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Running head (shortened title): Assessing adaptive capacity in Concepción, Chile

Article type: Original Article

Assessing urban adaptive capacity to climate change

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Abstract

Despite the growing number of studies focusing on urban vulnerability to climate change, adaptive capacity, which is a key component of the IPCC definition of vulnerability, is rarely assessed quantitatively. We examine the capacity of adaptation in the Concepción Metropolitan Area, Chile. A flexible methodology based on spatial fuzzy modelling was developed to standardise and aggregate, through a stepwise approach, seventeen indicators derived from widely available census statistical data into an adaptive capacity index. The results indicate that all the municipalities in the CMA increased their level of adaptive capacity between 1992 and 2002. However, the relative differences between municipalities did not change significantly over the studied timeframe. Fuzzy overlay allowed us to standardise and to effectively aggregate 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 many indicators that individually influence adaptive capacity. Furthermore, it captured the complex, aggregated and continued nature of the adaptive capacity, favouring to deal with gaps of data and knowledge associated with the concept of adaptive capacity. The resulting maps can help identify municipalities where adaptive capacity is weak and identify which components of adaptive capacity need strengthening. Identification of these capacity conditions can stimulate dialogue amongst policymakers and stakeholders regarding how to manage urban areas and how to prioritise resources for urban development in ways that can also improve adaptive capacity and thus reduce vulnerability to climate change.

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

1. Introduction

The world is becoming increasingly urbanised, with 70% of the global population projected to live in cities by 2050 compared to 52% in 2010 (UN-DESA 2011). It is expected that most urban growth will be concentrated in the developing world, with urban population rising from 47% in 2011 to 67% in 2050 (UN-DESA 2011). This trend has major social and economic consequences, including the marginalisation of rural areas and a concentration of economic activity in urban centres. In a developing country as Chile, more than 25% of the population lives in nine dense coastal urban cities, covering 46% of the country's urban land surface (INE 2012). The concentration of human, financial and manufactured capital makes cities especially vulnerable to climate change (Revi et al. 2014; Rosenzweig et al. 2011). For this reasons, knowing and understanding the baseline conditions of cities to carry out the adaptation process becomes critical to start thinking about adaption actions.

The IPCC (2014) defines adaptive capacity (AC) as *“the ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences”*. AC could thus be seen as 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; Smit and Wandel 2006), and to reduce climate change vulnerability (Metzger et al., 2008; IPCC, 2014). Spatially explicit vulnerability studies can support governance and decision-making by providing information to know and understand the basic underlying condition that allow a city to adapt to change.

AC is a relative concept, both in terms of spatial distribution and the way it responds in different contexts (Lemos et al. 2013). AC is also an aggregated condition which can be explained through a series of determining factors and processes that affect the ability of a region, area or community to adapt (Smit and Pilifosova 2001; Metzger et al., 2006). The IPCC Third Assessment Report (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, through focusing on social, human and political capital, health, social status, perception of society as well as spreading mechanisms (Adger et al. 2004; Armitage and Johnson 2006; Brooks et al. 2005; Eakin and Lemos 2006; Smit and Wandel 2006; Tol and Yohe 2007).

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 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 (EEA 2012; Swart et al. 2012), an arena where there is a strong demand for suitable methods of analysing urban AC (Schauser et al. 2010).

This paper builds on the work of Acosta et al. (2013) and Swart et al. (2012) to assess AC for the nine municipalities of the Concepción Metropolitan Area (CMA) in Chile. This research is the first to track the temporal and spatial distribution of AC in the recent past (for 1992 and 2002) through a fuzzy overlay approach with Geographic Information Systems (GIS). Using fuzzy set theory (Zadeh, 1965) in GIS allows for flexibility and transparency in the development of the AC index. Fuzzy logic is a multi-valued logic approach which involves the assignment of partial or intermediate values over a well-defined range (0 to 1). Thus allows the identification of varying degrees of AC (Acosta et al. 2008). Fuzzy set theory can be used to represent the

continuous nature of socioeconomic indicators and better addresses the inherent uncertainty and subjectivity of the data used in AC assessments (Acosta et al. 2013). In turn, it allows the straightforward comparison of the spatial objects of different values by first creating standardised value ranges for them (Espada et al. 2013). This enables a comparison of differences in the AC level between municipalities and over time. GIS makes this analysis easier to implement, whilst also allowing flexibility in the combination of maps (Pradhan et al. 2011).

This research is framed around the following questions: a) what was the AC of each of the municipality in 1992 and 2002?; b) how did the AC of each municipality change between 1992 and 2002? and c) which indicators, components and determinants have the greatest influence on the calculation of the AC index for each municipality?. This approach can be readily applied in urban municipalities worldwide with some refinements based on the use of census-based statistics to develop the indicator framework. Our findings can help stakeholders and policymakers in municipalities, contributing to their understanding of the precondition for planned adaptation, supporting the *situational analysis*, the first step in the planning process for climate change in cities (Grafakos et al., 2015).

2. Study Area and Methods

2.1. The Concepción Metropolitan Area

With just over 1 million inhabitants, the CMA is Chile's second city by population. Located in the coastal area of the Bío-Bío Region in the country southern-central area (Figure 1), it covers 2,077 km², has 220km of coastline and comprises ten municipalities (listed in Figure 1). The CMA has a warm-temperate coastal Mediterranean climate, with winter rainfall and high atmospheric humidity, and a dry season lasting from 4 to 5 months (Errázuriz et al. 1998).

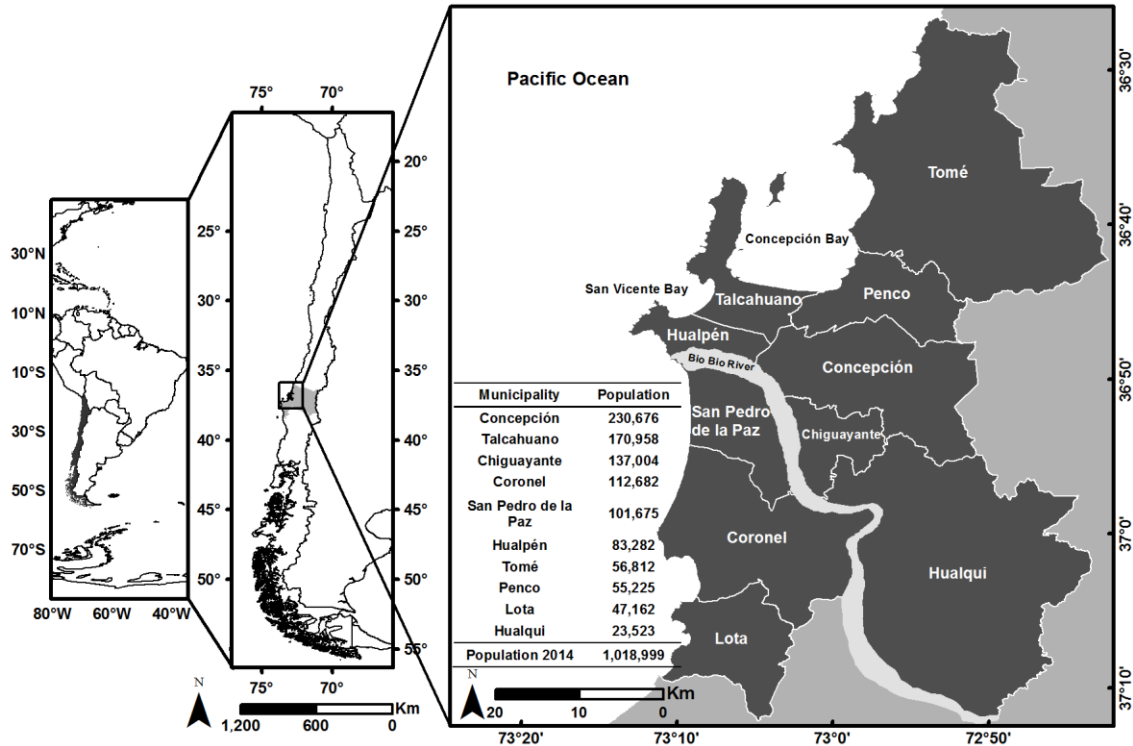


Figure 1. CMA location and table of population projections of CMA municipalities for 2014 (NIS, 2011).

Floods and earthquakes have been particularly damaging to the CMA 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), and the most recent earthquake and tsunami that affected the area in 2010 was one of the most devastating in recent times in the country (Fritz et al. 2011). Consequently, the city's location changed once and the city has been rebuilt several times in response to natural disasters. As in many developing countries, the processes of reconstruction was in many cases unplanned and irregular, with lower-income families who lost their homes occupying risk areas in self-built poor quality housing.

2.2. Developing the adaptive capacity index

This research was structured around three stages as illustrated in Figure 2. First, the overall indicator framework was developed through a critical review of the literature regarding AC and urban vulnerability. From this an aggregation framework of the indicators was established to calculate and create an AC index. Finally, sensitivity, uncertainty and correlation analyses were carried out to evaluate the robustness, relevance and significance, respectively, of the selected indicators for the model outputs (see Appendix A5). All analyses were done in ArcGIS v10 (ESRI, 2012).

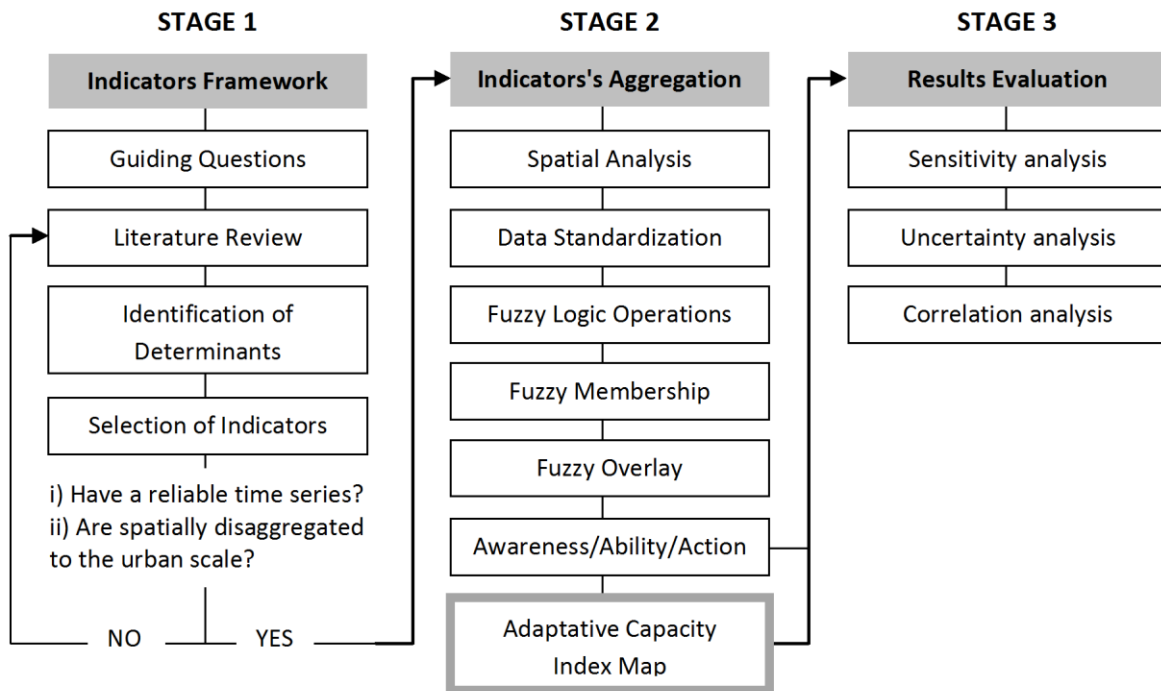


Figure 2. Stages in developing an AC assessment to address climate change in the CMA.

Stage 1: Conceptualisation of the indicator framework

Table 1 presents the selected indicators, these indicators were defined based on a literature review, experience of local stakeholders and data availability. Appendix A1 presents a detailed description of the CMA indicators. Further criteria for indicator selections included the availability of a reliable 20-year time series from 1982 to 2002 for each municipality. Schauer et al. (2010) and Swart et al. (2012) presented an extensive review of indicators that was used to study urban AC.

Table 1. Details of the urban indicators of AC for the years 1992 and 2002

"Awareness" : knowledge and equity			
Indicators	Unit/description	Determinant	Source ^b
Female activity rate ^{1,3,7}	% of working population in total working population	Equity	NIS
Income inequality ¹	Ratio income of top quintile to lowest quintile	Equity	MSD
Literacy rate ¹	% of population aged 15–24	Knowledge	NIS
Tertiary qualification ⁹	% of population aged 15-64 qualified at tertiary level	Knowledge	NIS
"Ability": technology, infrastructure and human health			
Indicators	Unit/description	Determinant	Source ^b
Capacity to undertake research ^{2,6}	Number of scientists in R&D per thousand inhabitants	Technology	ME
Patents ^{1,9}	Number of patent applications per thousand inhabitants	Technology	ME
Distance to hospital facility ³	Distance to public hospitals in minutes	Infrastructure	MH
Hospital beds ^{6,10}	Beds per thousand inhabitants	Infrastructure	MH
Physician ^{1,6}	Physicians per thousand inhabitants	Infrastructure	MH
Transport ⁶	Kilometres of road per square kilometre	Infrastructure	NIS
Physical housing conditions ⁹	% dwellings lacking basic infrastructure and amenities	Infrastructure	NIS
Informal networks ^{1,9}	% of the households with (telephone, mobile phone or internet) connections	Infrastructure	NIS
"Action": economic resources, institutions and social capital			
Indicators	Unit/description	Determinant	Source ^b
Income per capita ^{1,4,6}	Income per inhabitant in national currency	Economic Resources	MSD
Poverty ^{4,6}	% of the population living in extreme poverty or poverty	Economic Resources	MSD
Dependency ratio ^{4,6,9}	Population aged <14 and >65 to population aged 15–65	Economic Resources	NIS
Municipal budget ⁸	Municipal budget per inhabitant in national currency	Institutions	MSD
Master plan updates ^{6,8}	Frequency of official reviews of master plan	Institutions	MSD

^b Source: NIS - National Institute of Statistics. MSD - Ministry of Social Development. ME - Ministry of Economy. MH - Ministry of Health.

Previous examples of using particular indicators: (1Acosta et al., 2013; 2Brooks et al., 2005; 3Cutter et al., 2003; 4EEA, 2012; 5Greiving, 2011; 6Juhola et al., 2012; 7Klasen and Schüler, 2009; 8Posey, 2009; 9Swart et al., 2012).

Stage 2: Standardisation and Aggregation of indicators through fuzzy logic

Standardisation of Indicators

Before fuzzy aggregation can take place the first step is the standardisation of each indicator into a range of 0-1, with indicator values closer to 1 reflecting a greater contribution to AC.

The attribute values for all the indicators were each transformed using linear or non-linear "fuzzy membership functions" to create standardised indicator values within the common range 0-1. 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 3 presents the graphical representation of the types of membership functions used. Appendix A2 present four examples of the fuzzy membership functions.

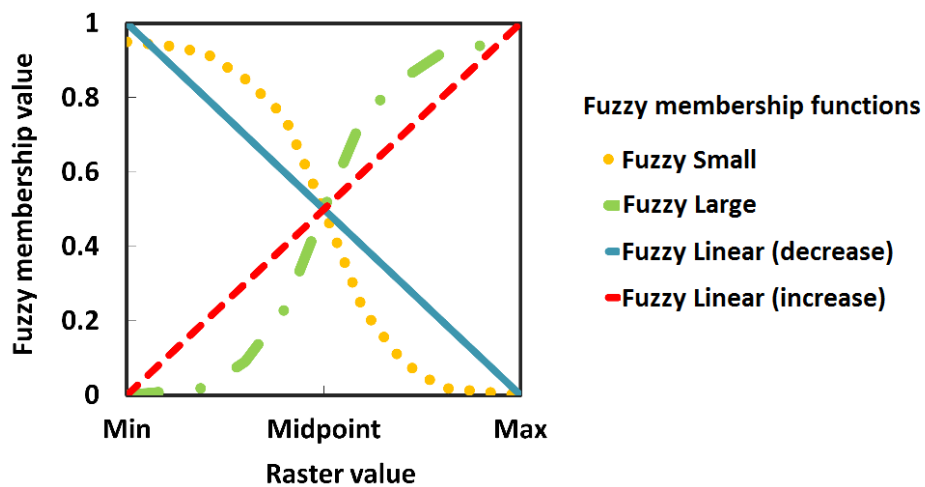


Figure 3. Fuzzy membership functions used for standardization of the indicators. The horizontal axis shows the range of attribute values for each layer to be standardised, while the vertical axis indicates the corresponding membership values for each point.

A positive linear function (either increasing or decreasing) was used to standardise most indicators for which actual minimum and maximum values for Chile were available, in order to represent an assumed positive or negative linear relationship between a change in the indicator and a change in AC. For example *Female activity rate*, *Tertiary qualification*, *Capacity to undertake research*, *Patents*, *Transport*, *Physical housing conditions*, *Informal networks* and *Master plan updates* were all standardised using a positive linear membership function, because as these indicator values increase, the population in an urban area is generally considered to have greater opportunities to adapt successfully to climate change. Similarly, a negative linear relationship was applied to the *Distance to hospital facility* since populations with greater distances to travel to medical facilities are considered to have lower ability to cope with disasters such as flooding.

However, it was not possible to use a linear function to characterise some relationships where there was not enough robust data to determine true minimum and maximum values for the membership function; sometimes only a midpoint value (e.g. a national average) was available. In those cases the functions 'Fuzzy small' and 'Fuzzy large' were used instead, since these two membership functions allow a relationship with AC to be characterised based on knowledge of a known midpoint value and an approximate idea about the possible range of values that the indicator could have and how AC would vary across this range. Fuzzy large

and small functions are more suitable in these cases because they are less sensitive to uncertainties about the extreme values of an indicator, and more sensitive to deviations above and below a known midpoint. For these reasons, Fuzzy small was applied to standardise Income Inequality, Literacy rate gap, Poverty and Dependency ratio, since although each of these are known to have an inverse relationship with AC, accurate maximum and minimum values for these indicators are not published and only median values exist. Using similar reasoning, Fuzzy large was used to model the assumed positive relationships between Hospital beds, Physicians, Income per-capita and Municipal Budget for which again, only median values are available.

Aggregation of indicators

Figure 4 presents the conceptual model of the three components of AC (i.e. awareness, ability and action), and the six determinants (i.e. equity, knowledge, technology, infrastructure, economic resources and institutions) which are constructed from the set of 17 individual indicators. For example, following the work of Acosta et al. (2013) equity and knowledge were used as determinants of awareness. While 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. Finally Action refers to the availability of social, economic and institutional resources that allow the implementation of adaptation actions. Our research utilised the terms Economic Resources and Institutions as determinants adapted from other research (EEA 2012; Greiving 2011; Juhola et al. 2012).

Once the membership values were assigned to each indicator, fuzzy overlay functions were used to conduct three stages of aggregation (Figure 4):

First level of aggregation: the individual indicators were aggregated to create six determinants

Second level of aggregation: determinants grouped into three components.

Third level of aggregation: three components combined into the generic AC index

To accomplish the process of aggregation, various Fuzzy Overlay Functions in ArcGIS 10 (detailed in Appendix A4) were evaluated. GAMMA function was deemed most appropriate for taking multiple inputs into consideration as it does not simply return the value of a single membership set, as do Fuzzy OR and Fuzzy AND, neither does it give greater influence to a single variable, as do Fuzzy SUM and Fuzzy PRODUCT. This is fundamental since when one is assessing AC the combination of the evidence is usually more important than any single input. In this regard, Lewis et al. (2014) indicates that the "GAMMA function provides the best combination of evidence while other overlay methods gave too much weight to single variables at a given location while downplaying others". Further discussion on the relative merits of using the GAMMA function for aggregating multiple sources of information can be found in (Ki and Ray 2014; Malins and Metternicht 2006; Vafai et al. 2013).

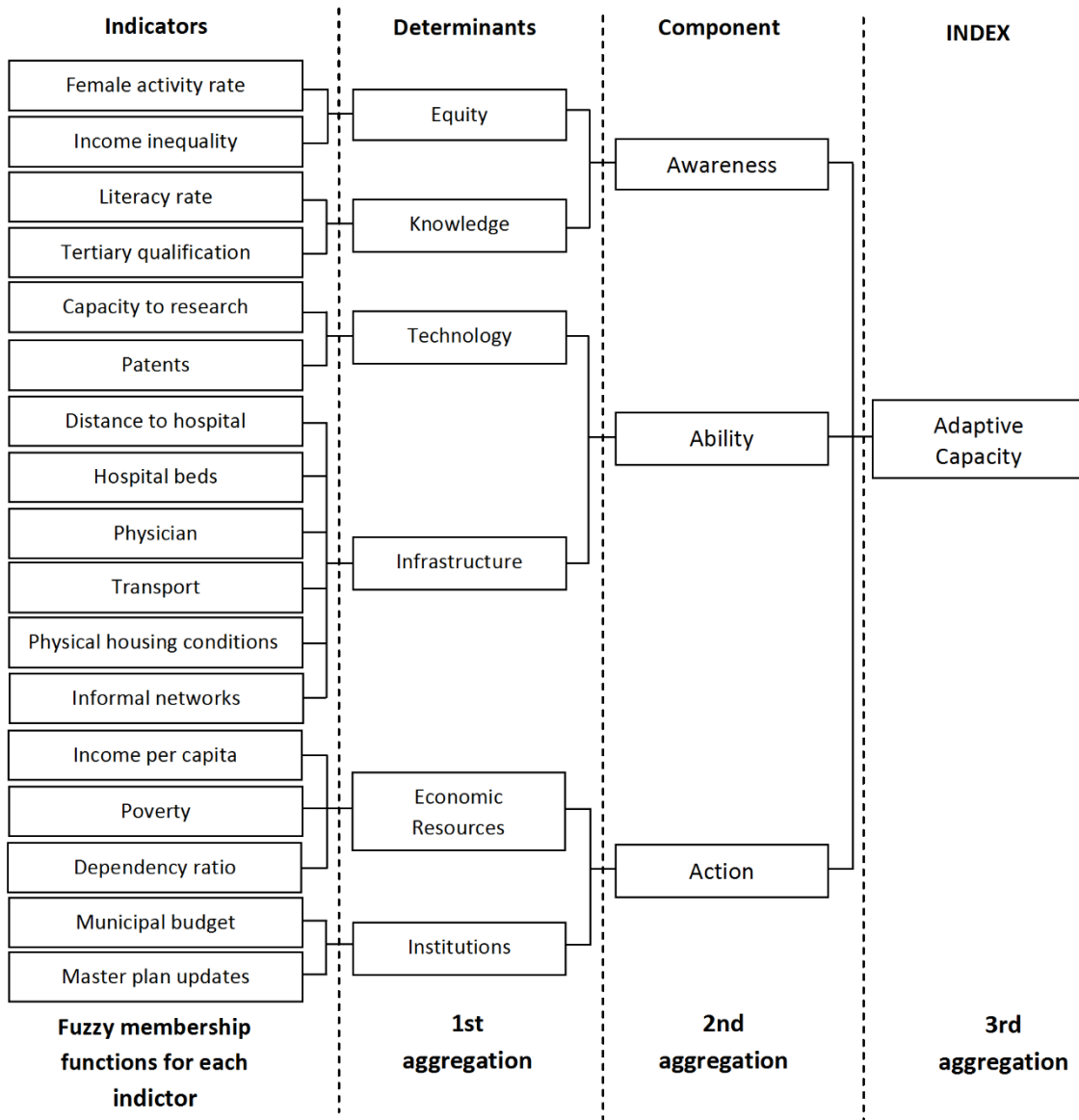


Figure 4. Indicators, determinants and components used to assess AC. Modified from Acosta et al. (2013).

In fuzzy GAMMA, when the gamma (γ) value is set near to 1 the result is more similar to a fuzzy SUM, whilst when GAMMA is set near to 0 the result is similar to a fuzzy PRODUCT. To have a superior comparative representation of the differences in the level of AC across the urban area, outputs of overlays were tested using a sensitivity analysis for values of (γ) in the range [0, 1] in increments of 0.1. Values of (γ) below 0.5 were found to give too much weight to the indicator which had the lowest values, creating values that were unrealistically low, whereas values of (γ) > 0.9 gave too much weight to the single indicator with the highest membership values. For values of (γ) between 0.6-0.8 these effects tend to decline and the resulting values of the overlay tend to produce results which fall within the range of values of the input indicators and take the full range of indicators into account. In this study, for all our aggregations, we consistently used $\gamma = 0.7$ because From the sensitivity analysis this was found to maintain the results of the aggregation within the initial values of the indicators, which assisted interpretation, whilst also maximising the range of output values, which enabled greater differentiation between the municipalities in terms of their AC. Using a constant gamma value also enabled comparative analysis for the different time periods for all the municipalities. The

detailed results of the sensitivity analysis and testing of the full range of GAMMA values to reduce potential distortions or inadvertent weighting of certain variables are presented in Appendix A3.

3. Results

3.1. Determinants, components and adaptive capacity index

First level of aggregation: CMA determinants

Figure 5 shows radar charts for the six AC determinants in each municipality within the CMA. The values are represented from a range of 0 to 1. 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 on the 1992 chart.

The results show contrasting values between determinants in each period and an overall increase in the value of the determinants between 1992 and 2002. Only *equity* is 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* is the most 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 level of literacy rate present in all municipalities. *Knowledge* is only constrained by the low levels of *tertiary qualifications* that the majority of the municipalities display, with the exception of Concepción and San Pedro de la Paz, which are higher. Low values of *economic resources* are in turn determined mainly by indicators of *poverty* and *per capita income*. The low values for *institutions* are likely due to the combined effects of low municipal budgets and a lack of master plan updates. Moreover, the low values for *infrastructure* are mainly explained by the low availability of health services (i.e. doctors and hospital beds per thousand inhabitants).

According to the analysis of the determinants, as of 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 are 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 show a relatively high level of *equity*. This is likely because they present a combination of low per capita income and a low level of income inequality, (i.e. the population in these municipalities was equally poor) with the exception of Lota in 2002 which showed an increased level of income inequality.

Concepción presents the highest values in all the determinants for the study periods of 1992 and 2002. San Pedro de la Paz presents the highest *income per capita values* while also showing the highest levels of *income inequality* for 2002. *Knowledge* levels remain mostly constant through the study period excluding in Concepción for both 1992 and 2002 and San Pedro de la Paz in 2002 which present increased levels for *knowledge*. This relative constancy in the *knowledge* determinant appears to be mainly due to the combination of low levels of *tertiary qualifications* and high levels of *literacy rate* among the municipalities.

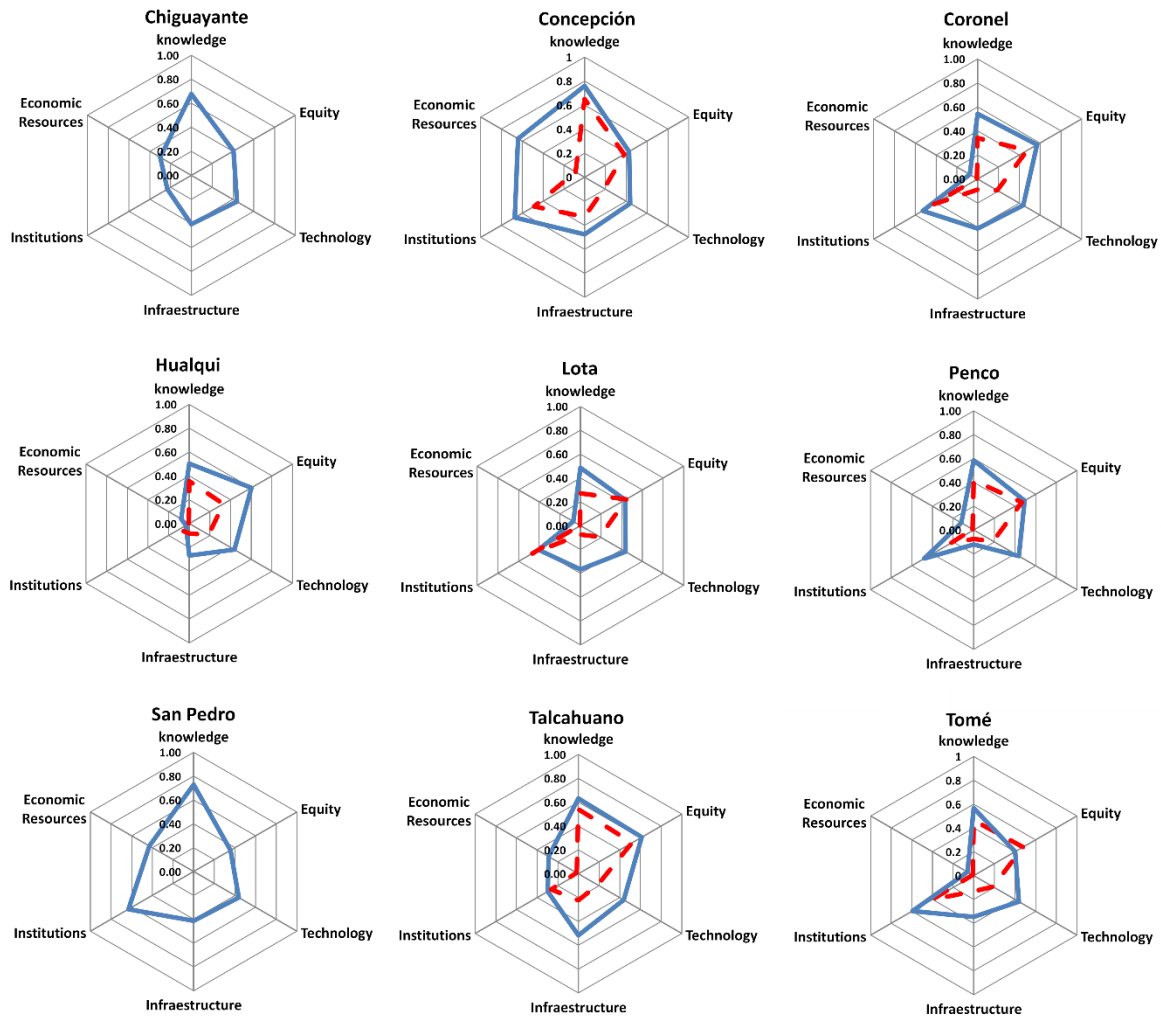


Figure 5. Determinants of AC from first fuzzy aggregation by Municipality. The dashed red line and the blue line denote years 1992 and 2002. San Pedro de la Paz and Chiguayante were created in 1996 and 1992 and they therefore have no values plotted for 1992.

Second level of aggregation: CMA components

Figure 6 shows that all the municipalities increased their levels for the components *awareness*, *ability* and *action* from 1992 to 2002. This is more apparent for *action* and less for *awareness* as the latter appears more constant over time and comparatively higher than *ability* and *action*. For 2002, Coronel, Lota and Hualqui have the highest increase for *ability* and *action*. This increase is likely explained by the improvement in *economic resources* and *infrastructure*, while Concepción and Tomé show less overall improvement over the period, which is mainly explained by the low increase in both *economic resources* and *institutions*.

On average the CMA showed an increase in all components during the study period of 1992 - 2002. More specifically, there were increases in *awareness* of 34%, in *ability* of 153%, and 193% for the *action* component over the studied period. One interpretation that can be drawn from this research is that during the decade of 1992-2002, the CMA had greater increases in the *action* component for almost all municipalities, with the exception of Hualqui. The *ability* component also presents 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* are explained primarily by the overall economic improvement in the country as a whole during the 1990s.

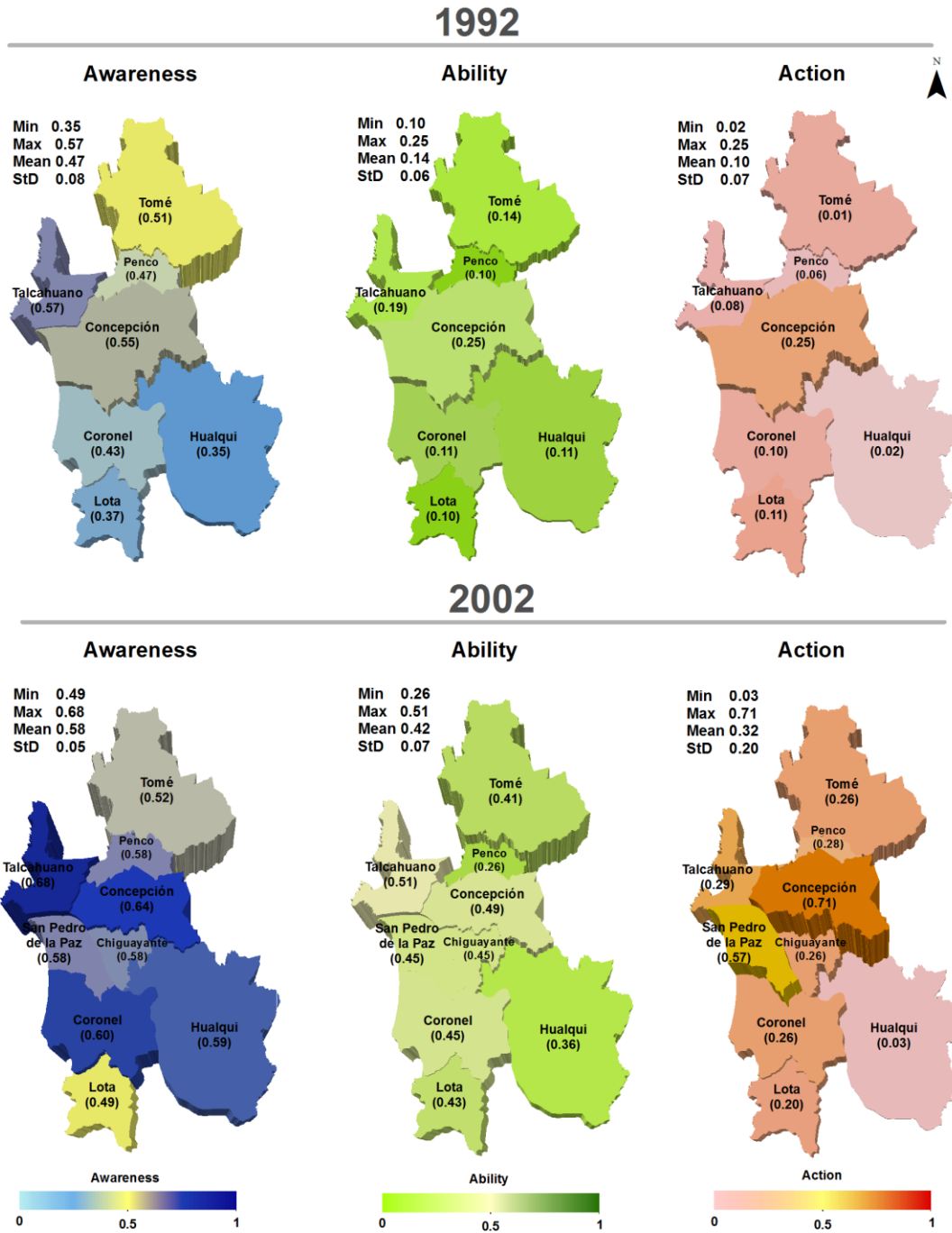


Figure 6. The three main components of AC by Municipality (1992-2002). Blue, green and red denote awareness, ability and action, respectively.

When the variation of the absolute value of a component with respect to its distance from the maximum value (1) is analysed, Concepción, San Pedro and Talcahuano are the closest to the maximum value (1), while Hualqui, Lota and Tomé are furthest away. Generally for all the municipalities, *awareness* is closer to 1, while

ability is generally further away from the maximum. Whilst displaying progress within the municipalities, it is possible to observe that only Concepción, Talcahuano and San Pedro exceeded the average of 0.5, and the other six municipalities are below the average.

Third level of aggregation: CMA Adaptive capacity index

Figure 7 shows that for 1992, Concepción, Talcahuano and Tomé and those with higher AC and Hualqui, Lota and Penco are those with the lowest. An AC ranking (i.e. municipalities were arranged from highest to lowest level of AC) reveals that for 2002 the municipalities with higher and lower levels of AC remains the same. However, with the creation of San Pedro de la Paz and Chiguayante, the municipalities in the middle position changed their relative position in the ranking, placing San Pedro de la Paz as the second municipality (replacing Talcahuano) and Chiguayante in the fifth position over Tomé. The other municipalities maintain their positions, though the most notable change was seen between Hualqui and Lota with a decrease of 20%.

Over the period of analysis the differences between all municipalities decreased. The relative change shows that in 1992 the percentage difference between the AC of the municipalities with the highest value and lowest value was 349%. In 2002 this gap decreased to 224%, which means a decrease in the inter-municipality gap of 125%. Meanwhile, the AC index of the CMA has increased on average by 160%. Municipalities with lower values of AC experienced the greatest increases over the period. For example, in Coronel the index increased by 201%, Hualqui by 186%, and in Lota by 176%. By contrast, Concepción, which has the highest levels of AC, increased by 106%.

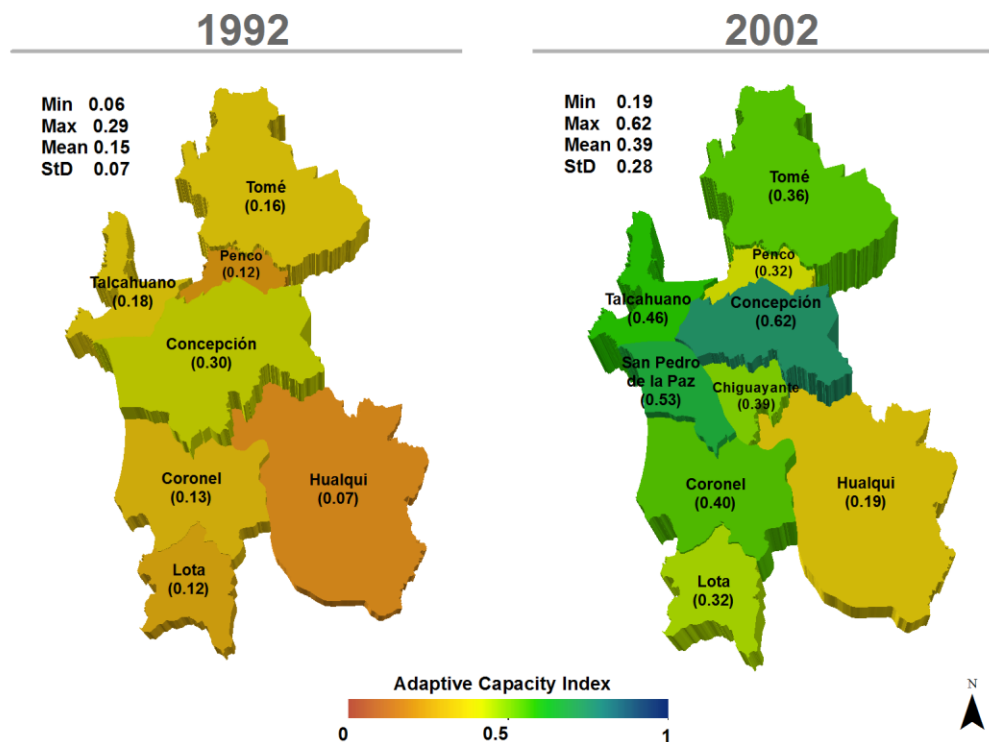


Figure 7. Absolute changes in the CMA AC Index, 1992 - 2002.

4. Discussion

4.1 Assessing the adaptive capacity

This research demonstrated the potential of urban indicators to represent the conditions that we currently understand as constituting AC. Selected indicators help to understand baseline conditions and its evolution in each municipality, which is important for starting a planned adaptation process. They are useful for simplifying complex but typical urban realities by summarising information and facilitating comparison between municipalities (Malone and Engle 2011). They also allow the identification of adaptation hotspots and the monitoring of AC over time, which is relevant for climate policy (Engle 2011). The indicators also proved to be valuable tools for communicating results (Malone and Engle 2011). Through the creation of the set of indicators this study extends growing knowledge on urban AC indicators.

To construct the AC index different membership functions and fuzzy overlay functions were studied. We found that the positive and negative linear functions and fuzzy small and large best represent how the indicators influence 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 was done to give a realistic approach to the determinants as well as to allow the subsequent calculation of the indicators in other municipalities in country. From this first process, it was possible to establish that the CMA presents low values for most of the determinants. This is due to comparison with national urban values which, in the case of Chile, are driven by the metropolitan area of Santiago (e.g. Santiago has 0.37 full-time academics per thousand inhabitants while the CMA had 0.26 in 2002), thus highlighting strong inequalities on a national level which are also observed within the CMA.

The GAMMA function allowed the most effective aggregation of determinants to components, and then to the AC index. GAMMA allowed us to explore the relationships between multiple input criteria, which is critical because in the adaptation process the combination of evidence is often more important than any single input. Unlike other overlay functions, GAMMA takes into account all the indicators in the process of aggregation, better integrating low and high membership from multiple eligibility criteria. Similar results have been highlighted by Lewis (2014), who showed 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 $\gamma = 0.7$, since this value allows the maximum differentiation between the municipalities of the CMA. While lower (0 to 0.5) and higher values (0.8 to 1) of GAMMA reduced the spread and for the other values the process of aggregation resulted in indicator values lower than any entry criterion.

4.1.1 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.

4.1.2 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 the socioeconomic 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 98%. 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.

The hierarchical structure used in this work, has advantages from an operational point of view if structured correctly (including reduction of indicator interdependence). However, in the future, when a greater understanding of the phenomenological relationship between indicators exists, this aspect can be improved, for example, by adding some concepts of network theory which have already been applied in biology, computer science and social sciences as suggested by (Melorose et al., 2015). Since it provide some insight in the complicity in the possible relationship between indicators.

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 the country 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 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 Watkriss, 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).

4.3 Contribution and applications

There are several reasons why this type of evaluation can be considered useful to vulnerability assessments and adaptation policies with regard to climate change in urban areas. Results derived from it can support a broader dialogue on the future of climate adaptation, paying special attention to the areas that require more support throughout the adaptation process (e.g. for more specific purposes such as studies on AC in the face of heat waves in the light of an aging population). Identifying AC by taking into account location and specific urban conditions provides a better understanding of vulnerability, in particular for locally-oriented adaptation measures.

The analysis at the municipal scale of city complexes provides information suitable for the design of urban policies. In addition, it facilitates access to information, since statistical and spatial information is usually available down to the municipal scale. As adaptation measures are usually implemented on a local level by local governments, it is necessary to explore AC at this scale to identify the strengths and weaknesses faced by local governments (Preston et al. 2009; Eriksen and Kelly 2006). O'Brien (2006) suggests that a high AC on a national level may not necessarily translate into high AC locally. In turn, Glaas et al. (2010) argues that the lack of legislation on a national level may hinder local action, while Juhola and Westerhoff (2011) argue that the lack of legislation on a national level could impede the flow of resources to different scales. Therefore, high quality information on a local level and coordination between different levels of government are needed to successfully address the process of adaptation on a city scale (Heidrich et al., 2016). The AC index created and presented in this research provides information on an urban scale which favours the development of plans and urban policies of adaptation which are normally framed in the National Adaptation Plan.

The structure of the index into three components, *Awareness*, *Ability* and *Action*, allows a simple examination of the various components in relation to each other. This type of analysis is necessary because it emphasises the differences that can be seen in urban areas in developing countries such as the CMA. In these urban areas there are significant local variations, which are clearly shown by the components and determinants, demonstrating that this design eases communication of the results. The methodology here developed is highly transportable, being applicable for other cities around the world, particularly since similar datasets are available in other countries and fuzzy aggregation processes can be applied, providing the limits of the functions are determined specifically for the urban context in question. Moreover, the model design incorporating ArcGIS, a widely used tool, which support a transparent and a straightforward aggregation process; in turn allowing flexibility in the combination of maps. This favours implementation in other urban areas around the world. In addition, the model design allows integration with impact models on vulnerability assessment. The model design also allows future application with climate and global change scenarios, thus allowing analysis and comparison of the costs and benefits of long-term climate change and climate policy to society.

5. Conclusion

This paper assesses the capacity for generic adaptation in the CMA based on the aggregation of available indicators through a Fuzzy-based model, which 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 reflect a realistic measure of continuous factors of the dynamics of AC across the CMA. The model development and result analysis in the GIS software ArcGIS environment was straightforward and demonstrates the benefits of fuzzy set modelling to future research in the field of vulnerability to climate change. The method here proposed to assess the urban adaptive capacity to climate change can be used by scientists, stakeholders and policymakers, in urban areas worldwide as a base to track spatially and temporally the adaptive capacity.

The model's results show that between 1992 and 2002, all the municipalities in the CMA increased their level of AC. The municipalities with lower levels of AC were those with highest increases over this period. The AC gap between the poorest and richest municipalities had been reduced by 2002. However, the relative differences in the levels of adaptation between municipalities were maintained over the decade. Our analysis also shows that of the three components of AC, *awareness* was the highest in all the 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.

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References

- Acosta L, Kavi Kumar KS, Klein RJT, Campe S (2008) Application of fuzzy models to assess susceptibility to droughts from a socio-economic perspective. *Reg Environ Change* 8(4): 151–160
- Acosta L, Klein RJT, Reidsma P, Metzger MJ, Rounsevell MDA, Leemans R, Schröter D (2013) A spatially explicit scenario-driven model of adaptive capacity to global change in Europe. *Global Environ Chang* 23(5): 1211-1224
- Adger WN, Brooks N, Bentham G, Agnew M, Eriksen S (2004) New indicators of vulnerability and adaptive capacity. Tyndall Centre for Climate Change Research Technical Report 7, Norwich, UK
- Armitage, D. R. and D. Johnson. 2006. Can resilience be reconciled with globalization and the increasingly complex conditions of resource degradation in Asian coastal regions? *Ecology and Society* 11(1): 2
- Brooks N, Neil Adger W, Mick Kelly P (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environ Chang* 15(2): 151–163
- Burton I (2004) Climate Change and the Adaptation Deficit. Occasional Paper 1. Adaptation and Impacts Research Group, Meteorological Service of Canada, Environment Canada, Ottawa Canada
- Cutter et al., (2003) Social vulnerability to environmental hazards. *Soc. Sci. Q.* 84, 242–261
- Eakin H, Lemos MC (2006) Adaptation and the state: Latin America and the challenge of capacity-building under globalization. *Global Environ Chang* 16(1):7–18
- EEA (2012) Urban Adaptation to Climate Change in Europe: Challenges and Opportunities for Cities Together with Supportive National and European Policies. EEA Report, No. 2/2012, European Environment Agency (EEA), Copenhagen, Denmark, 143 pp
- Engle NL (2011) Adaptive capacity and its assessment. *Global Environ Chang* 21(2): 647–656
- Eriksen SH, Kelly PM (2006) Developing Credible Vulnerability Indicators for Climate Adaptation Policy Assessment. *Mitig Adapt Strategies Glob Chang* 12(4): 495–524

- Errázuriz AM, Cereceda P, Gonzales JI, Gonzalez M, Henriquez R, Rioseco R (1998) Manual de geografía de Chile. Editorial Andrés Bello, Santiago, Chile
- Espada R, Apan A, Mcdougall K (2013) Using spatial modelling to develop flood risk and climate adaptation capacity metrics for assessing urban community and critical electricity infrastructure vulnerability. In 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1–6 December 2013
- ESRI 2012. ArcGIS Release 10.1. Redlands, CA: Environmental Systems Research Institute
- Fitzsimons P, Bond M, Webber S (2010) Creating a participatory adaptive capacity index for climate change adaptation - Report of engagement process in the South-West of Victoria. Department of Primary Industries Victoria, Victoria, Australia
- Fritz, H. M., et al., (2011). Field survey of the 27 February 2010 Chile tsunami, *Pure Appl. Geophys.*, 168(11): 1989–2010
- Gallopín GC (2006) Linkages between vulnerability, resilience, and adaptive capacity. *Global Environ Chang* 16(3): 293–303
- Glaas E, Jonsson A, Hjerpe M, Andersson-Sköldb Y (2010) Managing climate change vulnerabilities: formal institutions and knowledge use as determinants of adaptive capacity at the local level in Sweden. *Local Env* 15(6): 525-539
- Grafakos S., et al., (2015) Integration of climate adaptation and mitigation: Opportunities and challenges for cities. In *Cities and Climate Change: Second Assessment Report of the Urban Climate Change Research Network*. Cambridge University Press
- Greiving S (2011) ESPON Climate - Climate change and territorial effects on regions and local economies, Dortmund
- Heidrich, O., et al., (2016). National climate policies across Europe and their impacts on cities strategies. *Journal of Environmental Management*, 168, 36–45. <http://doi.org/10.1016/j.jenvman.2015.11.043>
- Henríquez C, Azócar G, Romero H (2006) Monitoring and modeling the urban growth of two mid-sized Chilean cities. *Habitat Int* 30(4): 945–964
- Hunt A, Watkiss P (2010) Climate change impacts and adaptation in cities: a review of the literature. *Climatic Change* 104(1): 13–49
- INE (Instituto Nacional de Estadísticas) (2011). CHILE: Proyecciones y Estimaciones de Población. 1990-2020 País, Regiones y Comunas. Santiago, Chile
- INE (Instituto Nacional de Estadísticas) (2012). Compendio estadístico 2012, Santiago, Chile
- IPCC (The Intergovernmental Panel on Climate Change) (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. (C. B. Field, V. Barros, T. F. Stocker, and Q. Dahe, Eds.). Cambridge University Press, Cambridge, UK
- IPCC (The Intergovernmental Panel on Climate Change) (2014). Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Five Assessment Report of the Intergovernmental Panel on Climate Change. Annex II: Glossary. Cambridge, UK
- Juhola S, Peltonen L, Niemi P (2012) The ability of Nordic countries to adapt to climate change: assessing adaptive capacity at the regional level. *Local Env* 17(6-7): 717–734
- Juhola S, Westerhoff L (2011) Challenges of adaptation to climate change across multiple scales: a case study of network governance in two European countries. *Environ Sci Policy* 14(3): 239–247
- Klasen, S., Schüler, D (2009) Reforming the Gender-Related Development Index and the Gender Empowerment Measure : Implementing Some Specific Proposals In:, Discussion Papers No. 186. Ibero-America Institute for Economic Research (IAI). Georg-August-Universität Göttingen. doi:10.1080/13545701.2010.541860

- Ki SJ, Ray C (2014) Using fuzzy logic analysis for siting decisions of infiltration trenches for highway runoff control. *Sci Total Environ* 493: 44–53
- Lemos et al., (2013) Building adaptive capacity to climate change in less developed countries G.R. Asrar, J.W. Hurrell (Eds.), *Climate Science for Serving Society*, Springer, Dordrecht, The Netherlands (2013), pp. 437–457
- Lewis SM, Fitts G, Kelly M, Dale L (2014) A fuzzy logic-based spatial suitability model for drought-tolerant switchgrass in the United States. *Comput Electron Agric* 103: 39–47
- Malins D, Metternicht G (2006) Assessing the spatial extent of dryland salinity through fuzzy modeling. *Ecol Model* 193(3-4): 387–411
- Malone EL, Engle NL (2011) Evaluating regional vulnerability to climate change: purposes and methods. *WIREs Clim Change* 2: 462–474
- Melrose et al., (2015) Adaptive capacity of geographical clusters: Complexity science and network theory approach. *Statew. Agric. L. Use Baseline* 2015 1. doi:10.1017/CBO9781107415324.004
- Metzger MJ, Leemans R, Schröter D (2005) A multidisciplinary multi-scale framework for assessing vulnerabilities to global change. *Int J Appl Earth Obs Geoinf* 7(4):253–267
- Metzger MJ, Schröter D, Leemans R, Cramer W (2008) A spatially explicit and quantitative vulnerability assessment of ecosystem service change in Europe. *Reg Environ Change* 8(3):91–107
- O'Brien, K et al., (2004) Mapping vulnerability to multiple stressors: climate change and globalization in India. *Glob. Environ. Chang.* 14, 303–313. doi:10.1016/j.gloenvcha.2004.01.001
- O'Brien K (2006) Are we missing the point? Global environmental change as an issue of human security. *Global Environ Chang* 16(1): 1–3
- Patt AG, Tadross M, Nussbaumer P, Asante K, Metzger M, Rafael J, Goujon A, Brundrit G (2010) Estimating least-developed countries' vulnerability to climate-related extreme events over the next 50 years. *Proc Natl Acad Sci USA* 107(4): 1333–1337
- Pradhan B (2011) GIScience Tools for Climate Change Related Natural Hazards and Modelling. In Joshi PK, Singh TP (eds) *Geoinformatics for Climate Change Studies*, The Energy and Resources Institute, New Delhi, India
- Preston B, Brooke CC, Measham TG, Smith TF, Gorddard R (2009) Igniting change in local government: Lessons learned from a bushfire vulnerability assessment. *Mitig Adapt Strategies Glob Chang* 14(3):251–283
- Posey J (2009) The determinants of vulnerability and adaptive capacity at the municipal level: Evidence from floodplain management programs in the United States. *Glob. Environ. Chang.* 19, 482–493 doi:10.1016/j.gloenvcha.2009.06.003
- Poumadère M, Mays C, Le Mer S, Blong R (2005) The 2003 heat wave in France: dangerous climate change here and now. *Risk Anal* 25(6):1483–94
- Revi, A., et al. (2014). *Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Chapter 8: Urban Areas.* Cambridge, UK
- Rosenzweig C, Solecki WD, Hammer SA, Mehrotra S (eds) (2011). *Climate Change and Cities. First Assessment Report of the Urban Climate Change Research Network.* Cambridge University Press, Cambridge
- Satterthwaite D, Huq S, Pelling M, Reid H, Romero P (2007) *Adapting to Climate Change in Urban Areas. The possibilities and constraints in low- and middle-income nations.* Human Settlements Group and the Climate Change Group at the International Institute for Environment and Development (IIED), London, UK

- Schauser, et al. (2010) Urban Regions: Vulnerabilities, Vulnerability Assessments by Indicators and Adaptation Options for Climate Change Impacts. Scoping study. [online] URL: http://acm.eionet.europa.eu/reports/docs/ETCACC_TP_2010_12_Urban_CC_Vuln_Adapt.pdf
- Smit B, Wandel J (2006) Adaptation, adaptive capacity and vulnerability. *Global Environ Change* 16(3): 282–292
- Swart, R., et al., (2012) Urban Vulnerability Indicators, ETC-CCA and ETC-SIA Technical Report 933, 01/2012, European Topic Centre on Climate Change Impacts, Vulnerability and Adaptation (ETC/CCA) and European Topic Centre on Spatial Information and Analysis (ETC/SIA), p.178
- Tol RSJ, Yohe GW (2007) The weakest link hypothesis for adaptive capacity: an empirical test. *Global Environ Chang* 17(2): 218–227
- UN-ISDR (2002) Natural Disasters and Sustainable Development: Understanding The Links Between Development, Environment and Natural Disasters Background Paper No. 5. United Nations International Strategy for Disaster Reduction, New York, USA
- UN-DESA (2011) World Urbanization Prospects The 2011 Revision. United Nations, Department of Economic and Social Affairs (DESA), New York, USA
- Vafai F, Hadipour V, Hadipour A (2013) Determination of shoreline sensitivity to oil spills by use of GIS and fuzzy model. Case study - The coastal areas of Caspian Sea in north of Iran. *Ocean Coast Manage* 71:123–130
- Van Heemst C, Willems J, Weller A, Van Verseveld H, Caamaño D, Aránguiz R (2013) Flood defence alternatives for the lower Bío Bío River, Chile. *Obras y Proyectos* 14:22–33
- Vincent K (2007) Uncertainty in adaptive capacity and the importance of scale. *Global Environ Chang* 17(1): 12–24