Urban vulnerability assessment of the coast of Chile

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Abstract

Vulnerability to weather-related hazards is a considerable humanitarian, economic and environmental concern for cities, especially in developing countries. However, there is a limited understanding of urban vulnerability and its specific implications. This study assesses the spatio-temporal vulnerability caused by climatic and societal change in Chile’s key coastal urban areas. In this urban vulnerability assessment, both regional and local approaches were undertaken, the former to give a broad sense of the possible futures that these cities face and the latter to explore, using all available and reliable data, how climatic and societal change affected one of these metropolitan areas. For the time points 2025, 2055 and 2085, the regional assessment shows that vulnerability is likely to vary across different scenarios and time frames. A significant future increase in exposure to hazards is mainly moderated, to a greater or lesser extent, by an increase in the adaptive capacity of the cities in question. Cities in central and southern Chile are more vulnerable. The local assessment provides a detailed evaluation of recent past vulnerabilities in the Concepción Metropolitan Area (CMA). In the local assessment, an urban indicator framework was first designed and then employed to explore changes in exposure and sensitivity of areas within CMA and the general ability of the urban system to adapt to different hazards. Five weather-related hazards were explored: coastal flooding, fluvial flooding, water scarcity, heat stress and wildfire, using a flexible methodology based on spatial fuzzy modelling with geographic information systems. Hazard-specific vulnerability and overall vulnerability indices were created.

The local assessment results indicate a high vulnerability in the CMA that decreased slightly between 1992 and 2002. The combined socio-economic factors of sensitivity and adaptive capacity influenced the index more than the biophysical factors of exposure. Changes in age structure and economic growth had a greater influence on vulnerability that other variables. Overall vulnerability varied across municipalities and hazards, with wildfires and water scarcity influencing overall vulnerability the most. Fuzzy modelling enabled realism and flexibility in the standardization and aggregation of indicators with different attributes. It permitted the exploration of the individual and aggregate influence of the indicators that comprise the indices. ArcGIS software favoured transparency and simplicity in the aggregation of multiple entry criteria, facilitating spatial representation through maps, which can help identify indicators, components and hazards or combinations thereof that influence municipal vulnerability. The results can be used to improve and promote dialogue among policymakers and stakeholders regarding the prioritization of resources for urban development in ways that can reduce vulnerability to climate change.
More than half of the world’s population lives within urban areas. It is expected that most urban growth will be concentrated in the developing world, with urban population growing from 47% in 2011 to 67% in 2050. These urban areas are overwhelmed by many stressors, particularly the vulnerability to multiple weather-related hazards, which is expected to increase in the near future due to climate change. However, there is still limited knowledge among local planners and policy-makers about the drivers of vulnerability. Compared to mitigation, vulnerability and adaptation to climate change have been investigated much less deeply at the city scale. Several authors argue that it is essential to understand the structural causes of current weather-related vulnerability more fully for planning purposes, especially in the current or near term (e.g. next decade). Therefore, there is a pressing demand for the development of suitable methods to analyse the biophysical and socio-economic causes of weather-related vulnerability in cities.

This research first seeks, to understand the differences in future vulnerability to climate and socio-economic change between nine of the largest coastal urban areas of Chile (Arica, Iquique, La Serena, Valparaiso, Metropolitan Area of Concepción, Valdivia, Puerto Montt, Punta Arenas). The purpose of doing this was to identify a city that, given its characteristics, provides the greatest possible insight into Chilean urban vulnerability. The results reveal an increase in the vulnerability of all cities at the end of the 21st century. This is largely due to a warmer and drier future climate and to socio-economic changes, such as a prominent increase in elderly population. The Metropolitan Area of Concepción was also identified as the city that requires a most detailed study of its vulnerability. The comparatively greater vulnerability of this city was largely explained by the combination of a large decrease in precipitation and the greatest proportion of land (among all cities) in areas susceptible to coastal flooding. Another key factor was a high and growing sensitive population, represented mainly by older adults, children and inhabitants in exposed areas.

In a second step, the recent past vulnerability to multiple weather-related hazards (coastal flooding, flooding, water scarcity, heat stress and wildfires) was assessed in depth in the Metropolitan Area of Concepción for 1992 and 2002. Results indicate a high vulnerability in this city that decreased slightly between 1992 and 2002. The socio-economic factors combined, such as municipal budget or income, influenced more the vulnerability than the biophysical factors such as very hot days or area prone to flooding. Overall vulnerability varied across time, municipalities and hazards, with wildfires and water scarcity influencing it the most.
The method developed here to study the urban vulnerability 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. The results can be used to improve and promote dialogue among policy-makers and stakeholders regarding the prioritization of resources for urban development in ways that can also reduce vulnerability to climate change.
I declare that this thesis was composed solely by myself and that this work has not been submitted, either in whole or in part, in any previous application for a degree.

Parts of this work have been submitted and/or published in (Araya-Muñoz et al., 2017, 2016)

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2016
Acknowledgment

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<td>Adaptive capacity</td>
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<td>AR4</td>
<td>Fourth Assessment Report</td>
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<td>AR5</td>
<td>Five Assessment Report</td>
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<td>CMA</td>
<td>Concepción Metropolitan Area</td>
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<td>ECLAC</td>
<td>Economic Commission for Latin America and the Caribbean</td>
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<td>EEA</td>
<td>European Environment Agency</td>
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<td>FWI</td>
<td>Fire weather index</td>
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<td>GDW</td>
<td>General Directorate of Water</td>
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<td>IIASA</td>
<td>International Institute for Applied Systems Analysis</td>
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<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
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<td>MA</td>
<td>Minister of Agriculture</td>
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<td>ME</td>
<td>Ministry of Economy</td>
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<td>MH</td>
<td>Ministry of Health</td>
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<td>MHI</td>
<td>Multi-hazard impact</td>
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<td>MoE</td>
<td>Ministry of Environment</td>
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<td>MPW</td>
<td>Ministry of Public Works</td>
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<tr>
<td>MSC</td>
<td>Meteorological Service of Chile</td>
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<td>MSD</td>
<td>Ministry of Social Development</td>
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<td>NAP</td>
<td>National adaptation plan</td>
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<td>NFC</td>
<td>National Forest Corporation</td>
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<td>National Institute of Statistics</td>
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<td>SISS</td>
<td>Superintendent of Sanitary Services</td>
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<td>TAR</td>
<td>Third assessment report</td>
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Thesis
1

Introduction
1.1 Introduction

Urban adaptation requires an understanding of urban vulnerability to climate change (Hallegatte and Morlot, 2011)

Most of the world’s population lives and will continue to live in urban centres (UN-DESA, 2011). Urban settlements thus have an important role, as they concentrate a great part of the population, economic activity and wealth into small areas. Such urban centres can be innovation and progress cores for their countries. Their extreme concentration makes them all the more vulnerable to climate change (Bicknell et al., 2009; Wilbanks et al., 2007). Therefore, understanding the vulnerability of urban areas to climate change is of utmost importance for the planning process and enhancing our ability to adapt to climate change (Rosenzweig et al., 2011).

Coastal urban areas play a particularly important role; not only do they contain 20% of the world’s population and economic resources (Nicholls and Small, 2002; Small et al., 2000; Wilbanks et al., 2007), but they are also exposed to many of the effects of climate change, including rising ocean levels, flooding, erosion and landslides (Nicholls et al., 2007), all of which can become especially problematic for poor or developing countries such as Chile (CONAMA, 2008; Nicholls et al., 2007). Chile’s coastal urban areas contain 26% of the population (NIS, 2011a), but Chile has not been the subject of any study of the vulnerability of its coastal urban areas to climate change.

This study thus serves as the first full-length attempt to understand the vulnerability to climatic and societal change faced by Chile’s most important coastal urban areas. This aligns with its goal of developing policy recommendations for the “Cities” section of the Chilean National Adaptation Plan (NAP). A vulnerability assessment is carried out in the thesis through a combination of a regional and local approaches, which enabled an examination of coastal cities’ current and future vulnerability, as well as providing the information necessary to develop policy recommendations for coastal urban adaptation. These complementary approaches address two of the most important aspects of urban vulnerability to climate change: regional assessments provide an overall vision of climate change vulnerability through climatic and socio-economic projections, while local assessments provide a detailed evaluation of the existing vulnerabilities of a specific city.
This research is funded by the National Commission for Scientific Research and Technology (CONICYT) of the Chilean Ministry of Education through the BECAS CHILE scholarship N° 72120124, and by the Climate Change on the Coast of Chile project N° 037-415/2012, funded by DI Regular of Research and Advanced Studies of the Pontifical Catholic University of Valparaiso, Chile. For this reason, the information required for this research was provided by numerous government agencies, while any information that was not available or was incomplete in Chile, such as climate information, was obtained from open-access or paid online catalogues. This research is expected to contribute not only to the academic knowledge of the discipline, but also to stakeholders and policymakers in municipalities by increasing their understanding of the preconditions for planned adaptation and supporting situational analysis, which is the first step in the planning process for climate change in cities (Grafakos et al., 2015).

1.2 Definition of the Problem

The world is becoming increasingly urbanised (UN-Habitat, 2016). Urban areas have increased their social and economic relevance because they have transformed countries’ demographic and economic cores (UN-Habitat, 2010). More than half of the world’s population now lives in urban areas, and urbanisation is expected to continue to increase, with urban areas becoming more dense and placing even greater pressure on the environment (Wilbanks et al., 2007). Latin America is no exception. Around 80% of the population living in poor and developing countries are concentrated in urban areas (UN-DESA, 2011). The urban areas of Chile contain more than 87% of the country’s total population (NIS, 2011b; UN-DESA, 2011; UNDP, 2007). Nearly 25% of Chile’s urban population lives in nine large cities on the coast, which house most of Chile’s economic activities the country, most new development and the majority of jobs created in recent decades (NIS, 2012a). Furthermore, they are also likely to see most of the population growth over the next 10 years (NIS, 2011a).

Chilean urban areas demonstrate high economic activity and demographic concentration, and are generally close to coastal areas. Given this situation and global climate vulnerability trends (Boulanger et al., 2014; ECLAC, 2012; IPCC, 2012a; Magrin et al., 2007), it is reasonable to assume Chilean coastal urban areas will be at risk from progressive change in climate,
extreme weather events and rising ocean levels. Nevertheless, Chile has not developed an
assessment of vulnerability to climate change for coastal urban areas; only the inland capital,
Santiago, has received meaningful attention (e.g. Bell et al., 2008; Krellenberg and Barth,
2012; Krellenberg et al., 2013; Molina and Molina, 2004; Müller and Reinstorf, 2011; Romero
et al., 2010). This lack of research is hampering the development of efficient measures of
adaptation, mitigation and compensation through planning policies and instruments like
urban regulatory plans or local development plans for climate change. The 1999 and 2011
National Climate Change Communications and the National Action Plan elaborated in Chile
in 2008 only recognised the need to undertake assessments of urban vulnerability to climate
change, but actual plans for even assessing the vulnerability of urban areas to climate
change—let alone responding to those assessments—have not been developed. The recent
NAP of 2014 includes cities among its priorities and sets goals for their adaptation processes,
but does not specify how the vulnerability of those urban areas will be assessed (CONAMA,
1999; MoE, 2014, 2011, 2008). Consequently, the crucial information that an urban
vulnerability assessment to climate change would provide is simply not available. There is
thus a real risk of missing the opportunity of understanding the components of the urban
socio-environmental system. This system encompasses not only the biophysical aspects of
vulnerability, but also the social and economic components related to the sensitivity and
adaptive capacity of potentially affected areas and populations. Understanding these
systemic components will allow planners to ascertain which components might require
strengthening to face current and future crises that may result from climate change (Adger
et al., 2004; Adger, 2006). This situation exists not only in Chile, but also in most of the
developing world’s small or medium-sized cities, which do not have the technical or financial
capacity to perform these studies. Currently, most vulnerability studies focus on large cities
in developed countries. However, there is a growing interest in and scientific support for
carrying out vulnerability assessments in cities of all sizes (Romero and Qin, 2011).

Chile’s coastal urban areas are therefore awaiting the information required to perform a
situational analysis, the first step in the process of adaptation to climate change in cities.
Most cities are exposed to more than one hazard; there remains limited knowledge among
local managers about the vulnerability to the dynamics and spatial distribution of weather-
related hazards (Funfgeld, 2010), even though these hazards can entail high environmental,
economic and social costs for people, companies and governments (Kelly and Adger, 2000;
Luers, 2005; Metzger and Schröter, 2006; Hinkel, 2011). These are costs that, in countries like Chile, will have to be assumed almost completely by the government, since much of the population may not have the resources and tools to address the possible negative effects of climate change, which typically has more extreme effects in regions, sectors and populations with fewer resources (Kelly and Adger, 2000; UN/ISDR, 2002; Poumadère et al., 2005; O’Brien, 2006; Patt et al., 2010). The lack of urban vulnerability assessments increases the risk of failing to adapt quickly and efficiently to climate change, or even take advantage of certain changes, in order to ensure the protection of people and the sustainable growth and development of urban areas over the long term. Clearly, then, there is a strong demand for suitable methods to analyse urban vulnerability to climate-related hazards.

These methods must address one of the main challenges for urban areas in developing countries: the lack of reliable data sets to develop an assessment, primarily in terms of basic information. This information may not yet have been collected or evaluated, is not otherwise available, is incomplete, inaccurate, unreliable or costly, or various combinations of the above (Rosenzweig, 2012). For example, although Chile has historically been affected by weather-related hazards like droughts, landslides and storm surges (Urrutia and Lanza, 1993), there is no record of their social and economic effects (IDB-ECLAC, 2007). Therefore, data as to the number of injured or dead, damage to infrastructure and associated costs is simply not available. Only recently has this information begun to be recorded systematically, as local and national governments have begun to grasp that the havoc wrought by extreme weather events in urban areas are partly the result of inattention to risk reduction, the absence of vulnerability studies and a lack of planning. The causes of this poor understanding of urban response to stress situations is not explained solely by the lack of data, but also by a lack of rigorous analysis of the impact of disasters in local areas and their implications on the regional or national scale. Compounding the lack of information and analysis is the inability of local governments to address vulnerability and integrate development and vulnerability reduction. In the urban setting, hazards and vulnerability tend to combine and reinforce each other, thus increasing the level of risk (Hardoy and Pandiella, 2009).

Most cities in Chile, as in the rest of South America, were created near or in river floodplains, in the first few kilometres away from the coast in low-elevation areas (ECLAC, 2012b). In addition, the expansion of urban areas has been rapid, uncontrolled and often illegal or
irregular, without any planning for the infrastructure and services required. On the contrary, these generally arise in response to the expansion. The expansion process is determined by the illegal occupation of abandoned land by the poor population, which inhabits irregular areas in self-constructed housing of poor quality that is damp and cold in winter and very hot in summer (Hardoy and Pandiella, 2009). These poor houses are located in high-risk areas such as hillsides and floodplains (NIS, 2012b; Rosenzweig et al., 2011). These areas are more sensitive and vulnerable to climate change than other parts of cities, because they lack proper drainage systems to cope with heavy rains and their high density normally prevents the presence of green areas that reduce the risk of flooding (Bicknell et al., 2009; Rosenzweig et al., 2011). The urban planning and policy of cities in developing countries like Chile must be improved to address the current and future vulnerability of urban areas to extreme weather phenomena and gradual but inexorable changes in climate.

Finally, the study of the Chilean case provides a good opportunity to study the effects of climate change, due to Chile’s demographics and its proximity to the sea. Because the necessary information does not exist on a nationwide level, this study can serve as a contribution not only for Chilean coastal urban areas, but also as a contribution to the general understanding of the climate change vulnerability and its implications, particularly in developing countries. In addition, because the study of urban vulnerability to climate change through urban indicators is relatively new, this study also serves as a test of the standardisation and aggregation of indicators with multiple attributes. All these contributions are intended to enrich the available scientific knowledge in the field of urban vulnerability and adaptation to climate change.
**Vulnerability assessment**

There are numerous methods for assessing vulnerability on different scales and over varying periods of time. They respond to different purposes and therefore lead to very different results (Fuchs et al., 2012; Füssel, 2010). Many of the methods used to assess vulnerability are not even entirely clear (Eriksen and Kelly, 2006; Hinkel, 2011), so it has become necessary to unify these metrics to establish clear information for decision-making purposes. However, it must be understood that assessing vulnerability and building references is complex, as it must take into account two aspects: the availability of quality information (Patt et al., 2010) and the system itself in terms of temporal context, place, scale and complexity of relationships (Barnett et al., 2008).

It is difficult to find a single definition of what vulnerability to social and environmental change means (Romero and Qin, 2011). This has generated debate about the clarity of the concept, whether between individuals or institutions (Kelly and Adger, 2000; Brooks, 2003; Adger et al., 2004; Füssel and Klein, 2006; Adger, 2006; Füssel, 2007; Hinkel, 2011a). However, the discussion also demonstrates the richness of the subject, bringing together multidisciplinary approaches to analyse the complex systemic reality with multiple elements and relationships that explain vulnerability—this is what O'Brien (2012) calls the ‘hyper-complexity’ of climate change. Table 1 present the definitions used in this research.

From the socio-environmental approach, the most discussed and most accepted definitions are those that were generated by the Intergovernmental Panel on Climate Change (IPCC) in its 2001, 2007 and 2014 reports on impact, adaptation and vulnerability. The definition provided by the Fourth Assessment Report (AR4) in 2007 reflects advances in the discussion of the concept and incorporates the vision of multiple approaches. For that reason, this study will use the definition of vulnerability developed in this report:

[Vulnerability] is the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity. (IPCC 2007b)

Beyond noting several key aspects, such as a systemic view, anticipation and the negative implications of the concept, this definition identifies the main components of the concept of
vulnerability: exposure, sensitivity and adaptive capacity (Defined in Table 1). Figure 1 presents the conceptual framework that outlines this assessment of vulnerability. The negative implications of the concept are visible in how vulnerability is defined by the susceptibility of a system or its subsystems to suffer damage (Kelly and Adger, 2000; Turner et al., 2003; Luers et al., 2003; Luers, 2005; Adger, 2006). In addition, vulnerability takes into account exposure to shock or stress not only from situations that are related to the environment, but also from social and political realities. Vulnerability will thus differ in each context in terms of magnitude, frequency and duration. The sensitivity of the system is given by the level of modification that it suffers when facing a situation of stress, from which it follows that stress, sensitivity and the adaptive capacity are the key elements of the concept (Adger, 2006). Table 1 presents detailed definitions that will be used as the components of vulnerability.

Table 1. Definitions of the components of the vulnerability function.

<table>
<thead>
<tr>
<th>Term</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Potential impact</td>
<td>Total impact that may occur given projected environmental change, without considering planned adaptation (Metzger and Schröter, 2006)</td>
</tr>
<tr>
<td>(PI)</td>
<td></td>
</tr>
<tr>
<td>Exposure (E)</td>
<td>The nature and degree to which a system is exposed to significant climatic variations (IPCC, 2007)</td>
</tr>
<tr>
<td>Sensitivity (S)</td>
<td>The degree to which a system is affected, either adversely or beneficially, by climate variability or change. The effect may be direct (e.g., a change in crop yield in response to a change in the mean, range or variability of temperature) or indirect (e.g., damage caused by an increase in the frequency of coastal flooding due to sea level rise) (IPCC, 2007)</td>
</tr>
<tr>
<td>Adaptive capacity</td>
<td>The ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damage, to take advantage of opportunities or to cope with the consequences (IPCC, 2007)</td>
</tr>
<tr>
<td>(AC)</td>
<td></td>
</tr>
<tr>
<td>Action (Ac)</td>
<td>The resources in populations and institutions to create or develop actions for adaptation (Swart et al., 2012)</td>
</tr>
<tr>
<td>Awareness (Aw)</td>
<td>Knowledge of the society for coping with the negative effects of climate change (EEA, 2012; Swart et al., 2012)</td>
</tr>
<tr>
<td>Ability (Ab)</td>
<td>Access to technology and infrastructure to develop the adaptation processes (EEA 2012)</td>
</tr>
</tbody>
</table>

The concept of vulnerability does not exist in a vacuum; it is closely related to factors such as risk, exposure, hazard, susceptibility, containment and mitigation, along with adaptation,
resistance and resilience. These fundamental elements related to the concept are hardly new, and there is extensive research into the risks and dangers to both the environment and to society (Kelly and Adger, 2000; Cardona, 2001; Turner et al., 2003; Luers et al., 2003; Brooks, 2003; Adger, 2006; Metzger and Schröter, 2006; Füssel and Klein, 2006; Füssel, 2010). The study of vulnerability allows us to understand the internal and external factors that threaten social or environmental systems at present and those that will threaten it in the future, along with the factors that reduce the system’s possibility of responding to these threats. The study of vulnerability thus is a predictive science, since it is not enough to understand how we should act today in the face of a hazard; we must know how to act in the near or distant future (Cutter 2003; Satterthwaite et al. 2007; Hinkel 2011b).

Based on the exposition above, this study takes vulnerability as a function with two main components: potential impact (PI), which is the result of the study of exposure (E) and sensitivity (S); and adaptive capacity (AC), which is the result of the three factors of action (Ac), awareness (Aw) and ability (Ab).

\[ V = f(PI, AC) \]

Where Potential Impact (PI) = Exposure (E), Sensitivity (S)

Adaptive Capacity (AC) = Action (Ac), Awareness (Aw), Ability (Ab)
The study focuses on potential impacts due to both the level of exposure faced by urban areas prone to climate-related hazards and the sensitivity level of the socio-economic system, such as the population and assets in areas that are prone to climate-related hazards. AC is defined as the three components of action, such as the financial situation of the country and its population, awareness within the population and abilities, such as available technology, that the system can employ to confront the negative effects of climate change.

Carrying out a vulnerability assessment in the face of limited or non-existent basic data like rainfall projections, temperature and storms involves studying the recent past vulnerability situation and how this could be exacerbated by climate change. This approach has the value of strengthening the current understanding of climate change, rather than focusing on a specific period in the future. As Schauser et al. (2010) note, it is very difficult to define current and future vulnerability effectively, because future vulnerability depends on actions in both the past and present. There is also a widespread lack of urban-level projections of sensitivity and AC, because many of the socio-economic factors that implicate these components of vulnerability, which are the result of the analysis of specific information from the recent past, remain difficult to project due to their complexity. For this reason, the Asian Cities Climate Change Resilience Network (ACCCRN) and the European Environment Agency (EEA) have conducted studies to assess, through various urban indicators, current and future vulnerability to climate change (Greiving, 2011; EEA, 2012).

In this thesis, I address two levels of spatial analysis: regional and local. In the first part (Chapter 2) I do a regional assessment of nine cities based on global available climate and socio-economic data. In the second part of this research I do a local assessment of a specific city based on detailed past local data of the recent decades. In Chapter 7 includes a discussion of the regional and local scale of this study.

The National Adaptation (NAP) Plan explicitly mention among its objectives the need to create a set of indicators that allow the evaluation and monitoring of the urban vulnerability and climate change, in the frame of the urban sectoral adaptation plan to climate change (MoE, 2014). To meet these objectives a set of indicators was designed and created in this research to allow a quantitative spatial and temporal assessment of urban vulnerability to climate change. The NAP is responsibility of the ministry of environment, I met with this
ministry to know their specific necessities and type of outputs of interest. They suggested to find data to develop the set of indicators and this research from local ministerial local offices using the transparency low, which allow me to access to public data, as well as the main spatial and temporal scale of analysis of interest. Therefore, I contacted with six ministries, five ministerial offices and nine municipalities listed in Table 2 to get specific information and data details:

**Table 2.** Stakeholder data acquisition and consultation.

<table>
<thead>
<tr>
<th>Stakeholder</th>
<th>I get from them data of water exploitation index to develop the exposure index in Chapter 4.</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Directorate of Water</td>
<td>They provide data about the droughtiness used to develop exposure index in Chapter 4.</td>
</tr>
<tr>
<td>Minister of Agriculture</td>
<td>They provide data about the number of doctors and patent used in the adaptive capacity index, Chapter 5.</td>
</tr>
<tr>
<td>Ministry of Economy</td>
<td>I get from them data about hospital beds, physician and distance to hospitals used in the adaptive capacity index, Chapter 5.</td>
</tr>
<tr>
<td>Ministry of Health</td>
<td>They provided the initial guiding to build the set of indicators and define the type of outputs. This means, the spatial and temporal scale of interest, the quantitative outputs that allows for monitoring. They also provide initial advice on the possible sources of information to develop this research.</td>
</tr>
<tr>
<td>Ministry of Environment</td>
<td>I get from them logistical support in land to identify the proper information and sources as well as to performed the landfill. They also provide data about transport infrastructure used in Chapter 4.</td>
</tr>
<tr>
<td>Meteorological Service of Chile</td>
<td>They provide information about the climate data available, their quality and time extension as well as access to the data bases used across Chapters 2 and 4.</td>
</tr>
<tr>
<td>Ministry of Social Development</td>
<td>I get from them data about poverty, income inequality and income per capita to develop the adaptive capacity index used in Chapters 2, 4 and 5.</td>
</tr>
<tr>
<td>National Forest Corporation</td>
<td>They provide statistics about wildfires as wildfires events and total area burned used in Chapter 4.</td>
</tr>
</tbody>
</table>
National Institute of Statistics
I get from them all the census data of population and housing used in this research. Corresponding to census 1992 and 2002. The availability of this census data defined the specific temporal scale of analysis of the local vulnerability assessment in this research, described in Chapters 3 to 6.

Municipalities
Local planning instruments, Municipal Regulatory Plans, Inter-municipal Regulatory Plan, Chapters 4 to 6.

Superintendent of Sanitary Services
I get from them data of water consumption to develop the exposure index in Chapter 4.

Information received from these organisations mainly included data and guidance on how to access it, but also types of tools and software used by them and pertinent spatial and temporal scales of outputs. ArcGIS 10.1 was used because it is the GIS platform used by the different administrations of government. For the spatial analysis, the current administrative levels, the cities (regional) and the municipalities (local) were selected, to address the areas of interest of the climate change policy described in (MoE, 2015, 2014) to facilitate the access and later use of the information. In particular, municipalities are an explicit objective for the territorial implementation of the future urban adaptation plan (MoE, 2015). For the temporal analysis, the recent past and the future were considered. For the analysis of the recent past, the availability of census data defined the analysis time points 1992 and 2002 (NIS, 2008). In the case of the future evaluation of the vulnerability, time periods were defined according to the length of planning windows: short, medium and long term, and for the existence of previous studies in Chile with which to be able to contrast the results, (e.g. ECLAC, 2012; Jadrijevic, 2010; Welz & Krellenberg, 2016).

1.3 Aim and objectives
The aim of this thesis is to assess the vulnerability of the main coastal urban areas of Chile to offer an understanding of the preconditions for planned adaptation at the municipal scale. To accomplish this aim, the analysis focuses on the municipalities in which communities are most sensitive and exposed to the negative effects of climate change and the ability to adapt in the face of any negative effects. This research starts by comparing the future vulnerability to multiple hazards of nine coastal cities in Chile. The most vulnerable city is then selected to study in depth its vulnerability to multiple weather-related hazards in the recent past. The
purpose of this vulnerability assessment of a selected city is to better understand the spatial and temporal changes in the vulnerability components (i.e. exposure, sensitivity and adaptive capacity), so as to advance knowledge of the causes of its vulnerability. Hence, this study addresses two specific objectives:

Firstly, to understand differences in the future vulnerability to climate and socio-economic change of nine coastal urban areas of Chile.

And secondly, for the coastal city that is identified as the most vulnerable in Chile, to understand recent change in multi-hazard impact, adaptive capacity and vulnerability between 1992 and 2002.

1.4 Structure of the thesis

The thesis is divided into seven Chapters (see Figure 2). Following this introduction, Chapter 2 provides a regional assessment of nine coastal cities. The subsequent Chapters offer an in-depth, local analysis for the Concepción Metropolitan Area (CMA), with a description of the methodology development (Chapter 3), and separate Chapters devoted to specific components of the analysis (Chapters 4–6). Chapter 7 concludes with a general discussion and conclusion. These Chapters, described in slightly more detail below, combine to represent the first attempt to study urban vulnerability to climate related hazards in Chile.

Chapter 1: Introduction

This Chapter provides an introduction to the main subject of this research, presenting the study topic, the research problem and objectives, a description of the outline of the document structure and the key relevant concepts drawn from the literature to frame this research. That literature deals with the importance of assessing the general vulnerability of urban areas to climate change.

Chapter 2: Regional assessment

This Chapter provides an overall view of the vulnerability of Chile’s main coastal municipalities. Nine such areas were studied to assess what their future conditions might be. The changes in climate variables such as temperature, precipitation, sea level rise and
extreme weather events are discussed, as are societal changes related to sensitivity and AC. The results indicate that under all scenarios vulnerability in the municipalities will increase over time, due mainly to significant increases in exposure levels, though changes in the population’s age structure will also have an important influence on vulnerability. Finally, a graphical comparison of the level of vulnerability across the nine cities was generated, which helped to identify a study area to develop the local analysis that follows in the succeeding Chapters.

Chapter 3: Methods for the local assessment

This Chapter introduces the study area and the general method used in the local analysis. The salient features of the CMA are described. The flexible methodology based on spatial fuzzy logic modelling developed for the local analysis is presented. This method involves the development of a set of indicators derived from data available for all Chilean municipalities to study vulnerability in terms of exposure, sensitivity and AC. The process of standardisation of the indicators is described, after which the process of aggregating the indicators is developed through a stepwise approach. This method resulted in the creation of three indices: a multi-hazard impacts (MHI) index, a generic adaptive capacity (AC) index and finally a vulnerability (V) index, which are detailed in the subsequent Chapters.

Chapter 4: Assessing multi-hazard impacts

This Chapter provides a detailed description of the MHI assessment conducted in the nine CMA municipalities, which was developed in order to identify, understand and track the spatial patterns of recent past exposure and sensitivity to different weather-related hazards such as coastal flooding, fluvial flooding, heat stress, water scarcity and wildfires. 32 indicators were developed, standardised and then aggregated through a stepwise approach into an MHI index. Overall, the results show that all nine municipalities increased their level of impact between 1992 and 2002, due to an increase in exposure moderated to some extent by a reduction in sensitivity. Municipal sensitivity was driven mostly by changes in the population’s age structure. Wildfires and water scarcity had the largest impact on all municipalities.
Chapter 5: Assessing adaptive capacity

This Chapter explores the CMA’s general AC. The factors that either facilitate or constrain the adaptation process were explored in an effort to identify, understand and track the spatial patterns of AC in the different CMA municipalities. To evaluate AC, a set of 17 urban indicators was proposed, which comprises three main dimensions of the capacity to adapt: awareness, ability and action. The results indicate that all CMA municipalities increased their AC levels between 1992 and 2002 and that the relative differences between municipalities did not change significantly over the period studied.

Chapter 6: Assessing vulnerability

This Chapter presents the methodology for using the MHI and AC indices from previous Chapters to evaluate and map the vulnerability of the nine CMA municipalities. It summarises the main results of the vulnerability assessment, demonstrating that the index successfully tracked how vulnerability changed over time and across the study area and revealing differences in vulnerability in the municipalities over time. Among the main findings is that fuzzy modelling offers high flexibility in the data aggregation process by combining different fuzzy membership functions and testing different fuzzy overlay functions. The model development and analysis of results using the GIS software ArcGIS were straightforward, making clear the potential of fuzzy modelling for future research into climate change vulnerability.

Chapter 7: Discussion and Conclusion

This Chapter presents a synthesis of the main research results, offering a general discussion of the findings and placing it in the context of others vulnerability studies. Afterwards, the methodological choices made throughout the vulnerability assessments are examined, followed by a discussion of the original contributions to knowledge. Finally, the broader significance of the findings, including reflections on the research methods, are presented in the conclusion.
Figure 2. Schematic representation of the work undertaken in this thesis. The research effort is divided into regional and local assessments (blue) and synthesis (red). The line in light blue represents the time component in the vulnerability assessment.
2

Regional assessment
2.1 Introduction

In the coming decades, several thousand millions of people, especially in developing countries, are expected to suffer from extreme events such as floods, droughts and heavy precipitation, scarcity of water and food and increased risks to health and life, all as a result of climate change (Satterthwaite et al., 2007). Chile is facing a projected temperature increase of 3°C to 4°C, which increases from the coast to the mountains and from south to north (Sillmann et al., 2013). In central Chile, the main impact will come from precipitation decreases in the range of 20–30% (Sillmann et al., 2013). According to the Economic Commission for Latin America and the Caribbean (ECLAC), 2012, extreme weather-related events will only increase, with 14 drought events expected over only 30 years. Extreme precipitation events are expected to fall from 93 to 80 events over 20 years, but heavy precipitation events on days with high temperatures could increase from 21 to 63 events in the same time frame. These events all carry a risk of flooding (ECLAC, 2012a). According to the last IPCC report, sea level rise in the Chile’s north and centre could vary between 0.4 m and 0.5 m (Church et al., 2013). However, there are no studies that examine, at the local level, not only the increase in sea level, but also the height and direction of waves or the possibility of storm surges. All of these changes will have important implications for urban areas in terms of energy generation, water consumption, health, environment and even investment (Schauser et al., 2010).

Moreover, changes are also expected in the Chilean population, which was 17 million in 2010 (NIS, 2011b). That is expected to increase by 10% and 14% by 2025, by mid-century reach its peak by as much as 30% and to end of the century it is expected to decrease by as much as 29% (International Institute for Applied Systems Analysis, IIASA (2015). At the same time, a decline in the youth population is already evident from a decrease in the national fertility rate, which went from five children per woman in 1960 to 1.8 in 2012 (NIS, 2012c). If current trends continue, most of the population growth will occur in the elderly segment of the population, which is expected to rise from around 9% of the population in 2010 to between 23% and 34% by mid-century (IIASA, 2015a). These social changes will have profound implications for cities, especially given that even today Chilean cities account for 88% of the population (NIS, 2005), a proportion that is expected to reach 98.9% of the population by
2100 (IIASA, 2015a). A larger and longer-lived population increases demand for new infrastructure and services in cities (Campbell-Lendrum et al., 2014).

Since 1990, Chile has enjoyed rapid economic growth, like many developing countries. In 2010, GDP purchasing power (PPP) reached 13,000 per capita (USD2005). However, the growth that the country has experienced has not been equitable. In 2010, 18.9% of the population was in poverty; the mean of poverty of the Organization for Economic Co-operation and Development (OECD) to which Chile is member is 11% (OECD, 2011). Chile’s Gini index, which is normally used to measure of inequality has remained around 0.5 in recent decades, it was 0.55 in 1990 and 0.52 in 2011 (the OECD mean is 0.31). Poverty and inequality are factors that significantly influence cities’ vulnerability (Agrawal et al., 2014).

Despite these geographic realities and demographic trends, very little research has been conducted into coastal Chile’s vulnerability to climate change. For the inland capital of Santiago, which accounted for 30.1% of the population in 2002 (NIS, 2005), studies have been conducted to assess future vulnerability to climate change (Bell et al., 2008; Krellenberg et al., 2013; Krellenberg and Barth, 2012; Romero et al., 2010; Welz and Krellenberg, 2016). This lack of previous research is the motivation for this Chapter’s initial regional exploration of future changes in exposure, sensitivity and AC due to climatic and societal change for nine coastal cities in Chile. The method seeks to identify the changes that might affect vulnerability and its components in the future in an accessible, simple and transparent way. Changes in both biophysical and socio-economic indicators that could affect vulnerability were explored for 30-year periods as time windows for reporting results over the near (2011–2040, 2025), medium (2041–2070, 2055) and long (2071–2100, 2085) terms through a combination of scenarios (Turner et al., 2003a, 2003c). This Chapter is framed around the following questions:

1. How might the components of vulnerability change in the future?
2. Which cities have the highest vulnerability to climate and socio-economic change?

This Chapter is divided into five sections; this introduction (2.1) followed by materials and methods (2.2), results (2.3), discussion (2.4) and conclusion (2.5).
2.2 Methods

2.2.1 Study area: Main coastal Chilean cities

The nine Chilean coastal urban areas explored in this study are shown in Figure 3, with Table 3 providing their component municipalities, coordinates and populations. Between Arica and Punta Arenas, there is a difference of 35° latitude or 3,860 km, equivalent to the difference in latitude between the Canary Islands and Edinburgh. Chile’s extensive north-south geography results in a wide range of climatic conditions from a northern desert that is among the world’s driest places to Patagonia in the south, one of the wettest regions in the Southern Hemisphere (Montecinos and Aceituno, 2003). Charts of the average monthly precipitation and average monthly maximum, mean and minimum temperature for each studied area are shown in Figure 3.

Table 3. Cities under study

<table>
<thead>
<tr>
<th>Cities</th>
<th>Municipalities</th>
<th>Location</th>
<th>Population 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arica</td>
<td>Arica</td>
<td>18°28'S 70°20' W</td>
<td>210,920</td>
</tr>
<tr>
<td>Gran Iquique</td>
<td>Iquique, Alto Hospicio</td>
<td>20°14'S 70°11' W</td>
<td>280,248</td>
</tr>
<tr>
<td>Antofagasta</td>
<td>Antofagasta</td>
<td>23°36'S 70°25' W</td>
<td>346,126</td>
</tr>
<tr>
<td>Gran La Serena</td>
<td>La Serena, Coquimbo</td>
<td>29°55'S 71°20' W</td>
<td>412,586</td>
</tr>
<tr>
<td>Gran Valparaiso</td>
<td>Valparaiso, Concón, Viña del Mar, Quilpué, Villa Alemana</td>
<td>33°02'S 71°38' W</td>
<td>930,217</td>
</tr>
<tr>
<td>Concepción Metropolitan Area (CMA)</td>
<td>Concepción, Coronel, Chiguayante, Hualqui, Lota, San Pedro de la Paz, Talcahuano, Tomé, Hualpén</td>
<td>36°46'S 73°72' W</td>
<td>945,521</td>
</tr>
<tr>
<td>Valdivia</td>
<td>Valdivia</td>
<td>39°49'S 73°51' W</td>
<td>154,097</td>
</tr>
<tr>
<td>Puerto Montt</td>
<td>Puerto Montt</td>
<td>41°28'S 73°53' W</td>
<td>228,118</td>
</tr>
<tr>
<td>Punta Arenas</td>
<td>Punta Arenas</td>
<td>53°09'S 72°56' W</td>
<td>131,067</td>
</tr>
</tbody>
</table>


These nine urban centres were selected for two reasons. First, they are the largest urban centres on the coast, with a significant concentration of Chile’s population and economic assets. About 22% of Chile’s population live in these cities, which have seen the bulk of new jobs created in recent decades (NIS, 2012a). Second, because of their proximity to the coast and their physical characteristics, they are normally exposed to a wide range of hazards such as storms that produce high winds, storm surge and coastal flooding and landslides, river flooding, wildfires, droughts, etc. (Urrutia and Lanza, 1993). Their high concentration of goods and services and especially of people makes these cities vulnerable to climate change (IPCC, 2012a; Swart et al., 2012). Chile’s social inequality is among the highest in the OECD, which is reflected in urban segregation that is exacerbated by the unplanned growth of cities.
These Chilean cities have experienced intercensal growth from 1992 to 2012 of around 31.5%, which is similar to other cities in developing nations (Bárcena et al. 2009; UNDESA, 2011). This growth has been rapid, uncontrolled and often illegal or irregular, so there has been no planning of the infrastructure and services required; on the contrary, these vital needs have arisen in response to the expansion (Gutierrez, 1975; Martinez, 1997). The growth process has been uneven and has not always been accompanied by equity and development for the population living in urban areas (Satterthwaite et al., 2007; Bicknell et al., 2009; ECLAC, 2012b). For this reason, these urban areas are characterised by high segregation that concentrates the population with fewer resources in well-bounded areas of cities such as abandoned land (Sabatini et al., 2001). This low-income population inhabits areas considered risky due to their location on hills that are threatened by landslides, in floodplains or close to industrial activities. Often, they dwell in self-constructed housing of poor quality, which is damp and cold in winter and very hot in summer (NIS, 2012c). By and large, these urban areas do not have the infrastructure to adapt, which makes them especially vulnerable to climate change (Bicknell et al., 2009; Rosenzweig, et al., 2011).

Figure 3. Regional study area. On the left side, the location of the study areas. On the right side, charts indicating the average monthly precipitation (bars) and temperature (lines) for each of the studied areas. Source Meteorological Service of Chile.
2.2.2 Building the knowledge base

A scenario-based regional approach was applied to explore the possible future vulnerability of these nine cities. This was achieved through a semi-qualitative analysis of climatic and socio-economic data available for the study area. The vulnerability framework includes the exploration of future climatic and societal change (Figure 4). The effects of climate change on the average climate (temperature and precipitation), extreme weather conditions (droughts, heat stress, floods) and inhabiting a low-elevation coastal zone (LECZ) were identified to explain exposure in greater detail. Subsequently, to evaluate the future potential sensitivity changes in the society, population and GDP were studied. To identify future changes in society’s AC, changes in both human and financial capital were analysed. Finally, these results were explored for the study area, in order to identify and understand the factors related to future vulnerability across the cities and to select a single urban area to study in the local assessment presented in the following Chapters.

![Figure 4. Framework of the regional assessment.](image)

The assessment followed a scenario framework based on a combination of selected representative concentration pathways (RCPs) and shared socio-economic pathways (SSPs) (van Vuuren et al., 2014) developed for the IPCC Fifth Assessment report (AR5). The purpose of the RCP-SSP framework is to support the development of new scenarios to facilitate research and evaluation of climate impacts, and adaptation and mitigation strategies. The RCPs represent pathways of radiative forcing resulting from different greenhouse gas atmospheric concentrations (Moss et al., 2010; van Vuuren et al., 2011). The SSPs describe alternative trajectories of future global development (O’Neill et al., 2014; van Vuuren et al., 2014). All possible scenario combinations can be seen in Figure 5.
I chose five scenarios that allowed to fully explore high, medium and low adaptation challenges (van Vuuren et al., 2014) covering the whole spectrum of possible future socio-economic changes (O’Neill et al., 2014). Selected RCP-SSP combinations are shown in Figure 5. To cohere with previous assessments of climate change effects in Chile (ECLAC, 2012a), which explored a pessimistic scenario (A2) and an optimistic scenario (B1) from the earlier Special Report on Emission Scenarios in the Fourth Assessment Report (SRES), similar scenarios were studied here. A scenario with high population, low economic growth and with high mitigation and adaptation challenges was selected. This is RCP 8.5-SSP 3, which is similar to SRES A2 (Arnell and Lloyd-Hughes, 2014). Scenario RCP 4.5-SSP 1 is very similar to SRES B1 and represents the best conditions for environmental sustainability, with low population growth and adaptation challenges (van Vuuren and Carter, 2014). Facing challenges to mitigation, RCP 8.5-SSP 5 assumes rapid economic growth based on fossil fuel supplies and high mitigation challenges (van Vuuren and Carter, 2014). This scenario is similar to SRES A1F1. Additionally, RCP 4.5-SSP 4 and RCP 4.5-SSP 2 were explored. RCP 4.5-SSP 4 takes the middle ground, with intermediate ranges of population and economic growth and low mitigation but high adaptation challenges. Finally, RCP 4.5-SSP 2 presents intermediate ranges of population and economic growth.

The selection of scenario data was defined based on a literature review and the availability of global data accessible for the IPCC AR5. Other criteria for data selection included the availability of a reliable time series of 30-year periods as time windows for reporting results over the near (2011–2040, 2025), medium (2041–2070, 2055) and long (2071–2100, 2085) terms.

<table>
<thead>
<tr>
<th>Forcing Level (W/m²)</th>
<th>Shared Socio-Economic Pathway</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SSP 1</td>
</tr>
<tr>
<td>8.5</td>
<td></td>
</tr>
<tr>
<td>6.0</td>
<td></td>
</tr>
<tr>
<td>4.5</td>
<td></td>
</tr>
<tr>
<td>2.6</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5. Combinations of RCP-SSP used (in grey). For three scenarios, equivalent SRES scenarios are specified. Matrix adapted from (van Vuuren et al., 2014).
Climatic Change

To explore exposure, future climate data were obtained using SimCLIM software (ClimSystems, Hamilton, New Zealand), which offers a global database at high spatial and temporal resolution of a range of climate variables projected into the future (CLIMsystems, 2010). SimCLIM downscales the Coupled Model Intercomparison Project Phase 5 projections to a 0.0083° by 0.0083° grid on a monthly scale using bias-corrected pattern scaling developed for 21 global circulation models (GCMs) (see Yin et al., 2013 and Warrick, 2006). SimCLIM was designed to address issues related to the effects of climate change such as agricultural risks, flood risk, extreme heat risk and impacts on water resources at high temporal and spatial scales (Henderson et al., 2013; Mills et al., 2015; Wobus et al., 2014). It contains tools for importing and spatially analysing monthly and seasonal data, as well as time series for hourly, daily or monthly data. These characteristics make it a good platform for an analysis of current and future vulnerability to climate change at the urban scale. From among the data generated by SimCLIM, I used mean, maximum and minimum temperature, and daily and mean precipitation values (Table 4).

Table 4. Sets of observed and projected climate data in grid format

<table>
<thead>
<tr>
<th>Data set</th>
<th>Spatial coverage; Resolution</th>
<th>Temporal coverage; Resolution</th>
<th>Variables*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data sets representing observations</td>
<td>SimCLIM</td>
<td>30 arcsecond</td>
<td>1980–2010; daily, monthly, 30-yr avg.</td>
</tr>
<tr>
<td>Data sets representing projections</td>
<td>SimCLIM</td>
<td>30 arcseconds</td>
<td>1980–2010; 2011–2100; 30-yr avg.</td>
</tr>
</tbody>
</table>

* Tmean: mean surface temperature; Tmax: maximum surface temperature; Tmin: minimum surface temperature; Pre: precipitation.

To explore exposure to coastal flooding the LECZ was identified (McGranahan et al., 2007). A digital elevation model for the LECZ was obtained from the NASA Shuttle Radar Topographic Mission 90 metres elevation data (SRTM 90) (Jarvis et al., 2008). This data set provides grid information on elevation to a vertical resolution of 1 m and a spatial resolution of 3 arcseconds, with a vertical maximum error of 16 m and a horizontal maximum error of 20 m (Rodríguez et al., 2005). The LECZ layer incorporates land areas under 10 m above sea level, including areas below sea level, and enables the identification of information about land and population in a given area.
Exposure to climatic change

Changes in average annual maximum, minimum and average precipitation for 2025, 2055 and 2085 were calculated as differences between a future scenario and the reference period of observed data 1995 (1980–2010). The level of change in temperature and precipitation indicates exposure in terms of climate average change. Additionally, to understand more fully the evolution of the general condition of the climate in the nine cities, seasonal change was calculated (see Appendix A).

Changes in the frequency of extreme events were explored through extreme temperature and precipitation indices that represent specific hazards like flood, heat stress and drought (see Figure 7). The frequency of days with precipitation above the 95th percentile was identified to explore flood hazards. The frequency of very hot days, on which the maximum temperature is above the 95th percentile, and very hot nights, on which the minimum temperature is above the 95th percentile, were used to explore heat stress (Pizarro and Castillo, 2006). The standardised precipitation index (SPI) is a commonly used proxy for exposure to drought (McKee et al., 1993; Swart et al., 2012), and the SPI over 12 months (SPI-12) allows the researcher to calculate the likelihood of the occurrence of meteorological drought that would affect water resources like dam capacity and groundwater over a longer time period (Stagge et al., 2015, 2016). These hazards were explored since they are already affecting these areas.

To identify the percentage of land in the LECZ per city, LECZ boundaries were calculated by analysing the elevation data from the SRTM 90 and using ArcGIS 10.1 to delineate an LECZ through a mask for 10 m below sea level. Inland areas 10 m or less above sea level were excluded, as these areas are not susceptible to coastal hazards (McGranahan et al., 2007).

Exposure results were presented for all cities, SSPs and time slices. The raw value of the indicators represents changes in temperature and precipitation; the frequency of extreme events and the LECZ areas are presented graphically in Figure 6 in a colour range where red represents high exposure and blue low exposure. The standardised value of indicators was presented thought boxplots to show the overall exposure to climate change. The standardisation facilitates comparison of the results. A standardised value for each indicator
was obtained using min-max normalisation. For each indicator, the potential values run from 0 (low exposure) to 1 (high exposure).

**Societal change**

To explore sensitivity and AC, future GDP and population projections such as urbanisation, age, education and sex for SSPs were obtained from (IIASA, 2015b). These projections are available for five SSP scenarios from 2000 through 2100 in five-year increments and for five macro-regions of the world, including Latin America. They are based on storylines that describe future development pathways (Moss et al., 2010; O’Neill et al., 2014; van Vuuren et al., 2014).

Locations of populations were obtained from the 2010 version of the Global LandScan population distribution data set developed by the Oak Ridge National Laboratory. LandScan strives to represent real population distribution by using a highly modelled approach. These data are represented as a 30-arcsecond grid of the current population distribution, based on census population counts disaggregated at the municipal level and on information on land use, roads, slope, urban areas, village locations, vegetation cover and analysis of high-resolution images.

The GDP grid was obtained from the Global Risk Data Platform from (Peduzzi, 2010). This 30-arcsecond grid of the 2010 GDP was developed by the World Bank Development Economics Research Group (DECRG) for the Global Assessment Report on Risk Reduction (GAR) and extrapolated by UNEP/GRID-Geneva.

**Sensitivity**

To identify future changes in sensitivity, the receptors of exposure were identified as population and assets in the nine cities. Population groups that are normally sensitive to disasters, like the very young (below five years old) and the elderly (over sixty-five years old) were identified, as were economic assets, based on GDP (Table 8). Future values of these variables were compared with a 2010 baseline. This was carried out by applying IIASA population projections to the cities, in order to identify population distribution under different SSPs from 2000 to 2100 in five-year increments. The same process was applied for estimating future GDP scenarios. Changes in population and GDP were used as proxies for estimating the population and economic assets sensitive to climate change.
LECZ populations were obtained from the LECZ boundaries, LandScan population distribution grid and the IIASA rate of population growth. Estimates of population density under each scenario at each time period were obtained by applying IIASA’s population growth ratios for 2025, 2055 and 2085 to the static population LandScan grid. The extraction method involved cartographic overlaying of the LECZ boundaries for 1, 5 and 10 m and population grids, resulting in raster layers for LECZ population.

The same methodology was used to graphically represent exposure was used to represent sensitivity (Figure 7), with red representing high sensitivity and blue low sensitivity.

**Adaptive capacity**

To identify the changes in AC, human and financial capital were studied, as they contain elements identified as part of a society’s capacity to adapt to climate change (Smit and Pilifosova 2001). Education, health and income provide baseline information about the general human development of a society and are good indicators of conditions that enable the development of adaptation to climate change. (Lutz, 2010) notes that strengthening human development is not fundamentally different than strengthening AC to climate change. Human capital refers essentially to people’s productive abilities, levels of education and health. A good level of education not only favours anticipating risk and planning appropriately but also facilitate access to higher incomes, which also improves AC. Tertiary education qualification was used as indicator to identify the potential human capital related to educations goals. Smit et al. (2001) argue that the implementation of effective adaptation options requires a certain level of human capital. KC and Lutz (2014) offer projections of population by educational levels based on the SSPs.

To plan appropriately and undertake adaptation measures a society must not only be sufficiently educated but also must be healthy. The expectation of long and healthy lives promotes long-term planning (Lutz, 2010). However, a high proportion of very old people (over eighty years old) (United Nations Department of Economic and Social Affairs, 2013) means that an important segment of society is likely less healthy and therefore less capable of implementing adaptation measures. Indicators of the years of life lost (YLL), which inform of the average years a person would have lived without a premature died (WHO, 2006), and very old population were used to identify the general health condition of the population.
Financial capital refers to people’s standard of living; it favours AC because its availability permits the implementation of adaptation measures and recovery efforts after extreme events. From IIASA, data projections of GDP (Juhola et al., 2012) was obtained (IIASA, 2015a). While variables like the Gini coefficient would be ideal for this analysis, because it shows how equitable a society is and Chile has high levels of inequality, Gini projections are not yet available for the SSPs.

The same methodology used to graph exposure was used to graph AC (Figure 8), with red representing low AC and blue high AC.

Table 5. Indicators to evaluate exposure, sensitivity and AC to climate change

<table>
<thead>
<tr>
<th>Exposure to</th>
<th>Explained for</th>
<th>Unit/description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>Changes in temperature</td>
<td>Temperature change</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Changes in precipitation</td>
<td>Precipitation change</td>
</tr>
<tr>
<td></td>
<td>Very hot days</td>
<td>Frequency of very hot days, with maximum temperature &gt; 95th percentile</td>
</tr>
<tr>
<td>Heat stress</td>
<td>Very hot nights</td>
<td>Frequency of very hot nights, with minimum temperature &gt; 95th percentile</td>
</tr>
<tr>
<td>Flood</td>
<td>Very heavy rain days</td>
<td>Frequency of precipitation days &gt; 95th percentile</td>
</tr>
<tr>
<td>Drought</td>
<td>Water availability</td>
<td>Standardised Precipitation Index (SPI)</td>
</tr>
<tr>
<td>Coastal flooding</td>
<td>Low elevation coastal zone (LECZ)</td>
<td>% of area in the low elevation coastal zone</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sensitivity of</th>
<th>Explained for</th>
<th>Unit/description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>GDP (PPP)</td>
<td>Gross domestic product GDP</td>
</tr>
<tr>
<td>Population</td>
<td>Elderly people</td>
<td>% of population &gt; 65 years</td>
</tr>
<tr>
<td></td>
<td>Very young people</td>
<td>% of population &lt; 5 years</td>
</tr>
<tr>
<td></td>
<td>Population in the LECZ</td>
<td>% of population in the area at LECZ</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Adaptive capacity of</th>
<th>Explained for</th>
<th>Unit/description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>Tertiary qualification</td>
<td>% of population aged 15–64 qualified at tertiary level</td>
</tr>
<tr>
<td>Health</td>
<td>Very old population</td>
<td>% of population over 80 years old</td>
</tr>
<tr>
<td>Income</td>
<td>GDP (PPP)</td>
<td>Gross domestic product GDP</td>
</tr>
<tr>
<td>Potential years of life lost (YLL)</td>
<td>Years potentially lost per 1,000 inhabitants</td>
<td></td>
</tr>
</tbody>
</table>

Overall Vulnerability

To determine the cities’ overall vulnerability to climate and socio-economic change, the standardised values of each of the fifteen indicators that represent exposure, sensitivity and AC were plotted in three boxplots for all cities, SSPs and time slices. Values were between 0 and 1, with values closer to 1 represents greater vulnerability.
2.3 Results

Exposure to climatic change

Figure 6 shows the variables that characterise exposure, with red representing comparatively high exposure and blue representing lower exposure. The figure makes clear that almost all urban areas would present an increase of temperature in all seasons, with only Punta Arenas in 2025 showing a lower temperature (see Appendix A). The RCP 8.5 emissions scenario shows greater increases in temperature in 2055 and 2085, as it has a slightly higher minimum temperature. The increase in temperature affects cities in the north more intensely, with the effect decreasing to the south. In Arica, Iquique and Antofagasta the minimum temperature increases more in winter, while the rest of the cities have minimums that increase in summer and fall. As for maximum temperature, the average difference between Arica and Punta Arenas is 2°C under the RCP 8.5 2085 scenario, whereas RCP 4.5 is 1.8°C. This increase in both the maximum and minimum temperature is slightly higher in all urban areas in the winter.

Precipitation projections show in both scenarios a general decrease over time from La Serena to Puerto Montt, but the decrease is more intense under RCP 8.5. Projections in precipitation also present irregularities in trends and uncertainties, which increase with time but are greater under the RCP 8.5 scenario. Some contradictory results can be observed between some GCMs; for example, Arica, Iquique and Antofagasta present both increases and decreases in precipitation, which could be explained by the extreme aridity of those urban areas, as was previously observed (CONAMA, 2006). Excluding Arica, Iquique and Antofagasta due to the above and Punta Arenas, which shows an increase in precipitation in both scenarios in 2055 and 2085, the other five cities show decreases in precipitation. The largest decreases in precipitation occur in La Serena and Valparaíso in winter and spring, which are the months in which rainfall is normally most frequent. For this reason, an annual decrease is expected in these urban areas, reaching around -26% for the RCP 8.5 scenario in 2085 and around -13% in RCP 4.5. In the CMA, the largest decreases are projected for spring and fall. Between Valdivia and Puerto Montt the largest reductions occur in the spring and summer, reaching decreases of around -16.7% under the RCP 8.5 scenario (see Appendix A detailing changes in seasonal precipitation).
Results for both scenarios show that extreme events such as heat stress will increase. The same is true with droughts, while the number of days with very heavy rain would be reduced. The variables related to heat stress would increase especially in the northern cities of Arica, Iquique and Antofagasta and decrease towards the south. The frequency of very hot days would increase in northern cities from 17 days a year in 1995 (1980–2010) to over 70 days per year under both scenarios in 2085. The frequency of very hot nights would also increase for the same period, from 18 to over 80 days per year under both scenarios. Droughts will also be frequent in the coming decades, under both scenarios. In centre-south cities, the frequency of SPI-12 would increase from an average 2.8 episodes per decade in 1995 to around 12.6 episodes per decade under RCP 8.5 in 2085. The northern cities would maintain their current situation. Finally, days of very heavy rain present a slight decrease, particularly in central Chile, between La Serena and Puerto Montt. Only Iquique, Antofagasta and Punta Arenas show increases, while northern cities present nearly no change. Between La Serena and Puerto Montt, days of very heavy rain would decrease on average from 5.9 in 1995 to 3.1 under RCP 8.5 and 3.9 under RCP 4.5 in 2085. In Punta Arenas, very heavy rainy days would increase from 8.3 per year in 1995 to 10.9 under RCP 8.5 and 9.7 under RCP 4.5 in 2085. In Antofagasta, such days would increase from 0.4 in 1995 to 0.8 under both RCP 8.5 and RCP 4.5.

In 2010, LECZ (1, 5 and 10 m above sea level) is around 0.08%, 0.3% and 0.9% of the total area of the country. This amount of land below 5 m over sea level is consistent with that expressed by Füssel, (2012). Arica, Iquique and Antofagasta had the lowest amount of land under 10 m, around 0.02%, 0.9% and 0.03% respectively. Meanwhile, La Serena, Valparaíso, Puerto Montt and Punta Arenas had between 0.9% and 1.5% of the land under 10 m. The CMA and Valdivia presented the greatest area below 10 m, at 11.3% and 14.1% respectively. The CMA has 1.3% of its urban area below 1 m, 5.7% below 5 m, and 3.2% below 10 m. Meanwhile, Valdivia has 0.2% of the urban area under 1 m, 2.7% below 5 m, and 2.3% below 10 m (See in Appendix A, LECZ land per municipality). Between La Serena and the CMA, a higher concentration of droughts, coastal flooding and heat waves can be observed.
Figure 6. Exposure to climate change for all cities, SSPs and time slices: (a) Indicators of exposure; red represents high exposure and blue represents low exposure relative to the reference period (1980-2010). (b) Boxplots of the change in the value of the four indicators that represent exposure relative to the reference period. In each boxplot, horizontal lines represent, from bottom and top, the 10th percentile, 25th percentile, median, mean (dots), 75th percentile and 90th percentile of the indicators value relative the reference period standardized between 0 (low exposure) to 1 (high exposure). Vertical axes show the two RCPs for the nine cities. Letters denotes the cities: A – Arica. B – Iquique. C – Antofagasta. D - La Serena. E – Valparaiso. F – Concepción. G – Valdivia. H – Puerto Montt. I – Punta Arenas.
Urban sensitivity in the face of societal change

Figure 7 shows the variables that explain sensitivity, depicted from red representing comparatively high sensitivity and blue representing lower sensitivity. The analysis of changes in the potential sensitive population shows a significant increase in elderly people in all scenarios by end of the century. In 2010, this population represented in average an 8.8% of the population of these nine cities. By 2100, the elderly population could be nearly 60% under SSP 1 and SSP 5, around 25% under SSP 3 and between 28% and 41% under the other SSPs. Valparaíso is the city with the highest proportion of elderly, while Puerto Montt has the lowest. By contrast, in relation to the reference year of 2010, when the proportion of the very young people in these cities was around 6.9%, the very young population shows significant reductions in all SSPs. By 2100 under SSP 1 and SSP 5, the very young would represent only around 1.6% of the total population in the cities, while under SSP 3 they would be around 6%. Under SSP 2 and SSP 4, it would fall to around 3% and 4% respectively. Antofagasta and Iquique show the largest and smallest proportions of very young people respectively.

In 2010 Arica, Iquique and Antofagasta had between 0.2% and 18.2% of its total population in the LECZ. Meanwhile, from La Serena to Punta Arenas, with the exception of the CMA and Valdivia, cities had around 2.5% and 35.7% of the land under 10 m above sea level. The CMA and Valdivia had the greatest proportion of population in the LECZ. The CMA has 0.05% of the population in the area below 1 m, 23.9% below 5 m and 26.2% below 10 m, this urban area concentrates around 50% of its total population under 10 m above sea level. Similarly, Valdivia has 4.6% of its population under 1 m, 16.3% below 5 m and 34.2% below 10 m above sea level, so its LECZ population is more than half of its total residents. The majority of the LECZ population in these cities is concentrated in the area between 5 to 10 m below sea level (56%), while the lowest percentage of population in the cities is found in the area from 0 to 1 m (1.1%). By mid-century, the LECZ population grows in all cities under all SSPs, varying between 820,000 under SSP 4 and up to 970,000 people under SSP 3. The CMA and Valdivia concentrate more than 500,000 people in the area bellow 10 m, above sea level in all the SSPs. Towards the end of the century, the population living in the LECZ varies between 560,000 people (SSP 1) to 1,000 million people in SSP 3.
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Sensitivity vary according to the scenario. In 2025, SSP 3, SSP 2 and SSP 4 in that order were the scenarios with the greatest overall sensitivity. By 2055, the overall sensitivity was slightly reduced in almost all scenarios except for SSP 3, in which sensitivity increased, due to the presence of sensitive population and low levels of improvement in the economic condition of the cities. 2055 showed similar scenarios but in a different order: SSP 3, SSP 4 and SSP 2. By 2085, SSP 3, SSP 4 and SSP 1 show the greatest sensitivity. SSP 1 and SSP 5 present the greatest combinations of very young population and elderly population. By 2085, sensitivity declined with respect to 2055 in SSP 2, while it increased in the rest of the scenarios. Between Antofagasta and the CMA, a higher concentration of population and assets can be observed.
Figure 7. Sensitivity to socio-economic change for all cities, SSPs and time slices: (a) Indicators of sensitivity; red represents high sensitivity and blue represents low sensitivity relative to the reference period (1980-2010). (b) Boxplots of the change in the value of the four indicators that represent sensitivity relative to the reference period. In each boxplot, horizontal lines represent, from bottom to top, the values for each SSP and time slice.

Adaptive capacity in the face of societal change

Figure 8 shows the variables that explain AC, moving from red, representing comparatively less AC to blue, representing more AC. By mid-century, tertiary education increases in all cities and in almost all scenarios. This increase is greatest in SSP 1 and SSP 5, while SSP 3 shows nearly tertiary education values found in the present day: around 15% of the population has tertiary education. SSP 3 increases until mid-century and then stabilises around 30% of people with tertiary education, while SSP 2 presents a sharp increase over the years until it reaches around 60% of the population having tertiary education. Valparaíso and Valdivia present the highest increases in the population with tertiary education, while Puerto Montt and Arica show the lowest increases.

The very old population increases in all scenarios; only under SSP 3 will less than 20% of the population be over 80 in 2100. In the rest of the scenarios, the increase is greater, reaching as high 35% of the total population by 2100. Valparaíso has the largest population over 80, followed by Punta Arenas and Valdivia. Antofagasta, Puerto Montt and Arica have the smallest proportions of population over 80. Due to the increase in life expectancy that Chile is expected to experience, a decrease in the YLL in all scenarios would be expected, and it is indeed present. This decrease is greater in SSP 5 and SSP 1, while SSP 3 presents the smallest decrease and SSP 2 and SSP 4 have very similar declines. The southern cities of Puerto Montt and Punta Arenas present the highest YLL figures; Iquique and Valparaiso have the lowest. Under all SSPs, GDP increases in all cities. This growth is similar in SSP 1, SPP 2 and SSP 4, all of which show a GDP of around USD70,000 per capita, with the exception of Punta Arenas, Arica and the CMA, where incomes are 49% below this figure. SSP 5 shows that the majority of the cities exceed USD100,000 per capita near the end of the century, with only Puerto Montt, Arica and the CMA not reaching that level. SSP 3 presents much lower increases, with only Antofagasta reaching over USD100,000 per capita by the end of the century; the rest of the cities are situated around USD39,000 per capita.
As a result, AC grows in all scenarios, but especially in SSP 1 and SSP 5 and less so, in SSP 3 and SSP 4; Puerto Montt and Punta Arenas have comparatively low AC due to the proportion of very old people and to YLL.
Figure 8. AC to socio-economic change for all cities, SSPs and time slices. (a) Values near red represent low AC and values near blue represent high AC relative to the reference period (1980-2010). (b) Boxplots of the change in the value of the four indicators that represent AC relative to the reference

Overall vulnerability

(Figure 9) presents the changes through time in the distribution of the fifteen indicators that represent vulnerability under the range of climatic and socio-economic scenarios, where indicator values are expressed relative to the reference period 1995 (1980–2010). The vulnerability value is the result of standardising all indicators to values between 0 and 1, with 1 representing maximum vulnerability. The boxplots show that by 2100 the overall vulnerability increased under all scenarios, with the largest increase in RCP 8.5-SSP 3. In RCP 4.5-SSP 1, the vulnerability declines towards 2055 and returns to 2025 values thereafter up to 2085. Similarly, under RCP 4.5-SSP 4, vulnerability decreases towards the middle of the century and increases again towards the end, eventually reaching higher values than reported for 2025. For 2025, vulnerability is highest under scenarios RCP 8.5-SSP 3, RCP 4.5-SSP 2 and RCP 4.5-SSP 4. For 2055, the most vulnerable scenarios are RCP 8.5-SSP 3, RCP 4.5-SSP 4 and RCP 4.5-SSP 2 and for 2085, they are RCP 8.5-SSP 3, RCP 4.5-SSP 4 and RCP 8.5-SSP 5.

All cities are vulnerable to more than one hazard, with only exposure to coastal flooding markedly different between the urban areas. The most vulnerable cities under all scenarios and for all periods were the CMA and Valdivia, followed by Puerto Montt and Arica. By contrast, Iquique and Antofagasta presented the lowest overall vulnerability.
Figure 9. Boxplots show the distribution of the change in the value of the fifteen indicators that represent the vulnerability relative to the reference period 1995 (1980–2010) for the nine cities, five scenarios and three time slices. In each boxplot, horizontal lines represent, from bottom to top, the 10th percentile, 25th percentile, median, mean (dots), 75th percentile and 90th percentile of the indicators value relative the reference period standardized between 0 (low vulnerability) to 1 (high vulnerability). Vertical axes show the two RCPs for the nine cities. Letters denote cities: A – Arica. B –
2.4 Discussion

Overall Vulnerability

Exposure increases under both RCP 8.5 and RCP 4.5. Up to 2025, both scenarios present similar changes; they differ over time thereafter, with RCP 8.5 presenting a larger change. Temperature increased in all cities, especially in those in the north (Arica, Iquique and Antofagasta). Similar results in temperature change have been reported by Allen et al. (2013), Sillmann et al. (2013), Villarroel (2013), and Vincent et al., (2005). The largest increase was observed in the minimum temperature (Donat et al., 2013; Dufek et al., 2008); increased minimum temperatures have already been observed in the central Chile (Vincent et al., 2005). An increase in the minimum temperature could have adverse effects on night cooling, the absence of which can contribute to heat stress (Frich et al., 2002). The effects of temperature increase can be intensified due to the effect of urban heat islands (EEA, 2012).

Urban morphology also contributes to increased heat stress in cities, which is exacerbated by factors such as high population density and a lack of green areas and bodies of water (Steeneveld et al., 2011). Greener and better-distributed areas can lessen the urban heat island effect (Bowler et al., 2010). However, Chilean cities have less than the 9 m² per person of green areas that is recommended by the World Health Organization (WHO, 2010). This lack of green space severely hampers the possibility of increasing people’s thermal comfort and protecting their health (Armson et al., 2013; Bowler et al., 2010; Steeneveld et al., 2011). The nine cities had the following population densities (inhabitants per hectare) in 2002: Arica 54.5, Iquique 85.79, Antofagasta 106.2, La Serena 68.4, Valparaíso 73.2, Concepción 63.6, Puerto Montt 74.71 and Punta Arenas 53.81 (MHUD, 2002). Thus, cities with a combination of few green areas, high density and with high temperature increase like Arica, Iquique and Antofagasta will require special attention in the future.

Under both RCP 4.5 and RCP 8.5, the general decrease in precipitation will mainly affect the middle and middle-south of the country from La Serena to Puerto Montt. Towards 2025, both scenarios show a decrease from La Serena to the CMA. Towards the end of the century, the
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scenarios differ, showing a larger decrease under RCP 8.5 than under RCP 4.5. This general decrease in precipitation has been reported previously (Allen et al., 2013; Boulanger et al., 2014; Parish et al., 2012; Rijsberman, 2006; Sillmann et al., 2013; Villarroel, 2013). The projections also indicate a reduction in heavy rain days in cities in the centre-south of Chile, with northern areas remaining unchanged and only Punta Arenas showing an increase (ECLAC, 2012a). A decline in heavy rain days has already observed (Dufek et al., 2008), although Mizuta et al. (2005) found an increase in extreme precipitations. It has been pointed out that there is substantial uncertainty associated with future decreases in extreme precipitation (Allen et al., 2013; Sillmann et al., 2013). The central areas of Chile have already experienced a precipitation deficit (Boulanger et al., 2014; Donat et al., 2013; Parish et al., 2012; Rijsberman, 2006).

The decrease in rainfall has several implications for cities; it can trigger water scarcity, which is defined as water availability below water demand, and affect the long-term water supply of cities (EEA, 2012). This has consequences for domestic water consumption of drinking water, sanitisation, green areas and overall human health (Jenerette and Larsen, 2006; Vairavamoorthy et al., 2008). Cities must already compete for water with other sectors such as industry, energy and, particularly in the case of Chile, agriculture (EEA, 2012), which consumes 73% of the country’s water reserves (MPW, 2012a). Currently, coastal cities are only supplied water by precipitation, so they are already under water supply pressures (see Chapter 4) (Astaburuaga, 2004). However, cities have not yet taken actions to prepare for a reduced water supply. For example, 34% of current drinking water losses are due to leaks (SISS, 2015), while, as noted above, there are insufficient green areas to retain soil moisture (Astaburuaga, 2004). Chile also does not have a network of grey (non-potable) water for irrigation or urban cleaning (Astaburuaga, 2004). Therefore, cities require investments in the water supply and treatment sector that must be carried out in the near future and which will mean higher costs for citizens (ECLAC, 2012a). As well as further studies about their future water resources (Warren and Holman, 2012).

There are also indirect consequences of increased temperatures and decreased precipitation. González et al. (2011) note that they can favour degradation of vegetation and an increase in wildfires. Wildfire events in recent decades have already increased in the CMA (see Chapter 4) and elsewhere in Chile (NFC, 2014). These fires typically originate in the peri-
urban area of cities and are usually anthropogenic (GORE, 2014; Sernageomin, 2014). Chile’s peri-urban areas generally feature irregular or even habitation that causes environmental degradation and is favourable to wildfires (Marzano et al., 2004; Pauchard et al., 2006; Salvatierra and Montenegro, 2010).

An increase in cases of hantavirus cardiopulmonary syndrome (HCPS) related to drought has been reported since 1990 and the Bío-Bío Region, where the CMA is located, is among the most affected areas (Toro et al., 1998; Torres-Pérez et al., 2010). The CMA is also the city most exposed to coastal flooding due to its low elevation. It is widely expected that sea levels will increase throughout Latin America, (Basso et al., 2001; ECLAC, 2012b; Meehl et al., 2007; Rahmstorf, 2010; Tundi et al., 2005), but the many effects of possible changes in ocean levels are only beginning to be studied in poor and developing countries like Chile. Prospective studies commissioned by the Ministry of Environment on trends in sea levels on the Chilean coast show that in the case of an A2 scenario in 2100, sea levels would rise around 25 cm in the north and 15 cm in the south (CONAMA, 2006).

It is essential to highlight how sensitivity varies according to the scenario and time. Under all scenarios except SSP 3, sensitivity decreases between 2010 and 2025. From 2025 to 2055, it grows slightly under SSP 3, SSP 4 and SSP 5, while it remains stable under SSP 1 and decreases under SSP 2. Towards 2085, it grows under all scenarios except SSP 2. Sensitivity is heavily influenced by changes in the age structure observed under all scenarios, with the elderly proportion increasing and the proportion of young people declining. This is especially evident under SSP 1 and SSP 5, which indicate substantial increases in the elderly population. This demographic change has also been observed by the National Institute of Statistics (NIS), which has estimated that the very young population will decline by 30% and the population over 65 would grow by 180% between 1990 and 2020 (NIS, 2011b, 2007). This demographic change has profound implications for both vulnerability and sensitivity in the long term. Older people are not only more sensitive in terms of health, but are also economically sensitive to floods, heat stress, wildfires, etc. (Bell et al., 2008; Brender et al., 2013; Green et al., 2010; Johnston et al., 2007; Knowlton et al., 2009; Leonardi et al., 2006; Muggeo and Hajat, 2009). An older population implies not only a larger vulnerable population for cities, but also greater demands for land, infrastructure, and services such as energy and transport (Keys et al., 2014).
From 2010 through 2055, AC grows under all scenarios, though it is lower in SSP 3 and SSP 4. Between 2055 and 2085, AC decreases under SSP 4 and SSP 5, due mainly to a reduction in the health component that is attributable to the increase in the very old population. Cities like Valparaíso and the CMA see life expectancy increases and show a larger proportion of the very old, as much as 42% of the overall population in the most extreme case. The education component grows under all scenarios except SSP 3, where it remains constant at around 17% of the population. Arica and Puerto Montt are the cities with the lowest proportion of population with tertiary education; they thus face the greatest obstacles in carrying out adaptation processes.

The income component increases in all cities under all scenarios. Nevertheless, the GDP provides no information about people’s incomes or the degree of economic inequality. Therefore, it is useful to analyse the poverty percentage of these cities in 2011, which shows that the CMA had by far the highest percentage of people under the poverty line (22%), while Punta Arenas and Antofagasta had the lowest at around 6%. The rest of the cities presented similar proportions (approximately 15%) of people in poverty (see Appendix A).

The interaction of the vulnerability components of exposure, sensitivity and AC results in an overall increase in vulnerability to climate change in coming decades under all five scenarios. Vulnerability is influenced mainly by increases in overall temperature, drought and minimum temperature and by a reduction in precipitation, which results in a large increase in the overall exposure that is mainly moderated by an increase in AC. Sensitivity varies according to the scenario and time and its increase is mainly due to the growth of sensitive populations (the elderly and people living in the LECZ). AC is influenced by improvements in the health, income and education components. The only factor that lowers AC is the increase in the very old population. All the cities are exposed to more than one hazard and different hazards have different influences on the vulnerability of each city. Nevertheless, many of the indicators report a high value for overall vulnerability in the CMA. It not only has droughts, an increase in temperature and a large decrease in precipitation but also has the highest exposure to coastal flooding. Furthermore, this city is marked by a low increase in sensitivity, explained chiefly by its large proportion of senior citizens and the largest proportion of people living in the LECZ. The CMA’s high exposure to natural hazards has already been reported in other studies (e.g., Henríquez and Ruz, 2013).
However, all cities are vulnerable, if to different degrees. Cities in the north show significant increases in temperature, but precipitation remains largely uncertain. They could face an increase in extreme precipitation. Because the northern urban areas (see Figure 3) have very low rainfall at less than 6 mm per year, they are already highly exposed to landslides (Garreaud and Rutllant, 1996). As a result of intense precipitation, landslides have affected these cities in the past, at high cost in both human and economic terms (Vargas et al., 2000).

Cities in the central area have historically been vulnerable to droughts, storms, wildfires and storm surges (Urrutia and Lanza, 1993; Vidal and Romero, 2010). A reduction in precipitation will cause the loss or deterioration of vegetation, making them more vulnerable to wildfires and landslides: this is especially so in Valparaíso and the CMA (NFC, 2014, 2006). In 1999, an intense drought arose from an imported energy crisis in urban areas, which faced more than a year of voltage reductions, power outages, scheduled power cuts and energy restrictions. This caused modifications in the regulatory framework of electrical utilities, adding drought as a situation that companies must consider in planning (Ministry of Energy (ME), 1999).

Regional vulnerability assessment

This regional assessment provides information for identifying the urban areas that most urgently require a regional assessment of vulnerability. It also contributes to increasing knowledge about the future vulnerability of Chile’s main coastal cities. The identification of the future vulnerability of these cities is relevant for beginning to consider the adaptation process. The approach used to evaluate vulnerability enabled an examination of how vulnerability and its components will evolve over time in each city. The analysis in three time slices identified changes that will occur within a short-term horizon (through 2025) or a medium-term planning horizon that may be as much 20 years in the future (Dessai and Hulme, 2004).

This approach also provided transparency and coherence in the presentation of each indicator of vulnerability, favouring the comparison of indicators of diverse nature and between vulnerability components. For the purpose of comparability, the standardisation of individual indicators using min-max to assign them comparable values proved to be worthwhile (Schauer et al., 2010). The graphical representation of vulnerability using box plots permitted visualisation by scenario, time slice and city. Due to the great uncertainty
associated with the analysis of data projected into the future, the approach attempted to minimize the accumulation of further uncertainties by aggregating indicators into an index. As has been widely suggested, this regional assessment was designed to be complemented by a local analysis of the vulnerability (see Chapters 3–6) (Preston et al., 2009b), because a regional analysis on its own does not permit identifying the structural causes that explain vulnerability in cities (Dessai and Hulme, 2004; Miller and Bowen, 2013).

The indicators selected for evaluation enabled observation of progressive temperature increases experienced by the cities, and revealed that temperature behaves differently in each season and in the different cities. Seasonal analysis is thus relevant. The same phenomenon was observed with precipitation, with the overall progressive decrease in precipitation that cities in central-southern Chile will experience varying between seasons and cities. Indicators of extreme events also facilitated the identification of changes in the frequency of extreme events in relation to the reference period. The analysis of socio-economic changes to identify sensitive populations and assets highlighted clear differences between cities with larger sensitive populations as well and those with lower and higher assets.

The approach to assessing AC in relation to human and financial capital permits the analysis of the future enabling conditions for adaptation. Factors like education, health and income have been explored in the past to assess AC (Lutz, 2010; Patt et al., 2010). These components have been developed to evaluate the human development index on a national scale, provides information about general human development and is similar to AC (KC and Lutz, 2014). In terms of education, it is important to note that evaluating the literacy rate is effectively irrelevant in Chile, given that schooling is compulsory and literacy is thus very high; this point is elaborated in the local assessment (see Chapter 5). However, tertiary educational qualifications do provide relevant information regarding societal change in the different cities. The income component, represented by per capita GDP, offers initially relevant information, but requires complementary information, such as measurements of poverty, for genuine analysis, because the distribution of wealth has profound effects on vulnerability (Preston et al., 2008). The health component to identify a population that will enjoy longer life expectancies. This is relevant for adaptation, because the higher the proportion of older
people in a society, the longer it will take that society to recover fully from the aftermath of a disaster (Cutter and Finch, 2008).

**Limitations**

One source of uncertainty comes from using scenarios or SRES, even though they have been widely used in studying the effects of climate change. The storylines are a series of narratives that offer alternative accounts of the future driving forces of environmental change using measures like demography, economy, agriculture, technology and energy. These plausible futures do enable a reasonable assessment of the effects of climate change but it is essential to recall that all the storylines are partial and do not claim to represent an exact future. They are used because they offer internal consistency between the driving forces that make up various future scenarios.

This assessment used five scenarios that were based on assumptions about population and economic growth change. They were developed with the purpose of assessing possible national development patterns rather than focusing specifically on internal changes in cities. This assumption permits projection of population distribution in 2025, 2055 and 2085 under five scenarios. While some may regard this approach as an oversimplification, the methodology is appropriate enough for a regional assessment of coastal urban vulnerability to global climate change. Furthermore, one of the aims of the analysis was to identify the city that would be best-suited for a more detailed local assessment.

The selection of indicators that explain vulnerability is inevitably influenced by the availability of reliable data sets and the limits of existing knowledge about vulnerability. Therefore, vulnerability assessments can change, if new data sets become available or with as a result of advances in our knowledge about urban vulnerability. However, an indicator-based approach helps simplify a complex reality and can be used as a starting point for discussion and further analysis.

A third source of uncertainty corresponds to changes in topography caused by seismic activity in Chile. Coastal upheaval or subsidence caused by tectonic processes can significantly modify sections of the coast. Due to Chile’s seismic realities, an LECZ may experience modifications that are unrelated to changes sea levels. For example, substantial changes in coastal
topography were produced by earthquakes in 1960 and 2010 (Barrientos and Ward, 1990; Farias et al., 2010).

**Improvements and recommendations**

This regional analysis should be understood as an initial exploration of possible future vulnerability. Further research is clearly necessary to improve existing knowledge about future vulnerability. Subsequent evaluations of vulnerability can provide further insight, particularly at the sectoral vulnerability level in cities (e.g., cities water resources (Warren and Holman, 2012)), while also expanding on the extreme events studied.

To identify the potential vulnerability to coastal flooding, the LECZ was identified. However, sea level rise was not incorporated, which is a recommended area for further research. Some initial exploration has been carried out by CONAMA (2006), but ECLAC (2012a) notes that the results of these studies remain ambiguous, because there is insufficient data and knowledge to identify future sea level rises with real accuracy. Moreover, issues related to sea level rise such as wave intensity and height, changes in the intensity and direction of winds, storm effects and the saline intrusion into surface or ground waters have not yet been studied. These phenomena, combined with the anthropogenic activities on the coast like indiscriminate extraction of sediment from riverbeds, fixing erodible soil and the placement of infrastructure in low areas of high risk such as dunes, may deeply affect natural systems and the integrity and operation of coastal infrastructure (McGranahan et al., 2007; Nicholls et al., 2007; Füssel, 2012). In addition, extreme events such as storms and storm surges require further research, since Chile’s coast is often affected by storms that include strong winds and heavy seas.

As a way to produce more realistic future scenarios and thus reduce uncertainty, it is necessary to i) create socio-economic projections that recognise the internal growth of cities (Absar and Preston, 2015); ii) incorporate new hazards that have affected an area previously and may do so with greater intensity in the future, such as vector-borne diseases, wildfires, storm surges and landslides. To make that a reality, new weather-related indicators will have to be created, along of the forest fire weather index (FWI) and the water exploitation index (WEI) (see Chapter 4); iii) to incorporate indicators of inequality at the city level, such as a Gini coefficient by city, because vulnerability is heavily affected by social inequality.
(Boulanger et al., 2014); and iv) incorporate sectoral and cross-sectoral assessment of the vulnerability (Harrison et al., 2016; Holman et al., 2016).

2.5 Conclusion

This Chapter presents an evaluation of the future vulnerability to climate and socio-economic change in nine of Chile’s main coastal cities. It offers a first approximation of the different biophysical and socio-economic changes that cities could experience in the future. It adds to existing knowledge about the future vulnerability of those cities, while also identifying the city that most urgently requires further study of its vulnerability through a local assessment.

The results indicated a vulnerability increase under all scenarios by the end of the twenty-first century. The combination of decreased precipitation and increased temperature, droughts and heat stress due to increases in minimum temperatures influenced vulnerability most heavily. Changes in precipitation have less clear trends than temperature changes, with models showing both decreases and increases, and major differences in the future for the country’s northern cities. Changes in extreme precipitation also show some degree of uncertainty. The large increase in exposure is mainly attenuated by an increase in adaptive capacity. Sensitivity is strongly influenced by changes in age structure. The CMA presents the greatest combination of exposure, sensitivity and a lack of adaptive capacity over time. If possible, however, all cities should be studied in depth.

This assessment is based on scenarios that represent national patterns of development, and thus does not focus specifically on cities’ internal changes. An assessment based on indicators such as those used here makes clear that the selection of indicators is based on the availability of data and the current knowledge on vulnerability. Thus, results may change, perhaps dramatically, if new data becomes available or further knowledge of the vulnerability comes to light. Only a limited number of all hazards known to affect these cities in the past and expected to increase in the future were incorporated, due to data constraints. Nevertheless, it is advisable to incorporate all relevant hazards to provide the most realistic projections of the future and to reduce uncertainty. A regional assessment on its own does not allow for the identification of structural causes that explain vulnerability in cities.
Therefore, this assessment must be complemented with a local assessment of vulnerability, which follows for the CMA in Chapters 3–6.
3

Methods for local assessment
3.1 Introduction

An increasing number of authors have assessed spatial vulnerability since the concept of vulnerability to climate and global change was technically defined in TAR by IPCC (2001) (Lung et al., 2013; Metzger and Schröter, 2006; O’Brien et al., 2004a; Rød et al., 2012). The definition is based on three components: (1) exposure, (2) sensitivity, and (3) adaptive capacity. Despite the growing consensus about the definition, several methodologies have emerged to assess the vulnerability and its components. These different approaches are mainly due to the current difficulty to operationalize the concept, as the current specific interpretation of the definition depends on the general approach to study vulnerability (i.e. discipline, scientific vs political, quantitative vs qualitative) but also on the availability of information, scale, among others.

Indicators are a common mean to assess the vulnerability, for example, (Malone and Engle, 2011; Preston et al., 2008) have used them to assess a vulnerability index, because indicators provide a simplified and systematic way to assess the state and monitor changes in the vulnerability. But, the aggregation process of indicators into a vulnerability index is also still under discussion. Further research is still needed to identify and understand the interdependence between the components of vulnerability and how they relate to explain the vulnerability. For example, the concepts of sensitivity and adaptive capacity may overlap. This implies that indicators that represent sensitivity can also be associated to adaptive capacity. For instance, a poorer society is usually more sensitive, and it also has less possibilities to successfully adapt. In both cases measuring the level of poverty of the society is relevant to identify the level of sensitivity or adaptive capacity. So far, indicators are normally aggregated and then combined into vulnerability maps through additive, additive weighted, Boolean logic. However, none of these methods of aggregation addresses imprecisions and uncertainties, related with the knowledge and data in the vulnerability assessment. Different authors have recognized the potential of fuzzy logic to address the uncertainty related with the evaluation of the vulnerability and its components. (Eakin and Bojóquez-Tapia, 2008) used fuzzy logic to build categories of rural livelihood vulnerability (i.e. high, medium and low) in Tamaulipas, Mexico. Fuzzy classification has been also used by Krömker et al. (2008) and Cheng and Tao (2010) none of them map the vulnerability. Meanwhile, (Acosta et al., 2013) spatially assessed the adaptive capacity at the European
scale with fuzzy logic through Matlab. On the other hand different authors had mapped the vulnerability at national or regional scale (Lung et al., 2013; Metzger et al., 2008), and some have done it at local scale (Rød et al., 2012; Varadan and Kumar, 2015).

Due to the aforementioned this local analysis explored the urban vulnerability with a method that intends to be flexible, simple, accessible, practical and operable by other scientists, stakeholders, and especially planners. Throughout three Chapters each of the components of vulnerability to recent past climate related hazards were explored. This Chapter presents a detailed description of the study area and the methodology applied for the local analysis. The description of the study area section provides the criteria for the selection of the study area as well as a description of the CMA in terms of its physical, socio-economic and demographic characteristics. The description of the methodology applied is separated in five sections: 3.3) local approach, 3.3.1) local assessment structure, 3.3.2) indicators framework, 3.3.3) aggregation approach, and 3.3.4) model evaluation.

3.2 Study Area

3.2.1 Study area selection criteria

The CMA was chosen as a representative urban area in Chile for this research because it meets the general guidelines established for this analysis, which are a) being a medium- or large-sized urban area including three or more municipalities; b) having been exposed historically to different natural hazards such as fluvial floods, coastal floods, forest fires, droughts, etc.; c) being an urban area that may present an average condition of vulnerability to climate and global change in the future; d) having reliable databases for the years under study (1992 and 2002). In line with these criteria, the CMA presents the following conditions:

- It is one of the most populous urban areas in Chile.
- It has a diversified economic base, with important presence of the industrial sector.
- It is a complex city that is composed of nine municipalities.
- It presents a large asymmetry in the distribution of socio-economic characteristics among the municipalities.
- Some of its municipalities are experiencing rapid population growth.
3. Methods for local assessment

- Although the government recognises the need for a framework to evaluate and monitor the effects of climate change, it has not yet been created.
- It has faced major natural disasters in recent years: river floods in 2002 and 2006, large forest fires in 2007 and an earthquake and tsunami in 2010. All caused severe damage to property and infrastructure.

3.2.2 The Concepción Metropolitan Area

The CMA is located between 36°35’S latitude and 72°45’W longitude and 37°00’S latitude and 73°15’W longitude in the coastal area of the Bio-Bio Region in southern-central Chile (Figure 1). It has a population of 899,999 inhabitants, with an area of 2,103 km², a density of 423.3 inhabitants per km² and a population that is 95.2% urban (NIS, 2002). The CMA is Chile’s second most-populated urban area. Since 1950, with the development of industrial activities, the CMA has experienced strong population growth, which has translated into the expansion of the built-up area and in the creation of new administrative boundaries (Goycoolea and Lagos, 2004; Pérez and Salinas, 2007). Urban expansion in the CMA has been rapid and mostly uncontrolled, more than doubling in area over the last 50 years. Between 1992 and 2002, the focus period of this study, the CMA has grown by 8.7%, with two new municipalities (Chiguayante and San Pedro de la Paz) created out of the municipality of Concepción (see Table 6) (Pérez and Salinas, 2007). The CMA is currently comprised of ten municipalities that are depicted in Figure 10) (NIS, 2011a).
Methods for local assessment

Figure 10. Location and current distribution of the municipalities of CMA. Chiguayante and San Pedro de la Paz were created in 1996 and 1995 from the division of the municipality of Concepción. Source: National Institute of Statistics, census 2002.

Table 6. Demographics of the CMA in 2002

<table>
<thead>
<tr>
<th>Municipality</th>
<th>Population</th>
<th>% of urban population</th>
<th>Municipal area (Km²)</th>
<th>% urban intercensal growth 1992-2002*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chiguayante</td>
<td>81,302</td>
<td>99.8</td>
<td>75.1</td>
<td>3.7</td>
</tr>
<tr>
<td>Concepción</td>
<td>216,061</td>
<td>98.2</td>
<td>222</td>
<td>0.4</td>
</tr>
<tr>
<td>Coronel</td>
<td>95,528</td>
<td>95.8</td>
<td>279</td>
<td>1.4</td>
</tr>
<tr>
<td>Hualqui</td>
<td>18,768</td>
<td>78.2</td>
<td>530.5</td>
<td>3.8</td>
</tr>
<tr>
<td>Lota</td>
<td>49,089</td>
<td>99.8</td>
<td>136</td>
<td>-0.2</td>
</tr>
<tr>
<td>Penco</td>
<td>46,016</td>
<td>98.6</td>
<td>107.6</td>
<td>1.4</td>
</tr>
<tr>
<td>San Pedro de la Paz</td>
<td>80,447</td>
<td>99.6</td>
<td>112.5</td>
<td>1.8</td>
</tr>
<tr>
<td>Talcahuano</td>
<td>250,348</td>
<td>99.4</td>
<td>145.8</td>
<td>4.3</td>
</tr>
<tr>
<td>Tomé</td>
<td>52,440</td>
<td>87.6</td>
<td>494.5</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>CMA</strong></td>
<td><strong>889,999</strong></td>
<td><strong>95.2</strong></td>
<td><strong>2103</strong></td>
<td><strong>0.95</strong></td>
</tr>
</tbody>
</table>


The CMA’s site is mostly in coastal plains and valleys, in areas of low elevation and gentle slope, since the presence of the Chilean coastal mountain range has conditioned settlements. It has grown around the banks of the Bio-Bio River, one of the most important watersheds in Chile. The area is characterised by the presence of beaches, dunes, cliffs, rocky areas,
marshes, estuaries, wetlands, bays, peninsulas, islands, hills and a mountain range (Hoffmann and Gysling, 2010; Rojas et al., 2013) (see Figure 12). The presence of a lagoon system, urban wetlands and forests (mostly forest plantations) dominates the CMA. While plantations are predominant in the forest landscape, native forests can also be found, the best example of which is in Chiguayante’s Nonguén National Reserve. 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 Körner, 1998) (see Figure 11).

![Figure 11](image.png)

**Figure 11.** Climograph. Source Meteorological service of Chile.

The varied terrain of the region has influenced the expansion of the CMA, which has occurred predominantly around the municipalities of Concepción and Talcahuano, which form the centre 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), and in land use conflicts and environmental and ecological problems, particularly compromising the ecological functioning of watersheds (Mardones and Vidal, 2001; Pauchard et al., 2006). Due to the physical and climatic characteristics of the CMA more than 50% of the metropolitan area is exposed to varying degrees of risk from flooding, waterlogging, earthquakes, tsunamis and landslides (Mardones and Vidal, 2001).

Droughts, storms, forest fires, landslides, floods and earthquakes have affected the CMA. Floods and earthquakes have done the most damage, with the most recent major flood occurring in 2006 (Van Heemst et al., 2013). Earthquakes in 1939 and 1960 changed the
shape of the city (Muñoz, 2012), while the latest earthquake and tsunami that affected the area in 2010 was one of the most devastating in recent Chilean history (Fritz et al., 2011; Gobierno de Chile, 2010). Due to the large presence of biomass in the area, wildfires are a major concern; 70% of the CMA municipalities are on the list of the most critical municipalities in terms of the occurrence of wildfires (NFC, 2010). Between 1985 to 2002, 13,295 fires burned 22% of the wildland areas of the CMA (NFC, 2014). An increase in the intensity and frequency of wildfires has been observed in recent years, with most of them originating in the wildland-urban interface (Peña and Valenzuela, 2008).

Rainfall deficit is another major concern in the area due to changing rainfall patterns. Recurrent droughts have affected the area (Urrutia and Lanza, 1993), and since 2006 the region has faced deficits in precipitation. The growth in water demand and recurrent droughts have led to demand competition among different needs like agriculture, industry, sanitation and domestic use. Currently, the watersheds in the area have no resources available for any new developments that would entail permanent, continuous water consumption (MPW, 2012b). Furthermore, the city’s precise location has changed once and the city has been rebuilt several times in response to natural disasters. In many cases the processes of reconstruction were unplanned and irregular, with lower-income families who lost their homes occupying at-risk areas in self-built, low-quality housing.

Since 2003, the CMA has had a single cohesive Metropolitan Urban Plan (MUPC), with explicit policies aiming to regulate the physical development of the CMA and move towards sustainable development (SEREMI MINVU (Secretaría Regional Ministerial de Vivienda y Urbanismo Región del Bío Bío), 2003). Although climate change adaptation is not explicitly recognised in the plan, the MUPC does consider many of the social factors that underpin adaptive capacity. (Rojas et al., 2013) provide more information about the MUPC.
Figure 12. CMA land use map. Source National Forest Corporation 2008.
3.3 Local approach general methods

In this study, a local approach was used to assess the CMA vulnerability to different weather-related hazards through the use of indicators in two years (1992 and 2002). The comparison of results from two years allows the researcher to track spatially over time and across the study area any changes in vulnerability and its components. It also allows for an evaluation of whether the proposed indicators can be developed objectively and systematically over time.

3.3.1 Local assessment structure

The methodology used to develop the local approach is based on Lung et al. (2013), Acosta et al. (2013) and Swart et al. (2012), who developed indicators an aggregation framework to combine the components of vulnerability. Here, two indices are calculated: a multi-hazard impact (MHI) index and an adaptive capacity (AC) index. MHI and AC are assessed separately. Vulnerability is calculated by emphasising the differences between its components of exposure, sensitivity and adaptive capacity. Figure 13 shows the general aggregation process of different indices comprising the local assessment.

For a consistent assessment, the evaluation of each of these components is based on a set of indicators. Indicators were standardised and then aggregated through a stepwise approach into MHI and AC indices. The indices were subsequently aggregated to create the vulnerability index. Indices were constructed for the years 1992 and 2002. Fuzzy logic modelling was used to generate and spatially map the local assessment for the nine municipalities in the CMA. For further detail on the structure and development of the different components, see Chapters 4 and 5.
Stage 1: Indicators framework

An indicator-based approach was used for the local analysis. Indicators simplify complexity (Hinkel, 2011a), summarise information and facilitate comparison between municipalities (Malone and Engle, 2011). They also allow vulnerability hotspots to be identified and support monitoring of vulnerability over time, which is important in climate policy (Engle, 2011). Indicators also facilitate the communication of results (Malone and Engle, 2011).

In this study, indicator selection for the MHI and AC indices were defined based on the literature, the experience of local stakeholders and data availability. Further criteria for indicator selection included the availability of a reliable 20-year time series from 1982 to 2002 for each municipality. Figure 13 details the various sections of each Chapter and shows
that the first stages of Chapters 4 and 5 correspond to the study, design and construction of a set of indicators that explain vulnerability. A detailed description of the proposed indicators for assessing exposure, sensitivity and adaptive capacity can be found in the appropriate Chapters.

**Stage 2: Aggregation approach**

An indicator-based aggregation approach for the assessment of vulnerability and its components is not simply an additive process of indicators, and should be carried out in a way that avoids assigning arbitrary weights to particular indicators. A simple additive or multiplicative process for component aggregation tends to overweight or underweight the final index when outliers are present in the indicator data, as the index is quite sensitive to them. On the other hand, in order to reduce the complexity of the calculations and allow for implementation to be easily executed by policymakers and the scientific community, the aggregation process should be coherent, flexible and transparent throughout. Different approaches have been applied for index aggregation, including additive, additive-weighted, Boolean logic and fuzzy logic. Fuzzy is a multi-valued logic approach which involves the assignment of partial or intermediate values over a well-defined range (0 to 1). This contrasts with the classical Boolean or two-valued logic approach, which only allows for the unique assignment of a condition as being either true (0) or false (1) (Gottwald, 1995), resulting in maps that can display artificial precision. Using classical logic would only allow exposure, sensitivity and adaptive capacity to be graded as adequate or inadequate, while fuzzy logic allows for the more nuanced identification of varying degrees of exposure, sensitivity and adaptive capacity (Acosta et al., 2008). Among the benefits of using fuzzy logic, we found that it permits the straightforward comparison of spatial objects with different values by first creating standardised value ranges (Espada et al., 2013). This enables a comparison of differences in the exposure, sensitivity and adaptive capacity levels between municipalities and over time. It can be used to represent the continuous nature of socio-economic indicators and better addresses the inherent uncertainty and subjectivity of the data used in the assessment of exposure, sensitivity and adaptive capacity (Acosta et al., 2013). The non-linear approach of fuzzy logic allows for a better structure of the general data distribution and the component aggregation process by reducing the effect of outliers. Here the aggregation process was performed using fuzzy set theory in ArcGIS v. 10.1 (ESRI, 2012).
Aggregation of indicators through fuzzy logic

Zadeh introduced fuzzy set theory in 1965, but it was only with the development of geographic information systems (GIS) that all the capabilities of fuzzy set theory began to be explored and the modelling of fuzzy spatial events has become possible (Robinson, 2003). In analysis using fuzzy logic in GIS, it is possible to identify spatial objects on the map, such as areas of steep slope, as members of a set like areas of landslide risk where the fuzzy membership values fall in the 0–1 range, with the value 0 indicating non-membership and 1 indicating full membership, instead of the concept of steepness being evaluated by discrete and binary values of either 'steep' or 'not steep'. 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. So far, and considering that it is relatively novel, using fuzzy tools in GIS to assess weather-related vulnerability has not been explored in the fullest possible detail. However, the benefits of using fuzzy logic to conduct vulnerability assessments have been explored by (Cheng and Tao, 2010; Eakin and Bojórquez-Tapia, 2008; Krömker et al., 2008), though none of them have explored vulnerability spatially or have mapped specific areas. Only Acosta et al. (2013) have used fuzzy logic to assess varying degrees of adaptive capacity spatially through MATLAB.

To perform the analysis, the fuzzy logic operations of ArcGIS v. 10 were used first to standardise the indicator datasets. Fuzzy overlay was then employed to aggregate individual indicators in various stages to develop the MHI, AC and V indices maps. As the fuzzy overlay functions work with cellular data, vector data for all indicators for each municipality were rasterised into a grid of 5 metres. This resolution was selected to represent administrative boundaries accurately.

Fuzzy membership functions

The attribute values of the indicators reflecting exposure, sensitivity and adaptive capacity were each transformed using linear or non-linear fuzzy membership functions to standardise each indicator into a range between 0 and 1 (see Figure 14). According to the different ways that each indicator was thought to influence municipal vulnerability, one of four different fuzzy membership functions were used to standardise the actual ranges of each indicator.
into fuzzy membership values from 0 to 1. Membership values close to 1 reflect higher possibilities of vulnerability, whilst membership values approaching 0 indicate lower possibilities of being vulnerable.

For each indicator, one of the four membership functions was used. In each case the specific membership function chosen was the one that i) best represented the relationship between the indicator and the perceived vulnerability, ii) allowed the range of value in the indicator to be maintained in the range of membership values, hence enabling differences between the municipalities to be maxima and iii) was flexible enough to handle the limitations of the indicator data.

In most cases a fuzzy linear function, either an increase or a decrease, was selected to represent assumed positive or negative linear relationships between the indicator and vulnerability (see criterion i). This can be illustrated with the indicators of the adaptive capacity where indicators such as ‘female activity rate’, ‘tertiary qualification’, ‘capacity to undertake research’ were all standardised using a positive linear membership function. As these indicator values increase, the population is generally considered to have greater opportunities to adapt successfully to climate change. In contrast, a negative linear relationship was applied to the indicator ‘distance to hospital facility’, since as this distance increases the urban population is considered to have a lower ability to cope with disasters like flooding.

However, in some cases it was not appropriate to use a linear fuzzy function to characterise a relationship, as when there was not enough robust data to have access to real minimum and maximum values (see criterion i). In such cases, a midpoint value may be the best available data (see midpoint in Figure 14). In those cases, fuzzy small and fuzzy large functions were selected instead. For example, fuzzy small was applied to ‘income inequality’, ‘literacy rate gap’ or ‘dependency ratio’, since they have an inverse relationship with adaptation. For these indicators, available data to build the fuzzy small frame were ‘mean national income inequality’, ‘mean literacy rate gap’ and ‘mean dependency ratio’. Fuzzy large was used in the case of ‘hospital beds’, ‘physician’, ‘income per capita’ and ‘municipal budget’ due to their positive relationship with adaptation. Figure 14 presents the graphical representation of the types of membership functions used. Appendix B present four examples of the fuzzy membership functions.
Methods for local assessment

Figure 14. Fuzzy membership functions used for standardization 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.

**Fuzzy overlay functions**

Once the membership values were assigned to each indicator, fuzzy overlay functions were used to aggregate each of the various components (see Figure 13), first aggregating individual indicators and finally combining them to obtain the indices MHI, AC and V. This step can be seen in Figure 17 Chapter 4, in Figure 25 in Chapter 5 and in Figure 33 in Chapter 6. Different overlay functions were used, as described below.

The fuzzy AND overlay function selects the lowest value of all inputs (Eq. (1)); consequently, other inputs with higher membership values are effectively ignored. For example, if there are four input layers with membership values for a single cell of 0.0, 0.6, 1.0 and 0.3 respectively, the AND function will return a value of 0.0. By contrast, the overlay function “OR” selects the highest membership value among all the inputs (Eq. (2)), with the result that all criteria with lower membership values are ignored. Using the same example, the value using an OR overlay will be 1.0. Therefore, both AND and OR can be said to overemphasise in the results the value from just a single input criterion. Other overlay functions such as PRODUCT, SUM and GAMMA provide results that are influenced more by the interaction between all the input criteria, with some degree of trade-off between them.

The PRODUCT overlay function multiplies all fuzzy inputs so that the resulting membership value is equal to or lower than the individual inputs (Eq. (3)). Both PRODUCT and AND are
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more restrictive functions which have an overall reducing the effect of how individual inputs are combined (Malins and Metternicht, 2006). To evaluate the ability to adapt, this implies that the presence of a single indicator with low or zero membership can reduce or even omit the results of an entire set of indicators, despite the value of any other indicators in the same area.

The SUM function combines the inputs in a linear fashion so that the combination of the evidence is more important or larger than any single input (Eq. (4)). The SUM function, like the OR function, gives greater weight to high suitability criteria. For vulnerability assessment, this means that indicators with low suitability criteria can be overshadowed by indicators or even by a single indicator with high membership values, boosting the final result. This can occur despite the existence of low membership values for indicators in the same area.

Finally, the GAMMA overlay function, which combines the SUM and PRODUCT functions (Eq. (5)), was selected in order to assess the vulnerability comprehensively. The use of GAMMA allows for the exploration of relationships between multiple input criteria. It does not simply return one existing value in a set, as OR or AND do, nor does it give too much weight to any single variable like SUM or PRODUCT. These is a fundamental point, since in the vulnerability assessment process the combination of the evidence is more important than any one input. In this regard, Lewis et al. (2014) indicate that the "GAMMA function provides the best combination of evidence while other overlay methods may give too much weight to a single variable at a given location while downplaying others” (p. 45). More information about and support for the selection and use of the GAMMA function can be found in (Ki and Ray, 2014; Malins and Metternicht, 2006; Tien et al., 2012; Vafai et al., 2013).

Lewis et al., (2014) summarise the fuzzy overlay functions as:

\[
\text{Fuzzy AND Value} = \min (\text{Arg1}, \ldots, \text{Argn}) \quad (\text{Eq. 1})
\]

\[
\text{Fuzzy OR Value} = \max (\text{Arg1}, \ldots, \text{Argn}) \quad (\text{Eq. 2})
\]

\[
\text{Fuzzy PRODUCT Value} = \text{product} (\text{Arg1}, \ldots, \text{Argn}) \quad (\text{Eq. 3})
\]

\[
\text{Fuzzy SUM Value} = 1 - \text{product} (1 - \text{Arg1}, \ldots, 1 - \text{Argn}) \quad (\text{Eq. 4})
\]

\[
\text{Fuzzy GAMMA Value} = (\text{Fuzzy SUM})^\gamma \times (\text{Fuzzy PRODUCT})^{1 - \gamma} \quad (\text{Eq. 5})
\]
Given that there is some subjectivity in choosing appropriate GAMMA values, experimentation was required to find suitable GAMMA values for the different sets of indicators for MHI and AC that allow them to be combined most effectively. In each case the GAMMA value which produced the greater differentiation between the municipalities and the output values was selected, in order to maximise the range of output values of the indicators while retaining the possibility of their remaining within the ranges of the input values.

In order to maximise differences in the level of MHI (Chapter 4), AC (Chapter 5) and V (Chapter 6) the outputs were tested for values of GAMMA \( \gamma \) in the range \([0,1]\) in 0.1 increments. This was done while taking into consideration the fact that when the GAMMA \( \gamma \) value is near 1 the output results are similar to the results of SUM; when it is near 0, the results are similar to the output result of an overlay using PRODUCT (Lewis et al., 2014).

Slightly different GAMMA values were found to be required to meet the criteria outlined for each of the MHI, AC and vulnerability indices. This may be explained by differences in the complexity of the structure of each index; MHI has 32 indicators, AC 17 indicators and V only two components. Details about the structure of each index are offered in their respective Chapters. The following GAMMA values were used in each index.

**Table 7. Fuzzy GAMMA values**

<table>
<thead>
<tr>
<th>Index</th>
<th>( \gamma )</th>
</tr>
</thead>
<tbody>
<tr>
<td>MHI</td>
<td>0.8</td>
</tr>
<tr>
<td>AC</td>
<td>0.7</td>
</tr>
<tr>
<td>V</td>
<td>0.7</td>
</tr>
</tbody>
</table>

For this evaluation, all the indicators were assigned equal weights, since in fuzzy overlay analysis weighting is not applicable. Here, increasing the weight of one indicator in favour of others does not increase the possibility of that indicator belonging to one set, since the indicator can be a member of a set or not to different degrees.

**Stage 3: Evaluation of the results**

Careful evaluation of the results is necessary to establish confidence in any index. The process consists of verifying that all indicators, memberships and overlay functions are reliable and
consistent for the analysis. In this study three modes of such analysis were performed:

**Model structural sensitivity analysis**

For each of the MHI, AC and vulnerability indices, sensitivity analyses were applied to determine the level of response to defined changes in the input indicators. This analysis sought to determine if the indices were sensitive enough to detect variation while remaining broad enough to be transferable (Vincent, 2007). This information is valuable since it identifies which indicators cause less change in the computed indices when their magnitude is changed by a defined percentage. The analysis also has information on how the result for a component such as awareness (see Chapter 5) and the membership functions respond to changes in the magnitude of the indicators, allowing the model to be restructured if necessary.

For this purpose, in each index the average value of each indicator was modified by changing its magnitude according to the following percentage values: ± 5%, ± 10%, ± 25% and ± 50%; for each indicator the specific percentage value was calculated and then added to the indicator. The indices were subsequently calculated with the modified values of the indicators. Finally, the obtained values of the indices were compared to the mean values of the respective reference model for 1992 and 2002.

**Model structural uncertainty analysis**

A model structural uncertainty analysis was performed on the MHI and AC indices to determine the uncertainties associated with the selected indicators for each index. This was done to estimate both the confidence in the set of indicators proposed and their relevance in representing exposure, sensitivity and adaptive capacity. This information is valuable since it indicates which index structure emphasises differences and therefore promotes a better comparative analysis of each index by municipality and over time.

Alternative structures were built for each of the MHI and AC indices. In the MHI index, the analysis was carried out for 1992 and 2002 in two ways: 1) by removing one indicator at a time, including repeated indicators like elderly population (see Chapter 4) and 2) by removing one complete set of indicators at a time, such as elderly population and very young population (see Chapter 4). In both cases, those indicators defining components as whole—
exposure and sensitivity—as in the case of coastal flooding and fluvial flooding, were not removed.

For the AC index, the analysis was carried out for 1992 and 2002 by 1) removing one indicator at a time and 2) removing one determinant at a time. No more than one determinant was extracted at a time because if more were removed, the model would lose validity as it began to lose the components that provide its structure (see Chapter 5).

The differences between MHI and AC lie in the structure of the two indices. MHI is composed of five hazards, each explained by exposure and sensitivity and 32 indicators in total. In the MHI index, indicators can be repeated and a single indicator can define a component as exposure. Meanwhile, the AC index is composed of three components, six determinants and 17 indicators. Indicators are not repeated and each indicator plays a greater role in explaining each determinant.

In order to compare the index obtained from different sets of indicators, the percentage difference between the results obtained from the model with all indicators and the model with indicators removed was analysed. For comparison, the arithmetic means (mean) and standard deviations (SD) were analysed.

**Correlation analysis**

A correlation analysis was conducted to identify the explanatory power and the degree of spatial relationships of each indicator in the AC index only, because it has a small number of indicators (17). This was carried out to explore the relationship between the final index and the individual indicators. A Spearman correlation analysis was performed; to remove the interaction between the indicators, a partial Spearman correlation analysis was also carried out. In the partial correlation analysis, mutual association between indicators was extracted from the coefficient of correlation between the index and the indicators.

**3.4 Representation of vulnerability**

Different formats were tested to represent the results of the local assessment, with maps and graphs ultimately selected to present the results of the evaluation of each component of vulnerability. Thus the exposure, sensitivity and adaptive capacity explored in the MHI
index, the AC index and the V index (see Figure 13) were all represented through these formats. In order to be transparent, both the various stages of research and the components of each of the indices are reported in this study, because vulnerability by itself does not provide information about its origin.

Maps allow for the spatial visualisation of results throughout the study area. For both 1992 and 2002, maps of multi-impact hazards, adaptive capacity and vulnerability illustrate each index in values from 0 to 1, where 1 represents greater impact, adaptive capacity and vulnerability. The resulting maps provide information on rank order, range values and percentage change. For supplementary analytical purposes the components of each index were also mapped and can be viewed separately. However, the presentation of all results in map form involves having several maps of results, broken down by year, component, hazard, etc., which is hardly conducive to easy interpretation. Therefore, to make the results more accessible to both scientists and stakeholders, many of the results were summarised in graphs. Radar and scatter plots were used to provide a comparison of the components in each index between municipalities. These kinds of charts permit the researcher to display a large volume of information succinctly, favouring easy comparison of results.
4

Assessing multi-hazards impacts

This chapter was adapted and accepted for publication:

4.1 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 the large amount of evidence that the impact of hazards will increase (IPCC, 2012b), 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 and thus together with the adaptive capacity 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 impact (Forzieri et al., 2016; Lung et al., 2013; McCubbin et al., 2015; Preston et al., 2008), even fewer evaluate 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 interdependence 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 (Schauer et al., 2010). Finally, the interdependence that can exist among hazards, as with heat stress and wildfires, and different scales of analysis are additional complications (Forzieri et al., 2016).

Despite these challenges, there are important advantages to tacking a multi-hazard approach (UN, 2002), which provides a more realistic assessment of the complexity of an urban area as well as an integrated view of the total impact related with weather-related hazards (IPCC, 2012b). 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/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 provide some insight about the degree of harm that climate change can cause in the near future, this approach contributes 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).

Swart et al. (2012); Schauser et al. (2010) and EEA (2012) present comprehensive reviews of indicators to assess urban exposure and sensitivity in Europe. In other parts of the world, especially in developing countries, very few studies have used indicators to assess the impacts of multiple hazards in urban areas (Wisner et al., 2015). Specific hazards such as floods and heat waves have been widely studied due to their implications for urban areas, particularly in Europe (EEA, 2012). It is comparatively easy to find feasible indicators that represent their impact. However, other hazards have been less explored in urban areas, such as vector-borne diseases like hantavirus cardiopulmonary syndrome (HCPS) (Confalonieri et al., 2007; IPCC, 2012b), or are more difficult to limit to a strictly urban scale, such as water scarcity or droughts.

In this Chapter the temporal and spatial distribution of exposure and sensitivity to multiple hazards were tracked for the CMA’s nine municipalities through the 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 a set of urban indicators to assess vulnerability to climate change. Here indicators were used in the present study to track the temporal and spatial distribution of the impact of five weather-related hazards—coastal flooding, fluvial flooding, water scarcity, heat stress and wildfire—in 1992 and 2002 through a fuzzy overlay approach using GIS. Specifically, this Chapter assesses the impact of changes in multiple hazards in all nine CMA municipalities and is framed around the following questions:

1. Which were the most exposed and most sensitive municipalities of the CMA in 1992 and 2002?
3. Which hazards have the greatest influence on the calculation of the MHI index developed for the municipalities?

This Chapter is divided into five sections; this introduction is followed by materials and methods (4.2), results (4.3), discussion (4.4) and conclusion (4.5).

4.2 Methods

4.2.1 Developing the exposure, sensitivity and overall multi-hazard index

The CMA’s MHI index was assessed in three stages, as illustrated in Figure 15. 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.

Figure 15. Stages of MHI index assessment to address weather-related impact in the CMA.
Stage 1: Conceptualisation of the indicator’s framework

Five natural hazards were analysed: coastal flooding, fluvial flooding, water scarcity, heat stress, wildfire and hanta virus (vector-borne disease). 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. Indicators levels were calculated for each municipality considering the spatial extent affected by each hazard. Coastal flooding and fluvial flooding exposure and sensitivity indicators were assessed for the area affected by flooding within the municipality. Water scarcity exposure indicators were assessed using data from either meteorological stations allocated to each municipality or from the sub-basins found within municipalities. Water scarcity sensitivity indicators were assessed using data representative for the whole municipality. Heat stress exposure indicators were assessed using data from meteorological stations allocated to each municipality, and sensitivity indicator levels were assessed for each municipality. Indicators of exposure and sensitivity to wildfires were assessed for the area at risk of wildfire within the municipality. Table 8 presents the indicators that were selected based on the literature review, the experience of local stakeholders, and data availability. Further criteria for indicator selection included the availability of a reliable 20-year time series from 1982 to 2002 for each municipality. Appendix C presents a detailed description of the CMA indicators.

**Table 8. Details of selected indicators of exposure and sensitivity**

<table>
<thead>
<tr>
<th>Coastal flooding</th>
<th>Indicators/Proxies</th>
<th>Unit/description</th>
<th>Component</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area prone to coastal flooding</td>
<td>% of municipal area in the area at risk of coastal flooding</td>
<td>Exposure</td>
<td>NSGM</td>
<td></td>
</tr>
<tr>
<td>Residents in the area</td>
<td>% of residents in the area at risk of coastal flooding</td>
<td>Sensitivity</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Critical infrastructure</td>
<td>% of transport infrastructure in the area at risk of coastal flooding</td>
<td>Sensitivity</td>
<td>MPW</td>
<td></td>
</tr>
<tr>
<td>Elderly people</td>
<td>% of population &gt; 65 years in the area at risk of coastal flooding</td>
<td>Sensitivity</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Very young people</td>
<td>% of population &lt; 5 years in the area at risk of coastal flooding</td>
<td>Sensitivity</td>
<td>NIS</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fluvial flooding</th>
<th>Indicators/Proxies</th>
<th>Unit/description</th>
<th>Component</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area prone to fluvial flooding</td>
<td>% of municipal area in the area at risk of fluvial flooding, magnitude of a 50-year flood</td>
<td>Exposure</td>
<td>NSGM</td>
<td></td>
</tr>
<tr>
<td>Residents in the area</td>
<td>% of residents in the area at risk of fluvial flooding</td>
<td>Sensitivity</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Critical infrastructure</td>
<td>% of transport infrastructure in the area at risk of fluvial flooding</td>
<td>Sensitivity</td>
<td>MPW</td>
<td></td>
</tr>
</tbody>
</table>
### Assessing multi-hazards impact

#### 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

### Water scarcity Indicators to assess changes in the exposure and sensitivity to the water scarcity

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

### Heat stress Indicators to assess changes in the exposure and sensitivity to heat stress

<table>
<thead>
<tr>
<th>Indicators/Proxies</th>
<th>Unit/description</th>
<th>Component</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very hot days</td>
<td>Frequency of very hot days, with maximum temperature &gt; 95th percentile</td>
<td>Exposure</td>
<td>MSC</td>
</tr>
<tr>
<td>Very hot nights</td>
<td>Frequency of very hot nights, with minimum temperature &gt; 95th percentile</td>
<td>Exposure</td>
<td>MSC</td>
</tr>
<tr>
<td>Heat wave</td>
<td>Number of consecutive days with maximum temperature &gt; 95th percentile</td>
<td>Exposure</td>
<td>MSC</td>
</tr>
<tr>
<td>Population density</td>
<td>Population density, people/km²</td>
<td>Exposure</td>
<td>NIS</td>
</tr>
<tr>
<td>Poverty</td>
<td>% of the population living in extreme poverty or poverty</td>
<td>Sensitivity</td>
<td>MSD</td>
</tr>
<tr>
<td>Elderly people</td>
<td>% of population &gt; 65 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
<tr>
<td>People 65+ Living Alone</td>
<td>% of households composed of one adult &gt;65 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
<tr>
<td>Very young people</td>
<td>% of population &lt; 5 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
</tbody>
</table>

### Wildfires Indicators to assess changes in the exposure and sensitivity to wildfires

<table>
<thead>
<tr>
<th>Indicators/Proxies</th>
<th>Unit/description</th>
<th>Component</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wildfires events</td>
<td>Ratio of the total number of wildfire fires to the area at risk of wildfire</td>
<td>Exposure</td>
<td>NFC</td>
</tr>
<tr>
<td>Total area burned</td>
<td>Ratio of total area burned to the area at risk of wildfire</td>
<td>Exposure</td>
<td>NFC</td>
</tr>
<tr>
<td>FWI</td>
<td>Forest fire weather index (FWI)</td>
<td>Exposure</td>
<td>MSC</td>
</tr>
<tr>
<td>Residents in the area</td>
<td>% of residents in the area at risk of wildfire</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
<tr>
<td>Critical infrastructure</td>
<td>% of transport infrastructure in area at risk of wildfire</td>
<td>Sensitivity</td>
<td>MPW</td>
</tr>
<tr>
<td>Elderly people</td>
<td>% of population &gt; 65 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
<tr>
<td>Very young people</td>
<td>% of population &lt; 5 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
</tbody>
</table>

### *‘Vector-Borne Diseases Hantavirus’ Indicators to assess changes in the exposure and sensitivity to HCPS

<table>
<thead>
<tr>
<th>Indicators/Proxies</th>
<th>Unit/description</th>
<th>Component</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incidence rate</td>
<td>Cumulative incident rate of HCPS per 100,000 inhabitants</td>
<td>Exposure</td>
<td>MH</td>
</tr>
<tr>
<td>Cases</td>
<td>Cumulative number of cases of HCPS</td>
<td>Exposure</td>
<td>MH</td>
</tr>
<tr>
<td>Mortality rate of HCPS</td>
<td>Cumulative case-mortality rates of HCPS per 100,000 inhabitants</td>
<td>Sensitivity</td>
<td>MH</td>
</tr>
<tr>
<td>Morbidity rate of HCPS</td>
<td>Cumulative case-morbidity rates of HCPS per 100,000 inhabitants</td>
<td>Sensitivity</td>
<td>MH</td>
</tr>
<tr>
<td>Overcrowding rate</td>
<td>Ratio of people to bedrooms in a home</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
<tr>
<td>Poverty</td>
<td>% of the population living in extreme poverty or poverty</td>
<td>Sensitivity</td>
<td>MSD</td>
</tr>
<tr>
<td>Elderly people</td>
<td>% of population &gt; 65 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
<tr>
<td>Very young people</td>
<td>% of population &lt; 5 years</td>
<td>Sensitivity</td>
<td>NIS</td>
</tr>
</tbody>
</table>

<sup>b</sup>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,
Stage 2: Aggregation of indicators through fuzzy logic

After building the indicators, membership values were assigned to each indicator with values ranging 0 to 1, where 1 reflects a higher exposure and sensitivity (see Chapter 3). The process of aggregation was then carried out by the application of the GAMMA fuzzy overlay function. The four stages of aggregation in this Chapter can be seen in Figure 16. In a first level of aggregation the individual indicators for each hazard were grouped into sensitivity and exposure. Subsequently, in a second level of aggregation, exposure and sensitivity to each hazard were combined to analyse the impact of the different hazards: coastal flooding, fluvial flooding, water scarcity, heat stress and wildfires. In a third level of aggregation, the combined effect of the exposure and sensitivity to all the hazards under study was established. Finally, the overall MHI index was calculated by combining all the specific hazards in a fourth level of aggregation. As is detailed in Chapter 3, various fuzzy overlay functions were studied and the GAMMA function was deemed most appropriate to explore the MHI. For all the aggregation process $\gamma = 0.8$ was selected, since it produces the largest spread of the values of the index (see Appendix C).
**Figure 16.** Set of indicators for the hazard-specific impacts. H1 (coastal flooding), H2 (fluvial flooding), H3 (water scarcity), H4 (heat stress), H5 (wildfires), H6 (vector-borne diseases), according to their exposure and sensitivity. * Due to data constraints, H6 Vector-Borne diseases is not included in this analysis.
Stage 3: Evaluation of the multi-hazard model

An integrated assessment of exposure and sensitivity to multiple hazards was conducted. In order to evaluate robustness and establish confidence in the development of the index, model structural sensitivity and uncertainty analyses were performed. It is worth noting that the non-linear character of the developed model should be carefully considered, as significant differences between the results obtained can be derived using different input parameters (fuzzy membership functions and GAMMA parameters), so carefully defined thresholds for the input parameters must be established. Model structural sensitivity and uncertainty should not be analysed separately, because incorrect conclusions may be obtained through misinterpretation of results.

Model structural sensitivity analysis

In order to determine how the MHI index responds to changes in the indicators, a sensitivity analysis was conducted. This analysis sought specifically to identify which indicators caused less change in the MHI index when its magnitude was changed by a defined percentage. This analysis also provides information on how the associated components and the membership functions responded to variations in the indicators, thus allowing the researcher to restructure the model if necessary. For this purpose, the average value of the indicators was modified by changing its magnitude as is explained in Chapter 3. The values obtained for the indices were then compared to the mean values of the reference model for 1992 and 2002.

Model structural uncertainty analysis

A well-defined model consists primarily of a well-established set of indicators. The number and character of the selected indicators depends on the how they affect the resulting index. Neither an elevated number of indicators nor a very few selected indicators for the CMA, or as in our case a set of indicators selected to respond to Chilean reality, will give consistent results without carefully analysing the uncertainty of using different indicators. In this study, a model structural uncertainty analysis was carried out by removing indicators from the 46 input indicators. Note that some indicators are used several times for different hazards, as is the case of poverty (twice), elderly people (five times), very young people (five times), critical infrastructure (three times) and residents in the area (three times). Thus, of the 32 final indicators, 14 are not repeated. For the latter, the analysis was carried out in two ways: 1) one by one, including those repeated; and 2) by indicator, including those with more than
one appearance. In both cases, the analysis excluded those indicators that define exposure or sensitivity components as a whole, as in coastal flooding and fluvial flooding.

4.3 Results

4.3.1 Exposure, sensitivity and overall multi-hazard index

First level of aggregation: CMA exposure and sensitivity by hazard

At the first level of aggregation, Figure 17 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 small decrease in sensitivity. Wildfire, heat stress and water scarcity were the hazards to which exposure and sensitivity were generally highest in all municipalities. Additionally, 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 various 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 higher than sensitivity, as with water scarcity in Coronel. The following paragraphs describe in detail the most important results by hazard.
Figure 17. Hazards from the first level of fuzzy aggregation by municipality.

Exposure is in red and sensitivity is in blue. Continuous lines represent 2002, while segmented lines represent 1992. Chiguayante and San Pedro de la Paz were created in 1996 and 1995 respectively, which is why these municipalities have no values plotted for 1992.
Coastal flooding

All municipalities except Hualqui and Chiguayante had over 20% of their area in the LECZ in both periods, but the area of exposure had decreased in most of these municipalities by 2002, except Talcahuano and Lota, where it grew. Coronel and Talcahuano showed the highest exposure in both periods, with over 70% of their area at risk of coastal flooding. The municipalities of Talcahuano, Coronel and Tomé have more than 20% of their area below five metres above sea level. From 1992 to 2002 almost all the municipalities reduced their areas exposed to coastal flooding, due to their expanding into higher elevation areas. Figure 1 shows the area below 10 metres above sea level for the municipalities of Talcahuano and Coronel, the municipalities with the greatest sensitivity in both years. Penco and Lota showed the largest decrease in sensitivity, with over 30%. This decrease in sensitivity was explained by the substantial growth of cities in higher elevation areas.

Fluvial flooding

The municipalities of Hualqui and Concepción had higher exposure and sensitivity to fluvial floods in the studied period. From 1992 to 2002 most of the municipalities saw their exposure increase. The area prone to river flooding increased the most in Penco and Talcahuano, because their expansion was carried out in floodplains. In contrast, Hualqui’s area prone to river flooding decreased because it expanded in areas outside flood zones. Concepción and Hualqui still had the highest sensitivity to fluvial flooding, while Lota and Chiguayante were the municipalities with the lowest sensitivity to fluvial flooding. In line with changes in exposure, sensitivity also increased in almost all municipalities; Lota and Coronel showed the largest increases.

Water scarcity

Exposure to water scarcity was led in both years by the coastal municipalities of Lota and Coronel, while the municipalities of Concepción, Talcahuano and Hualqui showed the greatest increases over the intervening decade. The SPI in all municipalities showed a 75% increase over the previous period, while the average WEI increase was 30%. While sensitivity was most acute in Coronel, Concepción and Talcahuano in 1992, by 2002 the municipalities of Chiguayante, Hualqui and San Pedro were the most sensitive. The presence of Chiguayante and Hualqui is explained mainly by high intercensal population growth of around 3.8 % in
both cases; Chiguayante had the highest population growth in the entire Bio-Bio region from 1992 to 2002. While Concepción, Talcahuano, Chiguayante and San Pedro showed a high consumption of water per person, in the period under study only Tomé, Coronel and Talcahuano reduced their consumption of water. Coronel and Talcahuano had the largest decreases at 28.2 and 36.6% respectively.

**Heat stress**

Exposure to heat stress increased in the studied period in all municipalities except Hualqui. This increase was explained by an overall increase in temperatures, which were higher at night. This increase in exposure was moderated by a general reduction in the density of the municipalities, which is explained by their horizontal expansion. The increase was largest in Concepción, Penco and Talcahuano. In both 1992 and 2002, Lota and Talcahuano were the municipalities that had the greatest exposure to heat stress, which is explained primarily by their comparatively high density; Hualqui has by far the lowest density. Sensitivity to heat stress decreased in all municipalities, with the largest decreases occurring in Penco and Coronel. In the studied period, Lota and Tomé showed the highest sensitivity; these municipalities were among those with higher levels of elderly people and elderly people who live alone. The overall reduction of heat stress sensitivity was explained by reductions in the poor and very young populations, which was larger in magnitude than the increase in elderly people and elderly people who live alone.

**Wildfires**

During the study period, there were no significant changes in the percentage of area susceptible to occurrence and damage from wildfire. All municipalities had more than 50% of their area exposed to wildfires in both years, and exposure increased in all of them but Talcahuano and Tomé. The ratio of the total number of wildfires to the area at risk showed that Lota and Concepción were the most exposed in both years, though most of the fires in those areas were small. Lota and Coronel had the greatest increase in the number of wildfires over the decade (17.8% and 12.2% respectively), while Penco and Talcahuano had decreases of 4.1% and 8.3% respectively. In terms of surface area affected by wildfire, Penco and Hualqui were the most affected. Sensitivity decreased in all municipalities between 1992 and 2002 and Hualqui and Tomé were the most sensitive to wildfire.
Second level of aggregation: Hazard-specific impacts on CMA municipalities

Figure 18 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.
Third level of aggregation: Overall CMA exposure and sensitivity

Figure 19 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 19. 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 20 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.

Figure 20. Absolute changes in the CMA multi-hazard impact index, 1992–2002.

Figure 21 shows that 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.
4.3.2 Results evaluation

Sensitivity analysis
The results of the sensitivity analysis of all municipalities for all hazards (see Figure 22) show that changes in indicator values up to 10% had relatively little influence on the CMA’s MHI index. In addition, changes were relatively constant in both increases and decreases in values, indicating that the model is quite robust. Beyond a 25% of increase and decrease in the indicators it was possible to see that change is higher in all components of the index. This is explained because almost all the hazards contain indicators that were in the upper end of the membership function. Therefore, no additional effect on the index occurred by increasing the values of the indicators, while a decrease in the values did affect it. Water scarcity, wildfires, coastal and river flooding presented a level of exposure and sensitivity with similar degrees of robustness, indicating that their mean change was at almost the same magnitude.
for both increases and decreases in the studied period. Only heat stress proved to be more sensitive to negative changes in the input indicators.

![Figure 22. Sensitivity analysis of the model of MHI.](image)

**Model structural uncertainty analysis**

The general results of the model structural uncertainty analysis show that the removal of indicators one by one resulted in changes in the MHI index within the range of -10% to +10% compared to the index with all 32 indicators. None of the indicators’ removals changed the index by less than 0.5%. The sum of the average changes for all removed indicators was 53.3% in 1992 and 51.1% in 2002 (see Figure 23).

Comparing the results of removing indicators (one by one) between the years under study shows that every indicator had a similar behaviour for each year. On average, the removal of indicators one by one changed the MHI index by 1.78% in 1992 and 1.70% in 2002. When the changes produced by the removal of indicators were analysed from the point of view of the components, exposure showed the higher changes. ‘WEI’, ‘SPI’ and ‘population density’ produced comparatively higher changes to the index, at 11.45% for 1992 and 14.59% for 2002. On the other hand, ‘elderly people’, ‘very young people’ and ‘residents in the area’ had
the greatest influence on the sensitivity indicators in the index, at 13.6% in 1992 and 13.5% in 2002.

Figure 23. Model structural uncertainty generated when removing each indicator from each hazard. Pink is 1992, grey is 2002.

The percentage changes in the MHI when repeated indicators like 'residents in the area', 'poverty', 'elderly people', and 'very young people' were removed are listed in Figure 23. We can see that in 1992, indicators such as 'elderly people' (+9.29% mean and +2.9% sd), 'very young people' (+9.55% mean and 3.2% sd) and 'residents in the area' (+6.12% mean and 3.1% sd) generated a greater effect in the MHI index when they were removed from the model. For 2002, meanwhile, 'very young people' (+8.10% mean and +2% sd), 'elderly people' (+7.94% mean and +3.7% sd) and 'residents in the area' (+6.20% mean and +2.6% sd) had the greatest impact on the index.
When a single indicator is removed from the initial framework, the resulting change in the MHI depends on several factors, including the data distribution of the indicators, the GAMMA parameters used for the subsequent aggregation process and the fuzzy membership function parameters used for the fuzzification process. Due to the fact that in this study GAMMA usually lies between 0.7 and 0.9, the effect of the removal of indicators depends more markedly on the range within which the removed indicator lies, specifically in the distribution of the data (i.e., its percentile profile). In this study, we found that when a removed indicator had a data distribution with a median (50th percentile) closer to 1, the effect on the MHI was low in most cases low; when the indicator’s median was further from 1, the change in the magnitude of the MHI index tended be higher and positive, thus increasing the MHI index. This phenomenon occurs because indicators with lower values tend to have a greater effect in the multiplicative term in the GAMMA overlay function when GAMMA is higher than 0.7, while the additive term is important only when the associated indicator’s component has just a few indicators. Furthermore, the large number of indicators used in this work tended to increase the effect of the multiplicative term of the fuzzy GAMMA function. For example, the indicator ‘very young people’ had a distribution centred around 0.5 for both periods with an sd of 2.65. When ‘very young people’ was removed as an entire set of indicators (five in total), an increase of 9.5% was produced in the MHI index. When ‘very young people’ was removed
as single indicator, as in the case of fluvial flooding hazard in 1992, the effect on the MHI index was lower, at 2.98%. The indicator ‘total burned area’, which presented a distribution centred on 0.6 and had an sd of 2.65 in 2002, had comparatively less effect when it was removed, at 1.16%. It is important to note that the examples given above are specifically for their data distributions and their associated aggregation structure.

4.4 Discussion

4.4.1 Assessing the multi-hazard impact index

The present Chapter 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
Assessing multi-hazards impact

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.

Limitations

Any selection of indicators can be executed arbitrarily (Hinkel, 2011a; 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.

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 socio-economic 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.
4.4.2 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 wildfires (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 Bio-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 (ECLAC, 2000; GDW, 2007). 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 to understand current and future impacts of climate change of 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. It was 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.
4.5 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.
Assessing adaptive capacity

This chapter was adapted and accepted for publication:

5.1 Introduction

Spatially explicit AC studies can provide information about a set of enabling conditions that help drive successful adaptation in order to ensure the viability of economic and social activity and quality of life (Gallopín, 2006; Juhola and Kruse, 2015; Smit and Wandel, 2006). Spatial assessment of AC can thus be considered as a first step to understand the base conditions that allow a region to adapt to change.

AC is a relative concept, both in terms of spatial distribution and in the way it responds in different contexts (Lemos et al., 2013). AC is also an aggregated condition that can be explained through a series of determining factors and processes that affect the ability of a region, area or even an individual community to cope with change (Acosta et al., 2013; Metzger and Schröter, 2006; Smit and Pilifosova, 2001). The IPCC TAR (Smit and Pilifosova 2001) was prescient in being the first to list a set of AC determinants: economic resources, technology, information and skills, infrastructure, institutions and equity. Since then, many studies have sought to expand and refine this list by focusing on social, human and political capital, health, social status, the perception of society and mechanisms of spreading (Adger et al., 2004, 2007; Armitage and Johnson, 2006; Brooks et al., 2005; Eakin and Lemos, 2006; Smit and Wandel, 2006; Yohe and Tol, 2002).

Many studies have constructed AC indices, from sectoral studies (e.g., for the agricultural industry in Australia (Fitzsimons et al., 2010) and Canada (Swanson et al., 2007)), to broader multi-sectoral national studies (e.g. the National Adaptive Capacity Index, NACI) (Vincent, 2007). Acosta et al. (2013) provided European assessments, constructing an index based on three components—awareness, ability and action—as part of a wider European climate-change vulnerability assessment (Metzger et al., 2008). This method was subsequently used in others’ studies (Greiving, 2011; Juhola et al., 2012). It has also been adapted for cities (Füssel et al., 2012; Swart et al., 2012), an arena in which there is a strong demand for suitable methods of analysing AC (Schauser et al., 2010). In this approach it is understood that each component responds to a question regarding society’s awareness of the problem, its ability to address the problem, and its limitations in taking action (Table 1).
Table 9. Questions that frame the components that determine adaptive capacity.

<table>
<thead>
<tr>
<th>Component</th>
<th>Questions</th>
<th>Frame</th>
</tr>
</thead>
<tbody>
<tr>
<td>AWARENESS</td>
<td>Is society aware of the issue and does it perceive it as a problem?</td>
<td>This component acknowledges the necessary awareness to recognise the problem of climate change and the need for adaptation.</td>
</tr>
<tr>
<td>ABILITIES</td>
<td>Is society equipped to address the problem?</td>
<td>The ability reflects the enabling factors to develop adaptation and move from awareness to action.</td>
</tr>
<tr>
<td>ACTIONS</td>
<td>Is society limited in taking action?</td>
<td>Action refers to the social, economic and institutional resources available that allow the implementation of adaptation actions or activities.</td>
</tr>
</tbody>
</table>

Source: Adapted from Schröter (2004).

In response to these questions, society’s current AC is normally assessed to factor in vulnerability to future climate change (Lung et al., 2013). Few studies explore future AC (Acosta et al., 2013; Cuaresma, 2014) due to the difficulty of projecting the socio-economic factors that underlie AC (Vincent, 2007). Analysing current AC along with future impacts introduces even more uncertainties into the assessment, as possible changes in societal AC are not necessarily recognised. This must be taken into particular consideration given the rapid and dramatic changes experienced by societies in developing countries such as Chile.

This Chapter builds on the work of Acosta et al. (2013) and Swart et al. (2012) to assess AC for the nine CMA municipalities. The three components of AC were explored through a set of determinants relevant for the hazards affecting the CMA that are studied in this thesis: coastal flooding, river flooding, water scarcity, heat stress, and wildfires. As in Chapter 4, the temporal and spatial distribution of AC is calculated for 1992 and 2002 through a fuzzy overlay approach with GIS, using the methods and study area described in Chapter 3. Specifically, this Chapter analyses recent changes in AC in all CMA municipalities and is framed around the following questions:

1. What was the adaptive capacity of the CMA in 1992 and 2002?
2. How did adaptive capacity change between municipalities in the CMA from 1992 to 2002?
3. What are the most influential indicators, components and determinants of adaptive capacity for CMA municipalities?
The Chapter is organised into the following sections: section 5.1 presents a general introduction, section 5.2 explains the materials and methods applied, section 5.3 summarises the results and section 5.4 presents a discussion of the results. Finally, section 5.5 outlines the conclusions.

5.2 Methods

5.2.1 Developing the adaptive capacity index

The structure of AC is summarised in Figure 24 and consists of three stages; first, the overall indicator framework is established based on the literature regarding AC and urban vulnerability. Second, indicators are aggregated to calculate the generic AC index. Finally, model structural sensitivity and uncertainty analyses as well as correlation analysis are carried out to test the robustness, relevance and significance of the selected indicators of exposure and sensitivity for the model outputs. A detailed description of the methods used in stages two and three was provided in Chapter 3.

Figure 24. Stages of AC assessment to address weather-related impact in the CMA.
Stage 1: Conceptualisation of the indicator framework

The following sections describe the selection of AC indicators developed to build the framework for the CMA. As in Chapter 3 the indicators were defined based on a literature review, experience of local stakeholders and data availability. Further criteria for indicator selection included the availability of a reliable 20-year time series from 1982 to 2002 for each municipality.

Figure 25. Indicators, determinants and components used to assess AC. Modified from Acosta et al. (2013).
Indicators of Awareness

Awareness describes the ability of a society to recognise the need for adaptation. Acosta et al. (2013) describe equity and knowledge as the determinants of awareness.

Equity is important for awareness because it is based on the view that a more equitable society has more possibilities of accessing resources or decision-making processes to adapt successfully. Acosta et al. used the indicators female activity and income inequality. For the CMA we used the same indicators, as they provide information about the parts of the city where people with lower socio-economic standing live (Cutter et al., 2003; Grown et al., 2005; Klasen and Schüler, 2009; O’Brien et al., 2004a).

Knowledge is important for awareness since it is used to determine how well a municipality may be able to carry out adaptation actions which require the informed participation of the population (Keskitalo, 2010). Acosta et al. used the indicators literacy rate and university enrolment ratio. For Chile, the best available information is for literacy rate and tertiary qualification. The former is generally used to represent the basic level of instruction of the population, while tertiary qualification reports on the population with a high level of education. Since the level of knowledge influences the level of awareness of climate risks, a higher level of education is desirable in the process of adaptation (Acosta et al., 2013; Cutter, 2003; EEA, 2012; O’Brien et al., 2004a; Swart et al., 2012).

Indicators of Ability

Ability seeks to evaluate the potential of a society to design, develop, implement and maintain adaptation measures. Acosta et al. (2013) describe technology and infrastructure as the determinants for ability.

Technology is important in the AC context because it informs the possibilities of designing and developing adaptation actions. Research and development (R&D) expenditure and patents are two indicators of technological ability, according to Acosta et al. (2013) and Greiving (2011). For Chile, information on the capacity to undertake research and patents was available, including the number of full-time academics per thousand inhabitants in local universities, which provides information about research and technological capacity (Brooks et al., 2005; Juhola et al., 2012). The number of patents demonstrates an ability to innovate...
and likely to adapt (Acosta et al., 2013; Greiving, 2011).

Infrastructure is important for ability since it underpins the baseline conditions for urban areas to address climate change, and to identify areas or services that may require more support. Acosta et al. (2013) used telephone lines and physicians as infrastructure indicators. For Chile, the following were used: distance to hospital, hospital beds, physicians, transport, physical housing conditions and informal networks, since these indicators reflect the capacity to cope with climate change at the city level in a more specific way (EEA, 2012; Greiving, 2011; Swart et al., 2012). Cutter et al. (2003) note that the absence of immediate medical services delays immediate relief and extends the recovery time following a disaster. Distance to hospitals is used to determine accessibility, which indicates areas around the city where people have better access to medical care. To determine the availability of medical care, the number of physicians and beds per thousand inhabitants were used as indicators (Swart et al., 2012). The physical conditions of housing in terms of basic needs such as running water, plumbing and the building materials used in the floors, walls and roof may also reflect a deficiency in housing infrastructure (Bicknell et al., 2009; Krellenberg et al., 2013; Swart et al., 2012; Vincent, 2007). Social capital plays an important role in urban areas; it refers to networks, agreements and information flows between individuals, organisations and community leaders (Franke, 2005). A high level of social capital reflects a better ability to perform adaptation actions, as it supports informed collective community action. Social capital via such informal networks such as the number of landline phones, mobile phones and internet connections was the best information available for Chilean urban areas (Hampton and Wellman, 2003; Katz et al., 2001; Wellman et al., 2001).

Indicators of Action

Action refers to the availability of social, economic and institutional resources that allow the implementation of adaptation actions. Acosta et al. (2013) describe flexibility and economic power as the determinants for action, while our research utilised the terms economic resources and institutions adapted from other research (Füssel et al., 2012; Greiving, 2011; Juhola et al., 2012). Economic Resources are relevant civic indicators of the ability to take action, as they reflect how the wealth of a society may influence economic possibilities for designing and implementing adaptive processes. The best available data to examine the wealth levels of the population for Chilean municipalities were income per capita, poverty
and the dependency ratio; these were also used by the EEA (2012) and Juhola et al. (2012).

**Institutions**, as discussed by Posey (2009), are an important determinant of capacity for action, since appropriate governance structures and robust local governments that support participative and engaged societal input may be better prepared to anticipate, plan and implement the management and cost of an adaptation process. For Chile, the best available data on institutions were municipal financial resources and master plan updates during the study period.

**Table 10.** Details of the urban indicators of adaptive capacity for the years 1992 and 2002.

<table>
<thead>
<tr>
<th>Awareness: Knowledge and equity</th>
<th>Indicators</th>
<th>Unit/description</th>
<th>Determinant</th>
<th>Source$^b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female activity rate</td>
<td>% of female working population in total working population</td>
<td>Equity</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Income inequality</td>
<td>Income ratio of top quintile to lowest quintile</td>
<td>Equity</td>
<td>MSD</td>
<td></td>
</tr>
<tr>
<td>Literacy rate</td>
<td>% of population aged 15–24 able to read</td>
<td>Knowledge</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Tertiary qualification</td>
<td>% of population aged 15–64 qualified for tertiary-level education</td>
<td>Knowledge</td>
<td>NIS</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ability: Technology, infrastructure and human health</th>
<th>Indicators</th>
<th>Unit/description</th>
<th>Determinant</th>
<th>Source$^b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity to undertake research</td>
<td>Number of scientists in R&amp;D per thousand inhabitants</td>
<td>Technology</td>
<td>ME</td>
<td></td>
</tr>
<tr>
<td>Patents</td>
<td>Number of patent applications per thousand inhabitants</td>
<td>Technology</td>
<td>ME</td>
<td></td>
</tr>
<tr>
<td>Distance to hospital facility</td>
<td>Distance to public hospitals in minutes</td>
<td>Infrastructure</td>
<td>MH</td>
<td></td>
</tr>
<tr>
<td>Hospital beds</td>
<td>Beds per thousand inhabitants</td>
<td>Infrastructure</td>
<td>MH</td>
<td></td>
</tr>
<tr>
<td>Physician</td>
<td>Physicians per thousand inhabitants</td>
<td>Infrastructure</td>
<td>MH</td>
<td></td>
</tr>
<tr>
<td>Transport</td>
<td>Kilometres of road per square kilometre</td>
<td>Infrastructure</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Physical housing conditions</td>
<td>% of dwellings lacking basic infrastructure and amenities</td>
<td>Infrastructure</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Informal networks</td>
<td>% of households with telephone, mobile phone or internet connections</td>
<td>Infrastructure</td>
<td>NIS</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Action: Economic resources, institutions and social capital</th>
<th>Indicators</th>
<th>Unit/description</th>
<th>Determinant</th>
<th>Source$^b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income per capita</td>
<td>Income per inhabitant in national currency</td>
<td>Economic Resources</td>
<td>MSD</td>
<td></td>
</tr>
<tr>
<td>Poverty</td>
<td>% of the population living in extreme poverty or poverty</td>
<td>Economic Resources</td>
<td>MSD</td>
<td></td>
</tr>
<tr>
<td>Dependency ratio</td>
<td>Ratio of population aged &lt;14 and &gt;65 to population aged 15–65</td>
<td>Economic Resources</td>
<td>NIS</td>
<td></td>
</tr>
<tr>
<td>Municipal budget</td>
<td>Municipal budget per inhabitant in national currency</td>
<td>Institutions</td>
<td>MSD</td>
<td></td>
</tr>
<tr>
<td>Master plan updates</td>
<td>Frequency of official reviews of master plan</td>
<td>Institutions</td>
<td>MSD</td>
<td></td>
</tr>
</tbody>
</table>

5.2 Assessing adaptive capacity

**Stage 2: Aggregation of indicators through fuzzy logic**

The aggregation of the indicators followed the methods described in detail in Chapter 3. Here the value 1 reflects the greatest contribution to AC. Once the membership values were assigned to each indicator, fuzzy overlay functions were used to conduct three stages of aggregation: first aggregating individual indicators to create six determinants and then grouping determinants into three components and finally combining the three components into the generic AC index; see Figure 25. As explained in Chapter 3, various fuzzy overlay functions were explored and the GAMMA function was deemed most appropriate to explore the AC. For all the aggregation process $y = 0.7$ was selected, since it produces the largest spread of the values of the index (see Appendix D).

**Stage 3: Evaluation of the adaptive capacity model**

As discussed in Hinkel (2011), the ability of a city or societal group to adapt is a theoretical construction of phenomena that are not easily observable, so it is necessary to evaluate the findings carefully to establish confidence in the AC index. The process consists of verifying that all data elements and parameter values are valid for the analysis. For this purpose, model structural sensitivity and uncertainty analyses were all carried out with the methods described in Chapter 3.

5.3 Results

5.3.1 Determinants, components and adaptive capacity index

**First level of aggregation: CMA determinants**

Figure 26 shows radar charts for the six AC determinants in each municipality within the CMA. The values are represented from a range of 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—so those two municipalities have no values plotted on the 1992 chart.

The results show contrasting values between determinants in each period and an overall increase in the value of determinants between 1992 and 2002. Only equity was shown to have very similar values in both periods, with a small decrease in the municipalities of Tomé and Lota due to an observed increase in income inequality. Knowledge was the most
Assessing adaptive capacity

important determinant to reflect increased AC for most municipalities. By contrast, economic resources, institutions and infrastructure were revealed as determinants that lowered urban AC. The relatively high level of knowledge in relation to other determinants is explained by the high literacy rate present in all municipalities. Knowledge was only constrained by the low levels of tertiary qualifications that the majority of the municipalities display, with the exception of higher figures in Concepción and San Pedro de la Paz. Low values of economic resources were determined mainly by indicators of poverty and per capita income. The low values for institutions were likely due to the combined effects of low municipal budgets and a lack of master plan updates. Finally, the low values for infrastructure were due chiefly to the limited availability of health services, as represented by doctors and hospital beds per thousand inhabitants.

According to the analysis of the determinants, in 1992 the municipalities with the highest values were Concepción and Talcahuano, while Lota, Hualqui and Tomé had lower values. By 2002, Lota, Hualqui and Tomé still had the lowest values, while San Pedro de la Paz showed the highest values. Lota, Hualqui and Penco were among those with the lowest values for almost all determinants in both periods. The indicators related to economic resources and infrastructure were the lowest for Lota, Hualqui and Penco, though they showed a relatively high level of equity. This is likely because they had a combination of low per capita income and a low level of income inequality, meaning that the bulk of the population in these municipalities was equally poor, with the exception of Lota in 2002 which showed an increased level of income inequality.

Concepción had the highest values in all the determinants for both 1992 and 2002. San Pedro de la Paz had the highest income per capita values and highest levels of income inequality for 2002. Knowledge levels remained mostly constant through the study, except Concepción for both 1992 and 2002 and San Pedro de la Paz in 2002, which showed increased levels for knowledge. This relative constancy in the knowledge determinant was mainly due to the combination of low levels of tertiary qualifications and high literacy rates among the municipalities.
Figure 26. Determinants of AC by municipality from the first fuzzy aggregation. The dashed red line represents 1992 and the blue line 2002. San Pedro de la Paz and Chiguayante were created in 1996 and 1995 respectively and thus have no values plotted for 1992.

Second level of aggregation: CMA components

Figure 27 shows that all municipalities increased their levels for the components of awareness, ability and action from 1992 to 2002. This is more apparent for action and less for awareness as the latter was more constant over time and comparatively higher than ability and action. For 2002, Coronel, Lota and Hualqui had the highest increases for ability and action. This increase was most likely due to the improvement in economic resources and infrastructure, while Concepción and Tomé showed less overall improvement between the two years, due largely to the low increase in both economic resources and institutions.

On average, the CMA showed an increase in all components during the 1992–2002 period. There were increases in awareness of 34%, in ability of 153% and of 193% for the action component. One interpretation that can be drawn from this research is that during that
Assessing adaptive capacity

decade, the CMA had greater increases in the action component for all municipalities except Hualqui. The ability component also showed an improvement in the pre-condition states suitable for urban adaptation, as most of the municipalities increased their values over this 10-year period. Increases in action and ability were explained primarily by Chile’s overall economic improvement during the 1990s.

Figure 27. The three main components of AC by municipality, 1992–2002. Blue, green and red denote awareness, ability and action respectively.
When the variation of the absolute value of a component with respect to its distance from the maximum value of (1) was analysed (see Figure 28), Concepción, San Pedro and Talcahuano were the municipalities closest to the maximum, while Hualqui, Lota and Tomé were furthest away. For all the municipalities, awareness is closer to 1, while ability is generally further away from the maximum. Whilst progress can be observed within the municipalities, it is notable that only Concepción, Talcahuano and San Pedro exceed the average of 0.5.

![Figure 28](image_url)

**Figure 28.** The three main components of AC by municipality, 1992–2002. Blue, green and red denote respectively awareness, ability and action, while triangles and circles denote 1992 and 2002 respectively.

**Third level of aggregation: CMA Adaptive capacity index**

Figure 29 shows that for 1992 Concepción, Talcahuano and Tomé were those with the highest ACs and Hualqui, Lota and Penco were those with the lowest. An AC ranking in which municipalities were arranged from highest to lowest AC levels reveals that for 2002 the municipalities with the highest and lowest levels of AC remained the same as in 1992. However, with the creation of San Pedro de la Paz and Chiguayante, in 2002 San Pedro de la Paz took the second position displacing Talcahuano to the third position, and Chiguayante took the fifth position just over Tomé. The other municipalities maintained their positions, though the most notable change was seen between Hualqui and Lota with a decrease of 20%.
Figure 29. Absolute changes in the CMA AC Index, 1992 - 2002.

Interestingly, over the period of analysis the differences between all municipalities decreased (see Figure 30). In 1992 the percentage difference between the AC of the municipalities with the highest and lowest values was 349%, but in 2002 this gap decreased to 224%.
5.3.2 Results evaluation

Model structural sensitivity analysis

The results of the sensitivity analysis of all municipalities (see Figure 31) show that changing indicator values by up to 10% had relatively little influence on the AC index and its three components. Furthermore, the changes were relatively constant in both negative and positive directions, indicating that the model is fairly robust. The AC index components exhibited similar degrees of robustness, changing their mean values at almost the same magnitude for both negative and positive changes.

After changes of 25% in both 1992 and 2002, a higher value was observed mostly in the action component, attributable principally to an increase in municipal budgets and a reduction in poverty. The increase in the ability component was primarily a consequence of the combined
rise in its indicators. In the case of awareness, its behaviour can be explained by the low variation in the values for knowledge. Most municipalities had high literacy rates to begin with, so no additional effect on the AC index was produced by increases in the values of the indicators. However, stable levels of knowledge values were constrained by the high levels of income inequality seen especially in the richest municipalities, which did respond to increases or decreases in the values of the indicators.

Figure 31. Model structural sensitivity analysis of the AC model.

Model structural uncertainty analysis

The results of model structural uncertainty analysis showed that the elimination of any indicator generated an impact on AC that varied from -33% to +32%, though no indicator had an effect of less than 0.05% on the index. The effect on the index increased when more than one indicator was removed, with the limiting case being the removal of a complete determinant. Moreover, when the model was reduced to only one indicator for each determinant, indicators such as income per capita (+26.5% mean and +15.4% sd), municipal budget (-20.6% mean and +11.9% sd) and literacy rate (-33.1% mean and -20.2% sd) generated a greater effect when removed from the model inputs. It is noteworthy that despite the fact that the literacy rate had a large effect on the index when it was removed for both years, its effect on the sd was not significant. This is because this indicator has a very
low sd, because of the high levels shown by all municipalities. The indicator showing the lowest effect on both the mean and the sd was distance to hospital (+0.6 mean and -0.16 sd), while income inequality (-4.3% mean and 20.9% sd) and female activity rate (-7.4% mean and -13.7% sd) showed the greatest effect on the sd but little effect on the mean.

When a determinant of each component was removed, it can be seen that there was similar behaviour between the two studied years, which confirms the consistency of the model. The only variation was in the magnitude of change, which resulted from the improvement in the general condition of AC in 2002 (see Table 11). Of the components, action showed the highest changes when any of its determinants were removed; for example, when economic resources was removed from the model, this significantly affected the index: +60% in 1992 and +11.7% in 2002. This demonstrates the relative importance of economic resources to the AC of the municipalities. Along with economic resources, infrastructure also positively increased the index in both 1992 and 2002. Equity, meanwhile, affected the index negatively in 1992 but positively in 2002, due to the increase in the value for income inequality. In addition, when institutions was removed, a significant decrease in the index for both periods occurred, due to the contribution represented by the municipal budget indicator. When the sds were analysed, for 1992 it can be seen that the sd for institutions was 22.3% lower than the reference model, while for 2002 it was 9.77% above the reference model. This result arose because the CMA experienced a reduction in the gap between municipal incomes between 1992 and 2002.

Table 11. Percentage difference between models without a determinant and the reference model.

<table>
<thead>
<tr>
<th>Component</th>
<th>Removed determinant</th>
<th>1992</th>
<th>2002</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Index range difference</td>
<td>Index SD difference</td>
<td>Index average difference</td>
</tr>
<tr>
<td>Awareness</td>
<td>Equity</td>
<td>+12.96</td>
<td>+18.50</td>
</tr>
<tr>
<td>Ability</td>
<td>Technology</td>
<td>+17.76</td>
<td>+22.02</td>
</tr>
<tr>
<td></td>
<td>Infrastructure</td>
<td>-37.64</td>
<td>-39.76</td>
</tr>
<tr>
<td>Action</td>
<td>Economic resources</td>
<td>+20.02</td>
<td>+16.92</td>
</tr>
</tbody>
</table>
Removing more indicators caused the index range to tend to decrease. When six indicators were removed, the range decreased in 60.1% of cases. Moreover, indices calculated with fewer indicators tended to be larger and had lower spreads than the reference model, because the reference model compensated for values that increased or decreased the AC index. The index calculated by the reference model with all indicators was better distributed along the index interval than any models with removed indicators. This indicates that simple models tended to restrict the comparative analysis of the AC between municipalities in the CMA.

**Correlation analysis**

The Spearman's rank-order correlation analysis between the AC index and the indicators showed that in both years more than 50% of the indicators showed a significant correlation between the AC index and its indicators (two-tailed $p<0.01$ and $p<0.05$) (see Table 12). In 1992, 20% of the indicators showed very weak correlation between the index and the indicator, while no indicator in 2002 presented very weak correlation between the index and the indicator.

The partial Spearman correlation analysis revealed a stronger correlation between the index and each indicator in 1992. This means that indicators such as income inequality, hospital beds, distance to hospital facility, physician, municipal budget and income per capita were strongly influenced by the values of the other indicators, as Table 12 shows. By contrast, in 2002 almost all indicators showed a slight weakening in the partial Spearman correlation compared with the Spearman correlation, with the exception of physical housing and municipal budget. This analysis confirms that all indicators significantly contributed to the AC index, though to varying degrees. The indicators tertiary qualification, income inequality, poverty and dependency ratio showed the strongest correlation with the degree of AC in both 1992 and 2002.
### Table 12. Spearman's rank correlation coefficients for AC index and indicators.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Tertiary qualification</td>
<td>1.000</td>
<td>0.929**</td>
<td>0.833**</td>
<td>0.833</td>
</tr>
<tr>
<td>Literacy rate</td>
<td>0.821*</td>
<td>0.942</td>
<td>0.583</td>
<td>0.583</td>
</tr>
<tr>
<td>Income inequality</td>
<td>-0.214</td>
<td>-0.618</td>
<td>-0.550</td>
<td>-0.550</td>
</tr>
<tr>
<td>Female activity rate</td>
<td>0.821*</td>
<td>0.844</td>
<td>0.750*</td>
<td>0.750</td>
</tr>
<tr>
<td>Informal networks</td>
<td>0.811*</td>
<td>0.835</td>
<td>0.850**</td>
<td>0.850</td>
</tr>
<tr>
<td>Physical housing conditions</td>
<td>0.714</td>
<td>0.747</td>
<td>0.450</td>
<td>0.450</td>
</tr>
<tr>
<td>Distance to hospital facility</td>
<td>-0.250</td>
<td>-0.377</td>
<td>0.050</td>
<td>-0.047</td>
</tr>
<tr>
<td>Hospital beds</td>
<td>-0.360</td>
<td>-0.446</td>
<td>-0.306</td>
<td>-0.306</td>
</tr>
<tr>
<td>Transport</td>
<td>0.750</td>
<td>0.779</td>
<td>0.717*</td>
<td>0.717</td>
</tr>
<tr>
<td>Physician</td>
<td>0.324</td>
<td>0.420</td>
<td>0.531</td>
<td>0.531</td>
</tr>
<tr>
<td>Municipal budget</td>
<td>0.286</td>
<td>0.396</td>
<td>0.067</td>
<td>0.064</td>
</tr>
<tr>
<td>Master plan updates</td>
<td>0.709</td>
<td>0.742</td>
<td>0.707*</td>
<td>0.707</td>
</tr>
<tr>
<td>Income per capita</td>
<td>0.321</td>
<td>0.418</td>
<td>0.817**</td>
<td>0.817</td>
</tr>
<tr>
<td>Poverty</td>
<td>0.821*</td>
<td>0.844</td>
<td>0.567</td>
<td>0.566</td>
</tr>
<tr>
<td>Dependency ratio</td>
<td>0.750</td>
<td>0.898</td>
<td>0.594</td>
<td>0.593</td>
</tr>
</tbody>
</table>

Sample size n=7

Sample size n=9

### 5.4 Discussion

The model provided detailed information to track the general patterns of AC within the CMA in 1992 and 2002. It also made it possible to identify the relative importance of several indicators, determinants and components of AC and their response to different social and economic changes. In addition, it showed the potential of fuzzy modelling to represent the capacity for adaptation, which offers greater flexibility in the data aggregation process by allowing partial memberships. In the following paragraphs we discuss the method and the results in greater depth.

#### 5.4.2 Assessing adaptive capacity

Compared to the two-valued logic approach, our approach provides a more close measure of the continuous factors that explain the enabling conditions for adaptation, since it represents the degree to which a given indicator belongs to the adaptation set, rather than a binary yes/no answer to the question of whether an indicator belongs (Malczewski, 2004).
This research contributes to knowledge on the assessment of multiple hazards in the urban context, especially considering that there have been few attempts to track them over time and study the impacts of multiple hazards in the context of urban climate vulnerability. The method is flexible enough to assess hazards of different nature, allowing further evaluation as a whole, since the indicators that explain exposure and sensitivity were standardised through membership functions to generate comparable values. The index structure provides access for the exposure and sensitivity of each hazard and for aggregated exposure and sensitivity as an additional value. Reporting on socio-economic and physical factors explains the impact of these hazards.

To construct the AC index, different membership functions and fuzzy overlay functions were studied. We found that the positive and negative linear functions fuzzy small and fuzzy large best represented how the indicators influenced AC. The linear functions were based on maximum and minimum values on a national level, while the small and large functions used national average values. This approach was chosen both to give a realistic approach to the determinants and to permit the subsequent calculation of indicators in other cities in the country. From this first process, it was possible to establish that the CMA had low values for most of the determinants in comparison with nationwide urban values which in Chile are driven by the metropolitan area of Santiago. For example, Santiago had 0.37 full-time academics per thousand inhabitants while the CMA had 0.26 in 2002, which highlights wide inequalities on a national level that are also observed in the CMA.

Sensitivity analysis showed that the best value of aggregation is $\gamma = 0.7$, since this value allows for the maximum differentiation between CMA municipalities, while lower (0 to 0.3) and higher (0.8 to 1) values of GAMMA reduced the spread and for the other values (0.4 to 0.6) the process of aggregation resulted in indicator values lower than any entry criterion.

**Limitations**

There are also uncertainties and limitations related with this kind of indicator-based approach. Indicator selection is based on assumptions related to current knowledge regarding adaptive capacity. Therefore, changes in the selection of indicators can modify index results (Brooks et al. 2005; Juhola et al. 2012). Interdependence between indicators, duplication (i.e. redundancy), indicator aggregation, as well as the assignation of inappropriate weight in the aggregation process can also produce uncertainties since these
intricacies could hide the real factors behind adaptive capacity (Metzger et al. 2005; Swart et al. 2012). To partially address these uncertainties and make the process of aggregation transparent, an extensive literature review was conducted, which was combined with reliable data to build the set of indicators, followed by the overlay sensitivity analysis to find the most suitable GAMMA value.

Also, the use of a generic indicator framework, may limit the applicability of the model with regard to the evaluation of specific adaptation measures (e.g. urban adaptation to floods). While it is argued that the factors that determine AC are different according to the hazard (Tol and Yohe, 2007). This research did not take into consideration hazard-specific AC. However, the determinants here explored, are relevant to explore the enabling conditions for adaptation for different hazards. Additionally, this research focuses on the assessment of the set of enabling conditions for planned adaptation at the urban scale, and thus did not directly assess the capacity of autonomous unplanned adaptation nor the individual abilities to adapt.

**Improvements and recommendations**

Further analysis should identify the components, determinants and indicators that influence most the ability to adapt, shedding light on the drivers of AC in the urban context nationwide. These are likely to change depending on the urban context and time, but in conjunction with an impact assessment, they may show specific areas that require deeper study.

It is also necessary to re-evaluate the indicators that represent AC through time, because in a developing country like Chile the socio-economic factors that explain the AC can change very fast. For instance, between 1992 and 2002 the 'literacy rate' indicator lost significance to assess the adaptive capacity, as it grew from 88% to 95%, and by 2020 it is expected to be 99%. Consequently, indicators such as 'tertiary education' become more significant to assess the awareness among the factors that explain the AC. Monitoring AC is therefore relevant not just to see changes in its spatial distribution across a city, but also to identify the most appropriate set of indicators. New census of population and housing can provide the information needed to re-evaluate AC and see if there are other indicators in the same circumstances or if new indicators could be more significant to represent the AC.
5.4.2 Adaptive capacity in the CMA

Results highlight strong differences observed between rich and poor municipalities in the CMA. All municipalities show a general increase in AC for the study period. This is explained by the economic growth experienced in Chile in the 1990s. The spatial distribution patterns of the AC index do not show significant changes between 1992 and 2002. Thus, municipalities maintain their relative positions. The low level of AC presented by poor municipalities implies that processes to alleviate the potential impacts of climate change through increased AC will not always be simple, since it will first be necessary to address the adaptation gap between rich and poor municipalities. Poor communities in developing countries such as Chile face even more challenges than the rest of society (Patt et al. 2010; Poumadère et al. 2005; UN-ISDR 2002) since they present a historical deficit of adaptation (Burton 2004). This adaptation deficit is explained not only by their economic condition but also by their location and the inequalities rising from uncontrolled and unplanned urban sprawl seen in recent decades (e.g. socio-economic residential segregation) (Henríquez et al., 2006; Hunt and Watkiss, 2010). These areas today are mostly ill-equipped for adaptation, with weak local governments, and insufficient infrastructure and services to reduce risk and vulnerability to climate change (Satterthwaite et al. 2007)

5.5 Conclusion

This Chapter assesses the capacity for generic adaptation in the CMA based on the aggregation of available indicators through a fuzzy-based model that successfully tracked how AC and its components and determinants change over time and across the study area. The main findings of this work were that fuzzy modelling has a high flexibility in the data aggregation process, combining different fuzzy membership functions and testing different fuzzy overlay functions. The fuzzy GAMMA operator was found to be an effective function for displaying the differences in AC between the CMA municipalities. In addition, the partial membership model outputs reflected a close measure of continuous factors of the dynamics of AC across the CMA. The model development and results analysis in the GIS software ArcGIS environment were straightforward and demonstrate the benefits of fuzzy set modelling to future research in the field of vulnerability to climate change. The method proposed here to
assess urban AC to climate change can be used by scientists, stakeholders and policymakers in urban areas worldwide as a basis from which to track AC both spatially and temporally.

The model’s results show that between 1992 and 2002, all the municipalities in the CMA increased their AC levels. The municipalities with lower AC levels were those with the highest increases over this period. The AC gap between the poorest and richest municipalities was reduced by 2002, but the relative differences in the levels of adaptation between municipalities were maintained over the decade. Our analysis also showed that of the three AC components, awareness was the highest in all municipalities in the study period, while action was the lowest. Action appears to have had the greatest influence upon the change in the overall AC over the decade, followed by ability and awareness.
6 Assessing the vulnerability
6.1 Introduction

The spatial assessment of the local vulnerability and its components provides information on the socio-economic and biophysical characteristics that explain the vulnerability of a given urban area. The assessment of weather-related impact in combination with the assessment of AC from the recent past provides indicators of exposure thresholds to which it would be difficult to adapt in an urban area. Therefore, it provides information on the current thresholds of vulnerability and potentially about future thresholds associated with exposure to climate change (Mastrandrea et al., 2010). Several authors argue that it is essential to understand the structural causes of current weather-related vulnerability fully in terms of planning (Blaikie et al., 2003; Bohle et al., 1994), which is seen as a priority to exploring future causes (Miller and Bowen, 2013). To understand the structural causes behind weather-related vulnerability is a pressing challenge for urban areas already overwhelmed by the impact of current weather-related change.

Despite the still open discussion on the concept of vulnerability and its components (Hinkel, 2011b; Rothman et al., 2014), there is agreement on the factors that make up vulnerability, exposure, sensitivity and capacity for adaptation (Foden et al., 2013; Ford et al., 2010; Lung et al., 2013; McCarthy et al., 2001; Polsky et al., 2007). There is also agreement that vulnerability depends on place and time (Barnett et al., 2008; O’Brien et al., 2004b). Thus, vulnerability is the result of a specific context explained by different stressors, because of which vulnerability assessments must take this complex reality to the fullest degree possible (Turner et al., 2003a).

In order to explain this complex reality, considerable progress in the factors that explain vulnerability, particularly related to poverty and inequality, has been made (Burkett et al., 2014). Nevertheless, it is still unknown how these factors interact and therefore how they should be aggregated to determine their influence on vulnerability (Hinkel, 2011b; Metzger et al., 2006). Many agree that it this is a complex, difficult concept which is not easy to assess quantitatively, so the concept has been operationalised through indicators (O’Brien et al., 2004a; Turner et al., 2003c). Today we know that vulnerability is characterised as a multidimensional concept (Cutter et al., 2003; Klein and Nicholls, 1999), and fuzzy where it is not possible to establish precise boundaries or categories (Eakin and Bojórquez-Tapia, 2008).
This final local Chapter explores vulnerability by comparing the recent weather-related hazard exposure and sensitivity (see Chapter 4) with the generic AC (see Chapter 5) of the CMA. To be coherent, the temporal and spatial distribution of vulnerability within the CMA was tracked in two recent years (for 1992 and 2002) through a fuzzy overlay approach that used GIS (see Chapter 3). This Chapter explores recent changes in vulnerability all municipalities in the CMA and is framed around the following questions:

1. How vulnerable to the different hazards studied in Chapter 4 were the municipalities in 1992 and 2002?

2. How has vulnerability changed between CMA municipalities from 1992 to 2002?

3. Which of the three components of vulnerability—exposure, sensitivity or adaptive capacity—have the greatest influence on the calculation of the vulnerability index in the municipalities?

4. Which hazards have the greatest influence on the calculation of the vulnerability index developed for the CMA’s municipalities?

This Chapter is organised with a general introduction in section 6.1, an explanation of the methods applied in section 6.2, a summary of the results obtained in section 6.3, a discussion in section 6.4 and, finally, conclusions in section 6.5.

6.2 Methods

6.2.1 Developing a vulnerability index

This research was structured around two stages, as illustrated in Figure 32. First, to obtain the overall vulnerability of the CMA, the MHI and ACI indices developed in the previous Chapters were aggregated according to the same aggregation scheme developed in the previous stages, based on a fuzzy overlay approach using ArcGIS (see Chapter 3). Finally, to test the robustness of the index a model structural sensitivity analysis was carried out.
Stage 1: Aggregation of indexes through fuzzy logic

Figure 33 shows a scheme of the two aggregation levels based on fuzzy logic. To obtain the hazard-specific vulnerability the hazard-specific impact (see Chapter 4) was combined with the lack of AC (see Chapter 5) in the first level of aggregation. The lack of AC was calculated to be coherent across the assessment of vulnerability, since here high values represent high vulnerability. To do this, aggregation of the lack of AC was calculated first by subtracting the AC from 1. The resulting values were ranked between 0 and 1, where 1 reflects a higher lack of AC. Then, to obtain the overall CMA vulnerability, MHI and the lack of AC were aggregated at a second level. The process of aggregation was carried out through the application of GAMMA fuzzy overlay function (see Chapter 3 for details).
Figure 33. Stages of vulnerability assessment to address weather-related impact in the CMA.

Stage 2: Evaluation of the results
To evaluate the robustness and confidence in the development of the index, a model structural sensitivity analysis was performed (see Chapter 3).

6.3 Results

6.3.1 Multi-hazard impact, adaptive capacity and vulnerability index

First level of aggregation: CMA hazard-specific vulnerability
Figure 34 shows the level of vulnerability of each of the five hazards evaluated for each municipality in the CMA in 1992 and 2002. Vulnerability values range from 0 (no membership) to 1 (full membership). The results show differences between municipalities by hazard and, in general, between 1992 and 2002, indicated a decrease in vulnerability. Also, most hazards showed a vulnerability above 0.5 for both years. The decrease in vulnerability experienced by the municipalities for each hazard was due primarily to the increase in AC and a decrease in sensitivity between 1992 and 2002. It is also noticeable that wildfires, heat stress and water scarcity remained the hazards with higher vulnerabilities in the CMA.
Coastal flooding follows (which does not affect the municipalities of Hualqui and Chiguayante), with fluvial floods presenting the lowest vulnerability.

Figure 34. Municipal vulnerability by hazard from the first fuzzy aggregation level, 1992–2002. The Chiguayante and San Pedro de la Paz municipalities were created in 1996 and 1995 respectively, and thus are not plotted for 1992.

**Coastal flooding**

Almost all CMA municipalities showed vulnerability to coastal flooding, though only in lower-altitude areas near the ocean. Coronel and Talcahuano were the most vulnerable in both years because of their topography, their urban development in at-risk areas and low general AC. Between 1992 and 2002 all municipalities showed a reduction in vulnerability, which is explained principally by the urban expansion undertaken at higher altitudes and by improvements in AC.
Fluvial flooding

Vulnerability to fluvial flooding is restricted to specific areas of the municipalities, which explains their widely different levels of vulnerability. Hualqui and Concepción had the highest vulnerability to fluvial flooding, while Lota was least vulnerable. Between 1992 and 2002, vulnerability decreased in all municipalities except Lota, where the increase is explained primarily by its low AC and an increase in its exposure. The overall vulnerability for the CMA is due largely to the extension of urban areas into areas at risk of fluvial flooding, aggravated by the fact that their populations are more sensitive for demographic and socio-economic reasons. Finally, the low AC presented by the majority of municipalities further contributes to the CMA’s overall vulnerability.

Water scarcity

Between 1992 and 2002 vulnerability to water scarcity remained largely unchanged; despite the increase in AC for the municipalities, the increase in exposure was larger. Factors such as low AC, population growth and high drinking water consumption determined vulnerability in the municipalities. Hualqui and Tomé experienced increases in vulnerability, while Talcahuano presented the largest decrease, explained mainly by its augmented AC and decreased sensitivity. Coronel and Lota proved to be particularly vulnerable in both 1992 and 2002, caused primarily by their high exposure and their low AC.

Heat stress

Lota was the municipality with the highest heat stress vulnerability in both years due to its low AC and combination of high population density and sensitive population. Between 1992 and 2002, all municipalities showed a small decrease in vulnerability to heat stress, explained by sensitivity decreases and improved AC. Lota, Tomé and Penco had the smallest vulnerability decreases, with Tomé and Lota featuring high proportions of sensitive populations like elderly people and elderly people living alone.

Wildfires

Wildfires were the largest contributor to vulnerability in the CMA in both 1992 and 2002. Due to high proportions of areas susceptible to wildfires, all municipalities had high vulnerability, though there were additional reasons at play in each case. In municipalities like Lota and Concepción a significant increase in the number of peri-urban wildfires was observed, while
Assessing the vulnerability

Penco presented the highest surface affected by wildfires in relation to the area at risk. The most exposed and sensitive municipalities to forest fires were also those where vulnerability was aggravated due to low AC in both years. Talcahuano and Concepción had the highest reduction in vulnerability, while Hualqui’s remained virtually unaltered.

Second level of aggregation: CMA Vulnerability index

Figure 35 presents the MHI, AC and overall vulnerability indices. The components of vulnerability are presented to favour transparency and ease of understanding of the results. Final vulnerability must be understood in relative rather than absolute terms, so the results are presented as a ranking.

Figure 35 shows that vulnerability was higher than 0.5 in both 1992 (mean 0.68) and 2002 (mean 0.56), with Penco, Tomé and Talcahuano having the highest levels of vulnerability in both years. These municipalities had exposure to all studied hazards and low AC. Concepción, San Pedro and Chiguayante had the lowest vulnerabilities, mainly due to having conditions that favoured their adaptation processes (see Chapter 5). Between 1992 and 2002, the ranking of municipalities remained largely unchanged in spite of significant socio-economic changes experienced during the study period. Additionally, between 1992 and 2002 vulnerability was reduced, due mainly to the increase in AC. The overall vulnerability represents the intrinsic predispositions of municipalities’ being adversely affected by multiple hazards. Between 1992 and 2002 the CMA’s vulnerability index declined by an average of 16.7%. The gap between the highest and lowest municipalities’ vulnerability increased from 35.4% in 1992 to 73.3% in 2002. Hualqui, Lota and Tomé had the lowest decreases in vulnerability with 7.8%, 4.5% and 9.4% respectively; Talcahuano showed a large decrease 15.36%.
Figure 35. Results show the MHI, AC and VI. White indicates low vulnerability, dark purple high vulnerability, and other colours within the spectrum intermediate levels of vulnerability.

Figure 36 shows that between 1992 and 2002 the vulnerability index of the CMA declined by an average of 16.7%. The gap between the highest and lowest municipalities’ vulnerability increased from 35.4% in 1992 to 73.3% in 2002. Hualqui, Lota and Tomé had the lowest...
decreases in vulnerability with 7.8%, 4.5% and 9.4% respectively; Talcahuano and Concepción showed a decrease.

![Figure 36. Relative changes in CMA vulnerability index, 1992–2002.](image)

### 6.3.2 Result evaluation

#### Model structural sensitivity analysis

The results of the sensitivity analysis of the vulnerability index and its components are presented in Figure 37. As in the MHI and the AC indices, changes in the indicator values up to 10% had relatively little influence on the vulnerability index. The model was observed to be fairly robust, since the changes were relatively constant with either increases or decreases in values. With a change of 25% or more, changes were higher in all components of the index, with AC the most sensitive. This is because all three components of AC—awareness, ability and action—are more sensitive after 25%.
6.4 Discussion

6.4.1 Assessing the vulnerability

It is critical for urban planning to understand a city’s baseline conditions and monitor urban evolution and geographical changes (Mastrandrea et al., 2010). This is particularly important for cities developing countries such as Chile, where social, economic, environmental and spatial changes are vertiginous. Furthermore, impacts related to the current climate, such as the effects of natural hazards, can result in considerable humanitarian, economic and environmental concerns (Miller and Bowen 2013). There is presently a limited understanding of vulnerability and its implications among local stakeholders (Funfgeld 2010; Miller and Bowen 2013). Adequate, simple and transferable methods are required to consider the specific conditions of each urban area and address temporal and context-specific vulnerability (Barnett et al. 2008; O’Brien et al. 2004).

The local assessment of the CMA’s vulnerability provides a coherent, flexible, transparent and accessible method that is operable by other scientists, stakeholders and especially planners. The method assesses the vulnerability of components, exposure, sensitivity and adaptive capacity through indices. For this vulnerability assessment, an indicator-based
Assessing the vulnerability approach, managed through ArcGIS fuzzy tools, was selected to craft a method with the aforementioned characteristics.

Fuzzy analysis proved to be a useful tool to address all uncertainties, inaccuracies or ambiguities related to data and knowledge of vulnerability assessment. Where it is not possible to establish clear boundaries, this means that class boundaries cannot be not sharp. Since vulnerability is inherently a phenomenon that cannot be classified into binary or other rigid classes, any fixed assignment of vulnerability would be strictly subjective; it might be modified according to changes in the definition of vulnerability and thus lack validity. Fuzzy logic enables vulnerability to be assessed in a consistent manner, taking into consideration its relative and nuanced nature. It is flexible enough to analyse diverse input types and powerful enough to recognise differences among them. The GAMMA function allows the effective aggregation of all components of vulnerability, providing the opportunity to explore the relationship between multiple input criteria. Unlike other aggregation functions, fuzzy GAMMA takes all entry criteria into consideration during the process, integrating multiple input criteria with high and low memberships in the most efficient way. The results obtained with fuzzy logic were presented so as to highlight the differences in rankings among municipalities. Since it is not possible to say, for example, that the vulnerability of Penco is 0.50, this kind of analysis lacks the precision required to perform this representation accurately; therefore, the wrong message could be delivered.

The entire assessment of vulnerability is built on the fuzzy tools of ArcGIS. Since ArcGIS provides an efficient platform to assess spatially and map vulnerability and its components at the same time, it is widely used, thus providing access to a broader user audience. Fuzzy tools provide a flexible, transparent and simple assessment of the multiple criteria that explain vulnerability. They not only favour spatial assessment of vulnerability, but also spatial representation through maps and temporal assessments, which is consistent with the benefits of using fuzzy logic in GIS (Pradhan, 2011).

Furthermore, the structure of the index, based on MHI and AC, promotes transparency and a greater understanding of the factors that explain vulnerability. Its structure not only allows interested users to review vulnerability by overall results or by specific hazards, but also to review the results of the various stages of aggregation to identify the causes of the final results. The index also permits a simple examination of the hazards and components of vulnerability in relation to one another, highlighting the observable differences between
CMA municipalities, which proved be significant. Combining spatial and temporal vulnerability analysis allows for the monitoring of historical processes that explain vulnerability and its evolution, such as lack of planning, inequalities, etc. Finally, the index structure enables the identification of both overall vulnerability and hazard-specific vulnerabilities. According to Preston et al. (2007), vulnerability assessments are much more useful if they favour the understanding of the factors behind vulnerability, including socio-economic and biophysical causes.

The application of the method provides potentially valuable information, especially for the identification of municipalities that are more vulnerable, changes in vulnerability across municipalities, vulnerability components that were most influential in determining overall vulnerability and the hazards that were most relevant to overall vulnerability.

**Limitations**

Specific limitations arise from this vulnerability assessment, especially in the selection of indicators and in assessing the vulnerability components MHI and AC, which are being presented separately (Chapters 4 and 5). Generally, because researchers are still exploring how components of vulnerability interact to explain overall vulnerability (Hinkel, 2011b; Metzger et al., 2006), the obtained results should be used with caution. Fuzzy logic was selected in this study precisely because of its capacity to address uncertainties inherently related to the analysis of vulnerability. To mitigate uncertainty to the greatest extent possible, a model structural sensitivity analysis was performed to identify the most appropriate value of GAMMA for aggregating components. The overall vulnerability index should be understood as additional information that can enrich the discussion on the methods and processes of aggregation. Thus, the emphasis of the vulnerability assessment should be on hazard-specific factors, which were presented here by ranking municipalities rather than in numerical terms to avoid any false sense of precision.

Moreover, it is important to highlight the sometimes diffuse line between sensitivity and AC. While some key indicators are the same for both, a given indicator can carry different meanings. For example, a poorer society will be more sensitive to climate change, but a poorer society will also have less capacity to adapt successfully to climate change. This has different implications from the point of view of vulnerability assessment; since poverty was considered twice in the assessment, its importance in the analysis has more influence than
an indicator that appears only once. Thus, it is necessary to explain the context of these indicators and investigate further the relationship between the components of vulnerability.

**Improvements and recommendations**

To improve the CMA’s vulnerability assessment, it would be beneficial to incorporate additional hazards that have historically affected the CMA but for which there was insufficient data for the 1992 and 2002 period. It would also be advisable to analyse the capacity for adaptation to specific hazards.

Because the vulnerability of different groups or sectors varies (Barnett et al., 2008), it is recommendable to explore the CMA’s sectoral vulnerability to climate change to strengthen the overall understanding of the urban city scale system. Some nationwide attempts at sectoral analysis of impacts have already been carried out in Chile (ECLAC, 2012c), but the metropolitan scale is more suitable, as many scholars have pointed out that vulnerability is temporally and spatially specific (Barnett et al. 2008; Burkett et al. 2014; Hinkel 2008; O’Brien et al. 2007). For example, CMA municipalities are affected in different ways and to varying degrees by a single storm (Pizarro and Castillo 2006). Further studies can address cross-sectoral vulnerability (Holman et al., 2016).

It is also necessary to continue to monitor vulnerability. Tracking changes in the factors that explain vulnerability not only expands our understanding of a city’s condition, but also provides knowledge of the elements that structure vulnerability; for example, this study showed that literacy rate was an indicator that will cease to be relevant in Chile to assess AC, because it is already so high in all municipalities. Moreover, since the MHI, AC and vulnerability indices developed here are based largely on census data, the hazards, components and ultimately the indices can be updated with new census data.

In this study, MHI and AC were assessed separately and vulnerability was calculated by emphasising the differences between the components of exposure, sensitivity and AC, which have been widely adopted to analyse the complex and interdependent reality of vulnerability in a simplified way (Greiving, 2011; Lung et al., 2013). Such a simplified analysis makes it possible to generate a standardised and transferable evaluation method. However, it does not consider or evaluate the interdependence among vulnerability components, which remains an avenue of future research.
Finally, it would be advisable to make a formal presentation of the vulnerability assessment process and results to key stakeholders like municipal planners, decision-makers from ministries and experts from relevant sectors universities and non-governmental organizations NGOs. This would validate the results with empirical knowledge and provide feedback to improve the user-friendliness, transparency and relevance of the method.

6.4.2 Vulnerability on the CMA

The vulnerability index revealed that vulnerability varies from place to place; some municipalities presented high levels of exposure or sensitivity to hazards, while others were affected by low AC. The differences in vulnerability components are relevant to urban planning and for providing a better understanding of the evolution of the factors that explain vulnerability throughout the CMA. The MHI and AC were evaluated, tracked and analysed in all nine CMA municipalities. From the combination of the MHI and AC indices in both 1992 and 2002, it is possible to make some general statements about vulnerability across the CMA.

The overall vulnerability of the CMA municipalities was meaningfully high in both 1992 and 2002. Most municipalities were exposed to more than one hazard, with wildfires shown to be of greatest concern in both years. In the CMA, both exposure and AC were relevant to explain vulnerability, with sensitivity of lesser importance, because the CMA’s exposure is historical and explained by its initial location and subsequent expansion. Meanwhile, the AC, which is explained mainly by socio-economic factors, proved to be low in nearly all CMA municipalities; outside of San Pedro and Concepción, the rest had poor conditions for favouring adaptation. However, consistent with what was reported by Burkett et al. (2014), it was observed that socio-economic characteristics may become much more important than biophysical factors in the definition of municipal vulnerability. Factors such as socio-economic conditions, infrastructure and the demographic structure of the municipalities influence vulnerability through the conjunction of sensitivity and AC.

In the studied period, an increase in exposure, a decrease in sensitivity and an increase in the AC were generally observed, due to the CMA’s demographic changes and a general improvement in Chile’s economic conditions. Exposure grew because nearly all hazards, led by water scarcity and excluding coastal flooding, increased their exposure (Chapter 4). The sensitivity decreases in almost all hazards except fluvial floods were explained mainly by demographic changes; there are fewer children and a larger adult population (Chapter 4).
Meanwhile, AC increased mainly due to Chile’s improved socio-economic conditions (Chapter 5). These changes in the components of vulnerability meant that the CMA’s overall vulnerability decreased. However, this decline was small and vulnerability was still high, ranging between 0.5 and 0.6 out of 1 in 2002, particularly in Tomé, Penco and Talcahuano, which in both 1992 and 2002 showed the greatest vulnerability. Moreover, based on current indicators, only Concepción and San Pedro presented better conditions for coping with the impact of multiple hazards. Another important aspect of the CMA’s vulnerability is that the municipalities’ ranking did not change; the most vulnerable municipalities in 1992 were also the most vulnerable in 2002. This implies that the economic changes experienced by the municipalities were not sufficient to alter their ranking.

Most municipalities presented different levels of vulnerability between 1992 and 2002, with the exception of Hualqui and Coronel. Final vulnerability was explained by different factors depending on the municipality; Lota’s vulnerability was largely due to its low AC and Tomé’s to its exposure, while San Pedro’s vulnerability was explained by its sensitivity. These differences demonstrate the importance of studying the specific factors that explain vulnerability, which may vary widely from place to place (Barnett et al., 2008).

Wildfires, water scarcity and heat stress demand special attention, but all hazards should be considered because they affect almost all municipalities. Their effect throughout the CMA and the population they could affect should be considered carefully. Due to the observed and expected reduction in precipitation in the area, the exposure to these hazards could be increased (González et al., 2011).

### 6.4.3 Relevance to planning

These assessments were carried out to inform the future sectorial urban adaptation plan, which is framed within the NAP (MoE, 2014). This plan explicitly describes the necessity to develop a set of indicators to identify and track the vulnerability of the urban areas to provide a better understanding of the basal condition of the cities for adaptation. Therefore, understanding the drivers that explain the vulnerability of urban areas to multiple hazards is the ultimate goal to strengthen urban planning regulations in the cities. Nevertheless, neither the NAP nor the National Action Plan on Climate Change 2017-2022 (NAPCC) specify how this should be done (MoE, 2015).
Results presented here are primarily meant to inform local stakeholders (not just the government, but also the community) and increase their awareness about the relative vulnerability to multiple hazards. This is necessary since many initiatives are designed and implemented at the local level (Bulkeley and Betsill, 2003). This is the first assessment of the vulnerability to multiple hazards in Chile and the CMA. Therefore, it can provide substantial insight about the vulnerability drivers their interactions as well as help to identify areas that require further support or deeper study. Also, it can stimulate the discussion among stakeholders about the drivers, the necessity of deeper study and/or coordination between municipalities (i.e. coordination in supramunicipal planning as in the Intermunicipal Regulatory Plan). In turn, it can promote capacity building and knowledge transfer, because there is no urban adaptation plan in Chile, there has not been enough training or knowledge transfer. Considering the Chilean administrative structure, it is necessary that the results of the vulnerability assessment be integrated into the structure of decision-making, territorial planning, resource management, risk management (see the next Strategic Plan on Disaster Risk Management (PDR) 2015-2018) etc. Therefore, results of this evaluation are not only relevant to urban planners in municipalities or regions, but also to risk and natural resource managers in ministerial offices. The use of the results by all of them would allow to transcribe what was learned in the future territorial implementation of the adaptation actions. It is important to note that this is a benchmark multi-hazard vulnerability assessment in 1992 and 2002 and should not be understood as an isolated effort. Instead, it should be the starting point for a continuous process of research, discussion and development of adaptation actions.

Stakeholders have access to the desegregated results for each of the components of vulnerability, from which the specific determinants and indicators that explain vulnerability by the municipality can be consulted. This information is relevant for the comparative analysis of municipalities, but also for the temporal analysis to identify the evolution of specific indicators of interest. This information at the municipal or city scale could help to focus response actions, either as a part of the spatial planning process or independently. For example, in the case of the municipalities of Concepción and San Pedro, which presented the highest value in the indicator water consumption, it could help to study the possibility of reducing the sensitivity to water scarcity through the reduction in the drinking water. Identify specific areas to address by the municipality permit to manage the resources that are always scarce at the local level.
The results can also be used to inform future specific research in the field. For example, here it was demonstrated how the older and, even more, the older and poorer population represents a major challenge for the CMA in the face of climate change. Therefore, I suggest to perform an update of the cadastre of this population for it to fulfil at least two functions. In the case of risk planning, it would enable a faster and more efficient evacuation of these population groups (this information can feed the PDR). In turn, it would allow to identify municipalities and areas of the city that would require improvements in the urban design, such as developing accessible evacuation routes. Another example from the results shows that even though an increase in the adaptive capacity of the CMA was observed, this remained low. However, there is an intrinsic knowledge in this population due to its repeated exposure to diverse hazards that, surely, if evaluated, would help in the development of adaptation actions.

6.5 Conclusion

This Chapter presents a local assessment of the CMA’s vulnerability, based on the aggregation of MHI and AC indices through fuzzy logic. The methodology successfully tracked changes in the components of vulnerability spatially and over time through all nine CMA municipalities. The potential of fuzzy logic to address the complex nature of vulnerability and to assess and monitor vulnerability in a coherent way was demonstrated. The role of the fuzzy overlap function GAMMA was particularly recognised, as it favours a better balance in the aggregation of several indicators, components and hazards, because it can account for the particularities of each entry in the process of aggregation. Moreover, ArcGIS proved to favour flexibility, transparency and simplicity in the aggregation of multiple input criteria, allowing for spatial representation on maps. This assessment provides a method that is simple, accessible, practical and operable by scientists, stakeholders and especially planners to expand their knowledge of the structural factors that explain weather-related vulnerability. The method favours the benchmarking of the components of vulnerability to be explored through all the municipalities and over time and its implementation in other urban areas.

The results establish that vulnerability was high throughout all CMA municipalities in both 1992 and 2002, which was mainly explained by relatively high exposure levels and relatively low AC levels among the municipalities. Tomé, Penco and Talcahuano showed the most
vulnerability in both 1992 and 2002, while the overall vulnerability of the CMA declined slightly. This was due primarily to increased AC and decreased sensitivity, suggesting that socio-economic characteristics may become much more important than biophysical factors in defining the CMA’s vulnerability. There was no change in the ranking of the municipalities from 1992 to 2002; wildfires and water scarcity were the most influential hazards on vulnerability. However, all hazards should be equally considered, as most municipalities were affected by multiple hazards.
General discussion and conclusion
7.1 Introduction

The aim of this thesis is to assess the vulnerability of the main coastal urban areas of Chile to offer an understanding of the preconditions for planned adaptation at the municipal scale. Chapter 2 assessed the future vulnerability of nine coastal cities in Chile for the years 2025, 2055 and 2085. The Concepción Metropolitan Area was identified as the city most vulnerable, and was subsequently selected to study in depth its vulnerability to multiple weather-related hazards in the recent past in 1992 and 2002. The main research findings are discussed in section 7.2, where the novelty of this research and its consistency with other studies are identified. Section 7.3 then discusses and justifies several subjective methodological choices in this research. Subsequently, section 7.4 details the original contributions to knowledge followed by the overall conclusions, which are presented in section 7.5.

7.2 Research findings

7.2.1 Future vulnerability of the coastal cities

The first objective of my research was to understand the differences in future vulnerability to climate and socio-economic change between nine of the largest coastal urban areas of Chile, and I found that:

**Different drivers explain the increasing overall vulnerability of the cities**

This novel vulnerability assessment indicates that all the cities are exposed to more than one hazard, and different hazards have a different influence on the vulnerability of each city. I also found that the increasing overall vulnerability of the cities is mainly driven by the increase in the exposure and adaptive capacity. The exposure of the cities is driven by a warmer and drier future. The general increase in temperature affects cities in the north more intensely (about 3°C by 2080). Precipitation projections show a strong decrease over time from La Serena to Puerto Montt (about 20% by 2080). These cities could face an especially significant increase in drought by 2050. This means that communities and business in these cities may be more exposed to water scarcity than they are today. The largest decreases in precipitation occur in La Serena and Valparaíso in winter and spring, the months in which rainfall is normally most frequent. Concepción and Valdivia present the greatest exposure to coastal flooding. On the other hand, over time, cities from Iquique to Valparaiso appear to...
be better placed to cope with the combined climatic and socio-economic change than the rest of the cities, mainly due to the economic improvement. Nevertheless, this area historically presents great economic inequality. Therefore, an estimated greater overall adaptive capacity driven by general economic improvement does not imply that cities or people will necessarily be more capable of adapting. Through time and across scenarios, Concepción Metropolitan Area is the city with the highest number of indicators that drive vulnerability and as a result is the most vulnerable. This new knowledge implies that cities therefore need to have the capacity to address vulnerability to different hazards, and to coordinate measures across municipalities to address these hazards. It also implies that all cities, even the less vulnerable, require deeper long-term studies to identify future vulnerability trends within the cities. Studies like this one can help stakeholders to improve their understanding of the driving factors of the spatial and temporal patterns of vulnerability in the urban context, focusing attention on those factors rather than in the final vulnerability score (Smit and Wandel, 2006).

**All coastal cities in Chile will be warmer and drier**

Consistently with other research in the area, I found that almost all the cities under the studied climate scenarios could experience a reduction in precipitation in the future (Allen et al., 2013; Boulanger et al., 2014; Parish et al., 2012; Rijsberman, 2006; Sillmann et al., 2013; Villarroel, 2013). According to my findings, over the next 60 years precipitation is expected to change between +15% in the northernmost cities and -26% in central cities. Contradictory results were observed between some GCMs; Arica, Iquique and Antofagasta present both increases and decreases in precipitation, which could be explained by the already very small amount of precipitation in those urban areas. This was previously observed by CONAMA, (2006). Water scarcity is, as a result, one of the major challenges for urban areas. Cities will need to share increasingly scarce water resources with the main economic activities of the country: mining and agriculture (ECLAC, 2012a). It is also expected that under all future climate scenarios the cities will experience temperature increases (Allen et al., 2013; Sillmann et al., 2013; Villarroel, 2013; Vincent et al., 2005). My findings show mean temperature increases over the next 60 years can range from 3.2°C in the northernmost cities to 0.5°C in the southernmost cities. The increase is nevertheless largest for the minimum temperature (Donat et al., 2013; Dufek et al., 2008). Due to the increase in the minimum temperature heat
stress increase in all the cities, mainly in winter. Consequently, this is expected to have effects such as an increase of heat stress, vector diseases and/or wildfires (ECLAC, 2012a).

**Socio-economic change will greatly affect the vulnerability of coastal cities in Chile**

The socio-economic components of the future vulnerability to climate change had not been previously explored. In doing so here, I find that both sensitivity and adaptive capacity of all the cities will be strongly influenced by demographic changes, particularly by the growing elderly population (i.e. the increase in the elderly people, 65+, and the oldest old, 75+). Also, economic projections for the cities show an improvement in economic conditions across all scenarios (see section 2.3). The relevance of a growing elderly population has been widely highlighted in the study of future vulnerability (IPCC, 2007). A more long-lived and healthy society is in a better condition to adapt to climate change (Lutz, 2010). However, despite the fact that Chile has in recent years significantly increased life expectancy, the elderly population is largely affected by poverty or extreme poverty, a relationship that has increased in recent years mainly in cities (MPD, 2011). A similar relationship between poverty and the elderly is observed in other developing and developed countries, as has been described in (ECLAC, 2002; He et al., 2016; Jaspers-Faijer, 2008). Even though projections in my study present improving economic conditions for cities, it is not possible to say whether the increase in wealth will directly benefit the elderly. Given that poverty is one of the main factors contributing to social vulnerability (Cutter, 2003), it is necessary to go deeper into the issue. In doing so, the historical condition of poverty and inequality in Chile, which is particularly evident in urban areas, needs to be considered (OECD, 2011). Therefore, more research is required to understand whether the elderly population would have in practice not only health but also economic capacity to adapt in the near future. Currently few studies address the future vulnerability of the old population to multiple hazards (Carter et al., 2016), and none of them in urban areas.

**The Concepción Metropolitan Area is the most vulnerable city**

Overall, this study (Chapter 2) allows to understand the differences in future vulnerability to climate and socio-economic change between nine of the largest coastal urban areas of Chile. Furthermore, it enables the identification of a city that, given its characteristics, provides the greatest possible insight into Chilean urban vulnerability. Through time and across scenarios, I identify the Metropolitan Area of Concepción as the most vulnerable city. It was found to have comparatively greater exposure and sensitivity, and, as a result, greater vulnerability
than all other cities studied. This city could present temperature increases of 1°C to 1.5°C, and a large decrease in precipitation of 10% to 15% in the next 60 years. This city also has the greatest proportion of land in areas susceptible to coastal flooding, around 11.3% of LECZ. At the same time, it presents an initially high and growing sensitive population, represented by (mainly) older adults, children and inhabitants in exposed areas, which grow by 20-55%, 2-7% and 10.2% respectively in the next 60 years. These changes will have a great effect on the general vulnerability of the city, home to the second largest concentration of population in the country.

More broadly, the results allow to identify a city with a set of characteristics (See section 3.2.1) and exposed to a set of diverse biophysical and socio-economic factors that explain its vulnerability that enable to study the vulnerability to multiple hazards within a single urban area. This allows for a cost-effective way to study the vulnerability of Chilean cities, as it eliminates the need to study different cities in depth to get a full picture of the vulnerability to different hazards across Chilean urban areas.

### 7.2.2 Recent past vulnerability of the Concepción Metropolitan Area

The second objective of my thesis was to understand recent change in multi-hazard impact, adaptive capacity and vulnerability between 1992 and 2002 of the Concepción Metropolitan Area, the city that was identified as the most vulnerable in Chile in chapter 2. Important results and outcomes of this work are:

**A novel assessment of the vulnerability to multiple hazards in the Concepción Metropolitan Area**

This is the first study of the vulnerability to multiple hazards in the CMA and in Chile. I identify that a slight reduction in the overall vulnerability observed between 1992 and 2002 was driven by different causes in each municipality. I also observed that the vulnerability varies between municipalities and between different hazards. Additionally, I found that there was no change in the ranking of the relative vulnerability of municipalities from 1992 to 2002. This finding is most informative and useful for cities, since, it shows that despite the improvement in socio-economic factors, the inequity observed between the municipalities was the factor influencing vulnerability scores the most. Vulnerability is no longer just a matter of wealth but also of distribution of it across the municipalities. Similar findings in others urban areas have been reported (Lahsen et al., 2010; Satterthwaite, 2007). In 1992
and 2002, the vulnerability of municipalities was strongly influenced by the gaps in indicators such as poverty, municipal budget and tertiary education among municipalities (see chapter 5). For example, rich municipalities like Concepción and San Pedro de la Paz increase their population with tertiary education more than the rest of the municipalities. This increases the vulnerability gap between municipalities. In contrast, the municipal budget increases in almost all municipalities, decreasing as a result the vulnerability gap between them. Stakeholders in municipal governments can use this disaggregated information to improve their understanding to develop and plan measures for vulnerability reduction.

**Socio-economic factors influence more the vulnerability than biophysical factors**

Contrary to what was expected at the beginning of this research, the socio-economic factors (e.g. inequality, poverty, elderly population) were more determinant than the biophysical factors (e.g. very hot days, area prone to flooding) in the overall vulnerability of the municipalities. This is because, due to physical and climatic characteristics, more than 50% of the city’s area is exposed to varying degrees of risk from flooding, waterlogging, earthquakes, tsunamis and landslides (Mardones and Vidal, 2001). Sensitivity and adaptive capacity therefore play a significant role in reducing the widespread vulnerability. Other studies have also suggested that socio-economic conditions are often more important than biophysical ones in determining population vulnerability (e.g. Preston et al., 2008). Similar results have been observed in other developing countries and emerging economies. There, poverty and inequality, for instance, remain key determinants of the vulnerability. Consequently, strategies to promote poverty alleviation or facilitate income redistribution, present an opportunity to reduce vulnerability (ECLAC, 2013). Since the human component is so relevant, the decision-making processes and the planning of human development in the city may also reduce the vulnerability of the population. From just 1992 to 2002 an increase in adaptive capacity and a reduction of the sensitivity were observed, particularly in the poorest municipalities. Also, the change in exposure was shown to be the result of old patterns of urban and social development, for example the extension of the city to areas near forest or in the river flood area (see Chapter 4). This indicates the importance of thinking long-term about future urban management decisions.
Changes in the socio-economic condition and the ageing population were the key drivers of the vulnerability

This research is the first to identify the key drivers ‘socio-economic condition’ and ‘age structure’ in the definition of the vulnerability of the Concepción Metropolitan Area population. The economic growth experienced in the country in the 1990s was observed in factors such as the reduction in poverty, the increase in the municipal budget, and tertiary education. These strongly influence the adaptive capacity, which increased between the studied years. However, the improvement in the socio-economic condition was not accompanied by equity. The vulnerability gap between the richest and poorest municipalities is maintained over time. For municipalities to reduce their vulnerability by increasing adaptive capacity, one strategy could be to focus on reducing the vulnerability gaps through factors such as the municipal budget, master plan updates or physical housing conditions (see Chapter 5).

Changes in the age structure also had a great influence in the overall vulnerability. The elderly population was 5.3% in 1992 and 6.7% in 2002. Today, they comprise 10.6% of the CMA’s population (NIS, 2011b). This population is not equally distributed across the municipalities, with many older people concentrated in some of the poorest municipalities. The elderly population is vulnerable for both health and economic reasons. They typically have less financial resources and are often more susceptible to poverty. Between 2000 and 2003, Chile’s elderly population below the poverty line in urban areas increased from 5.3% to 6.9% (MPD, 2011). The elderly are also located in municipalities highly exposed to multiple-hazards, and must therefore be considered a priority group in terms of planning for their evacuation. To reduce their vulnerability, municipalities will have to provide the infrastructure and services needed by an ageing population (for example – access to hospitals).

Wildfires and water scarcity were the most influential drivers of the vulnerability

This research is the first to find that the overall exposure of Concepción Metropolitan Area, and therefore its overall vulnerability, was strongly influenced by wildfires and water scarcity. These hazards affect all the city’s municipalities to a different degree. Therefore, to reduce the vulnerability, the municipalities will require great coordination and clear definition of the responsibilities for the design of actions. The vulnerability to both hazards was strongly influenced by the reduction in precipitation and the socio-economic changes experienced by
the city. The urban expansion towards forest areas, the large presence of forests around the city and the reduction in precipitation are some of the main drivers of the increase in exposure and thus of vulnerability to wildfires. Similar factors have been highlighted by other studies (Lindner et al., 2008; Pauchard et al., 2006; Peña and Valenzuela, 2008). These results demonstrate the necessity of long-term coordination among municipalities in the city to reduce exposure to wildfires. There is an opportunity to reduce vulnerability through planning especially in the wildland-urban interface. Vulnerability to water scarcity is largely explained by its initially high and increasing exposure. Currently this area has no resources to meet new water consumption demands (MPW, 2012). Therefore, it is advisable that municipalities, the sanitary sector and the national government should look into coordinating and improving the management of the water available. Municipalities can coordinate incentives for efficient water consumption, leakage reduction in the network, increasing green infrastructure within cities, and collecting greywater for watering and cleaning.

### 7.3 Methods

Each chapter in this thesis includes a detailed review of the methods and their limitations. This section justifies and discusses a number of subjective methodological choices made across this research.

#### 7.3.1 Scale

The effects of climate change can vary at particular points in space and time according to the level of analysis. For example, even though all cities in the centre of the country are exposed to water scarcity, their sensitivity and capacity for adaptation are different, and consequently their vulnerability is too. Therefore, a multi-scalar spatial and temporal approach was used, which can provide a greater understanding of vulnerability and adaptation (O’Brien et al., 2004b).

In this thesis two levels of spatial analysis, were explored, regional and local, responding to the two main research objectives (see Section 1.3). To address the first objective, the future vulnerability to socio-economic and climatic change at the city (i.e. regional) level was evaluated. To address the second objective, the vulnerability to multiple hazards in the recent past was evaluated within a city at the municipal level (local). These two levels of analysis respond not only to the research objectives but also to the availability, processing
and management of the data. However, using two levels of analysis involves keeping certain factors in mind:

Spatial scale

The analysis of vulnerability at the regional level allows vulnerability to be addressed without requiring data with great level of detail, which could be economically costly to acquire or require a large processing time. In turn, data at this level is normally available for all cities and presents consistency. Therefore, this level of spatial analysis can be performed for all cities offering the possibility to make comparisons between cities, identifying hotspots, summarising information, and providing information about the regional patterns and processes. This simplified and understandable information can meet the demands of policy makers and planners, who generally need to make decisions within the administrative units. However, this scale does not provide a greater understanding of vulnerability within cities. Therefore, care should be taken to avoid transmitting erroneous messages associated to the degree of detail of the results at this level of analysis.

The local or municipal level is particularly useful for identifying in greater detail where and why certain areas are vulnerable within the city. It also considers the smaller administrative unit of the territory, the municipality, which is more appropriate to the needs of urban or regional planners, who must design and manage plans for municipalities. This level of analysis also allows access to a greater availability of detailed and complex data, particularly socio-economic data. However, this level of analysis requires more data and time, since there is much data to explore and not all the data has the required standard. There are hazards with spatial boundaries greater than city boundaries and obtaining the set of indicators that represent vulnerability to specific hazards within the city administrative limits can be complex and time-consuming (e.g. identification of Water exploitation data in the cities’ sub-basins). In such cases, it is important to consider that spatial scale acquires more relevance in the selection of the data.

Temporal scale

Vulnerability was found to vary depending on a specific place and time. Therefore, one of the benefits of a longer temporal analysis is that vulnerability can be assessed at different time points, even if each time point is only providing a static image of vulnerability (Fekete, 2012). The regional vulnerability was studied identifying the evolution of the future climate and
socio-economic changes between 2025 and 2085 across nine of the largest coastal urban areas of Chile. This temporal scale allows to understand the differences in future vulnerability between the nine cities. In addition, it enables the identification of a city that presents a comparatively high vulnerability across time, which can be studied in further depth. Nevertheless, there is room for improvement, as this temporal analysis did not include internal dynamics and changes within the cities (e.g. migration). Therefore, it is advisable that future studies further explore the future vulnerability inside the cities, and consider this scale of analysis for the identification of a city that provides the greatest possible insight into the urban vulnerability.

In this research, the local vulnerability was studied using census data for 1992 and 2002. This type of information is particularly useful at a local level where, due to misinformation, climate change is often considered a long-term problem (20-30 years). At the local scale, the information to draw links between current problems and climate change is scarce. Because census data provides regularly updated information to monitor changes, it is useful in informing policy decision-making. Furthermore, a temporal analysis allows to adjust to the changes as the vulnerability evolves allowing a process of flexible adaptation (UNDP, 2010). For example, it was observed between 1992 and 2002 the 'literacy rate' indicator grew from 88% to 95% (see Chapter 5). This is particularly relevant for studies in developing countries such as Chile, where social changes can occur abruptly. Therefore, it is recommended that future studies explore the use of recent past census databases for vulnerability assessment and monitoring.

7.3.2 Indicators

As for many other vulnerability assessments, an indicator-based approach was used to quantitatively operationalize the concept of vulnerability. This approach has proven to be useful for representing and monitoring changes in vulnerability (Adger et al., 2004). However, despite the efforts to represent vulnerability and its components in a clear, concise and replicable way, they are strongly determined by the availability of data and only provide a partial picture of reality in a specific area and time. Different authors have documented the data constraints around the vulnerability assessment, especially in poor and developing countries (ECLAC, 2013). Consequently, vulnerability results from my study must be analysed
and understood in the context of the specific set of indicators developed to represent the concept.

Additionally, the representation through indicators of factors that influence the vulnerability, such as social capital, has limitations. Even though social capital is recognised as an important factor in the measurement of the vulnerability, technically transposing the conceptual understanding to specific indicators is still a challenge. This is because even its evaluation responds to an indirect measure of observable phenomena or assumptions. For example, here social capital was represented by access to telephone and internet (Chapter 5) or, in the case of Acosta et al (2013), with access to the telephone line. Therefore, the indicators built are an attempt to represent the response to complex social phenomena given current knowledge and assumptions. As a result, the indices developed here should not be understood as representations of an absolute reality.

In addition, a generic indicator framework for the adaptive capacity was used. This assumes that the determinants explored here are relevant to explore the enabling conditions for adaptation for different hazards. However, it is argued that the factors that determine the adaptive capacity are different depending on the hazard (Tol and Yohe, 2007). Therefore, future studies of adaptive capacity may benefit from hazard specific assessments of this capacity to adapt.

### 7.3.3 Normalization

Another methodological choice that responds to the characteristics of the data used corresponds to the selection of the normalization method. In this study, the normalization was performed through the selection of fuzzy membership functions, which allow the comparison of phenomena of different nature and measured on different scales. This was done through the assignation of a common unit of measurement, in this case from 0 to 1. This process of normalization is the basis to perform the process of aggregation of indicators into composite indices. The fuzzy membership function recognizes the unique characteristics of each indicator through a wide range of normalization options (see Section 3.3.1). This is one of the most useful and relevant aspects of the fuzzy analysis tool, which allows the analysis of imprecise phenomena such as the vulnerability. But data normalization requires understanding of the measurement units of each indicator, and identifying the presence of outliers, as well as an important amount of information to define the boundaries of
membership functions for each indicator. Therefore, relevant indicators such as those used for assessing the impacts of heat stress (e.g. green areas) could not be included because there was not enough information to set the limits to perform the normalization process. Therefore, it is advisable for future studies to consider the characteristics of each indicator, its units of measurement and the presence of atypical values before starting the process of normalization.

### 7.3.4 Weighting and aggregation

I decided against the process of using expert judgement to assign weights during the process of aggregation of the indicators. Instead, fuzzy logic was chosen since it offers the possibility to consider the characteristics of each indicator during the aggregation process (see Section 3.3.1). At the outset, this study considered each indicator as equally important for representing vulnerability. The vulnerability is context- and time-specific. Therefore, to assign weights, it is relevant to consult stakeholders on the importance that they believe that different indicators could have in a specific place at a particular time. However, despite the collaboration of many stakeholders in this research, this resource-intensive consultation process was not possible within the study’s time frame or budget. For meaningful weight to be derived, significant comprehension and knowledge of theoretical vulnerability is required (Hiete and Merz, 2009). It also requires some consensus of opinion from the stakeholders about the importance of the inferred indicators. When it is possible to integrate expert knowledge, it usually provides support in weighting and aggregation of indicators, and it favours wider acceptance of the results (Schauer et al., 2010). In this study, I found that there were very few individuals who had a) sufficient knowledge and experience that they felt confident to determine weightings across the range of indicators used, and b) sufficient knowledge of how the importance of these had changed during the period 1992-2002. Initial consultations with the few people with such knowledge showed there was little consensus, with each expert proposing higher weights for indicators related to their area of interest. This is a common challenge in research of this kind (Cardona, 2005). In practical terms, finding a smaller set of indicators, for which data of acceptable quality and which are not highly inter-correlated, is a useful starting point even if the indicators themselves are not weighted.
However, it is important to highlight that during the aggregation process, indicators and components may indirectly acquire different weights. This can affect the measurement of the vulnerability. Therefore, to minimise involuntarily assigning weight actions were taken:

Given the structure of the vulnerability index, with a different number of indicators for each hazard, hazards that are represented using a higher number of indicators tend to produce lower index values. This is because fuzzy GAMMA overlay function consists of both fuzzy SUM and fuzzy PRODUCT elements, the latter of which is heavily influenced by the number of indicators. As a consequence, the higher the number of indicators, the lower the result of fuzzy PRODUCT will be. One could try to address this type of weighting problem by having the same number of indicators for each hazard. However, it is unrealistic to expect that every hazard will still be accurately described when forcing all of them to be represented with an equal number of indicators. Another strategy, which was used here, is to identify a GAMMA value that produces the lowest distortion and reduces the possibility of giving un-intentional weight to hazards with higher or lower number of indicators, and that enables comparative analysis for the different hazards and time periods for all the municipalities. For example, here a value of GAMMA over 0.6 allows to reduce the influence of the PRODUCT element of GAMMA, minimising the influence of a large number of indicators. To identify the GAMMA value a sensitivity overlay analysis is advisable.

Given the characteristics of the indicator set, the GAMMA value needs to be selected carefully to avoid unintentionally giving too much weight to any one indicator, and possibly to a certain municipality. For this reason, I undertook a careful sensitivity analysis to select an appropriate GAMMA value, which was then used consistently for all aggregations. When I used a GAMMA value below 0.5, the PRODUCT term of GAMMA becomes more important, giving more weight to the lowest components of the index. Therefore, results of the aggregation give lower values than any of the initial values of the indicators, offering unrealistic results (see GAMMA selection criteria Section 3.3). Conversely, for GAMMA values above 0.9, the fuzzy SUM element of GAMMA becomes more important, giving more weight to the indicator with highest values of the index. As a consequence, for these values of GAMMA, results of the aggregation produce higher values than any of the initial values of the input indicators, again offering unrealistic results. On the other hand, GAMMA values between 0.6 and 0.8, both the above influences tend to decline. Consequently, results of the aggregation fall within the initial values of the indicators, offering a result that is more
interpretable and more consistent with the ranges of the input data sets. Therefore, a strategy could have been to perform a sensitivity overlay analysis to identify a GAMMA value to minimise unintentional weighting of specific indicators during the stages of aggregation.

7.3.5 Relative vs absolute changes

To develop informative indices, it is important to clarify that the resulting maps should be used with caution, understanding that they are abstract and not a direct reflection of reality. Absolute index values are not informative on their own, but they do contribute important information about change when compared to others. Therefore, absolute index values are necessary to establish comparisons between municipalities and time periods, and to develop rankings that can assist decision-making. Absolute values allow to build rankings of municipalities that can be compared across time (chapters 3, 4, 5 and 6). Hence, absolute change is not presented, as showing a change in abstract values is not informative. Instead, a change in the ranking can be shown. Furthermore, to have a measure of change in index values through time, relative change between time points can be presented (chapters 2, 3, 4, 5 and 6; although the calculation of relative change differed between chapter 2 and all others). It should be pointed out that two different reference periods were used in this research (1992 and 2010) as it was not possible to use 1992 as the reference year for both the regional and the local analyses, due to the lack of information for 1992 for all cities under study in Chapter 2.

7.3.6 Maps

Maps of vulnerability and their components fulfil the role of reporting on the enabling conditions for the adaptation of the municipalities. Nevertheless, they should be considered as the starting point and not as the end point in assessing the vulnerability of cities. Maps should be used accounting for the methodology on which they are based, their assumptions and their limitations. Research as the one carried out here helps to build the guidelines for more in-depth research in cities. Maps allow the easy visualization of situations that are sometimes highly complex, but should be used with caution, because, despite efforts to explain and document the results to achieve transparency, misunderstandings can arise that will not only depend on the maps, but also on the level of knowledge or understanding of the users. These misunderstandings can lead to maps being interpreted and used differently
from their purpose. The indices mapped here inform about the socio-economic and biophysical status. They also inform about change in the components of the vulnerability in the municipalities, yet they do not report on the vulnerability of the people. The structure of the indices, and especially the components and determinants, provide a better understanding of the concepts they contain favouring transparency, and helping to identify what is necessary for adaptation and where it is located. But these maps do not inform about when and how these basal conditions could be used to finally adapt. Therefore, it is necessary to state openly that the maps of vulnerability, multi-hazard and adaptive capacity are the result of a conceptual representation and do not represent reality (Chapters 4, 5 and 6). To avoid misinterpretation and misuse of maps it is recommended to work closely with stakeholders and subsequently present the maps for further discussion.

7.3.7 Assessment of plausibility

Assessing plausibility for previous time periods is inherently difficult. Various means of providing a ‘sense-check’ of the results were explored, but historical evidence is very partial for this or similar cities, and independent secondary data sources for their verification are scarce. This is especially complex for local governments in poor or developing countries. Moreover, accounts of some recent events such as the 2010 tsunami or the 2006 flood are arguably of only limited use, because Chile has undergone rapid transformation in recent years. Therefore, any assessment of vulnerability has to be understood as being very dependent on the time at which it is carried out (e.g. levels of tertiary education or income per municipality have increased quite dramatically in the last ten years). Different possibilities of evaluation were explored:

i) I searched for evidence of the effects of previous weather-related hazards. However, it was not possible to compare the final indices with the effect of historical events (KC et al., 2015). This verification may have been useful, since Chile is highly exposed to extreme weather events, including those related to the El Niño and La Niña phenomena (Glantz et al., 1991; Nicholls, 1987; Philander et al., 1990; Quinn and Neal, 1987). However, reliable databases of human casualties and economic effects at the municipal or metropolitan scale are non-existent or sparse for the study period (IDB-ECLAC, 2007), so it is not possible to follow the effects of extreme events such as storms, floods or landslides.
ii) Another option for evaluating the results would be to compare the results of this research with similar studies. However, this research is the first vulnerability assessment in the study area. Therefore, it is not possible to find studies that analyse the socio-economic effect of a reasonable number of hazards for the study period to compare with the vulnerability assessment presented here. As a result, providing evidence to support the conclusion, for example, that municipalities with higher vulnerability indices in this assessment actually correspond to municipalities that face greater vulnerability in reality, is difficult.

iii) Results can also be verified by presenting them to stakeholders, experts and scientists (see Preston et al., 2008). Throughout this research, information and knowledge has been shared with stakeholders (see Section 1.2). However, as was explained in Section 7.3.4, in this research an intensive consultation process was not possible within the study’s budget. In addition, results were not presented or discussed with stakeholders due to the time frame of this study. Doing this is the next logical step for this research. Surveys or workshops can be useful for this purpose. Considering the Chilean administrative structure it is of particular interest that stakeholders from planning offices from the municipalities and the regional government, as well as the ministerial local offices participate in them (see Section 6.4.3), to identify their perceptions and opinions about methods and outcomes. It is useful to know if the results of the application of the indices reflect what they consider vulnerable; if the main drivers of vulnerability identified explain past or present vulnerability; if the municipalities identified as the most vulnerable are such in their experience; and if the changes observed in the indices developed have, in their experience, happened. In addition, it is also necessary to know if they understand the methods and results; if they consider the methods useful and replicable; if they identify or propose improvements; if the results help their understanding of the vulnerability and how they consider can be incorporated in the process of planning.

7.4 Original contributions to knowledge

This section discusses my four major contributions to the assessment of the vulnerability:

1. I proposed a new set of indicators to assess vulnerability at the municipal scale.
2. I developed a new method to aggregate the different theoretical components of the vulnerability.
3. This is the first assessment of the urban vulnerability using a single, coherent methodology based on fuzzy logic.

4. This research contributes new insight into urban vulnerability in Chile.

First, in relation to previous studies, this research expands the work developed by (Lung et al., 2013), who explore the vulnerability to multiple hazards, and (Acosta et al., 2013), who explore de generic adaptive capacity, both of them performing national level assessments in Europe in the future.

Implementing the theoretical model of Acosta et al., (2013), this research shows how it can be applied in practice at the municipal urban scale, making their approach tangible, with adjustments and updates, and showing its limitations. I maintain the general model structure of Acosta et al., (2013) based on components (awareness, ability and action), determinants and indicators, but I adjust and update part of the structure (i.e. choice of determinants and indicators) to better represent the capability of the municipalities to perform the process of adaptation in the recent past, as well as the progress in the literature. Acosta et al., (2013) themselves suggest exploring a different set of indicators depending the scale of analysis. In addition, in their study the future adaptive capacity is driven by changes in population and GDP. Here, the assessment is based on recent past data on adaptive capacity, and no indicator is intentionally used to drive the changes.

For the component ‘action’, a new set of determinants and indicators was proposed. They were defined after an extensive literature review about the social, economic and institutional resources available that allow the implementation of adaptation actions or activities at the municipal scale. As a result, to operationalize these components, I propose to use the determinants economic resources and institution (Greiving, 2011; Juhola et al., 2012), and the indicators Income per capita, Poverty, Dependency ratio, Municipal budget, Master plan updates, which were found to be relevant to the adaptive capacity at the municipal scale (EEA, 2012; Greiving et al., 2006; Juhola et al., 2012; Klasen and Schüler, 2009; Posey, 2009; Swart et al., 2012).

For the component ‘ability’, I suggest retaining the determinants technology and infrastructure, since an extensive amount of literature supports that they reflect the enabling factors to develop adaptation and move from awareness to action. Also, I propose to explore new indicators to represent these determinants, such as the Capacity to undertake research,
Distance to hospital facility, Hospital beds, Physical housing conditions, Informal networks (Brooks et al., 2005; Cutter et al., 2003; EEA, 2012; Greiving, 2011; Hampton and Wellman, 2003; Juhola et al., 2012; Katz et al., 2001; Swart et al., 2012; Wellman et al., 2001). For the component ‘awareness’, I propose to continue to use the determinants knowledge and equity, and the set of indicators, since they acknowledge the necessary awareness to recognise the problem of climate change and the need for adaptation in the municipalities.

It was also possible to implement the theoretical model of Lung et al., (2013), showing that their model can also be conducted at the urban municipal scale. It was possible to make their theoretical model more tangible, allowing to evaluate the impacts of multiple hazards and to identify the limitations in the model’s implementation. Similarly to Lung et al., (2013), a set of multiple hazards that have historically affected the area were selected and researched extensively. Different weather-related hazards were studied based on the structure of exposure and sensitivity by hazard proposed by Lung et al., (2013). Unlike them, who study three hazards (i.e. heat stress, river flood, and forest fire), here the assessment of five hazards is proposed, including coastal flooding, river flooding, water scarcity, heat stress, and wildfire. The set of indicators representing the exposure and sensitivity was updated by hazard according to the new literature and the availability of data for its implementation.

For wildfires, I propose a new set of municipal indicators based on historical data and socio-economic factors, unlike Lung et al., (2013), who focus on biophysical factors. To evaluate exposure to wildfires I propose to use Wildfires events, Total burned area and the Forest fire weather index (FWI) (Moriondo et al., 2006; Schauser et al., 2010; Swart et al., 2012). For sensitivity, I propose to explore Residents in the area, Critical infrastructure, Elderly people, Very young people (Brender et al., 2013; B. L. Preston et al., 2009; Swart et al., 2012; Tedim et al., 2014). For river flooding, I suggest retaining the indicators proposed by Lung et al., (2013) Area prone to river flooding, Residents in the area and Critical infrastructure, since they reflect the exposure and sensitivity at the municipal scale. Besides those, I propose to identify the sensitivity groups Elderly people and Very young people (Fekete, 2009; Kasperson and Kasperson, 2001; Krellenberg et al., 2013). For coastal flooding, I suggest the following indicators at the municipal scale: Area prone to coastal flooding, Residents in the area, Critical infrastructure, Elderly people and Very young people (Barredo et al., 2008; Kleinosky et al., 2006; McGranahan et al., 2007; Mondal and Tatem, 2012; Torresan et al., 2008). For water scarcity, I propose to assess the exposure through Droughtiness and Water exploitation
(Chuluun et al., 2015; Kurian et al., 2016; McKee et al., 1993; Polsky et al., 2009; Sehgal and Dhakar, 2016; Silva and Lucio, 2014; Swart et al., 2012). To evaluate the sensitivity to water scarcity I propose to use Water consumption, Growth of water demand, Poverty, Elderly people and Very young people (EEA, 2012; Swart et al., 2012). Lung et al., (2013) propose to assess exposure to heat stress by looking at the summer days with a maximum temperature above 25°C and the tropical nights with a minimum temperature above 20°C. However, for the study area the tropical nights are rare, so I propose to use Very hot days, Very hot nights and Heat wave to assess the exposure (Vincent et al., 2005). For the sensitivity assessment, I used the same indicators as Lung et al., (2013), since there is literature and data to perform their selection. The new set of indicators presented here can be implemented in other urban areas with adjustments that will depend in the particular urban context.

This research therefore advances the work of Acosta et al., (2013) and Lung et al., (2013), by developing the biophysical and socio-economic frameworks of exposure, sensitivity, awareness, ability and action. It updates the indicators that represent the components of the vulnerability, in the context of global change, to help to understand the vulnerability within a city. This new knowledge is transferable to the study of vulnerability in other urban areas, mainly in developing countries where the adaptation process is at the initial stage. These models have a role in enabling scientists, policy-makers and planners to better understand the enabling conditions for adaptation, thereby informing the planning process for climate change adaptation in cities.

Second, this research presents a new way to aggregate the different theoretical components of the vulnerability.

I have observed how the concept of vulnerability allows the identification of areas of interest for the adaptation process. Additionally, I have shown that it is technically feasible to evaluate the vulnerability as a composite index. However, as discussed, vulnerability results cannot be understood as an absolute reality and, therefore, their verification is a challenge. The vulnerability is imprecise, complex and changing, and cannot be approached and understood as the simple sum of its parts (Chapters 4 and 5). Instead, it has been argued that the value of a vulnerability assessment is in identifying differences between its components exposure, sensitivity and adaptive capacity. This approach helps to identify and understand how each component contributes to the overall vulnerability, which results from a combination of socio-economic factors and (the traditionally considered) biophysical ones.
As a result, I showed how the approach can favour the identification of areas determined by their socio-economic status rather than just their exposure to hazards. It is, nevertheless, still necessary to explore factors such as the interdependence between vulnerability components.

This research has shown how the conceptual framework of the vulnerability can be implemented through indicators, which has benefits and limitations. The selection of these indicators, despite the efforts, is still somewhat arbitrary and subjective. In this case, it depends on the evidence found in the literature and, more importantly, on the availability of reliable data. This issue is particularly relevant in developing countries. For example, because of lack of data, relevant indicators (e.g. those associated with hanta virus assessment, see section 4.2.1) were not included here. In addition, if new data becomes available or new knowledge on vulnerability assessment emerges, results of this evaluation could change. All these factors behind the technical assessment of the vulnerability must be clearly exposed and accounted for, since the indicators are only a means to represent, challenge and explain the underlying theory of the elements that contribute to vulnerability.

Third, this is the first assessment of the urban vulnerability using a single, coherent methodology based on fuzzy logic.

The use of fuzzy tools in GIS to assess weather-related vulnerability has not been deeply explored before, although some benefits from conducting vulnerability assessments with fuzzy logic have already been reported (Cheng and Tao, 2010; Eakin and Bojórquez-Tapia, 2008; Krömker et al., 2008). Still, none of these studies explored vulnerability spatially or mapped specific areas. Only Acosta et al. (2013) used fuzzy logic to assess varying degrees of adaptive capacity spatially using MATLAB. The non-linear approach of fuzzy logic allows for a better structure of general data distribution and aids the component aggregation process by reducing the effect of indicators with extreme overlay values. GIS facilitates the implementation of fuzzy logic while providing great flexibility in the combination and presentation of maps (Pradhan et al., 2011).

Among the contributions of the present study to the learning process there is the incorporation of a new form of spatial vulnerability assessment. The fuzzy overlay enabled standardisation and effective aggregation of indicators with differing ranges and granularities of attribute values into an overall index. It also provided a conceptually sound and
reproducible means of exploring the interplay of the many indicators that influence vulnerability. Additionally, it reveals pitfalls in the process of aggregation that were not considered in the conceptual design of the assessment, such as the number of indicators by hazard.

**Fourth, this research contributes new insight into urban vulnerability and its components in Chilean cities.**

In Chile, there has been little or no focus on assessing the vulnerability of cities at the regional or local level. Several scholars have already noted that few studies address urban vulnerability in Chile and those that do focus on the capital, Santiago, underlining the paucity of studies on other smaller cities (ECLAC, 2012a; Monsalves-Gavilán et al., 2013). These scholars emphasized the need for methods that would allow for consistent and comparable analysis of small and mid-sized Chilean cities at a scale that is appropriate for urban planning processes.

This is the first study to comprehensively explore the vulnerability to climate change of Chilean urban areas into the future. It is also the first study to examine in detail the recent past vulnerability to multiple hazards of a mid-sized city at the municipal scale in the country, and is the first one to propose a methodology readily applicable to other cities in the country for a vulnerability study. This is a novel contribution to knowledge about vulnerability in Chile. It can also provide insight for these cities and others at the start of the process of adaptation.

As was explained in Section 6.4.3, this research is also relevant to urban planning, since it seeks to enhance the understanding of the drivers of spatial and temporal vulnerability. Such greater understanding is meant to promote discussion and increase awareness, especially at the municipal level. Generated information can be used to develop the situational analysis and feed the future urban adaptation plan framed within the National Adaptation Plan.

### 7.5 Conclusion

The overall vulnerability of nine of the largest coastal urban areas of Chile is expected to increase due to warmer and drier future conditions, as this is expected to increase the exposure of these cities. Socio-economic change and a growing elderly population will also greatly influence the vulnerability. All cities were exposed to several hazards, each having a
different effect on the vulnerability of each city. Among all cities, the Concepción Metropolitan Area is expected to be the most vulnerable. Its vulnerability would be mainly influenced by the increase in exposure, which would be moderated by its adaptive capacity. This city is expected to present the highest vulnerability among all cities to coastal flooding, and to be vulnerable to climate change. Consequently, the vulnerability of this city needs to be monitored more closely.

A set of forty-nine indicators is proposed to study the local vulnerability of the Concepción Metropolitan Area in the recent past, which were aggregated into multi-hazard impact, adaptive capacity and vulnerability indices. Findings suggest that the slight reduction in the overall vulnerability observed in the studied period had different causes in each municipality, and that the vulnerability varies across municipalities, over time, for the different hazards. The findings suggest that socio-economic factors can be more determinant than biophysical factors to the overall vulnerability of municipalities. The socio-economic conditions and the ageing population played a dominant role in the final determination overall vulnerability. Additionally, the hazards that influenced the assessment of vulnerability the most were wildfires and water scarcity. The vulnerability ranking of municipalities did not change from 1992 to 2002. Knowing this is most informative and useful for cities, since, despite the improvement in socio-economic factors, the vulnerability is explained by the inequity observed within the municipalities. Sensitivity and adaptive capacity therefore play a substantial role in reducing the vulnerability. Hence, the vulnerability of this city is no longer a matter of wealth but of distribution of it through the municipalities.

Using this analysis and mapping of vulnerability allows one to identify drivers, components and areas of interest for the adaptation process. It is technically feasible to evaluate the vulnerability concept through composite indices that incorporate both biophysical and socio-economic components using fuzzy logic. Multi-hazard impact, adaptive capacity and vulnerability indices are useful to start monitoring spatial and temporal changes. Resulting maps may allow researchers to communicate a simplified version of a complex reality to e.g. urban planners or citizens. However, vulnerability results cannot be understood as an absolute reality and, therefore, their verification is a challenge. Vulnerability results must be analysed and understood in the context of the specific methodological choices used to represent the concept, regarding for instance the temporal and spatial scale, normalization,
weighting, or aggregation. Therefore, methodological choices and limitations should be extensively documented and discussed.

In this research, new way to technically representing the theory behind the vulnerability and its components was developed. Through a novel and coherent methodology based on fuzzy logic. Such methodology includes a tool to investigate spatial and temporal patterns of vulnerability, and improve the understanding of drivers in the urban context. This study also extends and updates previous knowledge by developing new indicators and components for vulnerability research in the context of global change at the municipal level. Finally, it provides new insight into urban vulnerability, its components, and their evaluation, in Chilean cities. This new knowledge is transferable to the study of vulnerability in other urban areas, mainly in medium-sized cities, where the vulnerability assessment and adaptation process is at the initial stage. This research can enable scientists, policymakers and planners to better understand the conditions that allow adaptation, thereby raising awareness and informing the planning process to adapt to climate change in cities.
Appendices
Chapter 2
### Table 1. Indicators of exposure

<table>
<thead>
<tr>
<th>RCP 8.5</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
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<td>2.07</td>
<td>-5.77</td>
<td>-6.09</td>
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<td>Very hot days</td>
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<td>1.20</td>
<td>77.20</td>
<td>90.30</td>
<td>84.30</td>
<td>80.60</td>
<td>65.30</td>
<td>35.40</td>
<td>25.40</td>
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<tr>
<td>Very heavy days</td>
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<td>1.20</td>
<td>77.20</td>
<td>90.30</td>
<td>84.30</td>
<td>80.60</td>
<td>65.30</td>
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<td>25.40</td>
</tr>
<tr>
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<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
</tr>
<tr>
<td>LECZ</td>
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<td>0.27</td>
<td>0.02</td>
<td>1.05</td>
<td>3.21</td>
<td>10.30</td>
<td>8.86</td>
<td>0.83</td>
<td>0.14</td>
</tr>
</tbody>
</table>

### Appendix A


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**2050s**

| T Max         | 3.18  | 2.86  | 2.84  | 2.37  | 2.16  | 1.80  | 1.83   | 1.83   | 1.41  |
| T Min         | 3.14  | 2.78  | 2.79  | 2.35  | 2.12  | 1.78  | 1.74   | 1.74   | 1.48  |
| Very hot days | 161.23| 131.47| 154.03| 135.12| 99.70 | 75.13 | 48.77  | 67.03  | 55.53 |
| Very heavy days | 190.00| 180.47| 186.83| 129.63| 137.00| 80.47 | 64.53  | 71.23  | 70.80 |
| SPI-12        | 0.29  | 0.23  | 0.60  | 0.47  | 1.10  | 3.30  | 6.19   | 8.48   | 9.76  |
| LECZ          | 0.19  | 0.27  | 0.02  | 1.05  | 3.21  | 10.30 | 8.86   | 0.83   | 0.14  |

### Appendix A


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**2080s**

| Precipitation | -0.65 | 7.07  | 3.72  | -9.74 | -10.29 | -8.89 | -7.19  | -6.40  | 1.17  |
| T Max         | 1.29  | 1.17  | 1.16  | 0.96  | 0.88  | 0.73  | 0.74   | 0.75   | 0.31  |
| T Min         | 1.28  | 1.13  | 1.14  | 0.95  | 0.87  | 0.73  | 0.71   | 0.71   | 0.32  |
| Very hot days | 79.87 | 61.33 | 76.33 | 62.07 | 48.30 | 41.50 | 30.63  | 38.60  | 31.53 |
| Very heavy days | 78.63 | 69.60 | 76.47 | 62.60 | 66.50 | 40.80 | 35.57  | 41.00  | 38.47 |
| SPI-12        | 0.29  | 0.23  | 0.40  | 0.47  | 1.20  | 3.65  | 6.68   | 9.02   | 9.75  |
| LECZ          | 0.19  | 0.27  | 0.02  | 1.05  | 3.21  | 10.30 | 8.86   | 0.83   | 0.14  |

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**2080s**

| Precipitation | -0.65 | 8.08  | 4.55  | -11.96 | -12.62 | -10.90 | -8.82  | -7.85  | 1.75  |
| T Max         | 1.59  | 1.43  | 1.42  | 1.18  | 1.08  | 0.90  | 0.91   | 0.92   | 0.48  |
| T Min         | 1.57  | 1.39  | 1.40  | 1.17  | 1.06  | 0.89  | 0.87   | 0.87   | 0.50  |
| Very hot days | 100.07| 74.50 | 94.40 | 76.37 | 57.20 | 46.37 | 34.20  | 43.73  | 35.47 |
| Very heavy days | 96.60 | 87.77 | 94.67 | 74.67 | 78.43 | 47.33 | 40.23  | 45.97  | 45.77 |
| SPI-12        | 0.29  | 0.23  | 0.80  | 0.47  | 1.10  | 3.34  | 6.24   | 8.57   | 9.68  |
| LECZ          | 0.19  | 0.27  | 0.02  | 1.05  | 3.21  | 10.30 | 8.86   | 0.83   | 0.14  |
A2. Seasonal change in precipitation and temperature

Figure 1. Percentage of change in the seasonal precipitation 1995 to 2100

Figure 2. Degree of change in the seasonal mean temperature 1995 to 2100

Spring  

Summer  

Autumn  

Winter  

A3. Population of the main coastal urban areas in the low elevation coastal zone boundary corresponding to 10 meters over the sea level

Figure 1. Population of the main coastal urban areas in the low elevation coastal zone boundary corresponding to 10 meters over the sea level, SSP3 time slice 2080s.
Appendix A

A3. Values of sensitivity indicators

Figure 1. Indicators of sensitivity
A4. Values of adaptive capacity indicators

Figure 1. Indicators of adaptive capacity
B1: Fuzzy membership functions examples

The attribute values for indicators reflecting awareness, ability and action 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 thought to influence the capacity of a municipality for adaptation, four fuzzy membership functions were used to standardise the actual ranges of each indicator data into fuzzy membership values from 0 to 1. Membership values close to 1 reflect a greater ability for adaptation, whilst membership values approaching 0 indicate the contrary. Figure B1 illustrated graphically the fuzzy membership functions.

Figure 1. Fuzzy membership functions used to standardise 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 attribute value.

Four examples are given below to describe the selection of the fuzzy membership functions:

1) A linearly increasing fuzzy membership function was applied to female activity rate. It is considered that an equitable society has more possibilities to adapt, thus a smaller employment gap between men and women would increase equity. Therefore, the membership function minimum of 0 is assigned to a value of 7.9% of active female population, which corresponds to the minimum of the active female population in an urban area in the country. Meanwhile membership 1 was assigned to a value of 55.6% of the working female population, which correspond to the maximum of the active female population in an urban area in the country. As such, the municipality of Lota, with a female working population of 20.3% in 1992, received the lowest membership value in the CMA
(0.259). On the other hand, the municipality of Concepción received the maximum membership value of 0.671, since in 2002 it had the largest percentage for female working population, around 39.9%.

2) A linearly decreasing fuzzy membership function was applied to distance to hospital facilities. Since it is considered that immediate access to medical facilities allows immediate relief from disasters, the minimum membership value of 0 is assigned to 104 minutes driving distance, which corresponds to a maximum in an urban area to the nearest public hospital in Chile. The maximum membership value of 1 is assigned to 5 minutes distance, which corresponds to the minimum driving distance to a public hospital in an urban area in Chile. As such, the municipality of Lota in 1992 had 5.3 minutes distance which correspond to a membership of 0.997, while in 2002 Hualqui has a distance of 43 minutes, receiving a membership value of 0.641.

3) A 'Fuzzy Large' membership function was applied to Hospital beds. It is considered that higher availability of medical care, represented by more hospital beds, reveals a higher response capacity in the case of extreme weather, for example. Membership of 0.5 is assigned to 2.1 beds in a public hospital per thousand inhabitants which corresponds to the national average, while the spread 1 is assigned for maximum differentiation between municipalities. Therefore, Lota in 1992 with 2.9 beds per thousand inhabitants receives a membership 0.582, while Coronel in 2002 with 1.7 beds per thousand inhabitants and receives a membership of 0.453.

4) A 'Fuzzy Small' membership function was applied to Income inequality, as a more equitable society has more possibilities to adapt. For this reason, the national average of the gap between the richest 20% and the poorest 20% in society is assigned the membership value of 0.5, while the spread of 3 shows the greater differentiation between municipalities. The Municipality of Coronel in 1992, with an income ratio of 10.2, received a membership value of 0.615, while in 2002 San Pedro de la Paz with an income ratio of 22.3 received a membership of 0.132.
C1: MHI Indicators

Indicators of coastal flooding

To assess the impacts on urban areas of the combined effects of sea level rise and the increased frequency and intensity of storms produced by climate change, this study used McGranahan et al. (2007) approach. They studied coastal low-lying areas around the world, defining the low-elevation coastal zone (LECZ) as the continuous area along the coast below 10 metres above sea level. However, in an urban scale, a 10-metre limit for the LECZ might use a resolution too coarse to study exposure and sensitivity to coastal flooding, as we might expect a drastically decreasing gradient as we move away from the coast within the 10-metre range. Therefore, the areas under 1, 5 and 10 metres above sea level were each identified as the LECZ in order to build a more robust analysis of exposure and sensitivity to coastal flooding.

Exposure: Coastal systems and low-lying areas are exposed to relative sea level rise, storms and storm surges, and so, with climate change, are expected to experience increasingly adverse impacts like immersion, coastal flooding and coastal erosion (Wong et al., 2014). Lewis (1989) noted that destruction by storm surge is often greater near the coast, where wind damage tends to be much worse, so urban areas are at risk. Normally the area considered at risk is defined by the area below 10 m.s.n.m (McGranahan et al., 2007; Mondal and Tatem, 2012; Vafeidis et al., 2011). In the case of Chile’s coast and specifically the study area, tsunamis have been a frequent and damaging occurrence, so the tsunami inundation area has been located at approximately 10 (m.s.n.m), which correspond to the maximum area affected by a tsunami in 1835 (Aranguiz and Shibayama, 2013; SHOA, 2013a, 2013b, 2013c, 2013d). Falcón et. al, (2012) considered land more than 20 metres above sea level to be safe in the face of an extreme tsunami event. Inside the LECZ, the percentage of areas less than 1, 5 and 10 metres above sea level were identified as indicators of exposure in the CMA. To unify the results, a weighted sum that assigned more importance to the lower-lying areas most exposed to coastal flooding, was used. Figure C1 shows the low-elevation coastal zone boundaries for 1, 5, and 10 metres above sea level for the municipalities of Talcahuano and Coronel.
Figure 1. Examples of low-elevation coastal zone boundaries in the CMA. The images show the municipalities with the greatest areas of exposure to coastal flooding at 1, 5 and 10 metres above sea level.

**Sensitivity:** Population and economic assets in the coastal system are sensitive to sea level rise and surge-driven flooding, depending on their exact locations and the characteristics of the area (Barredo et al., 2008). Data on population density and assets are the most common indicators, since they are used to determine the number of people and economic assets in an area at risk (Kleinosky et al., 2006; Torresan et al., 2008). For this study, the best available indicators for exploring the sensitivity of population in the area at risk were the percentage of residents in the area, the percentage of elderly people, the percentage of elderly living alone, and the percentage of very young people. Asset sensitivity was explored through the indicators of percentage of properties in the area, housing resistance and percentage of transport infrastructure in the area at risk (Kleinosky et al., 2006; Mondal and Tatem, 2012). To be consistent with the exposure analysis, sensitivity indicators in the areas under 1, 5 and 10 metres above sea level were identified and then unified with the same weighted sum as in the exposure analysis.
Indicators of fluvial flooding

Fluvial flooding can cause multi-faceted damage in urban areas, from loss of assets, functions and services to homelessness and even death (EEA, 2012; Jonkman and Kelman, 2005). This disruption affects the normal functioning of cities, which can have an impact not only in the affected city itself but also through its long-distance connections with other cities and rural areas (Revi et al., 2014).

Exposure: In many cases, with the consolidation of urban areas, vegetation and soil have been replaced with impermeable covers, land surface has been levelled and artificial drainage systems have been built (Hildén et al., 2012). As a result, runoff from rain can increase the frequency of floods in streams and rivers. The area of soil sealing is a common indicator of fluvial flooding exposure at the city level, and the area prone to floods is a standard indicator of exposure to flooding (EEA, 2012; Fekete, 2009; Swart et al., 2012). In the case of the CMA, the same indicators were selected, since data are available about soil sealing and areas within the city that historically have been affected by floods due to overflow of courses over a period of 50 years (LEU, 2013).

Figure C2 shows an example of the area prone to fluvial flooding in the municipalities of Talcahuano, Concepción, San Pedro de la Paz and Hualqui.
Figure 2. Examples of fluvial flooding areas in the CMA. The images show the municipalities with the largest exposure areas to fluvial flooding.

Sensitivity: The rapid urbanisation experienced by cities, especially in developing countries, has led to the irregular occupation of at-risk areas like river floodplains. Areas at risk for flooding are usually inhabited by poor people, who are ultimately the most affected since they have fewest resources to repair assets or recover from losses. Given the sensitivity of the urban population and its property to fluvial flooding, determining the elements among that the population most likely to be affected is vital for urban planning. The indicators commonly used to assess sensitivity to fluvial flooding are urban density, properties, flood insurance, elderly people and single-parent households (Balica et al., 2012; Fekete, 2009; Holsten et al., 2011; Kubal et al., 2009; Zahran et al., 2008). For Chile the most relevant and usable information available for the studied period is, with in the area at risk, the percentage of residents, the percentage of elderly people, the percentage of elderly people who live alone, the percentage of very young people, the percentage of properties in the area, housing resistance and the percentage of transport infrastructure (Fekete, 2009; Kasperson and Kasperson, 2001; Krellenberg et al., 2013).
Indicators of water scarcity

The long-term unavailability of water in the urban system can result from exposure to both naturally arising droughts and water scarcity, which is influenced by human activities like agriculture and industry. The increase in the risk of water supply shortages is a major concern for the central area of Chile (29°S to 39°S) due to changing rainfall patterns, particularly a recent precipitation deficit (Boulanger et al., 2014; Parish et al., 2012; Rijsberman, 2006) that has already affected the central area of the country with extended periods of drought.

Exposure: Water scarcity can cause problems in biodiversity, energy supply, food supply, social and human health and in the long-term water supply of a city, which could have multiple consequences for domestic consumption of drinking water, sanitation, human health, green urban areas and industrial output (Darrel Jenerette and Larsen, 2006; Vairavamoorthy et al., 2008). Water shortages can place urban needs in competition with other cities or entire sectors like energy and agriculture (EEA, 2012). Two indicators—the standardised precipitation index (SPI) and the water exploitation index (WEI)—are well established as proxies of exposure (Chuluun et al., 2015; Kurian et al., 2016; McKee et al., 1993; Polsky et al., 2009; Sehgal and Dhakar, 2016; Silva and Lucio, 2014; Swart et al., 2012), and both were used in this study. The SPI1 over 12 months (SPI-12) allows the researcher to calculate the likelihood of the occurrence of meteorological drought, here it is argued that the annual deficit of precipitation (meteorological drought) is a good proxy indicator of exposure to drought or “Droughtiness”. WEI facilitates identifying those municipalities that have high demand in relation to their water resources and are therefore more prone to problems of water stress.

Sensitivity: A higher consumption of water per capita could imply a greater sensitivity to water scarcity, so per capita water consumption is normally used as an indicator of sensitivity (EEA, 2012; Swart et al., 2012). The growth in water demand caused by variation in an urban population served by drinking water is also used as a sensitivity indicator. Increases in population could imply water stress, while higher urbanisation and greater density could cause more pressure on this resource. Therefore, the need to maintain the water supply in

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1 The Standardized Precipitation Index measures the difference of precipitation from the mean for a specified time divided by the standard deviation, where the mean and standard deviation are determined from the climate record (Swart et al., 2012).
the face of growing demand for drinking water means greater sensitivity to water scarcity. Indicators such as population over 65 years of age, population under five years of age and low-income households are all used to identify social sensitivity to water scarcity (Swart et al., 2012). For Chile, per capita water consumption, growth in water demand and sensitive population groups such as elderly people, very young people and population living in poverty were used, since they provide information about the different CMA municipalities that are under greater pressure.

**Indicators of heat stress**

In cities, the effects of heat stress can be even more severe due to the urban heat island (UHI) effect (EEA, 2012). In Chile, as in the rest of the world, an increase in temperatures is expected; urban areas in central Chile have already experienced an increase in temperature which is more pronounced at night (Vincent et al., 2005). The increase in temperature has often been aggravated by the lack of water caused by extended periods of drought.

**Exposure:** The indicators normally used to assess exposure to heat stress are summer days with a maximum temperature above 25°C and tropical nights with a minimum temperature above 20°C (Lung et al., 2013; Swart et al., 2012). Other indicators of heat stress include the frequency of very hot days, on which the maximum temperature is above the 95th percentile, very hot nights, on which the minimum temperature is above the 95th percentile, and the heat wave duration index (HWDI) (Pizarro and Castillo, 2006). In the Chilean case, particularly in the area of study, tropical nights are rare. Therefore, the most representative indicators of exposure to heat stress are very hot days, very hot nights and the HWDI (Vincent et al., 2005). The indicator very hot days is used to reflect days with unusually high temperature while the very hot nights indicator is used to reflect the possible adverse effects of a lack of night cooling, which is a major contributor in the heat stress (Frich et al., 2002). Urban population density and the lack of green areas are the other indicators used to represent exposure to heat stress in this study. A higher population density generally implies a higher density of built area, which favours the UHI effect. A lack of green areas also exacerbates the UHI effect, as the presence of green areas inside cities favours thermal comfort by providing shade and cooling. Green areas inside the urban microclimate of densely populated cities can improve thermal comfort (Steeneveld et al., 2011) and the health and general quality of life of inhabitants (Bowler et al., 2010). The beneficial effect of green infrastructure in UHIs is
primarily due to the evapotranspiration and shade they provide (Bowler et al., 2010). Consequently, the more green areas a city contains, whether in the core or the periphery, and the better these green spaces are distributed, the lower the UHI effect will be. Beyond the effect at the city scale, green spaces can provide considerable relief and thermal comfort in individual neighbourhoods, providing shade for residents (Armson et al., 2013).

**Sensitivity:** People are sensitive to extreme temperatures, which are a serious threat to human health, a threat that is even greater for those living in urban areas. The usual indicators of sensitivity to heat stress in relation to population are elderly people, people older than 65 living alone and the population in poverty (Lung et al., 2013; Swart et al., 2012). In this research, these indicators were explored. Elderly people may be more sensitive to changes in temperature (Bell et al., 2008; D’Ippoliti et al., 2010; Muggeo and Hajat, 2009; WHO, 2004), especially if they are in social isolation (Fouillet et al., 2006; Kieran Healy, 2003; Semenza et al., 1996). The poor population not only usually inhabits precarious housing without proper ventilation or insulation to cope with high temperatures, but also faces challenges in affording cooling systems (McGeehin and Mirabello, 2001; Schuman, 1972; Semenza et al., 1996). Since the health of very young people can also be affected by high temperatures (Green et al., 2010; Knowlton et al., 2009; Leonardi et al., 2006; Nitschke et al., 2007; Xu et al., 2012), this indicator was included.

**Indicators of wildfire**

Wildfires that threaten urban and primarily suburban areas can cause indirect or direct effects such as loss of ecosystem services, economic loss, loss of life and air pollution; they have negative implications for human health and cause disruptions in transport, energy, water and food supplies (Schauser et al., 2010). Factors such as prolonged drought and high temperatures increase the risk of wildfire (Füssel et al., 2012; Kitzberger et al., 2001; Lindner et al., 2008). In recent decades in Chile, there has been a significant increase in both the number and intensity of wildfires. From 2004 to 2014 there were 87% more wildfires than in the average decade from 1963 to 1993, while the burned area increased by 31% in same period (NFC, 2014). 80% of these wildfires originated in the wildland-urban interface. In many cases these incidents have severely affected the normal functioning of the affected cities by causing loss of human life, property and infrastructure (GORE, 2014; Sernageomin, 2014). In this respect, it must be noted that in Chile and elsewhere wildfire are primarily of human
Appendix C

origin, voluntarily or otherwise (Montenegro et al., 2004; NFC, 2014; Peña and Valenzuela, 2008). However, the prolonged droughts, high temperatures and strong winds that have affected the central area of Chile in recent years have favoured the rapid spread of wildfire (Peña and Valenzuela, 2008). In addition, the irregular occupation of peri-urban areas by low-income dwellers has degraded and fragmented the environment, facilitating the generation and spread of fires (Marzano et al., 2004; Pauchard et al., 2006; Salvatierra and Montenegro, 2010).

Exposure: Cities are exposed to wildfire either by their continual process of expansion or by climatic conditions that favour its rapid spread. Prolonged droughts generate fuel for the generation of large fires, increasing the exposure of cities. To report the past exposition of CMA municipalities to wildfire, we used the following indicators: fire occurrence, total burned area and the forest fire weather index (FWI) (Moriondo et al., 2006; Schauser et al., 2010; Swart et al., 2012). Figure C3 shows the wildland-urban interface buffer of 100 metres established in planning instruments in Chile (NFC, 2006).

Figure 3. Buffer zone of 100 metres over the wildland-urban interface (NFC, 2006).
Sensitivity: Specific characteristics of an urban area define the sensitivity of the population, assets and functions of the city. Indicators such as seniors, young population, buildings, infrastructure and residents in the risk area are normally used to represent sensitivity to wildfire (Preston et al., 2009; Swart et al., 2012). For the study area, the same indicators were developed from the best available information. Old or young people in the areas on fire would have more trouble protecting themselves and evacuating areas affected by the fire (Tedim et al., 2014); in addition, they might also be more susceptible to indirect effects of worsening air quality (Brender et al., 2013; Hänninen et al., 2009; Johnston et al., 2007; Künzli et al., 2006). The low-income population is usually the group most affected by wildfire, since they often live in areas at risk, and have little chance of autonomous recovery (GORE, 2014; NFC, 2010; Tedim et al., 2014). Because of the fragility of the materials of construction of the houses as well as due to the distribution of the houses which do not allow the movement of vehicles. Both properties and transport infrastructure in the area of risk are sensitive to wildfire. The greater the number of houses in the area of risk, the more likely wildfires are likely to cause homelessness and the greater the economic loss. A higher percentage of roads in an area at risk implies economic loss and disruption of transport networks, which can affect access to the affected area and isolate other areas of the city not affected by the fire.

**Indicators of vector-borne diseases**

Since the release of the IPCC’s AR4 in 1990, the direct or indirect relationship between climate change and disease and premature death has been recognised. Among the causes are changes in the distribution of some vectors of infectious disease, including HCPS (Confalonieri et al., 2007; IPCC, 2012b). The hantavirus in the Chilean context is related to Andes virus (ANDV), which is transmitted by rodents such as the long-tailed pygmy rice rat (Oligoryzomys longicaudatus), the akodontines Abrothrix longipilis, Abrothrix olivaceus and the phyllotines Loxodontomys micropus and Phyllotis darwini (Spotorno et al., 2000). Klempa (2009) pointed out that outbreaks of hanta virus have been associated with changes in the density of rodent populations. Changes affecting the population dynamics of rodents are often weather- or climate-related (Carbajo et al., 2009; Clement et al., 2009; Engelthaler et al., 1999; Klempa, 2009; Morand et al., 2013; Tersago et al., 2009; Wilson, 2001).

**Exposure:** Humans are at risk of exposure, most commonly through the inhalation of aerosolised virus from the excrement of infected rodents (Kruger et al., 2014), but human-
human ANDV transmission has also been documented in Chile and Argentina (Torres-Pérez et al., 2010; Wells et al., 1997). Magrin et al., (2007) identified evidence that prolonged drought and wildfire have been associated with outbreaks of HCPS in South America including Chile. Since 1990, Chile has presented an increase in HCPS cases, with the Bío-Bío Region being among the most affected (Toro et al., 1998; Torres-Pérez et al., 2010). Contagion usually occurs during recreational or occupational outdoor activities in rural areas, but, in the Chilean case as in some others, exposure to the virus has also been documented in buildings like houses, barns, cellars, etc. and their surroundings in urban areas. It has been observed that exposure to the virus is actually greatest inside buildings (Cantoni et al., 2001; Hjelle and Glass, 2000; Langlois et al., 2001; Murua and Padula, 2004). Indicators such as the yearly cumulative number of cases, HCPS incidence rate and the spatial distribution of HPS cases have been used to study the exposure (Carbajo et al., 2009; WHO., 2012). The best available information for this research corresponds to the cumulative number of cases, the cumulative incident rate, an increase in cases and incidence rate.

**Sensitivity:** The population in direct contact with rodent excrement is more sensitive to acquiring the virus; the most affected in Chile are the male population between 20 and 39 years old who work in forestry or agricultural activities (EPI, 2009). However, there are also recorded cases in both females and males in various occupations, including homemakers, students, tourists, etc. It has been observed that people under five and over 65 years old tend to be more sensitive to the virus. The average virus fatality rate between 1975 and 2015 was 43.7%. The fatality rate reached its peak in 1998 at 75% and was at its lowest in 2008 at 10%. Recent years have seen an increase in both infections and fatalities; there was a 69.2% HCPS fatality rate in 2014 (EPI, 2014). Indicators such as poor, young, senior and sick people and the fatality rate are generally used as indicators of sensitivity to vector-borne diseases (English et al., 2009; Gerba et al., 1996; Schauer et al., 2010; WHO, 1999). For Chile, the best available information corresponds to the HCPS the mortality rate, the overcrowding index and the percentages of poor, elderly and very young people. An increase in the mortality and morbidity rates can be interpreted as evidence of the sensitivity of the population to HCPS. The poor population is more sensitive to viruses because the inadequate environmental conditions associated with people in lower socio-economic conditions favour the existence of rodents (EPI, 2009). The old and young populations appear to be more sensitive to HCPS, since their mortality rate is 15.2% and 5.9% higher than the general population respectively.
People in areas with higher rates of overcrowding are more sensitive to acquiring the virus, since reported cases have occurred in clusters affecting two or three people in the same household, workplace or place of recreation at the time of infection (EPI, 2009).
C2: Fuzzy overlay sensitivity

In order to identify the most appropriate association required to compare differences in the MHI across the four steps of aggregation, in both periods 1992 and 2002, the overlay function GAMMA was varied within a range from 0 to 1, in steps of 0.1. Adjusting the GAMMA values allows multiple thematic layers interact between two extremes: the more restrictively fuzzy PRODUCT or the more expansive fuzzy SUM. Low gamma values (i.e. near 0) result closer to fuzzy product, in this case, a pixel is classified as high when all entry criteria possess high values, and otherwise a pixel is classified as low when only one of the entry criteria has a low value. Whereas when $\gamma = 0$ the result is equal to fuzzy PRODUCT. By contrast, using gamma values close to 1, produces results close to fuzzy SUM, in this case, a pixel is classified as high when at least one of the entry criteria is high, without considering the lower values. When $\gamma = 1$ the result is equal to fuzzy SUM. The variation analysis of GAMMA allows determining the most appropriate association within different levels of aggregation.

1st Fuzzy aggregation

The results of the sensitivity analysis for the first level of aggregation, which combines the set of indicators in the hazard-specific exposure and sensitivity can be seen in Figure C4 and C5. For gamma values below 0.6, most of the resulting exposure and sensitivity for both studied years 1992 and 2002, gives lower values than any entry criterion (i.e. indicators values per municipality). For gamma values over 0.7, the resulting exposure and sensitivity aggregation that mostly falls within the entry criteria values. For values of gamma over 0.9, the resulting exposure and sensitivity for both 1992 and 2002 periods presented mostly higher values than any entry criterion. Moreover, the standard deviation increases and reaches its highest value for gamma values over 0.7. Figures C4 and C5 shows the maximum, mean and standard deviation for each of the hazard-specific exposure and sensitivity for 1992 and 2002. In this first aggregation of information, it is possible to see that a gamma value of 0.7 presents the optimal aggregation, since it represents values for the resulting determinants for both periods 1992 and 2002 between the values of the entry criteria. Furthermore, presents a range and standard deviation that allows to appreciate better the differences in the level of the determinants in urban areas in both studied years.
Figure 4: Fuzzy overlay values of each component of the 1st Fuzzy aggregation, 1992. The specific exposure and sensitivity by hazard were show in a minimum and maximum graph and bar graph represents the standard deviation, for each Gamma value.
Figure 5: Fuzzy overlay values of each component of the 1st Fuzzy aggregation, 2002. The specific exposure and sensitivity by hazard were shown in a minimum and maximum graph and bar graph represents the standard deviation, for each Gamma value.
2nd Fuzzy aggregation

The second aggregation process corresponds to the hazard-specific exposure and sensitivity into hazard-specific vulnerability. To determine the optimal combination of the exposure and sensitivity into the hazard-specific vulnerability, the Gamma function was evaluated. This aggregation process indicates in most of the cases gamma values under 0.6, the components in both years 1992 and 2002 falls below the values of any entry criteria. For gamma values between 0.7 and 0.8, hazard-specific vulnerability are within the values of the inputs criteria. For gamma values above 0.9, the resulting hazard-specific vulnerability for both 1992 and 2002 periods have higher values than any input criterion. While the standard deviation reaches its maximum values for gamma between 0.7 and 0.9. In this process of aggregation gamma value 0.8 is in general represents the best combination of the data, since the resulting values of the components are between the values of the inputs criteria in both years 1992 and 2002. Gamma value of 0.7 typically produces ranges and standard deviations which permit to appreciate better the differences in the level of the components.
Figure 6 Fuzzy overlay values of each component of the 2th Fuzzy aggregation (years 1992 and 2002). The hazard-specific vulnerability was show in a minimum and maximum graph and bar graph represents the standard deviation, for each Gamma value.
3rd Fuzzy aggregation

Third level of aggregation process corresponds to the combination of the exposure and sensitivity. To determine the optimal combination of the exposure and sensitivity, the Gamma function was evaluated. As was analyzed in the above section, this aggregation process indicates that for gamma values under 0.6, the components in both years 1992 and 2002 falls below the values of any entry criteria. For gamma values between 0.7 and 0.8, the exposure and sensitivity are within the values of the inputs criteria. For gamma values above 0.9, the resulting components for both 1992 and 2002 periods have higher values than any input criterion. While the standard deviation reaches its maximum values for gamma between 0.7 and 0.9. As in the case of the previous process of aggregation, this step of aggregation indicates that gamma 0.8, represents the best combination of the data, since the resulting values of the exposure and sensitivity are between the values of the inputs criteria in both years 1992 and 2002. Furthermore, as can be seen in Figure C7 a gamma value of 0.8 typically produces ranges and standard deviations which permit to appreciate better the differences in the level of the components.

Figure 7. Fuzzy overlay values of each exposure and sensitivity of the 3rd Fuzzy aggregation year (years 1992 and 2002). The specific exposure and sensitivity were show in a minimum and maximum graph and bar graph represents the standard deviation, for each Gamma value.
4rd Fuzzy aggregation

From the sensitivity analysis of the overlap function GAMMA, it is possible to observe that for values of gamma lesser than 0.6, the adaptive capacity index presents values lower than any input criteria while its standard deviation decreases. For values of gamma between 0.7 and 0.8 the MHI index presents values close to any input criteria, while its standard deviation increases and reaches its highest values for gamma of 0.8. For gamma values above 0.9, the presence of high suitability values increases, and thus the possibility of obtaining higher values on the multi-hazard impact index. By contrast, low suitability values decreases, and in the case of the studied years the standard deviation decreases.

A value of GAMMA of 0.8 provides the best combination for four processes of aggregation since other overlapping ranges give associations that do not allow better differentiation in the multi-hazard index. Comparatively, gamma 0.8 integrates better the low and high memberships of the multiple input criteria. Thus, Gamma 0.8 gives the best association to compare differences in the level of MHI in urban areas in both studied periods, achieving the largest spread between the values of the index across the studied area. For these reasons, gamma 0.8 was chosen for the MHI analysis in both 1992 and 2002 in the CMA. Table 1 list detailed information about fuzzy GAMMA and its effect on MHI, for Gamma between 0 and 1 in steps of 0.1.
Table 1. Fuzzy GAMMA and its effect on adaptive capacity, for Gamma between 0 and 1 in steps of 0.1.

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<td></td>
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<td>Max</td>
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<td>StD</td>
<td>Min</td>
<td>Max</td>
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D1. Fuzzy overlay sensitivity analysis

In order to identify the most appropriate association required to compare differences in the level of adaptation in the study area, in both periods 1992 and 2002, the GAMMA overlay function was varied within a range from 0 to 1, in steps of 0.1.

Adjusting the GAMMA values allows multiple thematic layers to interact between two extremes: the more restrictive fuzzy PRODUCT or the more expansive fuzzy SUM. Low gamma values (i.e. near 0) give results closer to fuzzy product, in this case, a pixel is classified as high when all entry criteria possess high values, and otherwise a pixel is classified as low when only one of the entry criteria has a low value. When $\gamma = 0$ the result is equal to fuzzy PRODUCT. By contrast, using gamma values close to 1, produces results close to fuzzy SUM, in this case, a pixel is classified as high when at least one of the entry criteria is high, without considering the lower values. When $\gamma = 1$ the result is equal to fuzzy SUM. The variation analysis of GAMMA determines the most appropriate association within different levels of aggregation.

1st Fuzzy aggregation

The results of the sensitivity analysis for the first level of aggregation, which combines 17 proxies on 6 determinants (see Figure 3), indicates that the overlapping function fuzzy GAMMA better recognise the differences between combinations of multiple criteria. For gamma values below 0.5, the resulting determinants for both studied years 1992 and 2002 gives lower values than any entry criterion. For gamma values between 0.6 and 0.8, the resulting determinant aggregation falls within the entry criteria values. For values of gamma over 0.9, the resulting determinants for both 1992 and 2002 periods presented mostly higher values than any entry criterion. Moreover, the standard deviation increases and reaches its highest value for gamma values between 0.5 to 0.7. Figure D1 shows the maximum, mean and standard deviation for each of the 6 determinants for 1992 and 2002. In this first aggregation of information, it can be seen that a gamma value of 0.7 presents the optimal aggregation, since it represents values for the resulting determinants for both periods 1992 and 2002 between the values of the entry criteria. Furthermore, it presents a range and standard deviation that give better appreciation of the differences in the level of the determinants in urban areas in both years.
Figure 1. Fuzzy overlay values of each determinant for the 1st Fuzzy aggregation (years 1992 and 2002). The specific determinant were show in a minimum and maximum graph and bar graph represents the standard deviation, for each Gamma value.
2nd Fuzzy aggregation

The second aggregation process corresponds to the combination of the 6 determinants (i.e. equity, knowledge, infrastructure, technology, economic resources and institutions) into the three components of adaptability (i.e. awareness, ability and action) (see Figure 3 on the main document). To determine the optimal combination of the determinants into the components, the GAMMA function was evaluated. As was analysed in the section above, this aggregation process indicates that for GAMMA values under 0.5, the components in both years fall below the values of any entry criteria. For gamma values between 0.6 and 0.7, the components are within the values of the input criteria. For GAMMA values above 0.8, the resulting components for both 1992 and 2002 have higher values than any input criterion. While the standard deviation reaches its maximum values for gamma between 0.5 and 0.7, particularly for ability and action, while awareness presents its highest standard deviation for GAMMA values between 0.3 and 0.5. As in the case of the first process of aggregation, the second process of aggregation indicates that a gamma of 0.7 represents the best combination of the data, since the resulting values of the components are between the values of the input criteria in both years, 1992 and 2002. Furthermore, as can be seen in Figure D2, a gamma value of 0.7 typically produces ranges and standard deviations which give a better appreciation of the differences in the levels of the components.
Figure 2. Fuzzy overlay values of each component of the 2nd Fuzzy aggregation (years 1992 and 2002). The specific component was shown in a minimum and maximum graph and bar graph represents the standard deviation, for each Gamma value.

3rd Fuzzy aggregation

From the sensitivity analysis of the GAMMA overlap function, it can be seen that for values of GAMMA less than 0.5, the adaptive capacity index presents values lower than any input criteria while the standard deviation decreases. For values of GAMMA between 0.6 and 0.8 the adaptive capacity index presents values close to the input criteria, while the standard deviation increases and reaches its highest values for a gamma of 0.7. For gamma values above 0.9, the presence of high suitability values increases, and thus the possibility of obtaining higher values of adaptive capacity. By contrast, low suitability values decrease, and in the case of the studied years the standard deviation decreases.
A GAMMA value of 0.7 provides the best combination for three processes of aggregation since other overlapping ranges give associations that do not allow better differentiation in the level of adaptability. Comparatively, a gamma of 0.7 better integrates the low and high memberships of the multiple input criteria. Thus, this value gives the best association to compare differences in the level of adaptive capacity in urban areas in both periods in question, achieving the largest spread between the values of the index across the studied area. For these reasons, 0.7 was chosen for further adaptation capacity analysis in both periods (1992 and 2002) in the metropolitan area of Concepción. Table D1 lists detailed information about the fuzzy GAMMA and its effect on adaptive capacity, for GAMMA values between 0 and 1 in steps of 0.1.

Table 1 Fuzzy GAMMA and its effect on adaptive capacity, for Gamma between 0 and 1 in steps of 0.1.

<table>
<thead>
<tr>
<th>N°</th>
<th>Fuzzy Function</th>
<th>1992</th>
<th>2002</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td>Mean</td>
</tr>
<tr>
<td>1</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>2</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>3</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>4</td>
<td>0.000</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>5</td>
<td>0.000</td>
<td>0.020</td>
<td>0.012</td>
</tr>
<tr>
<td>6</td>
<td>0.005</td>
<td>0.078</td>
<td>0.051</td>
</tr>
<tr>
<td>7</td>
<td>0.038</td>
<td>0.223</td>
<td>0.162</td>
</tr>
<tr>
<td>8</td>
<td>0.167</td>
<td>0.470</td>
<td>0.384</td>
</tr>
<tr>
<td>9</td>
<td>0.459</td>
<td>0.749</td>
<td>0.682</td>
</tr>
<tr>
<td>10</td>
<td>0.821</td>
<td>0.942</td>
<td>0.920</td>
</tr>
<tr>
<td>11</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>
D2. Correlation among the components, determinants and indicators

In Figures D3 and D4, a low correlation can be seen between many of the indicators, with only income per capita showing a high correlation with several other indicators in both 1992 and 2002. The determinants were also shown to have relatively low inter-correlation between them, and this was lower in 2002 than 1992. Only economic resources and institution had relatively high correlation with the other determinants and this was evident for both the 1992 and 2002 data. For the components awareness and ability have quite a high inter-correlation in 1992 although this is less so in 2002, whilst ability has a low correlation with the other many components in 1992, which is even lower in 2002. Whilst some inter-correlation of economic resources with other determinants may be expected overall this finding of generally low intercorrelation between the indicators demonstrates that the indicator pre-selection process has removed unnecessary redundancy and that the structure of the index is sound, with the remaining indicators all contributing to explaining the adaptive capacity.

Figure 3. Spearman’s Rank correlation coefficients for components, determinants and indicators 1992.


Note: The significance level refers to *significant correlation at the 0.01 level (bilateral) and ** significant correlation at the 0.05 level (bilateral).
Figure 4. Spearman’s Rank correlation coefficients for components, determinants and indicators 2002.

<table>
<thead>
<tr>
<th>Components</th>
<th>Determinants</th>
<th>Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Awareness</td>
<td>Knowledge</td>
<td>Literacy rate</td>
</tr>
<tr>
<td>Ability</td>
<td>Equity</td>
<td>Inequality</td>
</tr>
<tr>
<td>Action</td>
<td>Technology</td>
<td>Female activity rate</td>
</tr>
</tbody>
</table>

Note: The significance level refers to *significant correlation at the 0.01 level (bilateral) and ** significant correlation at the 0.05 level (bilateral).


longicaudatus spatial distribution sensitivity to climate change scenarios in Argentine Patagonia. Int. J. Health Geogr. 8, 44. doi:10.1186/1476-072X-8-44


CONAMA, 2006. Estudio de la Variabilidad Climática en Chile para el Siglo XXI. Santiago, Chile.


Appendix D

ECLAC, 2012a. La Economía del Cambio Climático en Chile. Santiago, Chile.

ECLAC, 2012b. Vulnerabilidad y Exposición - Efectos del cambio climático en la costa de América Latina y el Caribe. Santiago, Chile.


Greiving, S. et al., 2011. ESPON Climate. Climate change and territorial effects on regions and local economies. Dortmund.


Gutierrez, R., 1975. La población de Chile. CICRED Series, Paris, France.


Hinkel, J., 2011b. "Indicadores de vulnerabilidad y capacidad de adaptación": Hacia una clarificación de la interfaz ciencia-ciencia-política.


Holsten, A.K., Jürgen, W., Carsten, L., Tabea, R., Olivia Klaus, M., 2011. Climate Change and Territorial Effects on Regions and Local Economies Final Report Annex 3 Case Study North Rhine-Westphalia (NRW) Project Leader: Prof. Dr. J. P. Kropp Authors:


IIASA, 2015a. SSP Database (Shared Socioeconomic Pathways) - Version 1.0 [WWW

doi:10.1017/CBO9781139177245


doi:10.1186/1471-2458-7-240


doi:10.1080/13549839.2012.665861


doi:10.1177/0002764201045003004

KC, B., Shepherd, J.M., Gaither, C.J., 2015. Climate change vulnerability assessment in
Appendix D


Krellenberg, K., Barth, K., 2012. Plan de Adaptación al cambio climático para la Región Metropolitana de Santiago de Chile. Santiago, Chile.

Appendix D


LEU, (Departamento De Planificación y Diseño Urbano - Laboratorio de Estudios Urbanos), 2013. Estudio de Riesgos de Sismos y Maremoto para Comunas Costeras de la Región del Biobí Capítulo II: Metodología. Concepcion, Chile.


MoE, 2011. Segunda Comunicación Nacional de Chile ante la Convención Marco de las Naciones Unidas sobre Cambio Climático. Santiago, Chile.


Muñoz, M., 2012. Transformaciones del paisaje por efectos de megaproyectos urbanos:


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


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

NIS, 2005. Chile Hacia el 2050, Proyecciones de Poblacion. Santiago, Chile.


O’Brien, K., 2006. Are we missing the point? Global environmental change as an issue of


Pizarro, J., Castillo, C., 2006. Eventos meteorológicos severos ocurridos en Chile
Continental: descripción y patrones sinópicos tipos asociados. Inf. Dir. Meteorológica Chile 173.


mapping for wards in Mid-Norway. Local Environ. 17, 695–716. doi:10.1080/13549839.2012.685879


Schuman, S., 1972. Patterns of urban heat-wave deaths and implications for prevention:


SEREMI MINVU (Secretaría Regional Ministerial de Vivienda y Urbanismo Región del Bío Bío), 2003. Memoria Explicativa Plan Regulador Metropolitano de Concepción. Concepción, Chile.


SHOA, (Servicio Hidrográfico y Oceanográfico de la Armada de Chile), 2013a. Carta de inundación por Tsunami, Talcahuano San Vicente. Valparaíso, Chile.

SHOA, (Servicio Hidrográfico y Oceanográfico de la Armada de Chile), 2013b. Carta de inundación por Tsunami, Coronel. Valparaíso, Chile.

SHOA, (Servicio Hidrográfico y Oceanográfico de la Armada de Chile), 2013c. Carta de inundación por Tsunami, Lota. Valparaíso, Chile.

SHOA, (Servicio Hidrográfico y Oceanográfico de la Armada de Chile), 2013d. Carta de inundación por Tsunami, Tomé, Lirquen y Penco. Valparaíso, Chile.


doi:10.1016/j.gloenvcha.2006.08.001


UN, 2013. World Population Ageing, Department of Economic and Social Affairs, Population Division. doi:ST/ESA/SER.A/348


Appendix D


Warrick, R., 2006. SimCLIM: Recent developments of an integrated model for multi-scale, risk-based assessments of climate change impacts and adaptation. Area 1–11.


