, T., Marcomini, A., 2016. A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment. J. Environ. Manage. 168, 123–132. doi:10.1016/j.jenvman.2015.11.011

González, M., Lara, A., Urrutia, R., Bosnich, J., 2011. Cambio climático y su impacto potencial en la ocurrencia de incendios forestales en la zona centro-sur de Chile (33o - 42o S). Bosque 32, 215–219. doi:10.4067/S0717-92002011000300002

Grafakos, S., Pacteau, C., Delgado, M., Landauer, M., Lucon, O., Driscoll, P., Wilk, D., Zambrano, C., O'Donaghue, S., Roberts, D., 2015. Integration of climate adaptation and mitigation: Opportunities and challenges for cities, in: Cities and Climate Change: Second Assessment Report of the Urban Climate Change Research Network. Cambridge University Press.

Greiving, S., Fleischhauer, M., Lückenkötter, J., 2006. A Methodology for an integrated risk assessment of spatially relevant hazards. J. Environ. Plan. Manag. 49, 1–19. doi:10.1080/09640560500372800

Hinkel, J., 2011. "Indicators of vulnerability and adaptive capacity": Towards a clarification of the science–policy interface. Glob. Environ. Chang. 21, 198–208. doi:10.1016/j.gloenvcha.2010.08.002

Hinkel, J., Nicholls, R.J., Vafeidis, A.T., Tol, R.S.J., Avagianou, T., 2010. Assessing risk of and adaptation to sea-level rise in the European Union: an application of DIVA. Mitig. Adapt. Strateg. Glob. Chang. 15, 703–719. doi:10.1007/s11027-010-9237-y

NFC, 2015. Estadísticas Plantaciones Forestales 1998 al 2014 por Región y comuna. Consult December 18th 2015. Available at http://www.conaf.cl/nuestros-bosques/bosques-en-chile/estadisticas-forestales/.

NFC, 2010. Las comunas críticas en cuanto a la ocurrencia de incendios forestales. Santiago, Chile.

NFC, 2006. Manual con medidas para la prevención de incendios forestales. Santiago, Chile.

NIS, 2011. CHILE: Proyecciones y Estimaciones de Población. 1990-2020 País, Regiones y Comunas. Santiago, Chile.

NIS, 2007. Adulto Mayor en Chile. Santiago, Chile.

NIS, 2005. Chile Hacia el 2050, Proyecciones de Población. Santiago, Chile. doi:10.2307/1528387

IPCC, 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. Cambridge University Press, Cambridge, UK, and New York, USA.

Kappes, M.S., Keiler, M., von Elverfeldt, K., Glade, T., 2012. Challenges of analyzing multi-hazard risk: A review. Nat. Hazards 64, 1925–1958. doi:10.1007/s11069-012-0294-2

Ki, S.J., Ray, C., 2014. Using fuzzy logic analysis for siting decisions of infiltration trenches for highway runoff control. Sci. Total Environ. 493, 44–53. doi:10.1016/j.scitotenv.2014.05.121

Klempa, B., 2009. Hantaviruses and climate change. Clin. Microbiol. Infect. 15, 518–23. doi:10.1111/j.1469-0691.2009.02848.x

Lehner, B., Döll, P., Alcamo, J., Henrichs, T., Kaspar, F., 2006. Estimating the impact of global change on flood and drought risks in Europe: A continental, integrated analysis. Clim. Change 75, 273–299. doi:10.1007/s10584-006-6338-4

Lewis, S., Fitts, G., Kelly, M., Dale, L., 2014. A fuzzy logic-based spatial suitability model for drought-tolerant switchgrass in the United States. Comput. Electron. Agric. 103, 39–47. doi:10.1016/j.compag.2014.02.006

Luers, A.L., Lobell, D.B., Sklar, L.S., Addams, C.L., Matson, P. a, 2003. A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. Glob. Environ. Chang. 13, 255–267. doi:10.1016/S0959-3780(03)00054-2

Lung, T., Lavalle, C., Hiederer, R., Dosio, A., Bouwer, L.M., 2013. A multi-hazard regional level impact assessment for Europe combining indicators of climatic and non-climatic change. Glob. Environ. Chang. 23, 522–536. doi:10.1016/j.gloenvcha.2012.11.009

Malins, D., Metternicht, G., 2006. Assessing the spatial extent of dryland salinity through fuzzy modeling. Ecol. Modell. 193, 387–411. doi:10.1016/j.ecolmodel.2005.08.044

Mardones, M., Vidal, C., 2001. La zonificación y evaluación de los riesgos naturales de tipo geomorfológico: un instrumento para la planificación urbana en la ciudad de Concepción. EURE 27, 97–122.

Mastrandrea, M.D., Heller, N.E., Root, T.L., Schneider, S.H., 2010. Bridging the gap: linking climate-impacts research with adaptation planning and management. Clim. Change 100, 87–101. doi:10.1007/s10584-010-9827-4

McCubbin, S., Smit, B., Pearce, T., 2015. Where does climate fit? Vulnerability to climate change in the context of multiple stressors in Funafuti, Tuvalu. Glob. Environ. Chang. 30, 43–55. doi:10.1016/j.gloenvcha.2014.10.007

Miller, F., Bowen, K., 2013. Questioning the assumptions: the role of vulnerability assessments in climate change adaptation. Impact Assess. Proj. Apprais. 31, 190–197. doi:10.1080/14615517.2013.819724

MPW, 2012. Plan Regional de Infraestructura y Gestión del Recurso Hídrico al 2021 Región del Biobío. Santiago, Chile.

Partnership, G.W., 2000. Informe nacional sobre la gestión del agua en chile, in: Agua Para El Siglo XXI: De La Visión a La Acción - América Del Sur. Buenos Aires.

Preston, B.L., Smith, T.F., Brooke, C., Gorddard, R., Measham, T.G., Withycombe, G., McInnes, K., Abbs, D., Beveridge, B., Morrison, C., 2008. Mapping climate Change Vulnerability in the Sydney Coastal Group. Prepared for the Sydney Coastal Councils Group by the CSIRO Climate Adaptation Flagship. Canberra.

Rosenzweig, C., Solecki, W.D., 2001. Climate Change and a Global City Learning from New York. Environ. Sci. Policy Sustain. Dev. 43, 8–18. doi:10.1080/00139150109605128

Schauser, I., Otto, S., Schneiderbauer, S., Harvey, A., Hodgson, N., Robrecht, H., Morchain, D., Schrander, J., Khovanskaia, M., Prutsch, A., Mccallum, S., 2010. Urban regions: Vulnerabilities, Vulnerability assessments by. Bilthoven.

Sperotto, A., Torresan, S., Gallina, V., Coppola, E., Critto, A., Marcomini, A., 2016. A multi-disciplinary approach to evaluate pluvial floods risk under changing climate: The case study of the municipality of Venice (Italy). Sci. Total Environ. doi:10.1016/j.scitotenv.2016.03.150

Swart, R., Fons, J., Geertsema, W., Hove, B. van, Gregor, M., Havranek, M., Jacobs, C., Kazmierczak, A., Krellenberg, K., Kuhlicke, C., Peltonen, L., 2012. Urban Vulnerability Indicators A joint report of ETC-CCA and ETC-SIA.

Taubenböck, H., Wurm, M., Netzband, M., Zwenzner, H., Roth, a., Rahman, a., Dech, S., 2011. Flood risks in urbanized areas – multi-sensoral approaches using remotely sensed data for risk assessment. Nat. Hazards Earth Syst. Sci. 11, 431–444. doi:10.5194/nhess-11-431-2011

Tol, R.S.J., Yohe, G.W., 2007. The weakest link hypothesis for adaptive capacity: An empirical test. Glob. Environ. Chang. 17, 218–227. doi:10.1016/j.gloenvcha.2006.08.001

UN, 2002. Plan of Implementation of the World Summit on Sustainable Development, Johaneesburg plan of implementation.

Vafai, F., Hadipour, V., Hadipour, A., 2013. Determination of shoreline sensitivity to oil spills by use of GIS and fuzzy model. Case study – The coastal areas of Caspian Sea in north of Iran. Ocean Coast. Manag. 71, 123–130. doi:10.1016/j.ocecoaman.2012.05.033