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The key factors of the level of urban resilience: an analysis of 13,000 cities worldwide

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Summary

Climate-related events have been increasing in frequency and uncertainty. The majority of the world's population is urban and, since future growth will occur in cities, people and resources will be even more concentrated, enhancing their vulnerability to shocks and stresses. In order to address the impacts of climate change and promote a sustainable development, cities must build resilience. Therefore, the main objectives of this research were to understand the factors (independent variables) that influence the level (dependent variables) of urban resilience, to what extent they can be measured by existing indicators and databases available, what is the level of urban resilience as calculated by a composite index, and what are the key factors influencing it. Despite this being a concept without a common definition and hard to be operationalized, a thorough literature review resulted in the definition of the variables and indicators for an integrated framework to measure urban resilience, which is divided into five dimensions – economic, environmental, institutional, physical and social. When comparing this theoretical framework with existing databases, it was possible to notice that none of them would allow a complete assessment, evidencing the importance of better data availability. However, since the GHS Urban Centre Database 2015 had indicators available for all dimensions, besides a sample of 13,000 cities worldwide, it was chosen for the purposes of this research. To build a composite index from the dependent variables, a technical procedure of supervised learning techniques – such as multivariate analysis, normalization, weighting and aggregation, and uncertainty and sensitivity analysis – was performed. The result was a robust score that is able to rank cities' performance. Its interpretation lead to the understanding that indeed a comprehensive assessment can provide a different perspective on what it means to be resilient. Parameters like emissions of CO_2 and PM2.5 emissions, green area per capita, built area and flood exposure carried a significant weight on the level of urban resilience. Some unsupervised learning techniques, such as dendrograms and cluster analysis, provided allowed the identification of some groups of cities with similar scores. Additionally, evaluating the relation of the independent variables with the composite index through regression analysis, it was evidenced that temperature, precipitation, land use efficiency and development level are the main factors influencing it. As a result, it was clear that the integrated framework proposed can provide urban planners and local governments an important decision-making tool.

Keywords

Urban resilience; framework; indicator; supervised techniques; unsupervised learning.

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Abbreviations

EW	Equal Weighting
ISO	International Standards Organization
MMF	Mori Memorial Foundation
PCA	Principal Component Analysis
UN	United Nations
UN-Habitat	United Nations Human Settlement Programme
WCCD	World Council on City Data

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Chapter 1: Introduction

1.1 Background

Climate-related events cause many impacts to cities and its inhabitants. Anthropogenic actions have been enhancing climate change and consequently increasing the intensity and frequency of these events, such as sea level rise, flooding, droughts, coastal erosion, heat waves and storms (Mogelgaard et al., 2019; UN-Habitat, 2014). Even though some threats and hazards might be partially predictable, most of them are uncertain (Collier et al., 2014). In addition, since the majority of world population is urban and future growth will occur in cities, people, infrastructure and services will be concentrated in the same locations, making urban areas more exposed to shocks and stresses (Hernantes et al., 2019; Kim and Lim, 2016). Over the past half century, climate related disasters have already caused more than 800,000 deaths, a trillion dollars in financial prejudice, and the Earth's warming and increasing (human-generated) emissions will make disasters more frequent and severe, maybe reaching an unchangeable level of disturbance (ECA, 2009). With environmental conditions becoming less predictable and more dynamic, urban planners are challenged to use historical information and future scenarios to predict the consequences of climate change (Milly et al., 2008; Opitz-Stapleton et al., 2011) and try to come up with adequate solutions to these complex problems. The current "trends in urbanisation and climate change mean that the world's cities are facing unprecedented uncertainty, which has the potential to undermine their ability to sustain the lives and livelihoods of their citizens" (Collier et al., 2014, p.89).

This environmental phenomenon is being seen worldwide, but it is not experienced the same way among urban areas. Cities that have lacking infrastructure and services, higher social segregation, non-favorable physical conditions, among many factors, are more vulnerable to the impacts of climate change – at the municipal scale, poor citizens suffer an even higher vulnerability (Mogelgaard et al., 2019). As highlighted by Figueiredo, Honiden and Schumman (2018, p.14) "spatial segregation and inequality create very different levels of vulnerability and resilience within the urban fabric". Therefore, while looking for solutions to environmental challenges it is necessary to address urbanization processes (Kaika, 2017) and their implications to a sustainable development. In that way, not only a forward-looking perspective is necessary, but also cities need to shape and overcome themselves by building resilience (The Rockefeller Foundation and ARUP, 2014). Despite only being proven while facing the effects of a shock or stress, and trying to recover and reorganize after it, resilience is an intrinsic characteristic of a system (Tyler and Moench, 2012). If a system is able to prepare to disruptions, its capacity of management will be improved and, to better consider the complexity of the system and deal with de dynamism and uncertainty, it is necessary to adopt a strategic planning approach (Walker et al., 2002).

Resilience is not built from scratch, it is a continuous process that should be executed on a daily basis, count with awareness and participation of all stakeholders (Hernantes et al., 2019), and an "objective which cities should try to achieve through appropriate planning, policies and interventions" (Béné et al., 2018, p.121). Similarly to the impacts of climate change, resilience depends on the social capacities of individuals and groups and, therefore, it is not spread equally throughout the population (Tyler and Moench, 2012). Cities that have less capacity to cope with shocks and stresses are more vulnerable to climate-related events (Shaw et al., 2009; da Silva, Kernaghan and Luque, 2012) and, thus, less resilient. Since different stakeholders and locations have distinct levels of vulnerability, it is crucial to provide urban planners with a robust tool to analyze urban resilience and measure the results overtime, supporting a just and efficient allocation of resources to address the most latent problems, because "ensuring that cities, their residents, assets, and infrastructure are prepared for and can withstand climate-change impact is integral to achieving and maintaining sustainable development" (Mogelgaard et al., 2019, p.5). By measuring resilience, local governments should be able to assess the conditions and determine the city's needs of improvement (Fu and Wang, 2018). To reduce the vulnerability of assets, it is necessary to understand what are the susceptibilities of the systems, what will happen if they fail and the impact of other connections (Collier et al., 2014). Additionally, considering the social, economic, physical and institutional dimensions and indicators to each of these aspects, the municipality would better understand the threats and priorities of action, being able to propose more effective strategies, optimize resources and enhance opportunities (Figueiredo, Honiden and Schumman, 2018) – what would be very useful because some municipalities still have to ensure an appropriate provision of basic services that are prepared to respond to climate change hazards (Béné et al., 2018).

Cities are considerably responsible for many unsustainable actions, they are pushing beyond the ecological limits (Olazabal et al., 2012), and "now, more than ever, cities are hot spots responsible for threatened global ecological boundaries" (Chelleri et al., 2012, p.5). The 2030 Agenda for Sustainable Development, the Paris Agreement and other international documents acknowledge that cities are both the cause of many challenges faced worldwide, and the potential for solutions to a more sustainable development, provided that they are planned and managed adequately and promote a transformation towards economic improvement, social and cultural inclusiveness and protection of the environment (UN, 2017). In fact, local governments increasingly have capacity to guide global climate actions (Grafakos et al. 2019), especially if they change their policy and planning strategy (Chelleri et al., 2012). Plans and policies in the urban context should then be seen as drivers of transformation and address regional and global scales to tackle the environmental challenges (Olazabal et al., 2012), and understand that climate change can result from abrupt or slow and steady built changes, so developing resilience is necessary because they are not immune to the impacts of climate events on its prosperity (Kim and Lim, 2016). Accepting the current scenario of unsustainability, the impacts of climate change and resources scarcity is just the first step to promote a change in systems and lifestyles, and, to encourage a transformation, it is necessary to be flexible, adapt and innovate (Chelleri et al., 2012). Cities must better manage their resources (Agudelo-Vera et al., 2012), use them with efficiency (Béné et al., 2018), reduce their consumption, and address the environmental, social and economic impacts that hazard events cause to the stakeholders distressed (Kim and Lim, 2016). This is not an easy task, yet "at this critical juncture in human history, rethinking the way we plan, build, and manage our urban spaces is not an option but an imperative" (UN, 2017, p. iv).

1.2 Problem statement

According to Tyler et al. (2016, p. 421) "if resilience is defined as a characteristic or state of a complex system, then in principle it should be possible to compare key factors that contribute to resilience over time, thus implying changes in the overall resilience of the system". However, addressing a complex and wide concept such as resilience is a challenge, and there needs to be further development in frameworks that operationalize the building process (Hernantes et al., 2019). Even with the increase of research in the past years, the progress made in the theories of urban resilience are yet not reflecting an integrative and comprehensive approach to different impacts and uncertainties that is able to provide guidance for decision-makers (Fu and Wang, 2018; Kaika, 2017; Collier et al., 2014). Additionally, urban resilience must consider properly the urbanization process and change the current situation, that may promote social injustice, environmental unsustainability and make vulnerable communities even more exposed to hazards (Béné et al., 2018). Plans, strategies and indicators should, therefore, identify the context, meaning to understand the risks and threats faced, through a participatory process (Figueiredo, Honiden and Schumman, 2018), take climate change into account (UN-Habitat, 2014), consider the local context, be careful to improve the conditions of all stakeholders (Chelleri et al., 2012), and consider social and environmental factors, instead of using urban development as a marketing strategy (Olazabal et al., 2012). If the development of these policies is reinforced by adequate supporting tools, they will be more assertive, improve the environmental and economical response (ECA, 2009), be easier mainstreamed into practice, promote adaptiveness and flexibility, consider cross-scale interactions and systematic thinking, as well as assimilating different agents to work towards the same goal to strengthen resilience (Béné et al., 2018).

Even though this is not an easy process, "increasingly, local governments are engaging in sustainability planning processes to encourage long-term thinking and integrate social, environmental and economic considerations into one framework" (Picketts, Déry and Curry, 2014, p.987). Also, both scholars and organizations have made several efforts to develop a framework to assess resilience and consider the climate change challenges. For example, Tyler and Moench (2012) developed a framework that aims to integrate ecological, infrastructure, social and institutional perspectives; The Rockefeller Foundation and ARUP (2014) developed the City Resilience Index based on four dimensions, namely 'health & wellbeing', 'economy & society', 'infrastructure & ecosystems', and 'leadership & strategy', considering that cities rely on their physical infrastructure, policies, social capital and institutions; Elias-Trostmann et al. (2018), developed a framework to assess resilience from a community level perspective looking at the vulnerability context, community resilience and individual capacity; the Global Power City Index (MMF, 2018) assess the attractiveness of cities according to their economy, research and development, cultural interaction, livability, environment, and accessibility functions; and, finally, the Global Urban Competitiveness Report (Ni, Kamiya and Ding, 2017) analyzes the competitiveness of urban areas considering the determining factors of company strength, local elements, local demand, software environment, hardware environment, and global connection. Despite each of these examples giving an important contribution to develop a specific tool to measure resilience, a holistic and comprehensive framework still has to be assembled, defining the quantitative indicators and aligning them with a common definition of what is resilience. Building this robust theoretical framework is of extreme importance because allows a better perception of the concept and choice of indicators the will constitute its measurement the composite index (Asadzadeh et al., 2017) that represents the level of urban resilience.

1.3 Research objective

Given the analysis of the relation between cities, climate change and resilience, as well as the importance of evaluating the latter, the objective of this research is to identify the key factors of urban resilience, through an integrated framework that considers the indicators proposed by the literature, and cross-checks those measurement with existing information in databases, to provide a robust and comprehensive assessment. Additionally, by performing a secondary quantitative data analysis the aim is to evaluate to what extent it is possible to measure resilience. More than that, with the results in hands, it might be possible to compare a relevant sample of cities across the world and verify what are main characteristics that make one city more resilient than others. Consequently, possibilities for local government to act towards a more sustainable development may be pointed – what can be even more useful for cities in the global south, that have a higher vulnerability to climate change.

To achieve such a framework, not only the existing models proposed by scholars and organizations will be assessed and compiled in a single table of indicators, but also they will be compared with data available in different sources, such as the Global Human Settlement Urban Centre Database 2015 (European Commission, 2019), Passport database (Euromonitor, 2019), Global Gridded Model of Carbon Footprints (Moran et al., 2019), World Council on City Data (WCCD, 2019), and Urban Data (UN-Habitat, 2019), among others. The aim is to ensure that the proposed framework for measuring urban resilience will incorporate as much information available as possible to enhance its effectiveness and validity of comparison among cities. To build this composite index grounded on existing methodology will be very important for the validity of the work, because as highlighted by Nardo et al. (2008, p.35), "a sound theoretical framework is the primary ingredient" for building a composite indicator.

1.4 Provisional research questions

Based on the background, problem statement and research objective presented so far, and given that there are not many researches that define and characterize the key determinants of urban resilience (Olazabal et al., 2012, Chelleri et al., 2012), the (provisional) main research question is: '*WHICH FACTORS DETERMINE THE LEVEL OF URBAN RESILIENCE?'*. However, answering this inquiry it is not plain and simple, but requires the support of some sub-questions, such as:

- *(Sub-question 1) To what extent the key dimensions and indicators of urban resilience can be measured?*

From the literature review, the key dimensions and indicators of urban resilience proposed will be determined and, by comparing them with existing datasets, it will be possible to evaluate to what extent available information allow the measurement of urban resilience.

- *(Sub-question 2) What is the level of urban resilience of a sample of 13,000 cities as measured by an urban resilience index?*

The comparison between the indicators and databases will also indicate the size of the sample of cities with accessible data. From that, a composite indicator for the level of resilience will be built according to recommended technical procedures to ensure a robust and valid index and, then, the level of urban resilience will be calculated for the sample of cities.

- *(Sub-question 3) What are the key determinants of the level of resilience in this sample?*

From the indicators determined, statistical analysis will indicate if there are key factors (and the influence between them) to a higher level of resilience, as well as identify clusters of factors and performance of cities.

- *(Sub-question 4) Does this urban resilience index allow the comparison among cities to identify advantages and disadvantages in certain groups of urban areas?*

Given that cities might be able to be clustered in groups of similar scores regarding the different criteria of the composite index, it should be possible to compare urban areas so that they can help each other improve the resilience.

1.5 Significance of the study

The climate change challenges cities are facing are a field of study that has gained a lot of attention from researchers and practitioners (Deal et al, 2017; Kim and Lim 2016), as well as private and public organizations and institutions (Collier et al., 2014). Indeed, urban areas are "hubs of economic, political and cultural activity, and centers of knowledge and innovation" (UN-Habitat, 2014, p.17), and, consequently, play a major role in achieving climate resilience (Kim and Lim, 2016; UN-Habitat, 2014). Also, because policies are each time more complex, interconnected, and embedded in population and technology tendencies, besides higher environment burdens that enlarge the negative impacts to economy and well-being, the importance of building resilience is increasingly important (Figueiredo, Honiden and Schumman, 2018). Trends in the concept and theories regarding the complexity of urban resilience are not yet fully translated into assessment tools, and there is a need for composite indicators that integrate different aspects of urban resilience (Fu and Wang, 2018). There is still a lack of instruments to assess the development of adaptation in plans and interventions within the local government (Tyler et al., 2016). Furthermore, despite efforts being made towards the development of a composite indicator, this process is still on its beginning and discussions about what are the factors that measure urban resilience are yet ongoing (Asadzadeh et al., 2017).

Giving continuity to some research areas, such as the measurement of resilience to climate change, development of indexes and techniques to mainstream climate change into planning, could help gaining more knowledge (Kim and Lim, 2016) and understand the factors behind adaptation and mitigation initiatives to address the climate threats (Sharifi and Yamagata, 2014). This way, it would be possible to develop "an integrated framework composed of various resilience related criteria can assist urban planners and decision makers in their efforts to identify areas that need work and improvement" (Sharifi and Yamagata, 2014, p.1491), and if those criteria are based on existing data, the measurement would be even more robust. In that sense, considering different indicators proposed by academia and organizations to ensemble the theoretical framework and cross-checking with information available on datasets, will guarantee the provision of a practical (and needed) tool for local government and practitioners.

1.6 Scope and limitations

The availability of data is usually the main constraining factor of the use of indicators, however, knowing what information is needed, local governments can also promote the acquisition of data that will be used for its indicators with more effectiveness (Tyler et al., 2016). Although eventually showing possible needs of improvement on data collection, this research does not intend to propose any recommendations on how to acquire more information for the indicators. It limits itself to analyzing existing indicators and comparing them with available information on databases to understand to what extent is it possible to measure urban resilience in the current scenario. The composite index that is going to be built also depends on the number of indicators that are found and, even though most of them are applicable, they have to follow the same theoretical definitions and be measure on the same scale to be comparable. In other words, this process enhances the validity and reliability of the research, but at the same time might incur on reducing the sample of cities that are going to be analyzed, as well as the integration of different measurements towards an integrated framework.

In addition, it is important to raise awareness to the fact that each city has (or should have) their own policy objectives and priorities, that depend on their context and most pressing risks, and, in this sense, they should develop context-specific resilience strategies as well as a set of corresponding indicators (Figueiredo, Honiden and Schumman, 2018). However, the objective of this research is not to propose new indicators or an assessment that incorporates the uniqueness of each city context, but to understand how existing data can be used to better understand and evaluate resilience in urban areas, if possible presenting a comparison of cities across the world. Hence, indicators that are particular to a specific case are not interesting for the purposes of this research, but mainly the ones that can be replicable.

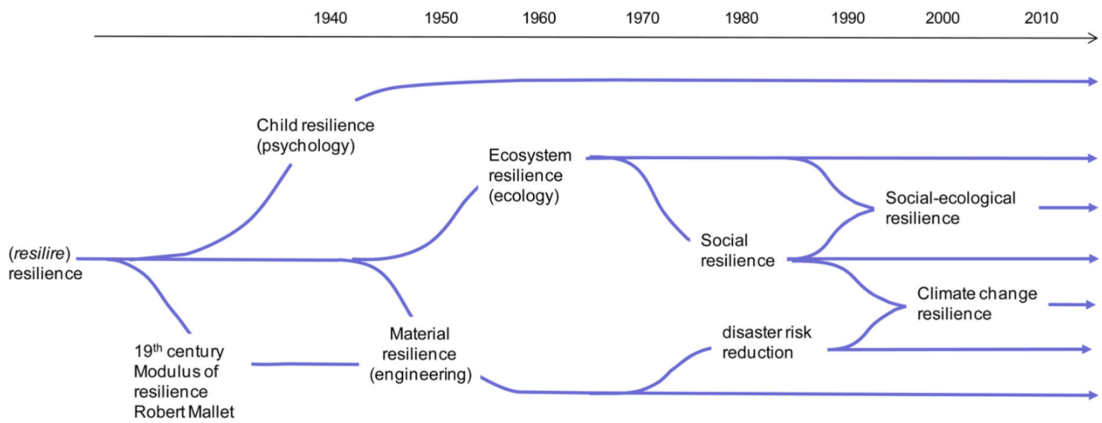
Chapter 2: Theory Review

2.1 Definition of urban resilience

The chronological evolution of the concept of resilience and its many different definitions can be used to explain how certain (planning) decisions were shaped by predominant interpretations (of the concept) and influenced policy strategies and guidelines (Béné et al. 2018). Particularly, in the urban context resilience can be used as an objective to be achieved, helping cities identify how to ensure it; as the means in which solutions will be considered to address current challenges, such as the impacts of climate change; as a metaphor to mainstream integrated approaches to urban planning; and as indicator of urban development (Béné et al., 2018). All these different uses of the concept certainly add value for the theoretical debate, but at the same time it is also necessary to be careful and not let its application be restrained (Kim and Lim, 2016), above all because still there is no common agreement on how to define and operationalize resilience (Asadzadeh et al., 2017), or even about how it relates to terms like recovery, vulnerability, sustainability and adaptability (Cai et al., 2018). Thus, urban planners have to be aware of the narratives' underpinnings and adequately understand how resilience was incorporated into urban planning (Béné et al., 2018) overtime, to later assume the perspective that best suits their needs. As appropriately highlighted by Sharifi and Yamagata (2018, p.168), "clarifying the concept and its underlying principles helps use the term in a more academic and scientific manner" and avoids misunderstandings.

The word resilience is originated from the Latin, and derives from verb 'resilire', meaning the action or act of rebounding (Macmillan Dictionary Blog, 2017), which introduces the notions of 'bounce back'. During the 1900s, Robert Mallet, in the context of naval design, began to use it as the capacity of a material to resist harsh conditions and, in the 1940s, it was applied by psychologists as the (negative) consequence of traumatic events on individuals, specifically on children (Béné et al., 2018). Both of these definitions, although in their particular context, therefore added the notion of resistance to a specific event. Back to the engineering field, Callister and Rethwisch's (2012, p.216) definition as "the capacity of a material to absorb energy when it is deformed elastically and then, upon unloading to have this energy recovered" not only gave strength to the previous concepts of resistance and to return to the original state, but also integrated the ideas of capacity of absorption, recovery and the existence of a point of equilibrium. Despite being commonly pointed as the origin of the concept, it was only following the perspectives from engineering and psychology fields of study that resilience began to be used in the ecological context (Béné et al., 2018) and to incorporate the idea of multiple systems, with the most famous definition being Holling's (1973, p.17) interpretation as "a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist". Researchers and ecologists continued to look for characteristics that could enhance the resilience of social systems, and even though they did not propose any formal definition, a parallel ramification focused on social resilience was created (Béné et al., 2018). As social aspects started to be aggregated on ecological perspectives, in the 1990s the concept of social-ecological resilience arose (Berkes and Folke, 1998; Walker et al, 2002), relating to the capability of coping with shocks and stresses, treating them as opportunities for development without compromising essential functions (Carpenter and Folke, 2006) and trying the address the environmental problems being faced (Berkes & Folke, 1998), which meant that it gained the dimensions of transformative and adaptive capacity (Béné et al., 2018) or, in other words, different resilience pathways. Alongside the development of the socio-ecological ramification, the engineering perspective evolved towards the disaster risk reduction, looking at the risk and hazards of specific events to a system, also incorporating the idea of adaptation. Most recently, in the context of climate change, resilience relates not only the idea of adaptation, but also vulnerability and disaster risk (Kim and Lim, 2016), broadening the perspective of disaster risk from one to multiple systems and also incorporating the preparedness to impacts of hazardous events, besides addressing currents problems, as it can be seen on IPCC (2012, p.5)'s definition as "ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner". Figure 1 illustrates the above-mentioned timeline of resilience definitions and Table 1 the concepts incorporated in each definition.

Figure 1 – Timeline of the definition of resilience



Source: Béné et al. (2018, p.119).

Table 1 – Evolution of the concepts incorporated on the definition of resilience

Period	~	1900s	1910s-1930s	1940s	1950s	1960s	1970s	1980s		1990s	
Concepts / Definitions	'Resilire'	Modulus of resilience		Child resilience	Material resilience	Ecosystem resilience		Social resilience	Disaster risk reduction	Socio-ecological resilience	Climate change resilience
'Bounce back'											
Resistance											
Absorption											
Recovery											
Equilibrium											
Multiple systems											
Adaptation											
Transformation											
Vulnerability											

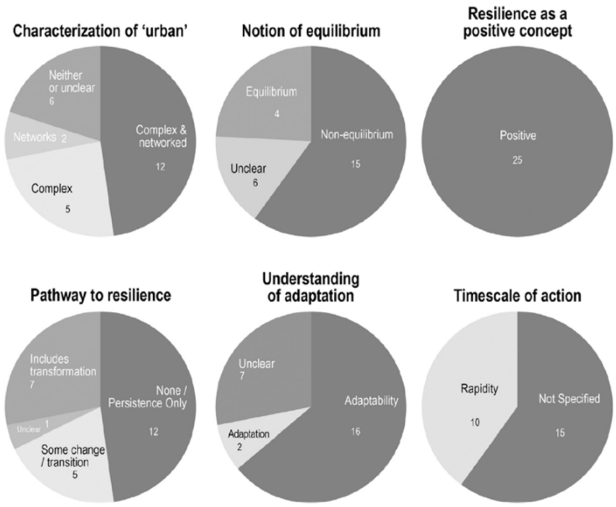
Source: author (2019), based on Béné et al. (2018), Berkes and Folke (1998), Callister and Rethwisch (2012), Carpenter and Folke (2006), Holling (1973), IPCC (2012), Kim and Lim (2016), Macmillan Dictornary Blog (2017), and Walker et al. (2002).

It is possible to visualize that resilience changed from considering a single system with one state of equilibrium to a more complex set of systems with multiple (or none) equilibria (Fu and Whang, 2018; Kim and Lim, 2016) and adding different resilience pathways such as resistance, recovery, adaptation, among others (Fu and Whang, 2018). That change is made clear when different ramifications of the concept are compared. For instance, Asadzadeh et al.'s (2017) research revealed that engineering based frameworks tend to be 'result-oriented', focusing in returning to a previous condition and achieving a specific result, while socio-ecological based frameworks are more 'process-oriented', or concerned about adaptation, effectiveness of responses and learning from the past. Also, the authors mention in their work the important to highlight that discussions regarding sustainability in the 1980s and 1990s influenced the concept of resilience in terms of changes in environmental conditions nowadays. Indeed, they have been "(...) an important concept in the contemporary debate on climate change and adaptation" (Kim and Lim, 2016, p.1), as well as there has been a proliferation of many definitions and meanings for resilience in international discussions of policy making and advisory related on how to address urban challenges, specifically the ones related to climate change. Figueiredo, Honiden and Schumann (2018, p. 10) presented a few examples of interpretations from institutions such as the United Nations Human Settlement Programme (UN-Habitat), Local Governments for Sustainability (ICLEI), United Nations Office for Disaster Risk Reduction (UNISDR), The Rockefeller Foundation, World Bank, and 100 Resilient Cities, among others, showing that the current definitions have in common the idea to "resist, absorb, adapt, transform, change, recover and prepare, in relation to certain events (…) or the possibility of them taking place". The terms used by these organizations represent the different pathways of development added to resilience overtime and, according to Cai et al. (2018), are among the most used words in literature related to resilience.

Aiming to establish common ground for future research and elaborating a robust and complete definition of resilience applied to the urban context, Meerow, Newell and Stults (2016) also presented an extensive literature review on the origin and characteristics of the definition. In addition to the theoretical underpinnings already presented, it was showed by the authors the existence of six conceptual tensions related to resilience, which are illustrated on Figure 2 and explained as follows. Understanding those strains and working to solve the challenges they imply can ensure resilience is being used with a proper approach, besides following an accepted definition.

- (1) Definition of ‘urban’: related to the location/scale of planning and complexity, which most papers analyzed defined ‘urban’ as either ‘complex systems’ and/or ‘networks’;
- (2) Understanding of equilibrium: the system can be balanced in a ‘single-state’, ‘multiple-state’ or ‘dynamic non-equilibrium’;
- (3) Positive, neutral or negative results: resilience might not always be a desirable outcome, and, more than that, not have the same consequences to all citizens;
- (4) Mechanisms for change: resilient actions can be developed through mechanisms of ‘persistence’, ‘transition’ and ‘transformation’;
- (5) Adaptation vs. general adaptability: the actions can be applied to a specific case or a general context;
- (6) Timescale of action: related to short or long-term perspectives, or how fast a system recovers from a shock and gradual events.

Figure 2 – Six conceptual tensions in definitions of urban resilience



Source: Meerow, Newell and Stults (2016, p.43).

Based on this study, the majority of definitions have at least the common aspects of non-equilibrium state, adaptability, and perceive resilience as a positive outcome to be achieved. However, at the same time, most of them do not determine a timescale of action, what is very important for developing plans and strategies. Therefore, the conceptual tensions highlight the importance of defining ‘what’, ‘where’, ‘when’, ‘who’, ‘why’ and ‘how’ on urban resilience’s definition to later be translated into a framework. They are necessary to be took into account while trying to understand the meaning of resilience and interpreting in which context it was conceived and, to facilitating this process, those considerations are further explained to set the ground for a common interpretation of which context they were applied.

- **What:** relates to the objectives and general conditions being considered to build resilience. Plans are most effective and equitable when they are designed in response to a community’s unique vulnerability and characteristics (Baussan 2015);
- **When:** relates to the focus on short-term shocks or long-term stresses and setting the system to adapt fast, as well as the timeframe of measurement for the indicators. More

specifically, “urban resilience operates in non-equilibrium, is viewed as a desirable state, recognizes multiple change pathways (persistence, transitions, and transformation) and emphasizes the importance of adaptive capacity and timescales” (Meerow, Newell and Stults, 2016, p. 45);

- **Where:** relates to the boundaries of action that are determined (Meerow, Newell and Stults, 2016) which, in the case of cities, is the urban area or regional scale. Adopting a place-based approach allows cities to effectively measure resilience and to be more reasonable to the local singularities (Baussan, 2015);
- **Why:** relates to the reasoning behind the choices of strategies to be adopted, based on the understanding of the vulnerability context. To be resilient, a city must perform functions such as providing basic needs, maintaining physical assets, promoting knowledge and cultural expression, and promoting a prosper and equitable economy (The Rockefeller Foundation and ARUP, 2014). Besides that, it should focus on being flexible and adaptable, because with the uncertainty and risk cities face, it is harder to become highly prepared for specific threats (Meerow, Newell and Stults, 2016);
- **Who:** relates to the stakeholders involved and that are targeted during this process. Strategies should make sure that the community and individual are aware of the risks and the actions to solve them, to effectively enhance urban resilience in general (Elias-Trostmann et al., 2018). Likewise, they should prioritize the ones that are not able to develop their adaptive capacity (Meerow, Newell and Stults, 2016) – meaning the most vulnerable citizens;
- **How:** relates to the institutional aspects, such as process of developing and implementing resilient plans. “Cities need to make sure that their development strategies and investment decisions enhance, rather than undermine, the city’s resilience” (The Rockefeller Foundation and ARUP, 2014, p.11). Also, if that is constructed through a participatory and inclusive process (Meerow, Newell and Stults, 2016), and with a transparent and aspiring leadership, it is more likely to have citizens comprehension and support (The Rockefeller Foundation and ARUP, 2014).

In order to unify all these concepts in a single definition, and address the three points (definition of ‘urban’, ‘pathway to resilience’ and ‘timescale’) not incorporate by most of the definitions, the following interpretation will be adopted by this research:

> “Urban resilience refers to the ability of an urban system-and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales-to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity” (Meerow, Newell and Stults, 2016, p.39)

This chapter will now follow with: (Section 2.2) some examples of frameworks proposed by researchers and organizations to better understand how they use the concept and compare to the definition adopted; (Section 2.3) the rationale behind the choice of dimensions and characteristics of resilience that will determine the conceptual framework of the research question; (Section 2.4) the explanation of how indicators and composite indexes can measure the phenomena, and how they can be applied, supporting the answer to research sub-questions 1 to 3; and, finally, (Section 2.5) the chapter will conclude with the theoretical framework adopted for this work, showing how it can aggregate on answering the last research sub-question and integrate all the previous steps to answer the main research question.

2.2 Existing frameworks

Tyler and Moench (2012) propose a framework to approach urban climate resilience and aim to integrate ecological, infrastructure, social and institutional perspectives. The authors define resilience by three factors, which should be integrated to the process of understanding vulnerability in a shared learning basis to build resilience. Those factors are:

- Systems: set of supporting networks that allows the provision of services and exchange between citizens (e.g., physical infrastructure and ecosystems). They can be characterized by their flexibility and diversity, redundancy or modularity and safe failure.
- Agents: contemplates people, households and private and public sectors, each of them with different interests and ability to shape their behavior according to the strategies, experiences and knowledge. They can be characterized by their responsiveness, resourcefulness and capacity to learn.
- Institutions: norms and traditions, formal or informal, that influence the behavior in a positive or negative way. They can be characterized by their effect on rights and entitlements, decision-making processes, information flows and application of new knowledge.

While emphasizing the need of integrating different perspectives on resilience, the framework intends to change from a perspective of trying to predict climate change and elaborate policies, plans and practices, to a more long-term vision that incorporates direct and indirect effects, as well as the importance of citizens and government working together and sharing knowledge. In other words, by underlining the importance of recognizing the vulnerabilities to be able to tackle climate change impacts through a participative process, an integrated and holistic approach is considered. A positive effort was made on determining a measurement that considers the factors to be taken into account and their importance (systems – 'what' and 'why'), the people involved in that process (agents – 'who'), and the organizational structure of the process (institutions – 'how') applied to the urban context ('where'). However, it lacks the specification of the timeframe ('when') on the analysis, and, despite examples of interventions being given, there are not clear indicators of how to apply those strategies in cities.

The Rockefeller Foundation and ARUP (2014) developed the City Resilience Index considering that to be resilient, cities rely on their physical infrastructure, policies, social capital and institutions. To measure that, four dimensions are proposed:

- Health & wellbeing: how the city allows citizens to have their basic needs attended and support their social and economic development. It includes goals such as: minimal human vulnerability, diverse livelihood & employment, and effective safeguards to human health & life;
- Economy & society: how the systems allow citizens to be in cohesion and safety. It includes goals such as: sustainable economy, comprehensive security & rules of law, and collective identity & mutual support;
- Infrastructure & ecosystems: how physical and natural assets are prepared and used. It includes goals such as: reliability and mobility, effective provision of critical services, and reduced exposure and fragility;
- Leadership & strategy: how the city uses past events knowledge to develop strategies. It includes goals such as: effective leadership and management, empowered stakeholders, and integrated development planning.

Through desk research and pilot studies on six cities (Surat, Concepción, New Orleans, Semarang, Cali and Cape Town), the City Resilience Index made an extensive effort to translate the four dimensions presented in a more measurable and detailed way. It presents 12 goals, 52 indicators and 156 questions to make a quantitative and qualitative analysis on cities' resilience. Some of the indicators, however, ended up being more subjective to local knowledge or requiring that time and resources are invested to collect the data in other sources, because were not based on available information. Additionally, even though the intention was to provide a common ground of measurement to help municipalities, some indicators might not be applicable for a general overview, since they are specific to local contexts and therefore must be comprehended before its application. On the other hand, a positive characteristic was the development of a digital platform to make available a series of documents that supports local governments and urban professionals in process of evaluating urban resilience (ARUP and The Rockefeller Foundation, 2018). Comparing to the definition of resilience adopted on this research, the framework also highlights the importance of defining 'what', 'why', and 'who' through the dimensions of health & wellbeing, economy & society, and infrastructure & ecosystems, and with the leadership & strategy dimension it emphasizes the 'how' to build resilience on cities ('where'). However, as it happened in the first example, it lacked to address the definition of the 'when' in the tool analysis.

Bringing a different perspective, the Urban Community Resilience Assessment (UCRA) developed by the World Resource Institute (WRI) focuses on the community level. Its goal is to assist urban planners in measuring climate resilience and consists in a "three-level resilience scorecard for cities" (Elias-Trostmann et al., 2018, p. 2). Those three perspectives of assessment are:

- Vulnerability context: consisting of the current physical and social conditions, the provision of services and medical & emergency assistance;
- Community resilience: unity and readiness of a local community;
- Individual capacity: how the inhabitants perceive the risk, know about them, are prepared for it, are communicated of the cautions necessary, act in case of emergency and are able to maintain their financial conditions.

Despite been developed with the perspective of climate change and focused on the social point of view, it can be argued that it contributes to a resilient development at the city level, given that it can be scaled-up to other neighborhood and eventually establish a broader strategy for the whole urban area. Although not considering an integrated set of dimensions like the previous examples and still being to some extent dependent on qualitative information that might not be available, the UCRA makes an effort to present more objective and measurable indicators for each perspective. The aspects to be considered while evaluating the vulnerabilities (from a physical, social and institutional aspect) are presented with clear indicators (focus on the 'what', 'why', 'who' and 'where'), but are not further developed on the timeframe of action ('when') and process to be followed ('how'). Nonetheless, lacking to consider more general indicators related to economic and environmental dimensions that could provide a baseline scenario of the influences over the community, the UCRA provides a deeper understanding of the local context and focuses on factors that directly influence climate change adaptation and mitigation, its consequences and the response to shocks and stresses – important assessments to be made.

Lastly, contrasting with the previous frameworks presented so far, the Global Power City Index (GPCI) (MMF, 2018) and the Global Urban Competitiveness Report 2017 (Ni, Kamyia and Ding, 2017) present an actual ranking among different urban areas worldwide. The GPCI was developed by the Mori Memorial Foundation and intends to measure the attractiveness of cities towards people, capital and business. It defines 6 functions of measurement (Economy, Research and Development, Cultural Interaction, Livability, Environment, and Accessibility) associated with 70 indicators to provide a multidimensional assessment. Despite considering economic, social, environmental and physical attributes and describing the results obtained in different years (annually from 2009 to 2018) that the index has been developed (approaching the 'what', 'why', 'who', 'where', and 'when'), it lacks the determination of 'how' to translate this numbers into actions. The Global Urban Competitiveness Report 2017 was developed by the Chinese Academy of Social Sciences (CASS) and the United Nations Human Settlement Programme (UN-Habitat). Considering the need for cities to be competitive in a globalized world, it focuses on establishing a comparison of the competiveness between urban areas, especially the ones in developing countries, and on identifying the elements that contribute to their performance. It divides the 22 indicators proposed in 6 determining factors (company strength, local elements, local demand, software environment, hardware environment, and global connection), which are more related to the economic dimension and just broadly approach other aspects. Nonetheless, it is an important information to be analyzed, because it also influences the availability of resources that a city can allocate to build resilience, and in this particular case, can compare an extensive list of cities worldwide. The competiveness report, therefore, provides the competition context ('what' and 'why') of urban areas ('where') over the period (since 2004) it has been published ('when'), but lacks to consider the actors involved ('who') and actions that could be that to improve the competition ('how'). Table 2 summarizes the five resilience frameworks analyzed above, highlighting their main contributions, indicators proposed and aspects considered by each of them. Despite not being presented on this section, all the indicators proposed by the frameworks mentioned, as well as from other sources, were used to composed the final list of indicators that will be presented on Section 2.4.

Table 2 – Summary of the resilience frameworks analyzed

Framework	Authors	Main contributions	Number of indicators proposed	Aspects considered
Urban Climate Resilience	Tyler and Moench (2012)	Mainstream the process of building resilience with the participation all stakeholders	None, but analyzes 3 factors	What, why, who, where and how
City Resilience Index	The Rockefeller Foundation and ARUP (2014)	Integrated approach of resilience dimensions and information support to local governments	56 indicators divided in 12 goals	What, why, who, where and how
Urban Community Resilience Assessment (UCRA)	Elias-Trostmann et al. (2018)	Understanding of the physical, social and institutional aspects related to the exposure to vulnerabilities	31 indicators divided in 3 perspectives	What, why, who and where
Global Power City Index (GPCI)	MMF (2018)	Multidimensional comparison of cities across the world focusing on their attractiveness	70 indicators divided in 6 functions	What, why, who, where and when
Global Urban Competitiveness	Ni, Kamiya and Ding (2017)	Deeper comprehension about the factors (mainly related to economic aspects) that distinguish competitiveness among an extensive list of cities worldwide	22 indicators divided in 6 determining factors	What, why, where and when

Source: author (2019).

2.3 Dimensions and characteristics of resilience

Resilience is a commonly adopted concept by researchers to assess the response to threats and disturbances (Béné et al., 2018). Given that it is an abstract concept and difficult to quantify in absolute terms, understanding what are the main factors is a major step towards prioritizing actions and building resilience (Asadzadeh et al., 2017). For that, it is also essential to consider the main dimensions, to be able to select the appropriate indicators. Trying to define those dimensions, Fu and Wang (2018, p.371) underline the importance of including "infrastructure, ecological, economic, and social subsystems into analysis" towards a holistic approach; Collier et al. (2014) divide resilience in six assets, namely social capital, people, economy, natural environment, manufactured assets, politics and governance, associate with indicators that would then compose the resilience framework; Figueiredo, Honiden and Schumman (2018) state that to strengthen resilience it is necessary to divide it into the areas of institutions, economy, society and environment; and Sellberg, Wilkinson and Peterson (2015) mention that to understand the complexity of the impacts of climate change it is necessary to consider social, economic, physical, environmental and institutional elements to measure resilience.

From this shortlist of references, as well as indicated by Sharifi and Yamagata (2018), most information available describes only social, economic, institutional and environmental dimensions, but do not approach the influence that the physical aspect has on urban resilience. In addition, the authors emphasize that more research is necessary to understand how urban form elements influence urban resilience, what can be done to emphasize synergies between them and what are the trade-offs. This paper does not intend to focus on the last two needs, but indeed by analyzing the influence of the physical dimension on the overall level of resilience it is expected to better comprehend how they affect each other. Hence, the five main dimensions that are going to be considered are: economic, representing diversity of industries and innovation; social, representing inclusiveness, cohesiveness, social networks and opportunities; environmental, representing sustainability and natural resources; institutional, representing government leadership and commitment, horizontal and vertical collaboration, and including stakeholders in the decision-making process (Figueiredo, Honiden and Schumman, 2018); and physical, representing the built infrastructure, transportation systems and aspects related to urban form.

Furthermore, the literature also commonly points some characteristics that represent the achievement of resilience in urban areas. Tyler and Moench (2012) mention: flexibility and diversity, redundancy and modularity, and safe failure (related to 'systems'); responsiveness, resourcefulness, and capacity to learn (related to 'agents'); and rights and entitlements, decision making, information, and application of new knowledge (related to 'institutions'). The Rockefeller Foundation and ARUP (2014) states that integration, inclusiveness, reflectiveness, resourcefulness, robustness, redundancy and flexibility are essential characteristics to be considered while building resilience. Additionally, Collier et al. (2014) argue that to function properly, a resilient system must demonstrate flexibility, redundancy, resourcefulness, responsiveness, and capacity to learn. To be able to better understand their meaning, some of the characteristics are described on Table 3. However, it is important to mention that other sources (for example, Cai et al., 2018; Figueiredo, Honiden and Schumann, 2018; Kim and Lim, 2016) also indicate similar characteristics.

Table 3 – Characteristics of resilience

Characteristics	Description
Robustness	Absorption of shocks and stress without compromising the system in terms of damage and function
Redundancy	Contingencies to failure on the system and to accommodate elevated pressures
Flexibility	Capacity to innovate and choose new alternatives in case circumstances change and still achieve the goal
Resourcefulness	Availability and mobilization of resources by citizens and institutions in case of disasters events
Inclusiveness	Participation of all stakeholders and consideration of their perspectives towards resilience
Capacity to learn	Education and community capacity towards mitigation and adaptation, as well as the use of previous experiences and knowledge

Source: author (2019), based on Collier et al. (2014); Figueiredo, Honiden and Schumann (2018), The Rockefeller Foundation and ARUP (2014); Tyler and Moench (2012).

2.4 Indicators

Indicators can be used as a tool for communicating and giving voice to citizens, combining expert and public or community driven approaches, and to collect criteria (Mileti, 1999). They are able to show variations during a time frame, compare different scenarios and identify points of improvement, thus allowing decision-makers to develop better strategies and enhance cities' resilience – nevertheless, they still need to be implemented to create actual change (Figueiredo, Honiden and Schumman, 2018). Given that (smart) technologies have become the main technique on measuring and representing sustainability frameworks, and an emblem of 'ecological modernization', sometimes they are interpreted as the solution to overcome social and environmental impacts, which "means that the pursuit of urban sustainable development goals becomes increasingly identified with the pursuit of smart cities" (Kaika, 2017, p.90). It is important to highlight, though, that this is not the case, it is not valid to assume that "global socio-environmental equality, social welfare or value creation can be reduced to indicators" (Kaika, 2017, p.94). Technology also causes many social and environmental impacts and is only a tool for helping cities to achieve resilience, not the action itself. That is why the objective of this research is to assess indicators of existing frameworks and cross-check them with the ones available in existing datasets, evaluating if they allow the development of a composite index that can be helpful to indicate the level of resilience of an urban area.

Being components of all parts of the process of building resilience, indicators can serve as assessment, information or monitoring tools. As further detailed by Figueiredo, Honiden and Schumman (2018, p.26):

> "As an assessment tool, they help identify risks and vulnerabilities. As an information tool, they can better instruct the design of early-warning systems, emergency response plans, land-use plans and building codes, as well as raise awareness and communicate about vulnerability and risks. As a monitoring tool, they can identify how well a city has responded and recovered to disasters and shocks and whether the targets have been met".

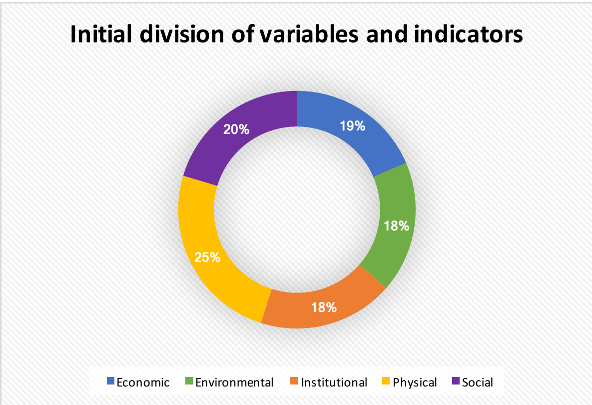
Moreover, Tyler et al. (2016) explain that the process of developing indicators can be driven by expert or local knowledge. In the first case, secondary data from trustful sources are used, providing an analytical perspective. In the second case, they can depend on targets set by stakeholders and, therefore, are more likely to be comprehended. As the author further elaborate, both approaches are valid and ideally there should be a combination of them while building indicators that mainstream the needs of local plans and strategies. To do so, they mention that the criteria for selecting indicators can be summarized to: observable and verifiable, quantitative or qualitative, relevant to local decision-making, specific, measurable, actionable (meaning that actions by local authorities should lead to changes in the indicator value), dynamic (change over relatively short time periods), and reliance primarily on available data. Even though locally developed indicators are said to provide better understanding of the particularities of specific regions, the result from the framework proposed on this research will be to evaluate to which extent urban resilience can be measured, and, consequently, provide a valuable assessment of the current scenario and overall parameters that should be considered while discussing the concept.

The conceptual framework needs to provide the means of analyzing relevant indicators combined in a composite index, an useful tool to complex problem analysis and that provides useful insights as long as it is adequate for the intended use (Nardo et al., 2008). For that, the "indicators should be selected on the basis of their analytical soundness, measurability, country coverage, relevance to the phenomenon being measured and relationship to each other. The use of proxy variables should be considered when data are scarce" (Nardo et al., 2008, p.17). Reviewing the existing frameworks and compiling the indicators they propose will be essential to later comparing the indicators to existing information, and ensure a robust theoretical framework. It is also important to highlight that the indicators, as well as the composite index, because they represent a multidimensional concept (in this case, urban resilience), have the limitation of not capturing the whole picture, given that some factors are hard to measure and be distinguished (Nardo et al., 2008). Besides that, in the position of assessing policy results, they can be influenced by other factors and therefore they do not represent alone the real outcomes (Figueiredo, Honiden and Schumman, 2018). Still, they can compare different performances, identify changes over time and support the development of better policies (Nardo et al., 2008).

2.5 Theoretical Framework

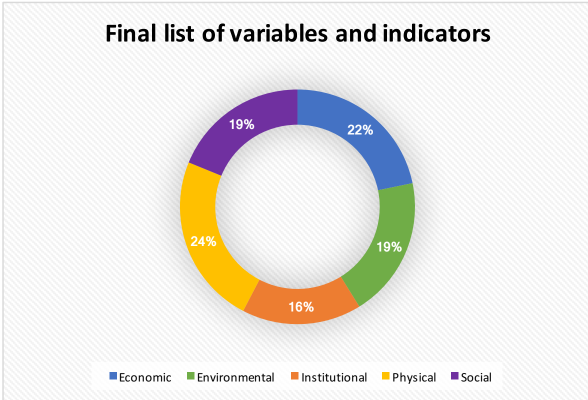
During this literature review, the variables and indicators proposed by the frameworks analyzed on Section 2.2, as well as from other researchers and organizations were compiled in a single list, resulting in almost 1,000 items. They were then divided into the five dimensions (economic, environmental, institutional, physical and social) of urban resilience adopted, in order to facilitate the process of defining the conceptual framework. The result was 185 measurements for the economic dimension, 178 for the environmental, 184 for the institutional, 246 for the physical, and 203 for the social (Graph 1). Given that the indicators were relatively balanced (around 20% of the total each), it is possible to argue, then, that the division into five perspectives proved itself to be valid for an integrated assessment. Furthermore, in opposite to its recommendation as a dimension of urban resilience, the physical aspect was the one that got the highest percentage of indicators, and, despite many researchers and organizations proposing several parameters for it, it should be better considered on frameworks as a unique aspect (and not embedded in others) for a holistic perspective on the topic – what gives validity to the Sharifi and Yamagata's (2018) argument presented on Section 2.3. From this initial assessment, the variables and corresponding indicators of both the factors and level of urban resilience were determined. To consider only the most important information and avoid redundancies, similar items were grouped together and the ones who had only one reference in the literature were not contemplated. With this additional filter, a total of 170 variables were obtained, being 37 for the economic dimension, 33 for the environmental, 28 for the institutional, 40 for the physical, and 32 for the social (Graph 2). The final conceptual framework kept almost the same representativeness per dimension as the initial. However, an exception happened for the economic and environmental dimensions that turned out to be more representative (increase of 3% and 1%, respectively) then initially – which makes sense, given that, to some extent, one of the biggest constraints regarding any adaptation and mitigation policy, plan or project is the financial aspect, and a current prevailing focus of the international policy-making agenda are the impacts on the environment and measurements for it.

Graph 1 – Percentage of variables indicators per dimension on the initial list.



Source: author (2019)

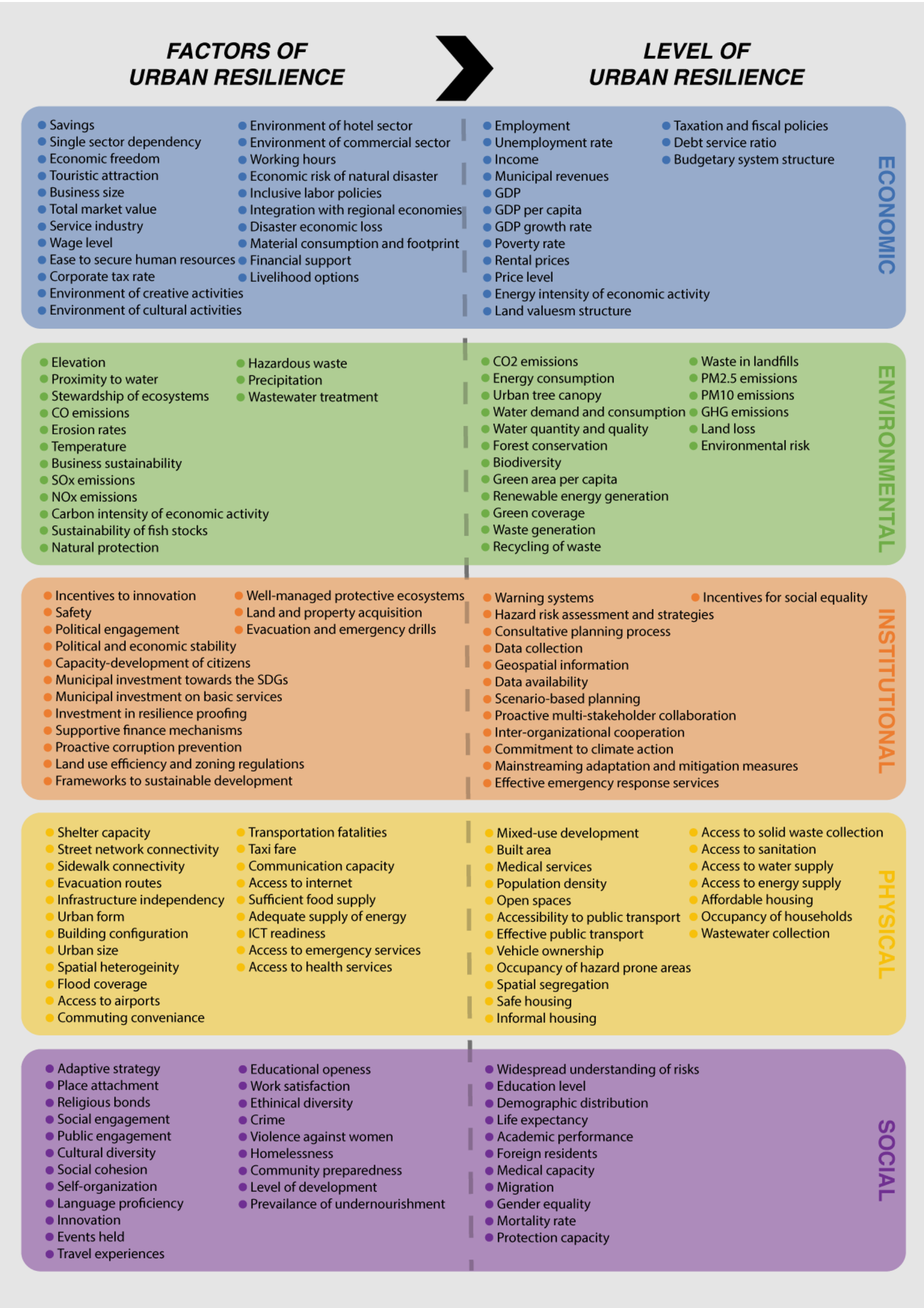
Graph 2 - Percentage of variables and indicators per dimension on the conceptual framework.



Source: author (2019).

Since the main research question aims at understanding what are the factors (independent variables) that influence the level urban resilience (dependent variables), it was still necessary to have a standard to divide the variables and corresponding indicators listed among these two groups of parameters. Initially it was though that the characteristics of resilience (see Table 3, Section 2.3) would represent a general level of resilience and the dimensions would represent the factors. However, analyzing the literature (for example, Tyler and Moench, 2012; and The Rockefeller Foundation and ARUP, 2014) it was possible to verify that actually the same indicators are used for both cases and, therefore, it would not be conceptually appropriate to use make this distinction. Since the concept of resilience is wide in scope and difficult to grasp, suggesting a division based on causal relations – in other words, trying to infer which indicators are the cause and which are the consequence of urban resilience – would be too broad and dangerously subjective. Thus, in order to adopt a sound criteria, the ISO37120:2018 – Sustainable cities and communities – Indicators for city services and quality of life (ISO, 2018), recently established by the International Standard Organization, helped overcome the challenge. Besides defining a set of indicators to evaluate the performance of urban areas, the ISO37120:2018 determines a methodological process for those parameters and divides them under 'core', 'supporting' and 'profile' categories. The first are the ones considered fundamental to be measured, the second are the ones which provide complementary information and, the third, provide a basic panorama of the city's main characteristics. Although being developed in the context of sustainable development and not just urban resilience, as it was already argued, building more resilient cities is a way in which the former is achieved (see Mogelgaard et al., 2019) and, therefore, this was selected as the criteria to separate the parameters. In general, the 'core' and 'profile' indicators were kept as dependent variables and the 'supporting' as independent, but given the clear correlation between some indicators – for example, Green coverage and green area per capita – this division had to be adjusted. Additionally, it is important to mention the it was chosen to still classify all the indicators among the dimensions (social, environmental, economical, physical and institutional) of resilience to provide insights on how each of these perspectives contribute to building and determining resilience. Figure 3 illustrates the final variables of the conceptual framework of this research, which was considered to be as a robust and comprehensive approach to evaluate urban resilience, and Annex 1 shows the detailed list of the indicators proposed by each of these variables, along with the respective sources.

Figure 3 - Theoretical framework.



Source: author (2019).

Chapter 3: Research Design and Methods

3.1 Revised research questions

Previous chapters have showed the theoretical and societal relevance of this research, and the content presented had the intention to state the importance of better understanding of the assessment of resilience in urban areas. A theoretical problem identified on the literature review, specifically on Section 2.5, provided the insight of not being possible to determine the division of the dependent and independent variables by using the dimensions of urban resilience to analyze the factors influencing it and the characteristics to determine its level, as it was initially expected. Given this shortcoming, it was decided to add one research question in order to be able to analyze if the division proposed for the parameters is indeed adequate, although based on an ISO standard methodology. In other words, and as it will be further explained on Section 3.3, both an analysis with the division of the indicators and other without any division will be tested to prove the validity of the model created. The outcomes shall provide positive and negative aspects, and because on sub-questions 2 and 3 the analysis will provide a comparison among cities, it was chosen to remove the original sub-question 4 and focus on investing time for making a solid evaluation of the indicators, namely the creation of a composite index. This research will, thus, focus on answering:

(Main research question) Which factors determine the level of urban resilience?

- *(Sub-question 1)* To which extent the dimensions and indicators of urban resilience can be measured?
- *(Sub-question 2)* What is the level of urban resilience of a sample of 13,000 cities as measured by an urban resilience index?
- *(Sub-question 3)* What are the key determinants of the level of resilience in this sample?
- *(Sub-question 4)* Are the indicators of the index proposed adequate to determine a general level of urban resilience?

With the literature review that was presented in this chapter, the indicators that explain the 'factors of urban resilience' and the 'level of urban resilience' shown on the conceptual framework were determine and, therefore, are going to help answering the research sub-question 1. Dividing them into the dependent and independent variables during the data analysis, it will be possible to build the composite index and understand what is the level of performance of the sample of cities available, consequently answering sub-question 2. Subsequently, checking the existence or not of a relation of this result with the independent variables, it will be possible to answer sub-question 3, analyze if they influence the resilience level, as suggested by the conceptual framework, and understand which of them are determinants. Finally, it is expected that comparing the outcome from the previous investigations (as proposed by the conceptual framework) and further analysis without any division among the indicators) it will be possible to have insights about sub-question 4, therefore, completely addressing the main research question.

To be able to answer the revised research question and sub-questions as explained, it is important to design a sound process, consistent between the objectives aimed and strategies chosen. With that in mind, this chapter will continue with the description of the strategy (Section 3.2) and methodology (Section 3.3) used to ensure a valid research, the detailing of how the conceptual framework will be operationalized (Section 3.4), the process of collecting and analysing data (Section 3.6), and the cautions taken to ensure a valid and reliable work (Section 3.7).

3.2 Research strategy

The research strategy chosen to achieve the proposed objective is the desk research associated with secondary quantitative data, which consists of using available data that can be adapted or re-used for the objectives of the research to perform statistical or trend analysis without the need of collecting external information (Thiel, 2014). This is the most appropriate strategy for the research aim for two main reasons. First, because it intends to assess if available databases allow the measurement of resilience at the city level, as explained by a set of indicators gathered from the literature. Secondly, because this strategy not only allows the comparison of a large number of variables (indicators) and units (number of cities), but also the analysis of data with statistical methods can identify the relations between the independent and dependent variables, what will assist on answering the research questions.

As mentioned by Thiel (2014), this type of research might involve combining different datasets, in full or partially, and analysing the datasets that results from this process. Indeed, from the databases chosen it shall be possible to determine whether or not they can be combined and which indicators can be measured to operationalize the theoretical framework. To calculate the level of urban resilience, a composite index based on the indicators determined for it will be built following a standard procedure based on a document developed by the Organization for Economic Cooperation and Development (OECD) and the Joint Research Center (JRC) from the European Commission (EC) of how to build a composite index to ensure its validity – which includes, but is not limited to, supervised techniques such as multivariate analysis, normalization, weighting and aggregation, and uncertainty and sensitivity analysis. Each step of this process will also give ground for insights of the results obtained. An extra analysis will be executed to determine if the initial division of indicators was appropriate and guarantee the creation of the best model possible. With the composite index determined, unsupervised learning techniques, such as dendrograms and cluster analysis will be used to help interpret the performance of cities and the existence (or not) of groups among them. Finally, to understand the influence of the factors of urban resilience and which ones are the most relevant, a regression analysis between those independent variables and the final aggregated indicator will be performed and commented.

3.3 Research methodology

Starting the research process, a thorough literature review was done by searching on databases from scientific academic journals such as Scopus, Web of Science, Science Direct, and sEURch (the online library of the Erasmus University Rotterdam) with the keywords ‘urban resilience’, ‘climate change’, ‘indicators’, and ‘framework’ to compose a broad initial reference list. After checking the titles and abstracts, a more specific collection of references was created with the main documents related to this thesis’ topic. While reading the papers, other relevant sources were also continuously added. This approach allowed to grasp the state of the art knowledge about urban resilience, its main underlying concepts, as well as a common set of dimensions, variables and indicators proposed by researchers and organizations.

During the stage of reviewing publications, it was brought to attention that OECD and the JRC developed a handbook on how to build composite indicators, aiming at providing detailed information about the complexity of this process and ways it can be improved (Nardo et al., 2008). The document lists all the steps necessary to be followed and ensure a robust, valid and reliable analysis, highlighting that the "methodological issues need to be addressed transparently prior to the construction and use of composite indicators in order to avoid data manipulation and misinterpretation" (Nardo et al., 2008, p.15). Despite being developed with a background context of country level analysis, since these procedures focus on technical and objective aspects behind the composite index building, they can (and should) also be applied on the development of an index at city scale. As presented on Section 2.4, indicators can monitor the performance of cities and, when built as a composite index, they can measure concepts with various dimensions and give new insights by providing a clearer visualization of the information (Nardo et al., 2018). To ensure the achievement of the objectives of the research and that the answers found will be valid, extra care was taken in determining the methods for the data analysis. Table 4Table 4 presents the step-by-step process that started and will continue to be followed during the data collection and analysis, which was based on the recommendations of this document and adopted for the purposes of this research. Apart from a description of each stage, a column of how it will be applied was included for clarifications.

For the steps 1 to 3, that involve more preparation of the database the program used was Microsoft Office Excel. However, for steps 4 to 10, it was chosen to elaborate the analysis and data visualization using Python (version 3.7), more specifically coding through Spyder's integrated development environment (IDE). Python is an open source programming language with many different libraries (programmed routines executed by the computer), packages (sets of tasks for a specific purpose) and methods (specific procedures of a package), that allows to easily perform statistical analysis on datasets and visualize the results, and in more advanced steps to train the computer to perform machine learning algorithms. It is currently one of the most used programming languages in the world, especially in the field of data science. Finally, to finish the edition of some graphs and design the conceptual framework, the program Adobe Illustrator was used.

Table 4 – Steps followed on the research.

#	Step	Description	Application
1	Theoretical framework	Development of a conceptual framework that combines indicators into a relevant composite index that fits its purpose (if possible, the involvement of experts and stakeholders is advised). As a result, the phenomena being measured will be clearly understood, structured in different dimensions if necessary, and will present a list of underlying variables.	Based on the literature review, a list with variables and indicators proposed by researchers and organizations was collected. Then, similar indicators were combined into one to avoid redundancy and those who were proposed by just one author were not considered. With all the list reviewed, the conceptual framework was obtained.
2	Data selection	Selection of indicators based on analytical soundness, measurability, relation to the concept and with other indicators. Proxies can be used with caution in case of data scarcity (if possible, the involvement of experts and stakeholders is advised). The quality, strengths and weaknesses of the indicators should be approached, and a table should be presented to summarize the data selected.	The selected parameters were cross-checked with the available information in databases, resulting in a set of indicators for the operationalization, which later were classified considering the dimensions of urban resilience and the division of 'core' and 'profile' or 'supporting' indicators.
3	Imputation of missing data	Use of additional sources to complement missing values in the dataset. However, imputed data should be assessed regarding their reliability and comparability with the existing information. The presence of outliers should be discussed.	To ensure the comprehensiveness of analysis, different databases were analyzed to determine whether it was possible to combine them and be able to measure a higher number of indicators or have a larger sample of urban areas.
4	Multivaria-te analysis	Assessment of the adequacy of the data. This way, groups of similar indicators can be identified to provide insights, and the structure of the dataset and theoretical framework can also be analyzed.	The indicators from of dependent variables of the conceptual framework will be analyzed to create a composite index, through the use of supervised techniques of inferential analysis (steps 4 to 7). Additionally, a descriptive statistic of all indicators will be presented.
5	Normali-sation	Normalization of indicators, respecting the properties of the data, so they can be comparable. Extra attention should be given to the influences of outliers in the result and to adjustments necessary to be made.	There are several methods (e.g., ranking, standardisation, Min-Max, distance to a reference, categorical scale, etc.) for this step. Some are going to be tested and the one that best suits the analysis will be chosen.
6	Weighting and aggrega-tion	Process of putting together the indicators as presented in the theoretical framework to compose an index. It has to consider issues regarding correlations and compensability between indicators.	Based on the correlation analysis performed during the multivariate analysis (Step 4), the adequacy of aggregation the indicators will be assessed. For the aggregation process, there are also several methods (e.g., Z-scores, Min-Max, Multi-criteria approach, etc.). Similarly to the previous step, the one that best suits the analysis will be chosen, focusing in being able to compare the data in the same scale.

#	Step	Description	Application
7	Uncer-tainty and sensitivity analysis	Analysis of how the previous steps influence the robustness of the composite indicator. If possible, it should consider alternative scenarios to select indicators. Also, uncertainties among the composite indicators and scores should be made clear as they might have a relevant influence on the results.	The uncertainty analysis will be useful to assess the influence of inputs (Steps 1 to 6) in the final composite indicator, and the sensitivity analysis to understand the influence of each indicator in the variation of the final result. In a second part, all the parameters will be analyzed without any division between dependent and independent variables, trying to determine if the classification proposed was adequate and validate the model. This step will also follow the previous supervised learning techniques.
8	Back to the data	Identify the key factors influencing the scores and the correlation between them. Explain the importance among indicators with transparency to be able to orient policymaking.	With the composite index built, it will be possible to verify the scores on each city and evaluate the ones that had the highest and lowest positions on the ranking. Also, the indicators that influenced the most the final score can also be identified. Complementing this assessment, unsupervised techniques of inferential analysis will be used, trying to identify whether there are any clusters of urban areas and generate more insightful information.
9	Links to other indicators	Identify the correlation with other measures based on the result of the sensitivity analysis and/or regression analysis, to develop a data-driven narrative.	The influence of the independent variables on the composite index built with the dependent variables will be evaluated with a regression analysis. Therefore, it will be possible to identify which one of these factors have a higher influence on the level of urban resilience.
10	Visuali-zation of the results	Present the results with the appropriate visualisation technique to convey the information in a comprehensive and accurate way, given the fact that it can influence the interpretability of the results.	This final step is actually incorporated in all the other since, for each result obtained, different forms of data visualisation will be tested to make sure the results are communicated in a transparent and clear way.

Source: adapted from Nardo et al. (2008)

3.4 Operationalization

The operationalization refers to the process of translating the conceptual framework into variables and indicators. As explained on Section 2.5, the parameters were obtained on the literature review, grouped into similar topics, divided according the dimensions of urban resilience (economic, environmental, institutional, physical and social) and, lastly, the ISO37120:2018 served as a basis for dividing the indicators into the 'factors' and the 'level' of urban resilience. Giving continuity to the process, and getting closer to the data collection and analysis phase, to determine what sources of information to compare, a proactive search was done to find databases and websites that could add value to the content of the research. Table 5 presents the list of main databases found and a brief description of their content.

Table 5 – Summary of main databases

Database	Description	Number of indicators / categories	Number of cities	Data year	Source
GHS Urban Centre Database 2015	Provide urban information based on density of built structures and population.	51[(1)] / 7	>13,000	1975, 1990, 2000, 2012, 2014, and 2015	European Commission (2019); Florczyk et al. (2019).
Passport Cities	Divides the cities in two groups, one composed by metropolitan areas and the other with cities from the same countries as the former.	70[(2)] / none	>1,200	2005 to 2018[(3)]	Euromonitor International (2019)
UN Urban Data	*Currently unavailable*				UN-Habitat (2019).
Global Gridded Model of Carbon Footprints (GGMCF)	Estimative of the carbon footprints (total and per capita) of cities	2 / none	>13,000	2013	Moran et al. (2019).
WCCD Supports the SDGs	Relation between the indicators proposed by the ISO37120 applied in the context of UN's SDGs. The parameters are divided in core, supporting and profile indicators.	128 / 17[(4)]	60 (only certified cities)	2017, 2018	WCCD (2019)

[(1)] besides the ones related to characteristics to identify the data code, and without considering that a single indicator can be measure in more than one time period.

[(2)] without considering the subdivisions of age groups or other types of bands of values within the same indicator.

[(3)] some reports also provide projections up to 2030.

[(4)] do not consider the additional and forthcoming indicators.

<u>Additional observation</u>: *in all databases, not necessarily all the indicators are available for all the time period and/or cities.*

Source: author (2019).

Having those options in hands, the indicators of the conceptual framework were cross-checked with them, to identify which had available information and could compose the operationalization of this research. Tables 6 and 7 presents, respectively, the resulting operationalization framework and the indicators each database had available. Given that the GHS Urban Centre Database 2015 was the only one that had indicators available on every dimension, besides the largest number of cities, it was the one chosen for the data analysis.

Table 6 - Operationalization framework.

GHS Urban Centre Database 2015		
Dimension	**IV**	**DV**
Economic	-	Income
	-	GDP
	-	GDP per capita
Environmental	Elevation	CO2 emission
	Temperature	PM2.5
	Precipitation	Green per capita
	-	Green coverage
Institutional	Land use efficiency	-
Physical	Urban size	Built area
	Flood coverage	Population density
	-	Open spaces
Social	Development Index	-

Source: author (2019).

Table 7 – Indicators available on databases.

#	Economic	Databases	Environmental	Databases	Institutional	Databases	Physical	Databases	Social	Databases
1	Employment	B	Elevation	A	Hazard risk assessment and strategies	-	Mixed-use development	-	Widespread understanding of risks	-
2	Total unemployment rate	B	Proximity to water	-	Warning systems	-	Built area	A	Adaptive strategy	-
3	Income	A*, B	Stewardships of ecosystems	-	Consultative planning process	-	Shelters capacity	-	Education level	B
4	Savings	-	CO2 emissions	A	Data collection	-	Medical services	-	Place attachment	-
5	Municipal revenues	-	CO emissions	B	Geospatial information	-	Street network connectivity	-	Religious bonds	-
6	Single sector employment dependance	-	Energy consumption	-	Incentives for innovation	-	Population density	A*, B	Social engagement	-
7	Poverty rate	-	Urban tree canopy	-	Data availability	-	Open spaces	A	Public engagement	-
8	Economic freedom	-	Water demand and consumption	-	Safety	-	Sidewalk connectivity	-	Demographic distribution	B
9	Tourist attraction	-	Water quantity and quality	-	Land use efficiency and zoning regulations	A	Accessibility to public transport	B	Cultural diversity	-
10	Business size	-	Forest conservation	-	Scenario-based planning	-	Evacuation routes	-	Social cohesion	-
11	GDP	A, B	Biodiversity	-	Proactive multi-stakeholder collaboration	-	Infrastructure independency	-	Self-organization	-
12	GDP per capita	A*, B	Erosion rates	-	Inter-organizational cooperation	-	Urban form	-	Life expectancy	-
13	GDP growth rate	B	Green area per capita	A*	Political and economic stability	-	Building configuration	-	Language proficiency	-
14	Total market value	-	Renewable energy generation	-	Political engagement	-	Urban size	A, B	Academic performance	-
15	Service industry	-	Green coverage	A	Capacity-development of citizens	-	Spatial heterogeinity	-	Innovation	-
16	Wage level	B	Temperature	A, B	Municipal investment towards the SDGs	-	Flood coverage	A	Events held	-
17	Ease to secure human resources	-	Business sustainability	-	Municipal investment on basic services	-	Effective public transport	-	Foreign residents	B
18	Corporate tax rate	-	Waste generation	-	Investment in resilience proofing	-	Vehicle ownership	B	Travel experiences	-
19	Environment of creative activities	-	Recycling of waste	-	Commitment to climate action	-	Occupancy of hazard prone areas	-	Educational openess	-
20	Environment of cultural activities	-	Waste in landfills	-	Mainstreaming adaptation and mitigation measures	-	Acess to airports	-	Work satisfaction	-
21	Environment of hotel sector	-	SOx emissions	B	Supportive finance mechanisms	-	Commuting conveniance	-	Medical capacity	-
22	Environment of commercial sector	-	NOx emissions	B	Effective emergency response services	-	Transportation fatalities	B	Migration	B
23	Workhing hours	-	PM2.5 emissions	A, B	Proactive corruption prevention	-	Taxi fare	-	Ethinical diversity	-
24	Rental prices	-	PM10 emissions	B	Well-managed protective ecosystems	-	Spatial segregation	-	Crime	-
25	Price level	B	GHG emissions	C	Incentives for social equality	-	Communication capacity	B	Gender equality	-
26	Energy intensity of economic activity	-	Carbon intensity of economic activity	-	Frameworks to sustainable development	-	Access to internet	B	Violence against women	-
27	Economic risk of natural disaster	-	Sustainability of fish stocks	-	Land and property acquision	-	Safe housing	-	Homelessness	-
28	Inclusive labour policies	-	Natural protection	-	Evacuation and emergency management drills	-	Sufficient food supply	-	Mortality Rate	B
29	Integration with regional economies	-	Hazardous waste	-			Adequate supply of energy	-	Community preparedness	-
30	Land values	-	Land loss	-			Information and communications technologiy readiness	-	Level of development	A, B
31	Disaster economic loss	-	Environmental risk	-			Informal housing	-	Prevalance of undernourshiment	-
32	Material consuption and footprint	-	Precipitation	A			Acess to water supply	-	Protection capacity	-
33	Financial support	-	Wastewater treatment	-			Access to energy supply	-		
34	Taxation and fiscal policies	-					Access to sanitation	-		
35	Debt service ratio	-					Access to solid waste collection	-		
36	Budgetary system structure	-					Access to emergency services	-		
37	Livelihood options	-					Access to health services	-		
38							Affordable housing	-		
39							Occupancy of households	B		
40							Wastewater collection	-		

LEGEND: A - GHS Urban Centre Database 2015 (European Commision, 2019), B - Passport Cities (Euromonitor International, 2019), C - GGMCF (Moran et al., 2018), *indicator calculated based on indicators from the same database

Source: author (2019)

3.5 Sample size and selection

Considering the fact that the dataset was selected according to the indicators and databases available, the sampling method can be classified as purposive – what is in alignment with the deductive research strategy. Since the GHS Urban Settlement Database 2015 was the only one that had at least on because indicators available for at least one variable on each dimension of urban resilience, even though some variables did not have any indicator, it was the one chosen for this research, resulting in the conceptual framework presented on Section 3.4. It is important to emphasize that the use of only this particular database also had the intention of ensuring that the data collected had the same technical procedure, the concepts used the same definitions and the largest number of cities (a total of 13,135 in this case) could be included. Consequently, this marks the conclusion of steps 1 and 2 (Table 4, Section 3.3).

3.6 Data collection and data analysis methods

With the database selected, the data analysis could begin. Descriptive statistics techniques were used to have a first look at the range of values of indicators and corrections that would have to be made in order to continue with the data investigation. There are two types of statistical techniques that can be adopted in the analysis, namely descriptive or inferential statistics. The first identifies the existing relations between variables in the dataset, and the second aim at exploring hypothesis and verifying if certain relations are systematic (Thiel, 2014). As previously mentioned on Section 3.3, initially the indicators related to the level of urban resilience will be aggregated into a composite index and the correlation with the factors of urban resilience will be calculated. Later, all the indicators will be analyzed, without the previous division between the dependent and independent variables, to ensure that the model generated to evaluate the level of urban resilience is indeed adequate. Both of these parts are going to follow supervised learning techniques of inferential statistics Lastly, aiming to identify clusters on the final score obtained, the performance of urban areas will also be examined with unsupervised learning techniques of inferential statistics. This process corresponds to steps 3 to 9 (Table 4, Section 3.3) and, in parallel to all of them, step 10 will be considered to make sure the results gathered are be presented in an adequate manner.

3.7 Validity and reliability

Besides the considerations already made on this chapter regarding the concerns with the strategy adopted, it is important to emphasize that to use secondary sources the researcher must be aware of the exact steps and procedures followed to collect the data, and if there is the need to use additional information, it is necessary to verify if the data can be adequately comparable, which means realizing a data inspection to make sure if it attends the statistical requirements (Thiel, 2014). As mentioned on Sections 3.4 and 3.5, despite a number of different datasets being available to be used, in order to ensure the internal validity and reliability of this research, only one database was selected. The extensive literature review made to determine a comprehensive and integrated set of indicators, besides the standard procedure adopted for the data analysis, will contribute to enhancing the internal validity. Furthermore, by selecting indicators from existing frameworks and cross-checking them with the databases, the aim was to ensure the external validity of the research or, in other words, that the analysis could be replicable for other cities worldwide in case more data is added. If the indicators used were context-specific, the analysis would most likely not be able to be replicated in other conditions. Lastly, it is important to highlight that all the steps and assumptions made during the analysis of indicators and visualization of the results will be openly explained to ensure transparency of this research.

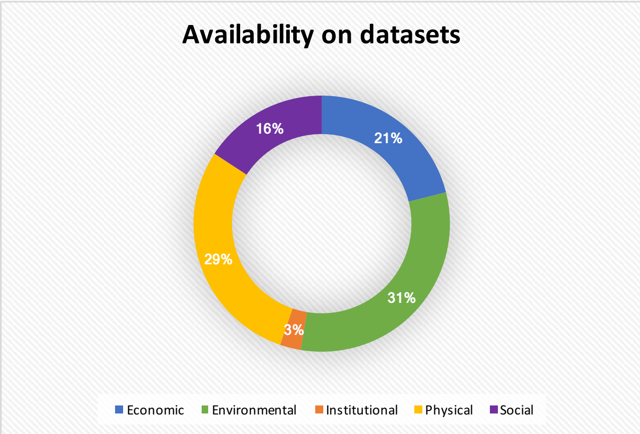
Chapter 4: Presentation of data and analysis

4.1 Theoretical framework and data selection

On Sections 2.4 and 3.5 the process to obtain, respectively, the theoretical and conceptual frameworks was explained. Boiling down the extensive literature review into a meaningful set of indicators allowed the establishment of an integrated framework that not only incorporates a balanced number of indicators per dimensions, but also is able to represent the factors and level of urban resilience. The framework obtained reassures the completion and interconnectedness of each perspective, because each of the dimensions have a particular focus of measurement and, therefore, they must to be considered together. In general, the economic dimension incorporates the performance of the local economy, how it is capable of generating financial value, how it translates into the life of citizens and attractiveness to regional, national and international commerce and tourism; the environmental dimension measures the unwanted impacts of productive activity (mainly emissions and waste generation), the consumption of natural resources and the quality of management and preservation of ecosystems and its services; the institutional dimensions indicates the existence of enabling conditions to planning, management, integrations across sectors and stakeholders, public participation, leadership, and engagement, besides mainstreaming important topics as sustainable development; the physical dimension accounts for the access to basic infrastructure, transport and health services that are necessary to all citizens, as well as living conditions and urban characteristics that reflect the execution of urban development and planning policies; and, lastly, the social dimension is related to citizens' life in the urban area, including their capacity development, health quality, education, violence, social and gender equality, social cohesion, migration and cultural diversity.

Even though the conceptual framework addresses the concept of urban resilience with a comprehensive approach, when it was cross-checked with indicators at one's disposal on databases, it was realized that current existing information does not allow a full assessment of the concept of urban resilience. Graph 3 shows the representativeness of each of the dimension within the accessible indicators in all databases searched together. Here, it is already possible to visualize that the representatives of some dimensions increased or decreased of more than 10% in comparison to the conceptual framework (see Graph 2, Section 2.5), as well as the environmental and physical dimensions were the one with the largest number of indicators available. This indicates the quantity and type of data available and starts to answer the first research sub-question *('To which extent the dimensions and indicators of urban resilience can be measured?')*. With this information, it will only be possible to evaluate the following perspectives: on the economic dimension, a broad overview of the macro and microeconomic status of the urban area; on the environmental, measurements of pollutions levels and green areas, besides some weather characteristics (temperature and precipitation); on the institutional, the ability of the government to limit urban expansions and reduce land loss despite population growth; on the physical, its size and use of public and private transportation; on the social, the level of education, demographics and migration flows. Nonetheless, since the analysis will consider more than 13,000 cities worldwide it is expected that, even if analyzing just a small number in comparison to the total of proposed parameters, some meaningful insights will be brought out.

Graph 3 – Availability of indicators on analyzed databases.



Source: author (2019)

4.2 Imputation of missing data

Pre-processing of the data

To understand what transformations would have to be done on the database to be able to perform the statistical analysis, first the items that were going to be used as indicators were marked with a different color to facilitate their visualization in such a large amount of data. Classification items, or even the indicators that were not part of the operationalization framework of this research, were kept unchanged. Given the interest to provide a recent overview and optimize the number of cities with existing data indicators for years different than 2015, specifically 1990 and 2012, were not considered – there was less information available in those cases. However, given that the measurement of emissions was only available for the year of 2012, an exception was made to provide more information about the environmental dimension and the overall aggregated indicator. It is worth highlighting that, during the correlation and later sensitivity analysis, this assumption will be tested, and in case it proves to be invalid, the indicator will have to not be included.

Starting the process of effectively cleaning the data, a filter of 'NAN' (non-existing) values for each indicator was used and these cells marked on a different color. Annex 2 shows further details about the number of cities that would have to be unconsidered in this case. Additionally, observing that there were a reasonably large number of '0' (null) values, the definition of each indicator was reviewed to verify if that information was logic or, in other words, whether it could be possible to happen or just in fact represented a missing value. The indicators related to precipitation, built area, population and GDP PPP were considered not to be possible to be null, and therefore were also marked to be corrected on the imputation process. To deal with the lack of information on the database, two methods of data imputation were tested: case deletion and single input. As explained by Nardo et al. (2008), the first simply deletes the non-existing information, but ends up ignoring systematic variances among the data and usually increases the standard deviation of the sample (a 'rule of thumb' is to not delete if there is more the 5% missing data); and, the second, substitutes the missing data with a single value (e.g., mean, median, regression, hot-and-cold deck, or expectation-maximization) trying to reduce the bias, but creating the illusion of a complete dataset or underestimating the variance. Both methods are valid, but they need to consider the particularities of the dataset in question and be assessed to understand how and if they alter the information measured.

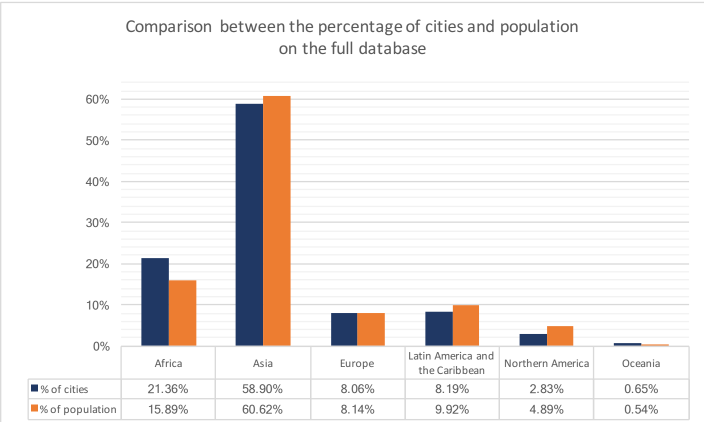
The deletion method resulted in 1,091 cities with data available for all indicators, which represents only 8.31% of the original sample. Even though a model created for this sample size could not necessarily be said to represent the full dataset, at the same time, since 9 out 31 indicators had more than 5% of missing data (some as high as 86%), it was also a concern that a model generated with data imputation would likewise have its bias. In order to counter this problem and still generate a representative model, it was decided to execute all the subsequently methodological steps considering both scenarios – with 1,091 cities (partial dataset) and with the total 13,135 cities (full dataset) – and comparing the results to check which one would be more adequate. Specifically for the data imputation, since the standard deviation showed a high variation among the values per continent and globally (as it will be shown on Table 8, Section 4.3), another caution taken to reduce the over or underestimation of the statistics was to consider the continent average where the city is located for the imputation process, besides calculating it only for the data available for each indicator – in other words, urban areas with missing data were not considered to calculated the average. This pre-processing step is important because it reduces any abnormalities the data might have, which can influence (positively or negatively) the statistical analysis. More importantly, the variation of data availability for the indicators already provides an idea about the difficulty of data collection, how some criteria might not be suitable to be measured or, even, that despite being available the information was not shared and thus could not be included on the database. In any of the cases, following the methodology itself already provides an important insight about points of improvement for municipalities, researches and organizations that work to provide this data, and safeguards the creation of a model that represent an accurate worldwide panorama, objective to be achieved with the research.

Comparison between the number of cities and population

Before effectively starting the analysis, to further ensure the reliability of this study, the relation between the number of cities and population was verified to check if they are proportional. The intention is to guarantee that the information available of cities represents the number of inhabitants on that urban area and also in comparison to the global scale. On the original dataset (Graph 4) the relative quantities are very similar, with the biggest variation (5.47%) occurring in the African continent. It is worth highlighting that, despite this meaning that the number of cities per location is not balanced it, in fact, is in accordance with the population on each location, and indicates that a larger number of cities imply in a large number of inhabitants (and vice-versa). Besides, the proportion among the continents are aligned with the urbanization phenomena and population growth happening worldwide, which is more intense in Africa and Asia (UN, 2018).

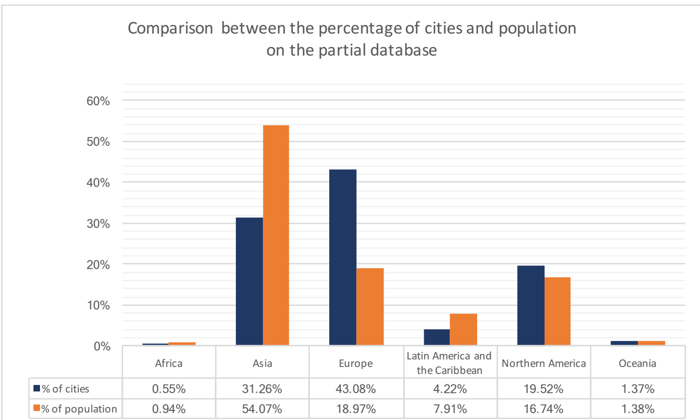
Since the deletion method is also going to be applied, it was necessary to better understand its limitations and if this proportional pattern among cities and population would repeat. Graph 5 shows that this was not the case. The high variation of representativeness for Asian and European cities – -22.82% and 24.11%, respectively – means that this database in particular was able to fully collect more information from Europe rather than Asia or, also, can be an indicative that the former has a more robust data collection and/or sharing procedure that the latter. The same reasoning can be applied to Northern America, given that its representativeness varied in the order of 15% in comparison to the original data. For Latin America and the Caribbean and Oceania both the representativeness and the variation were similar, keeping relatively close to the original data, which can signalize a balance between the database being able to collect information and the existence of procedures to ensure data access. Lastly, in the case of African cities, the data availability reduced almost completely, from more than 20% to less than 1%, which means that either it was not possible to collect data about that region, the information was not available, or a sum of partially both causes. As a consequence, it is important to keep in mind that the index built to calculate the level of urban resilience might not well represent cities in Africa, as well as European and Asian cities that also had a large reduction of data available. This point of attention will be commented on Section 4.6 where the level of urban resilience will be effectively calculated.

Graph 4 - Percentage of cities from each continent based on the original data.



Source: author (2019).

Graph 5 - Percentage of cities from each continent with all indicators available.



Source: author (2019).

4.3 Multivariate analysis and normalization

Descriptive statistics

Starting the process of describing the data, some adjustments had to be made on the indicators. The population density was calculated by dividing the indicators of population (number of inhabitants) and area (square kilometres) available on the database. Similarly, the GDP per capita was calculated dividing the GDP PPP (USD 2007) by the population, and the Green coverage per capita dividing the Total Green (square kilometres) by the population. For the Income Level, since the data was given with a nominal classification, it was converted into an ordinal classification attributing number to the labels provided by Florczyk et al. (2019) as follows: 1- ‘low income countries’ (LIC), 2- ‘lower-middle income countries’ (LMIC), 3- ‘upper-middle income countries’ (UMIC), and 4- ‘high income countries’ (HIC), besides 0-others. Using the same process, the Development Level was converted from nominal to ordinal as follows: 1- ‘least developed countries’ (LDCL), 2- ‘less developed regions, excluding least developed countries’ (LCD), 3- ‘more developed regions’ (MDR). It is important to mention that even though both the Income and Development level indicators had to be transformed, they are still not continuous values and, differently from the other indicators, they were not calculated in a city level scale of the city level. Therefore, initially the income level is not going to be considered to build the composite index (as it is one of the dependent variables) and the development level to determine the factors that influence urban resilience (as it is one of the independent variables), and only during the sensitivity analysis and regression analysis their influence will be assessed. Lastly, since the CO_2 and PM2.5 emissions indicators were given divided by industry, they were added up to calculate the total emissions. With those changes made, the minimum, maximum, average and standard deviation for each indicator was calculated (Table 8). It is worth to reinforce that, to not create a bias on the results, the values presented (minimum, maximum, average and standard deviation) were determined based on the information available for each indicator and not considering if they were available for every city. The indicators of Income and Development level were not included on the descriptive table because it would not be valid to calculate their statistics since they are not continuous values, instead, it was chosen to represent them on a ‘100% stacked-column chart’, which is able to show the percentage of cities in each category per continent and have an indicative of how many cities are classified on these categories (Graphs 6 and 7).

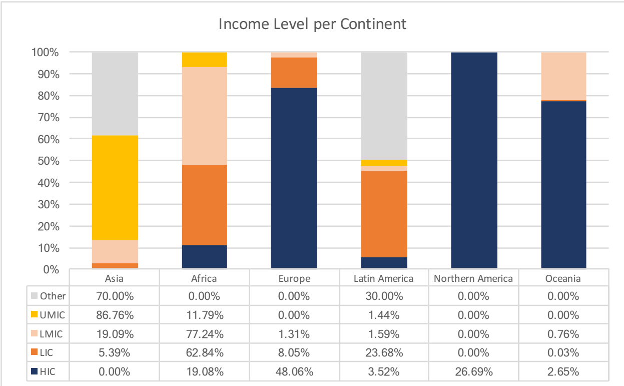
Table 8 – Descriptive statistics.

Indicator	Measurement	Scale	Minimum	Maximum	Average	Standart Deviation
GDP	USD (2007)	**Global**	**3.389**	**1.007.759.196.160**	**2.866.397.855**	**20.196.718.680**
		Africa	*27.344*	*139.322.441.728*	*651.264.425*	*2.042.276.791*
		Asia	*3.389*	*1.007.759.196.160*	*2.582.325.821*	*15.977.154.388*
		Europe	*4.703.337*	*332.856.197.120*	*4.675.846.665*	*5.146.114.528*
		Latin America and the Caribbean	*998.597*	*371.525.091.328*	*3.823.407.567*	*5.804.749.604*
		Northern America	*968.329.920*	*675.538.075.648*	*16.007.861.119*	*9.294.958.949*
		Oceania	*37.683*	*112.955.924.480*	*5.899.892.509*	*1.375.941.148*
GDP per capita	USD (2007) per inhabitant	**Global**	**0,05**	**206.073,54**	**7.920,72**	**11.686**
		Africa	*0,36*	*36.641,58*	*2.457,15*	*2.870*
		Asia	*0,05*	*206.073,54*	*6.373,40*	*6.551*
		Europe	*83,93*	*141.243,03*	*13.919,45*	*3.348*
		Latin America and the Caribbean	*17,57*	*90.159,38*	*14.446,45*	*5.196*
		Northern America	*14.273,84*	*48.152,72*	*31.077,83*	*4.011*
		Oceania	*1.575,26*	*114.577,87*	*69.643,46*	*5.579*
Elevation	meters above sea level	**Global**	**(38,14)**	**4.509,89**	**422,64**	**596,61**
		Africa	*(38,14)*	*3.287,55*	*805,38*	*402,75*
		Asia	*(24,92)*	*4.509,89*	*301,82*	*353,91*
		Europe	*(22,93)*	*908,54*	*144,20*	*89,89*
		Latin America and the Caribbean	*1,19*	*4.338,07*	*607,87*	*227,03*
		Northern America	*2,50*	*1.923,18*	*260,72*	*66,00*
		Oceania	*5,35*	*2.399,37*	*624,34*	*67,12*
Green area per capita	km2 per inhabitant * 1000	**Global**	**0,0029**	**1,8211**	**0,1966**	**0,1549**
		Africa	*0,0029*	*0,8299*	*0,1147*	*0,0547*
		Asia	*0,0031*	*1,0735*	*0,1799*	*0,0891*
		Europe	*0,0059*	*1,2855*	*0,3325*	*0,0478*
		Latin America and the Caribbean	*0,0054*	*0,8492*	*0,2069*	*0,0238*
		Northern America	*0,3051*	*1,8211*	*0,7249*	*0,0981*
		Oceania	*0,0077*	*1,1826*	*0,2890*	*0,0243*
Temperature	ºC	**Global**	**(8,74)**	**30,85**	**21,02**	**596,61**
		Africa	*9,86*	*30,85*	*23,66*	*402,75*
		Asia	*(1,79)*	*30,68*	*21,72*	*353,91*
		Europe	*(8,74)*	*20,20*	*10,30*	*89,89*
		Latin America and the Caribbean	*4,34*	*29,36*	*22,29*	*227,03*
		Northern America	*2,72*	*25,58*	*13,39*	*66,00*
		Oceania	*9,43*	*27,40*	*20,76*	*67,12*
Precipitation	mm	**Global**	**0,18**	**6.281,83**	**1.110,02**	**679,61**
		Africa	*2,33*	*2.866,95*	*967,13*	*250,01*
		Asia	*16,40*	*5.465,45*	*1.177,76*	*560,04*
		Europe	*114,35*	*2.552,25*	*734,44*	*102,84*
		Latin America and the Caribbean	*0,18*	*6.281,83*	*1.348,60*	*234,74*
		Northern America	*60,50*	*2.264,98*	*954,56*	*74,64*
		Oceania	*409,55*	*4.923,00*	*2.010,48*	*120,29*
Total emission of CO2	tonnes per year	**Global**	**528,02**	**444.529.837,17**	**1.385.592,46**	**6.125.323,20**
		Africa	*528,02*	*37.050.931,81*	*474.441,07*	*862.526,13*
		Asia	*4.065,05*	*444.529.837,17*	*1.679.103,65*	*5.418.211,82*
		Europe	*4.668,29*	*135.453.835,20*	*1.578.479,28*	*1.617.823,03*
		Latin America and the Caribbean	*6.602,65*	*68.497.295,26*	*719.672,61*	*900.009,07*
		Northern America	*39.954,83*	*141.145.912,83*	*3.560.597,41*	*1.976.115,05*
		Oceania	*34.151,85*	*24.905.514,16*	*1.246.572,83*	*293.624,33*
Total emission of PM2.5	tonnes per year	**Global**	**0,43**	**485.305,56**	**770,08**	**5.522,30**
		Africa	*1,08*	*73.776,97*	*374,49*	*991,44*
		Asia	*0,43*	*485.305,56*	*1.013,66*	*5.319,63*
		Europe	*2,76*	*18.447,94*	*339,33*	*372,00*
		Latin America and the Caribbean	*0,83*	*91.947,95*	*483,52*	*929,89*
		Northern America	*13,82*	*28.709,01*	*775,89*	*447,79*
		Oceania	*20,82*	*8.609,52*	*622,69*	*104,08*
Green area	km2	**Global**	**0,86**	**6.590,63**	**50,07**	**188,56**
		Africa	*0,86*	*1.630,66*	*24,27*	*37,16*
		Asia	*0,88*	*6.590,63*	*44,32*	*135,47*
		Europe	*0,99*	*1.888,84*	*74,97*	*39,79*
		Latin America and the Caribbean	*0,95*	*2.102,41*	*54,39*	*39,61*
		Northern America	*17,95*	*5.618,92*	*272,25*	*110,73*
		Oceania	*0,93*	*1.606,80*	*87,17*	*20,18*

Indicator	Measurement	Scale	Minimum	Maximum	Average	Standart Deviation
Land use efficiency	Ratio of land consumption divided by population growth	**Global**	**(4.268,93)**	**1.904,38**	**0,97**	**0,99**
		Africa	*(116,65)*	*340,69*	*1,29*	*402,75*
		Asia	*(4.268,93)*	*1.904,38*	*1,07*	*353,91*
		Europe	*(350,94)*	*125,73*	*(0,80)*	*89,89*
		Latin America and the Caribbean	*(169,61)*	*35,74*	*0,85*	*227,03*
		Northern America	*(38,79)*	*412,43*	*2,24*	*66,00*
		Oceania	*(3,00)*	*5,10*	*0,57*	*67,12*
Urban size	km2	**Global**	**1,00**	**6.622,00**	**50,26**	**189,17**
		Africa	*1,00*	*1.638,00*	*24,43*	*37,34*
		Asia	*1,00*	*6.622,00*	*44,52*	*136,05*
		Europe	*1,00*	*1.882,00*	*74,92*	*39,73*
		Latin America and the Caribbean	*1,00*	*2.114,00*	*54,68*	*39,80*
		Northern America	*18,00*	*5.633,00*	*272,77*	*110,94*
		Oceania	*1,00*	*1.610,00*	*87,42*	*20,23*
Area exposed to floods	km2	**Global**	**-**	**3.500,00**	**9,95**	**67,47**
		Africa	-	*1.005,00*	*4,09*	*12,40*
		Asia	-	*3.500,00*	*11,67*	*64,28*
		Europe	-	*583,00*	*13,13*	*10,92*
		Latin America and the Caribbean	-	*333,00*	*4,54*	*5,07*
		Northern America	-	*501,00*	*26,42*	*10,94*
		Oceania	-	*143,00*	*3,81*	*1,58*
Built area	km2	**Global**	**0,0006**	**4.632,77**	**22,44**	**113,07**
		Africa	*0,0008*	*900,36*	*8,40*	*18,62*
		Asia	*0,0006*	*3.664,91*	*15,94*	*66,81*
		Europe	*0,0301*	*1.294,46*	*42,87*	*25,65*
		Latin America and the Caribbean	*0,0017*	*1.397,38*	*26,86*	*24,76*
		Northern America	*8,2821*	*4.632,77*	*184,93*	*80,66*
		Oceania	*0,0009*	*1.141,57*	*54,16*	*14,05*
Population density	inhabitants per km2	**Global**	**546**	**332.278**	**10.646**	**15.852**
		Africa	*1.197*	*332.278*	*17.469*	*10.923*
		Asia	*929*	*312.312*	*10.075*	*10.491*
		Europe	*777*	*167.251*	*3.450*	*2.519*
		Latin America and the Caribbean	*1.172*	*201.671*	*6.173*	*2.531*
		Northern America	*546*	*3.269*	*1.536*	*1.536*
		Oceania	*845*	*121.145*	*23.448*	*2.610*
Open spaces	% of total area	**Global**	**17,7000**	**100,00**	**68,57**	**14,28**
		Africa	*26,6200*	*100,00*	*74,38*	*5,56*
		Asia	*20,2900*	*100,00*	*70,58*	*10,38*
		Europe	*17,7500*	*100,00*	*60,11*	*4,90*
		Latin America and the Caribbean	*23,6300*	*100,00*	*63,96*	*4,85*
		Northern America	*17,7000*	*98,72*	*56,81*	*3,98*
		Oceania	*28,3200*	*87,71*	*48,50*	*1,42*

Source: author (2019).

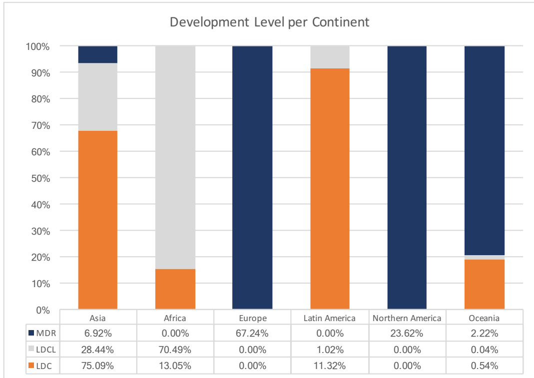
Graph 6 - Descriptive statistics for the Income Level.



	Asia	Africa	Europe	Latin America	Northern America	Oceania
Other	70.00%	0.00%	0.00%	30.00%	0.00%	0.00%
UMIC	86.76%	11.79%	0.00%	1.44%	0.00%	0.00%
LMIC	19.09%	77.24%	1.31%	1.59%	0.00%	0.76%
LIC	5.39%	62.84%	8.05%	23.68%	0.00%	0.03%
HIC	0.00%	19.08%	48.06%	3.52%	26.69%	2.65%

Source: author (2019).

Graph 7 - Descriptive statistics for the Development Level.

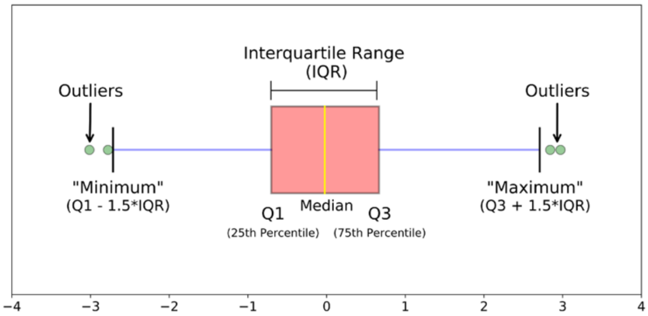


	Asia	Africa	Europe	Latin America	Northern America	Oceania
MDR	6.92%	0.00%	67.24%	0.00%	23.62%	2.22%
LDCL	28.44%	70.49%	0.00%	1.02%	0.00%	0.04%
LDC	75.09%	13.05%	0.00%	11.32%	0.00%	0.54%

Source: author (2019).

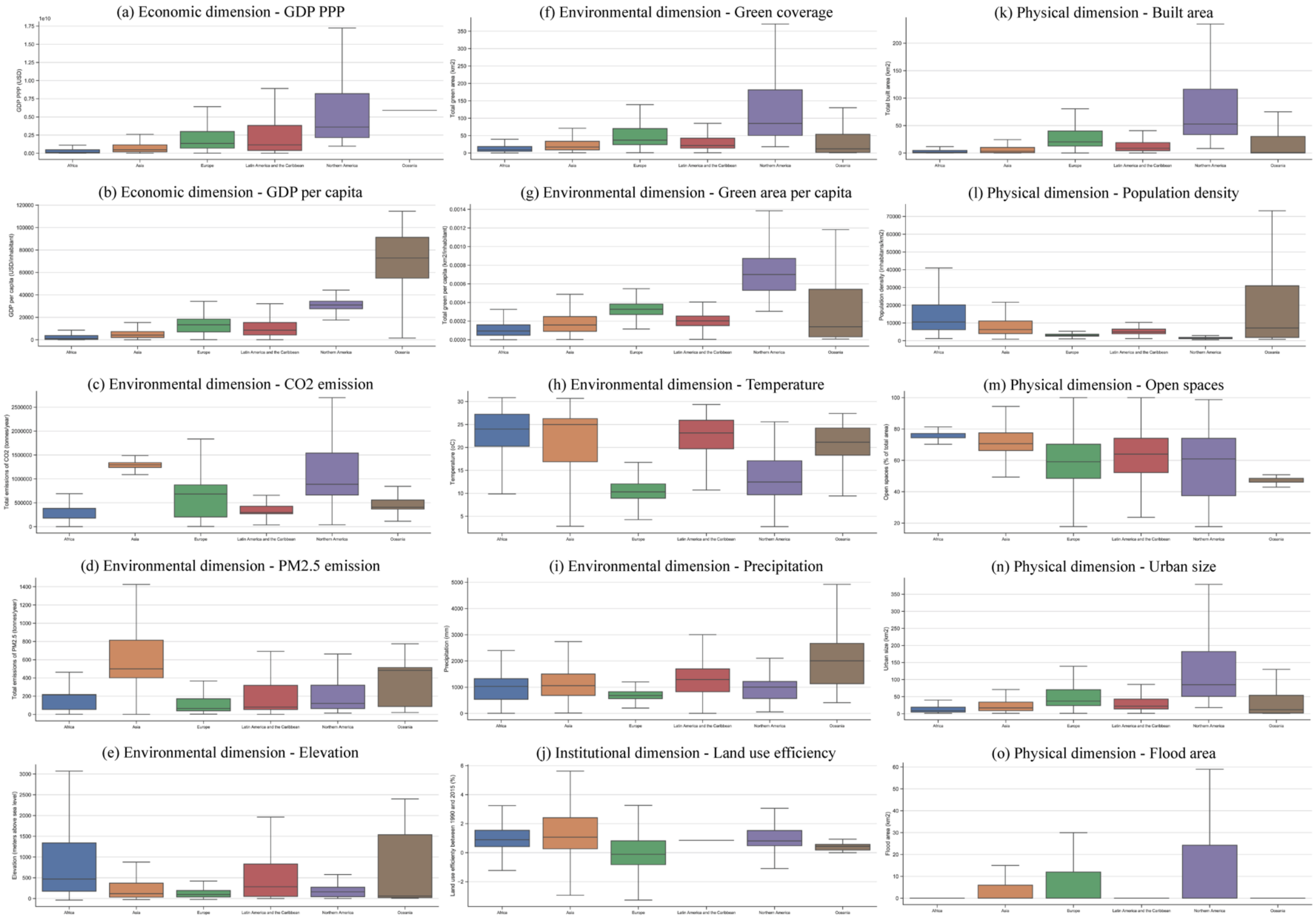
To represent the distribution of all the other indicators, it was chosen the 'box plot' type of chart, which allows the visualization of the average value, the 25th (Q1) and 75th (Q3) percentile (interval also called Interquartile Range – IQR), intervals 1.5 times above and below the IQR, and outliers (Figure 4). However, given that the standard deviations of the indicators showed to have high values, which means that they are very dispersed, a reasonable number of outliers would end up being represented in the graph and make difficult the comparison between them. Since the interval between *(Q1 - 1.5*IQR)* and *(Q3 + 1,5*IQR)* already includes the majority of data, the outliers were not shown (on Graph 8) to not cause distortions.

Figure 4 - Explanation of the box plot type of chart.



Source: Towards Data Science (2018).

Graph 8 - Visualization of the indicators' data distribution.



Source: author (2019).

The descriptive statistics is important to understand how the data is distributed and, associated with a visualization tool, can provide insightful information about the database. Indeed, that was the case for this analysis. Starting with the economic dimension, it is possible to visualize (Graph 8a) that Asian cities have both the highest and lowest GDP PPP (USD 2007), besides a high standard deviation, which means the even within the country, the wealth in very disperse or, in other words, not equally distributed – the same scenario happens for GDP per capita (Graph 8b). Northern American cities are on average the richest, with values almost 25 times higher than African cities. However, looking at the GDP per capita, surprisingly Oceania's cities turned out to have the highest income per inhabitant, with values almost 27 times higher than African cities (on average). Cross-checking these two indicators with the income level, it is possible to verify that indeed higher values of GDP PPP (and GDP per capita), are aligned with higher income levels (and the same goes for lower GDP PPP and income). It is important to highlight that around 40% and 50% of Latin American cities had their income levels classified as others, what can negatively affect the comparison and later calculation of the economic indicator on the composite index, and that was a complementary reason why it was not initially considered as part of the composite index. However, as it was also mentioned before, its influence will be evaluated during the sensitivity analysis.

On the environmental and physical dimensions, looking at some groups of indicators instead of them individually provide a better interpretation of the data. Comparing the CO_2 and PM2.5 emissions (Graphs 8c,d) allow to identify that Northern American and Asian cities are among the top polluters, followed by Europe and Oceania – to emphasize the difference of emissions, the first position is two times higher as the third, and between 4 to 8 times as the last. In other words, it can be argued that, although many investments are being made to reduce pollution levels and transition towards sustainability, the measurement validate the known relationship that a more developed or fast-growing economy implies, in general, in a higher emission of pollutants and impact to the environment – mentioned, for example, at the article 4 of The Paris Agreement (UN, 2015). At the same time, Northern American cities, for example, had a process urban development in suburbs with large houses and low population density, that not only contributes to higher values of green area per capita and large urban sizes, but also contributes to higher pollutant emissions because of the car dependency. Contrary to these figures, African cities have the lowest green area per capita, smaller urban sizes and the second highest population density, which means that citizens are more likely to be agglomerated into urban areas without green spaces.

Another interesting comparison is examining the indicators of elevation, precipitation, flood exposure and built area together. Cities with low elevation (or even below sea level), associated with high volumes of precipitation and percentages of built area (more impervious surfaces) tend to be more exposed to flooding – fact that, of course, depends on the municipal preparedness and response to such events. In particular, European cities have the lowest precipitation average and, even though they are at the third position on the average of built area (which means their impervious surfaces are not that predominant), but because they have the lowest elevation, they occupy the second place on flood exposure. Opposed to this relation, despite having the highest elevation, Asian cities also have the second highest average of precipitation and highest percentage of built area, in consequence, they are the cities most exposed to floods.

Lastly, two other useful insights result from the data visualization. As expected, on the social dimension, it is possible to see that Asia, Africa and Latin America and the Caribbean still have the higher percentage of its cities as underdeveloped or in development, while European, Northern American and Oceanic cities being majorly developed. On the physical dimension, analyzing the ratio of land consumption and population growth it is clear that Asian and African cities are demanding much larger urban area than the extent to which the number of inhabitants is growing, or in other words, their growth process is not being efficient and they are likely to experience higher urban sprawl rates. Unlike this situation, most of European cities have negative rate of land use efficiency, which can mean that even though they experience a population growth, urban areas are becoming denser.

Normalization

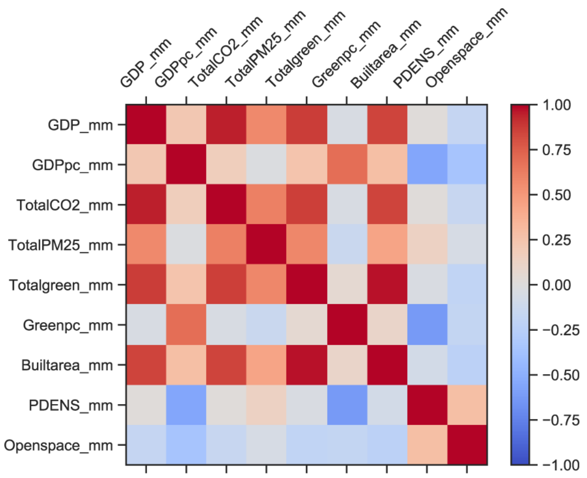
To be possible to compare all the indicators, they have to be normalized or, in other words, transformed to an equal interval. With this step, it is ensured that the parameters have the same continuous range and can be analyzed to understand their relative importance over certain hypothesis. There are different methods documented to perform such mathematical operation. For the purpose of this research, in order to have continuous values and not divide them into categories or compare to the country or continent average, the *Z-Scores* and the *Min-Max* were chosen to be tested. The first transforms the distribution to be centred in zero and vary between (multiple number of) standard deviation by considering this value and the average, whereas the second converts the distribution in the interval from 0 to 1 by considering the minimum and maximum values. After normalizing all the values and creating the box plots of their distribution, it was possible to visualize that all the indicators had similar dispersions within the two methods and very few divergences among them were observed. Additionally, a Pearson's correlation test was also done to verify if it would return different results, but that was not the case, practically all the values had the same coefficients and the minority diverged at the second decimal point or less. Therefore, given that *Min-Max* transforms the indicators at a common scale between 0 and 1, it was the method chosen as the normalization method on this study. Annex 3 summarizes some possibilities of normalization methods. Some of the graphs and tables that are going to be presented from now on will have, besides the name of the (aggregated) indicators, a nomenclature "_mm" to represent that the values being used went through the process of normalization using the *Min-Max* method.

Correlation analysis and Cronbach's Alpha Test

For the dependent variables, meaning the ones who are going to be weighted and aggregated in the next step to compose the index of the level of resilience in urban areas, the Pearson's correlation test was calculated. This method determines the extent to which two variables have a linear relationship and, therefore, it is important to visualize if the data can be simplified by a first-degree equation – in this case, the slope of the equation will be given by the weights attributed to each indicator. To facilitate the visualization, Graphs 9 and 10 show a 'heat map' of coefficients, where the values range from 1.0 (dark red) to -1.0 (dark blue) and are classified in continuous values on that color-scale. Considering that values higher than 0.5 or lower than -0.5 symbolize a strong correlation, between 0.3 and 0.5 or -0.5 and -0.3 a medium correlation, between -0.3 and -0.1 or 0.1 and 0.3 a low correlation, and from -0.1 to 0.1 absence of it, the correlation coefficient values are presented on Tables 9 and 10, using the same pallet of colors.

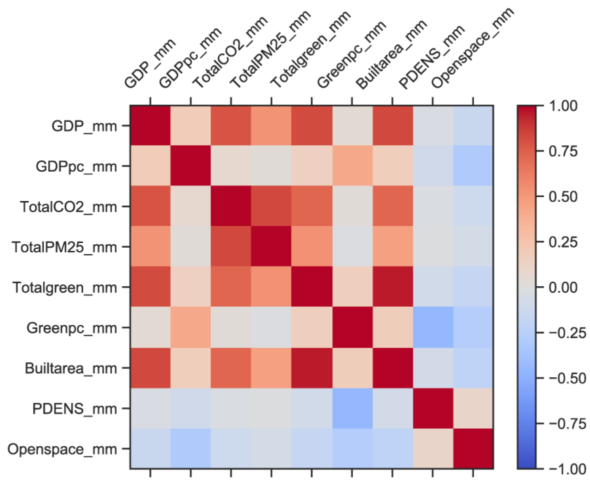
Looking at the heat maps, it is very clear that in both cases the correlation between the indicators is very similar, only slightly stronger for the partial dataset. Nonetheless, each one of the parameters have a coefficient bigger than 0.3 or smaller than -0.3 (medium correlation) with at least one of the others, what indicates that in fact there is a linear relationship among them and, therefore, gives validity for their aggregation into a composite index. It is worth highlighting, however, that while comparing the tables of correlation coefficients the most evident different is the relation between GDP per capita and population density, which increased approximately 0.45, going from a low to a high correlation. Three other indicators changed their category of correlation, but in a lower proportion: total CO_2 emissions and GDP per capita changed from none to low; GDP per capita and Green per capita change from medium to high; and Green per capita and population density changed from medium to high. For all the rest, level of correlation stayed in the same category.

Graph 9 – Correlation of the dependent variables (partial dataset).



Source: author (2019).

Graph 10 – Correlation of the dependent variables (full dataset).



Source: author (2019).

Table 9 – Correlation values of the dependent variables (partial dataset).

	GDP_mm	GDPpc_mm	TotalCO2_mm	TotalPM25_mm	Totalgreen_mm	Greenpc_mm	Builtarea_mm	PDENS_mm	Openspace_mm
GDP_mm	1								
GDPpc_mm	0,2233	1							
TotalCO2_mm	0,9517	0,1704	1						
TotalPM25_mm	0,5735	-0,0226	0,6107	1					
Totalgreen_mm	0,8736	0,2457	0,8663	0,5807	1				
Greenpc_mm	-0,0440	0,6952	-0,0412	-0,1366	0,0605	1			
Builtarea_mm	0,8475	0,2879	0,8449	0,4429	0,9727	0,1045	1		
PDENS_mm	0,0226	-0,5523	0,0219	0,1381	-0,0368	-0,6191	-0,0753	1	
Openspace_mm	-0,1702	-0,3447	-0,1519	-0,0479	-0,1888	-0,1795	-0,2261	0,2872	1

Source: author (2019).

Table 10 – Correlation values of the dependent variables (full dataset).

	GDP_mm	GDPpc_mm	TotalCO2_mm	TotalPM25_mm	Totalgreen_mm	Greenpc_mm	Builtarea_mm	PDENS_mm	Openspace_mm
GDP_mm	1								
GDPpc_mm	0,1827	1							
TotalCO2_mm	0,7935	0,0771	1						
TotalPM25_mm	0,5305	0,0236	0,8330	1					
Totalgreen_mm	0,8245	0,1467	0,7231	0,5339	1				
Greenpc_mm	0,0521	0,4179	0,0259	-0,0162	0,1634	1			
Builtarea_mm	0,8327	0,1676	0,7214	0,4623	0,9582	0,1739	1		
PDENS_mm	-0,0356	-0,1003	-0,0299	-0,0130	-0,0887	-0,4475	-0,0756	1	
Openspace_mm	-0,1388	-0,2999	-0,1123	-0,0686	-0,1673	-0,2662	-0,2069	0,1083	1

Source: author (2019).

To evaluate the internal consistency of the data and ensure that the correlations observed among the indicators are reliable, a Cronbach's Alpha test was performed. On the calculations, given that there are nine variables being analyzed (n=9), it was considered a degree of freedom (n-1) equal to 8. Besides, theoretically strengthening even more this analysis, the null-hypothesis, or the assumption that there is no correlation between the variables, was tested. In this analysis, the output are the *T-Scores* values, and the farther the number is from zero, the more likely that the null-hypothesis is false – meaning that there is no correlation. The α coefficient and the *T-scores* are presented on Table 11. Regarding the Cronbach's Alpha, in both the partial and full dataset the result was above 0.90, which is an indicative of an excellent internal consistency of the data, and diverged only at the third decimal point. As for the *T-Scores*, no value is close to zero, indicating that the none of the values can be said for sure to fully deny the null-hypothesis. At the same time, because the larger the number the higher the probability of no correlation among the variables, and just a few of stood out among the results obtained. In fact, we can clearly see the closer the value from the GDP PPP, the higher the Pearson's correlation coefficient was. In validation of this assumption, and highlight the fact that this test is an indicative of the existence (or not) of a correlation among the variables, not only the green per capita, population density and open spaces indicators showed to have the lowest linear relationship with the other indicators, but also the *T-scores* observed was also much higher than the rest of the parameters.

Table 11 – Results from the T-test and Cronbach's Alpha test.

Indicator	Partial dataset	Full dataset
T-Scores		
GDP_mm	16.347168	37.025194
GPDpc_mm	317.615675	504.858645
TotalCO2_mm	15.418564	40.926033
TotalPM25_mm	13.584658	20.830734
Totalgreen_mm	38.375415	99.788253
Greenpc_mm	232.805286	1,418.154079
Builtarea_mm	27.513137	63.579739
PDENS_mm	110.651470	399.906559
Openspace_mm	587.585117	8,262.502771
Cronbach's alpha coefficient		
α	0.990244	0.999391

Source: author (2019).

4.4 Weighting and aggregation

Nardo et al. (2008) explain that no matter the type of weight chosen, it represents an assessment over the values of an indicator. Two of possible methods are equal weighting (EW) and principal component analysis (PCA). As the authors further detail, the first technique gives the same weight for every indicator and, in the second, the weight is based on the correlation coefficients from the principal components. For the purposes of this study, these methods were applied for both the partial dataset, with 1,091 cities, and full dataset, with 13,135 cities. To illustrate, the aggregated indicator per dimension and final index for each case were calculated as:

(i) Equal weighting method

$$AGREG\_EC\_ew = (GDP + GDPpc)/2$$

$$AGREG\_EN\_ew = (-CO2 - PM2.5 + TotalGreen + Greenpc)/4$$

$$AGREG\_P\_ew = (- Builtarea + PDENS + Openspace)/3$$

$$TOTAL\_ew = AGREG\_EC + AGREG\_EN + AGREG\_P$$

(ii) Principal component analysis

$$AGREG\_EC\_ew = |w_{d,i}| * GDP + |w_{d,i}|*GDPpc$$

$$AGREG\_EN = - |w_{d,i}|*CO2 - |w_{d,i}|*PM2.5 + |w_{d,i}|*TotalGreen + |w_{d,i}|*Greenpc$$

$$AGREG\_P = -|w_{d,i}|*Builtarea + |w_{d,i}|*PDENS + |w_{d,i}|*Openspace$$

$$TOTAL\_pca = AGREG\_EC + AGREG\_EN + AGREG\_P$$

Observation: ***AGREG_EC*** *– aggregated indicator of economic dimension;* ***AGREG_EN*** *– aggregated indicator of environmental dimension;* ***AGREG_P*** *– aggregated indicator of physical dimension;* ***TOTAL*** *– composite index score, result from the sum of all aggregated indicators;* ***"_ew"*** *– value based on the use of the equal weighting method;* ***"_ pca"*** *– value based on the use of the principal component analysis method;* $\mathbf{w_{d,I}}$ *– weight of the indicator 'i' of the dimension 'd'.*

The equations show that indicators related to CO_2 and PM2.5 emission, besides the percentage of built area, received a negative signal, while the others got a positive. With this difference, it was intended to underscore a city that had higher measurements on indicators that cause a negative impact to sustainable development. Specifically, both the CO_2 and PM2.5 emissions cause air pollution and subsequent health problems, while built areas decrease the percentage of green areas and infiltration of rain, therefore increasing the likelihood of flooding, just to mention an example. However, in order to determine the weights ($w_{d,i}$), it was necessary to run the principal component analysis, a method of dimensionality reduction that simplifies the number of variables explaining the original data and identifies the main components for that. Annex 4 shows the graphs of the cumulative explained variance (Annex 4.1 and 4.2) of each principal component – that is the percentage of the data each of them represent, and the number of components, which range from 0 to 8 (numbers that express the nine indicators being considered to build this composite index) – as well as the tables with the coefficients of each component that were extracted from the principal component analysis (Annex 4.3 and 4.4).

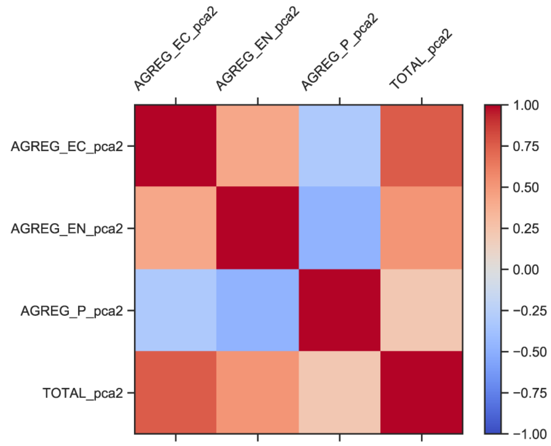
In the partial and full dataset, the total variance per component is quite similar, with the biggest difference (6.65%) being for component 1, albeit the others are below 3%. Furthermore, since using the first five components (from 0 to 4) it is already possible the reach a representation of over 90% of the data, that was the number of components chosen to the calculation of the weights. Adding their coefficients, it was possible to determine the weights of all indicators. On both cases, the majority of indicators that had previously received low correlations this time got the highest coefficients. In fact, as discussed by Nardo et al. (2008), attributing higher weights to parameters with lower correlations intends to address the compensability between the weighting and aggregation of indicators and, therefore, the result can be considered adequate for this process. With all the weights determined, it was possible to calculate the total scores of the two methods for the partial and full dataset, as well as comparing the results. Annex 4 also presents the heat maps of correlation coefficients, as well as the box plots with the final range of scores per continent obtained for the EW (Annex 4.5 to 4.8) and PCA (Annex 4.9 to 4.12) methods.

Overall, in the EW method the correlation between the aggregated indicators showed to be stronger for the partial dataset in comparison to the full. It is also interesting to notice that while on the partial database the strength of linear relationship between the total scores and the physical dimensions was the weakest, for the full dataset it was actually the opposite. If this were the principal component analysis, where the physical dimension indicators received higher weights, it was going to be possible to say that this happened as an effect of the pondering. Nevertheless, what can be said is that this variation might have occurred because of the imputation process, where some of the environmental and physical indicators (specifically emissions of CO_2 and PM2.5 and percentage of open spaces) had from 30% to more than 80% of missing information, whilst the others 2% or less (see Annex 2). This assumption is reaffirmed by the final scores of the indicators. Cities from Europe, Latin America and the Caribbean, Northern America and Oceania suffered the highest variations on the range of the index, and they were also the ones with less missing data – in other words, it is likely that the imputation process over dimensioned the scores of African and Asian cites.

Regarding the PCA method, its heat maps clearly shows that the process improved the correlation coefficients in both cases, validating the use of this technical procedure for building a composite index. As it was hypothesized previously, in this case, because all the environmental indicators received a higher weight and the physical lower ones, the correlation matrixes of the partial and full dataset turned out to be opposite to each other or, in other words, indicators that got higher coefficients in one dataset, in the other got lower ones. In addition, equivalent to what happened on the equal weighting method, Asian and African cities were favoured, and the other continents prejudiced. Consequently, we can indeed see that the existence of large percentages of missing data negatively influenced the result of the final index and note that this is a point of improvement for the data collection.

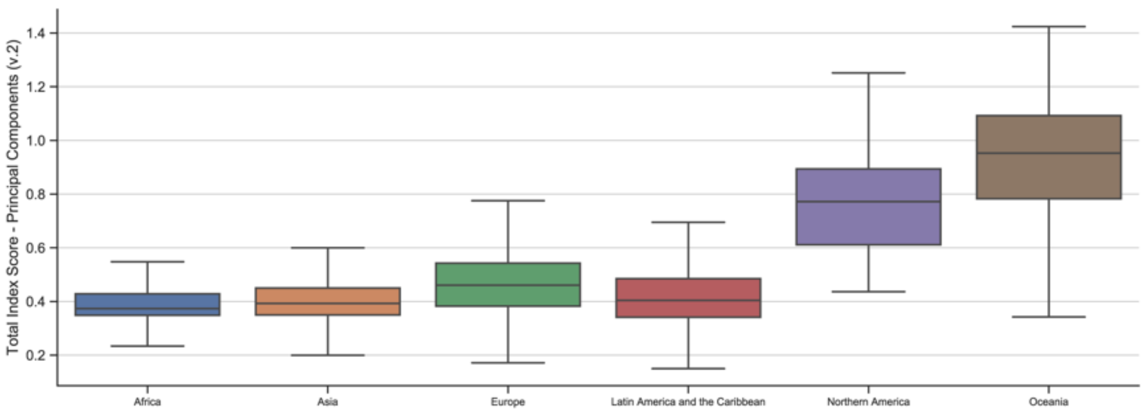
On both the EW and PCA methods analyzed, the latter proved to be overall more consistent and accurate to be applied on the calculation of the composite index. Although indicators with a negative impact to resilience building – namely, emissions of CO_2, emissions of PM25 and percentage of build area – were penalized with the negative signal during the calculations, attributing the weight for them and the other parameters made the result vary a lot between the methods. In fact, the results likewise diverged considerably between the partial and full datasets, whatever the method considered, which is most likely to have happened because of the data imputation. Since the weights used on the PCA applied to the partial dataset showed the best result out of the four models tested, it was decided to calculate the range of scores for the full dataset using those weights, in order to see if there was going to be any improvement. Graphs 11 and 12 show, respectively, the correlation heat map matrix and the index scores obtained for this case. Despite the result of Northern American cities seeming to be negatively influenced and urban areas in Oceania positively influenced, those cities had the least missing information, so this happened most likely happened strictly because of the weights themselves. Nonetheless, the model overall indicated better correlation coefficients and improved the difference between the other continents, indicating a better adequacy to the dataset in question. To use the largest sample of urban area available (full dataset), while still ensure a representative result, this was the model the best model elaborated so far – and the one that will be put to test on the uncertainty and sensitivity analysis.

Graph 11 – Correlation of aggregated indicators in the weights of the partial dataset on the full dataset.



Source: author (2019).

Graph 12 – Range of scores using the weight from the partial dataset on the full dataset.



Source: author (2019).

4.5 Uncertainty and sensitivity analysis

4.5.1 Hypothesis testing

The uncertainty and sensitivity analysis is important to verify if the model being proposed would be affected by any changes on the indicators chosen, as well as the inclusion of other indicators that might influence the phenomena. For this research, making hypothesis over the model involved testing three different scenarios: including income level as an indicator to test if even being a non-continuous value, because of the transformation from ordinal to categorical, it has an impact on the result; considering the built area as a positive contribution to the physical performance, or giving a positive signal on the equation, since it might be associated with infrastructure improvements that tackle the occurrence of floods; and, finally, excluding the population density indicator, because it was the one with the lower or none correlation with the other parameters (see Graph 10). It is important to remember that on Section 4.2 it was brought to attention that the indicators of CO_2 and PM2.5 emission were available only for the year of 2012 and not for 2015 as the rest of the indicators used. However, since both of them proved to be highly correlated with the other parameters and did not indicate to be prejudicing the results, they were kept on the analysis.

For the Income level hypothesis, a Pearson's correlation test showed that this indicator has a strong relationship with both the GDP per capita and Green area per capita, a medium with population density and open spaces, a small correlation with GDP PPP, total green coverage and built area, besides no correlation with CO_2 and PM2.5 emissions. The *T-scores* for the income level pointed a high value, in the same order as the open spaces (see Table 11), and the α coefficient varied positively at the fourth decimal point. So far, the results could be an indicative that it was valid to include this indicator, however, getting to the PCA it is possible to notice that this is not the case. Even though the first five components would explain around 90% of the data, as the previous analysis, not only the weight attributed to the income level would be in the order of 10^{-2}, which would almost not alter the composite index, but also it would give a similar weigh for population density and the highest weight to open spaces, which should not occur given that it has medium correlation with both of these indicators. Therefore, including the income level as an indicator was considered not to be adequate for calculating the composite index.

Now, considering a positive signal for the built area while calculating the aggregated indicator, a small variation was observed on the correlation coefficients. The physical dimension suffered a decrease of around 0.03 on the degree to which it is linear related to the economic and environmental dimensions, the composite index had its correlation with the economic and physical aggregated indicators increased by close to 0.01 and, with the environmental, by 0.03. Given that none of the changes were very significant, the box plot of the final scores was made to see how the results changed and try to confirm the validation or exclusion of this hypothesis. The variation was still barely noticeable, but since it provided a better correlation for the composite index, regardless if only at the second decimal point, it was considered to be more suitable for the model.

For the last case, the indicator of population density was excluded. Since this would not affect the correlation coefficient with other indicators, and only exclude its line from the heat map, the Cronbach's alpha test was directly calculated. Despite having a slight improvement (increase of 1×10^{-4} in comparison to before), the principal component analysis revealed that, this time, using the first four components (from 0 to 3) would be enough to represent approximately 90% of the data – which can also show that excluding this indicator contributed to reducing the dimensionality and, therefore, might be an indicative that it is not significant. The sum of the coefficients of those four components per indicator was inversely proportional to their linear relationship, theoretically validating the calculation, as it happened before. However, comparing the relationship between the aggregated indicators and the final scores, it was possible to see that the economic dimension decreased its importance by 0.3 (changing from a high correlation of approximately 0.77 to a medium of 0.47) and the environmental by 0.03 (although remaining as a high correlation), while the physical dimension increased by almost 0.38 (changing from a low to a high correlation). With the box plot it was possible to understand that in this scenario Northern American cities were prioritized, and ended up outperforming cities from Oceania (for the former, the score range interval went from close to 0.8 to over 1.2, and, for the latter, from over 1.0 to close to 0.6). Going back to the descriptive statistics (see Table 8), it is evident that this happened because Northern American cities are the ones with the lowest population density and, since this indicator received a high weight during the aggregation process, it was negatively affecting those urban areas. Therefore, to not promote this effect on the model, no alterations were made and this scenario was considered not valid.

4.5.2 Model validation

Until now, the analysis has been built on the assumption that the model, meaning the operationalization framework and the aggregation of indicators to calculate the composite index, was adequate. However, as described on the methodology (Table 4, Section 3.3), one of the goals of this study is also to understand whether this model is valid. This step involves the same supervised techniques that were applied before to analyze all the indicators *a priori* related to the factors and level of urban resilience. Table 12 shows the Pearson's correlation coefficients and Table 13 the *T-scores* and *α coefficient* obtained. It is important to highlight that the Income and Development level had a significant correlation with the indicators, however, because they are both non-continuous values and could be causing an unwanted influence on the model, they were not considered to build the composite index. Focusing on the coefficients that had a medium or high linear relationship among each other, it is possible to see that the model proposed so far was fairly accurate, but could still be improved. With more details: the indicators of elevation, precipitation, temperature and land use efficiency had only one or no relevant relation and, therefore, were correctly predicted and independent variables; population density, in the other hand, were initially said to represent the dependent variables, but are actually better suited as a factor that might influence resilience, given that only one coefficient was relevant; and, lastly, the urban size (area) and flood area proved themselves to be related to several indicators, hence, should compose the level of resilience. Additionally, the *α coefficient* kept the same value as calculated before, which means that still indicates an excellent internal consistency of the data, and the *T-scores* for the added parameters maintained the proportionality to the degree of correlation (higher values for lower linear relationships).

Table 12 - Correlation coefficients without division of indicators.

	GDP_mm	GDPpc_mm	TotalCO2_mm	TotalPM25_mm	Greenpc_mm	Totalgreen_mm	Elevation_mm	Precipitation_mm	Temperature_mm	Landuseef_mm	Builtarea_mm	PDENS_mm	Openspace_mm	AREA_mm	Floodarea_mm
GDP_mm	1														
GDPpc_mm	0,1827	1													
TotalCO2_mm	0,7935	0,0771	1												
TotalPM25_mm	0,5305	0,0236	0,8330	1											
Greenpc_mm	0,0521	0,4179	0,0259	-0,0162	1										
Totalgreen_mm	0,8245	0,1467	0,7231	0,5339	0,1634	1									
Elevation_mm	-0,0381	-0,1108	-0,0496	-0,0309	-0,2454	-0,0683	1								
Precipitation_mm	-0,0004	0,0181	-0,0013	0,0204	0,0308	0,0135	-0,1032	1							
Temperature_mm	-0,0548	-0,2425	-0,0512	-0,0006	-0,3990	-0,0823	-0,2106	0,2884	1						
Landuseef_mm	-0,0003	-0,0048	0,0014	0,0013	0,0086	0,0010	0,0029	0,0017	0,0023	1					
Builtarea_mm	0,8327	0,1676	0,7214	0,4623	0,1739	0,9582	-0,0558	-0,0168	-0,1110	0,0004	1				
PDENS_mm	-0,0356	-0,1003	-0,0299	-0,0130	-0,4475	-0,0887	0,2357	-0,0282	0,1945	0,0029	-0,0756	1			
Openspace_mm	-0,1388	-0,2999	-0,1123	-0,0686	-0,2662	-0,1673	0,0616	0,1996	0,3755	-0,0006	-0,2069	0,1083	1		
AREA_mm	0,8243	0,1465	0,7229	0,5344	0,1631	1,0000	-0,0682	0,0138	-0,0817	0,0010	0,9578	-0,0887	-0,1671	1	
Floodarea_mm	0,4571	0,0431	0,6164	0,6684	0,0615	0,6099	-0,0766	0,0185	-0,0221	0,0006	0,4811	-0,0487	-0,0581	0,6104	1

Source: author (2019).

Table 13 – Result from T-test and Cronbach's Alpha test without division of indicators.

Indicator	Full dataset
T-scores	
GDP_mm	37.025194
GPDpc_mm	504.858645
TotalCO2_mm	40.926033
TotalPM25_mm	20.830734
Greenpc_mm	1,418.154079
Totalgreen_mm	99.788253
Builtarea_mm	63.579739
Openspace_mm	8,2862.502772
AREA_mm	97.725570
Floodarea_mm	37.352857
Cronbach's Alpha	
α	0.999391

Source: author (2019).

With the review of initial forecasts about the indicators, the following step was to determine the weights of the aggregated indicators per dimension to be able to calculate the new composite index. Applying the PCA method, that gave the best result before, it was noticed that using the first 5 (from 0 to 4) components over 90% of the data can be represented, thus, its coefficients were added to determine magnitude of each indicators. As Table 17 shows, in general, the parameters with the lower correlation also got higher weights, what was already mentioned to be theoretically adequate. By adding two indicators (urban size and flood area) and excluding one (population density) the new equations for the aggregated indicators per dimensions and the total score are:

$$\boldsymbol{AGREG\_EC\_pca\_nd} = |w_{d,i}| * GDP + |w_{d,i}| * GDPpc$$

$$\boldsymbol{AGREG\_EN\_pca\_nd} = -|w_{d,i}| * CO2 - |w_{d,i}| * PM2.5 + |w_{d,i}| * TotalGreen + |w_{d,i}| * Greenpc$$

$$\boldsymbol{AGREG\_P\_pca\_nd} = |w_{d,i}| * Builtarea + |w_{d,i}| * Openspace + |w_{d,i}| * AREA - |w_{d,i}| * Floodarea$$

$$\boldsymbol{TOTAL\_pca\_nd} = AGREG\_EC\_pca\_nd + AGREG\_EN\_pca\_nd + AGREG\_P\_pca\_nd$$

Observation: ***AGREG_EC****: aggregated indicator of economic dimension;* ***AGREG_EN****: aggregated indicator of environmental dimension;* ***AGREG_P****: aggregated indicator of physical dimension;* ***TOTAL*** *– composite index score, result from the sum of all aggregated indicators;* ***"_pca_nd"*** *– value based on the use of the principal component analysis method**,** with no initial division of the indicators;* $\boldsymbol{w_{d,I}}$ *– weight of the indicator 'i' of the dimension 'd'.*

Table 14 - Coefficients for each indicator per principal component after the model validation (full dataset).

	GDP_mm	GDPpc_mm	TotalCO2_mm	TotalPM25_mm	Greenpc_mm	Totalgreen_mm	Builtarea_mm	Openspace_mm	AREA_mm	Floodarea_mm
0	0,017646	0,114246	0,009723	0,004795	0,168113	0,031370	0,032124	-0,977343	0,031291	0,007859
1	0,019072	0,327612	0,006421	-0,000689	0,917583	0,058379	0,048674	0,202018	0,058218	0,018105
2	0,325488	0,268415	0,202703	0,127564	-0,205163	0,500101	0,411811	0,051994	0,499409	0,225291
3	-0,065192	0,897648	-0,066307	-0,045824	-0,293807	-0,182462	-0,143817	0,035161	-0,182228	-0,093493
4	-0,127438	0,020058	0,219252	0,371697	0,009680	-0,115614	-0,301904	-0,004951	-0,114287	0,824278
5	0,621678	-0,028137	0,523360	0,347439	0,034077	-0,258920	-0,036318	0,000605	-0,259461	-0,285073
6	-0,662515	0,023857	0,328516	0,537048	-0,009667	0,069878	0,192167	0,003121	0,070232	-0,342511
7	0,139463	-0,002274	-0,272784	0,358955	0,003539	0,313368	-0,719413	-0,003383	0,320165	-0,242904
8	-0,167430	0,005616	0,670867	-0,552679	-0,001842	0,165347	-0,399210	-0,001760	0,163118	-0,055643
9	-0,000238	0,000011	0,002392	-0,002877	0,000049	-0,708086	0,003282	0,000005	0,706108	0,000411
0 to 4	0,169577	1,627979	0,371792	0,457542	0,596406	0,291775	0,046887	-0,693122	0,292404	0,982041

Source: author (2019).

Table 15 shows the results from the new version of the model that was calculated. Comparing the model presented on the previous section, which was seen as the best result from the hypothesis testing, with this new characterization of the aggregated indicators it was possible to identify a decrease of importance of 0.22 between the economic dimension and the total score (but maintaining the high correlation), the decrease of 0.12 for the environmental dimension (going from high to a medium correlation), and, surprisingly, an increase of 0.33 for the physical (going from a low to a strong relationship). Consequently, even though the linear relationship among of the economic and environmental aggregated indicators was lower than the previous model, this could also have happened because the physical indicator was not adequately aggregated. However, since overall the coefficients were still significant and the correlation among the individual indicators was better than before, this was considered to be the best model to effectively determine the total score of the composite index and calculate the ranking of cities.

Table 15 - Correlation coefficients values for the aggregated indicators on the final version of the model.

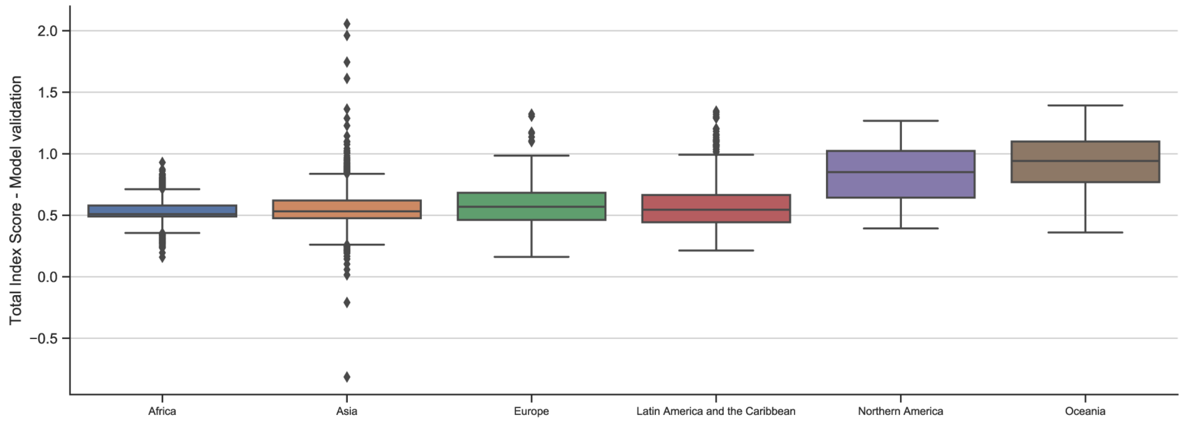
	AGREG_EC_pca_nd	AGREG_EN_pca_nd	AGREG_P_pca_nd	TOTAL_pca_nd
AGREG_EC_pca_nd	1			
AGREG_EN_pca_nd	0,4154	1		
AGREG_P_pca_nd	-0,2970	-0,2542	1	
TOTAL_pca_nd	0,5503	0,4215	0,5683	1

Source: author (2019).

4.6 Back to the data

Given the thorough process of testing different hypothesis, checking correlation coefficients, comparing relative scores and validating the model, it can be argued that the resulting composite index is the one that best represents the dataset analyzed and is a valid and reliable way of evaluating the sample of cities. Therefore, with the sensitivity and uncertainty analysis concluded, now it is possible to follow to steps 8 and 9, where the ranking of urban areas and main factors influencing their scores will be determined. In that sense, to compare the performance of cities and what (aggregated) indicators influenced the most on the index, Graph 13 shows the boxplot of the range of score obtained on the final version of the model. Two important comments are worth emphasizing. First, as mentioned on Section 4.2, the outliers were not shown on the previous graphs elaborated to facilitate the visualization, however, since now the interest is to indeed rank cities, they were included. Consequently, now it is possible to see that urban areas from Asia, Europe and Latin America and the Caribbean also appeared among the best scorers. Second, while the range of results obtained (see Graph 22) had a more expressive variation among the continents, especially comparing Northern America and Oceania with the others, on this final version pattern was not observed. In fact, this latest model showed to be more accurate, not only because of the correlation among the indicators, but also because the standard deviation – and interval between *(Q1 - 1.5*IQR)* and (*Q3 + 1,5*IQR)* represented on the boxplot – proved to be smaller and, more than that, there was a smaller presence of outliers. Table 16 and 17 present, respectively, the detailed scores for the top and bottom 100 urban areas.

Graph 13 - Scores of the final version of the composite index.



Source: author (2019).

Table 16 – Scores for the top 100 cities.

# rank	Cities[Country]	Continent	AGREG_EC_pca_nd	AGREG_EN_pca_nd	AGREG_P_pca_nd	TOTAL_pca_nd
1	Al-Hawr [QAT]	Asia	1,6298	0,0804	0,3452	2,0554
2	Abu Zaby (Abu Dhabi) [ARE]	Asia	1,1719	0,0865	0,7031	1,9615
3	Muhayil [SAU]	Asia	1,2596	0,0397	0,4461	1,7453
4	Al-Ain [ARE]; Al-Buraymi [OMN]	Asia	0,8080	0,1005	0,7039	1,6124
5	Mandurah [AUS]	Oceania	0,7468	0,3897	0,2568	1,3933
6	Ban Chang [THA]	Asia	0,8768	0,1469	0,3397	1,3634
7	Libertador General San Martin [ARG]	Latin America and the Caribbean	0,5954	0,0577	0,6935	1,3466
8	Villa Carlos Paz [ARG]	Latin America and the Caribbean	0,5216	0,1302	0,6942	1,3460
9	Eldorado [ARG]	Latin America and the Caribbean	0,5465	0,1106	0,6768	1,3340
10	Cairns [AUS]	Oceania	0,8717	0,2087	0,2462	1,3266
11	Jugorsk [RUS]	Europe	1,1170	0,0960	0,1094	1,3224
12	Sao Borja [BRA]	Latin America and the Caribbean	0,5914	0,1068	0,6199	1,3181
13	Norilsk [RUS]	Europe	0,6155	0,1078	0,5814	1,3047
14	San Francisco [ARG]	Latin America and the Caribbean	0,5121	0,0951	0,6939	1,3011
15	Tartagal [ARG]	Latin America and the Caribbean	0,5371	0,0700	0,6936	1,3008
16	Concepcion [ARG]	Latin America and the Caribbean	0,5248	0,0730	0,6937	1,2916
17	Redcliffe [AUS]	Oceania	0,8392	0,2180	0,2329	1,2901
18	San Pedro [ARG]	Latin America and the Caribbean	0,5454	0,0528	0,6910	1,2892
19	Macao [CHN]	Asia	0,6906	0,0521	0,5453	1,2881
20	Honiara [SLB]	Oceania	0,6337	0,1010	0,5451	1,2797
21	Hagerstown [USA]	Northern America	0,2818	0,3455	0,6409	1,2682
22	New York-Newark [USA]	Northern America	0,4483	0,2035	0,6114	1,2632
23	Palmerston North [NZL]	Oceania	0,9062	0,1601	0,1964	1,2627
24	Logan [AUS]	Oceania	0,8188	0,1831	0,2588	1,2607
25	Dunedin [NZL]	Oceania	0,6600	0,1775	0,4159	1,2534
26	Wynnum [AUS]	Oceania	0,8761	0,1705	0,1829	1,2295
27	Ras Laffan [QAT]	Asia	0,6964	0,1133	0,4187	1,2284
28	Macarthur [AUS]	Oceania	0,8726	0,2084	0,1382	1,2193
29	Leominster [USA]	Northern America	0,2955	0,2700	0,6504	1,2159
30	Villazon [BOL]; La Quiaca [ARG]	Latin America and the Caribbean	0,4571	0,0546	0,6936	1,2053
31	Fayetteville [USA]	Northern America	0,2630	0,3597	0,5800	1,2026
32	Neuquen-Plottier-Cipolletti [ARG]	Latin America and the Caribbean	0,4467	0,0634	0,6901	1,2002
33	Springfield [USA]	Northern America	0,2591	0,3354	0,6056	1,2001
34	Youngstown [USA]	Northern America	0,2172	0,3791	0,6009	1,1973
35	Panama [USA]	Northern America	0,2998	0,6009	0,2917	1,1924
36	Sunshine Coast [AUS]	Oceania	0,6792	0,2586	0,2507	1,1884
37	Bartlett [USA]	Northern America	0,2348	0,2979	0,6514	1,1840
38	Itaugua [PRY]	Latin America and the Caribbean	0,4241	0,0730	0,6843	1,1815
39	Longview [USA]	Northern America	0,2270	0,3807	0,5707	1,1784
40	Ilm [RUS]	Europe	0,5173	0,1361	0,5221	1,1755
41	Roanoke [USA]	Northern America	0,3069	0,3282	0,5386	1,1737
42	Belleville [USA]	Northern America	0,2741	0,2867	0,6111	1,1719
43	Saint Helier [JEY]	Europe	0,6861	0,1468	0,3339	1,1667
44	Elkhart [USA]	Northern America	0,2359	0,4877	0,4428	1,1664
45	Bumbu [PNG]	Oceania	0,8907	0,0130	0,2595	1,1632
46	Chicago [USA]	Northern America	0,3199	0,2853	0,5567	1,1618
47	General Roca [ARG]	Latin America and the Caribbean	0,3870	0,0793	0,6926	1,1589
48	Watabung [PNG]	Oceania	0,8900	0,0061	0,2594	1,1555
49	Brickship [USA]	Northern America	0,3517	0,3448	0,4570	1,1536
50	Ialibu [PNG]	Oceania	0,8826	0,0111	0,2595	1,1531
51	Villa Maria [ARG]	Latin America and the Caribbean	0,3613	0,0981	0,6915	1,1509
52	Kansas City [USA]	Northern America	0,2594	0,3325	0,5565	1,1484
53	Kinjibi [PNG]	Oceania	0,8837	0,0051	0,2594	1,1482
54	San Martin [ARG]	Latin America and the Caribbean	0,3829	0,0714	0,6936	1,1479
55	Port Arthur [USA]	Northern America	0,2489	0,5008	0,3961	1,1458
56	Canton [USA]	Northern America	0,2343	0,3466	0,5643	1,1452
57	Chesterfield [USA]	Northern America	0,2383	0,2878	0,6186	1,1448
58	Rayong [THA]	Asia	0,6081	0,1625	0,3736	1,1442
59	West Chester [USA]	Northern America	0,2660	0,2610	0,6162	1,1433
60	Parsippany-Tro [USA]	Northern America	0,2936	0,2323	0,6152	1,1410
61	Tauranga [NZL]	Oceania	0,5520	0,2734	0,3151	1,1404
62	Columbia [USA]	Northern America	0,3670	0,2332	0,5381	1,1383
63	Cary [USA]	Northern America	0,2177	0,2340	0,6859	1,1376
64	Frederick [USA]	Northern America	0,3148	0,2544	0,5675	1,1368
65	Palm Bay-Melbourne [USA]	Northern America	0,3177	0,5134	0,3055	1,1367
66	Winston-Salem [USA]	Northern America	0,2367	0,2999	0,5998	1,1364
67	Nizhenvartovsk [RUS]	Europe	0,7975	0,1211	0,2175	1,1362
68	Round Lake Beach-McHenry-Grayslake [USA]	Northern America	0,2750	0,3195	0,5379	1,1323
69	Artigas [URY]; Quarai [BRA]	Latin America and the Caribbean	0,5165	0,1113	0,5045	1,1323
70	St. Charles [USA]	Northern America	0,2667	0,3037	0,5617	1,1320
71	Columbus [USA]	Northern America	0,2407	0,3520	0,5323	1,1249
72	Lae [PNG]	Oceania	0,5154	0,0585	0,5485	1,1224
73	Indianapolis [USA]	Northern America	0,2331	0,3532	0,5357	1,1220
74	Apanaipi [PNG]	Oceania	0,8506	0,0113	0,2595	1,1214
75	Presidencia Roque Saenz Pena [ARG]	Latin America and the Caribbean	0,3357	0,0914	0,6913	1,1184
76	Ballarat [AUS]	Oceania	0,6952	0,2557	0,1671	1,1179
77	Birmingham [USA]	Northern America	0,2498	0,3747	0,4926	1,1171
78	Allentown-Bethlehem [USA]	Northern America	0,2537	0,2889	0,5716	1,1142
79	Palm Coast [USA]	Northern America	0,2720	0,3860	0,4541	1,1121
80	Rockford [USA]	Northern America	0,2661	0,2984	0,5475	1,1120
81	Cachoeira Do Sul [BRA]	Latin America and the Caribbean	0,4746	0,1132	0,5233	1,1110
82	Poko [PNG]	Oceania	0,8383	0,0104	0,2595	1,1083
83	Villa Mercedes [ARG]	Latin America and the Caribbean	0,3368	0,0768	0,6941	1,1077
84	Dayton [USA]	Northern America	0,2429	0,3203	0,5433	1,1065
85	Wareho [PNG]	Oceania	0,8180	0,0286	0,2596	1,1062
86	Tyumen [RUS]	Europe	0,7859	0,1063	0,2132	1,1054
87	Newport News [USA]	Northern America	0,3193	0,3078	0,4783	1,1053
88	Villarrica [PRY]	Latin America and the Caribbean	0,4894	0,0627	0,5528	1,1050
89	Pensacola [USA]	Northern America	0,3146	0,5066	0,2829	1,1041
90	Noumea [NCL]	Oceania	0,6609	0,1258	0,3167	1,1034
91	Carazinho [BRA]	Latin America and the Caribbean	0,5717	0,1188	0,4125	1,1030
92	Toms River [USA]	Northern America	0,3537	0,4208	0,3279	1,1025
93	Flint [USA]	Northern America	0,2079	0,3461	0,5482	1,1022
94	Olympia [USA]	Northern America	0,2385	0,2840	0,5796	1,1021
95	Itacoatiara [BRA]	Latin America and the Caribbean	0,5011	0,0756	0,5244	1,1011
96	Worcester [USA]	Northern America	0,3266	0,2018	0,5723	1,1007
97	N/A[SAU]	Asia	0,6062	0,0483	0,4457	1,1002
98	Rockingham [AUS]	Oceania	0,6998	0,2265	0,1738	1,1001
99	Ketarobo [PNG]	Oceania	0,8343	0,0049	0,2594	1,0986
100	Zug [CHE]	Europe	0,4072	0,1374	0,5535	1,0981

Source: author (2019).

Table 17 – Scores for the bottom 100 cities.

# rank	Cities[Country]	Continent	AGREG_EC_pca_nd	AGREG_EN_pca_nd	AGREG_P_pca_nd	TOTAL_pca_nd
13036	Braila [ROU]	Europe	0,0630	0,0736	0,1368	0,2733
13037	Novotroick [RUS]	Europe	0,0627	0,1259	0,0837	0,2723
13038	Samarkand [UZB]	Asia	0,0232	0,0933	0,1558	0,2723
13039	Cortazar [MEX]	Latin America and the Caribbean	0,0441	0,0505	0,1775	0,2722
13040	Zhengzhou [CHN]	Asia	0,0627	0,0266	0,1819	0,2712
13041	Lanzhou [CHN]	Asia	0,0680	0,0325	0,1703	0,2708
13042	Xingtai [CHN]	Asia	0,0567	0,0510	0,1630	0,2707
13043	Fazenda Rio Grande [BRA]	Latin America and the Caribbean	0,0078	0,0837	0,1791	0,2705
13044	Kumasi [GHA]	Africa	0,0246	0,0548	0,1905	0,2699
13045	Nzerekore [GIN]	Africa	0,0065	0,0518	0,2116	0,2699
13046	Kaiyuan [CHN]	Asia	0,0394	0,0520	0,1783	0,2697
13047	Volos [GRC]	Europe	0,0853	0,0799	0,1045	0,2697
13048	Asti [ITA]	Europe	0,0835	0,0614	0,1243	0,2692
13049	Aligudarz [IRN]	Asia	0,0384	0,0285	0,2021	0,2690
13050	Rosario [ARG]	Latin America and the Caribbean	0,0281	0,0821	0,1572	0,2674
13051	Oujda [MAR]	Africa	0,0284	0,0439	0,1950	0,2674
13052	Buenos Aires [ARG]	Latin America and the Caribbean	0,0028	0,0886	0,1746	0,2661
13053	Touba [SEN]	Africa	0,0147	0,0398	0,2115	0,2660
13054	Sao Leopoldo [BRA]	Latin America and the Caribbean	0,0897	0,0604	0,1149	0,2650
13055	Suihua [CHN]	Asia	0,0476	0,0526	0,1636	0,2638
13056	Cerkessk [RUS]	Europe	0,0293	0,0846	0,1497	0,2637
13057	Bangui [CAF]; Zongo [COD]	Africa	0,0031	0,0356	0,2241	0,2629
13058	Yuncheng [CHN]	Asia	0,0433	0,0792	0,1391	0,2616
13059	Shenyang [CHN]	Asia	0,1001	0,0242	0,1365	0,2609
13060	Jalal-Abad [KGZ]	Asia	0,0077	0,0982	0,1549	0,2608
13061	Cancun [MEX]	Latin America and the Caribbean	0,1239	0,0423	0,0941	0,2603
13062	Lecce [ITA]	Europe	0,0534	0,0747	0,1316	0,2597
13063	Cerignola [ITA]	Europe	0,0263	0,0511	0,1819	0,2592
13064	Celaya [MEX]	Latin America and the Caribbean	0,0693	0,0563	0,1325	0,2581
13065	Handan [CHN]	Asia	0,0685	0,0449	0,1438	0,2572
13066	Osh [KGZ]	Asia	0,0082	0,0625	0,1862	0,2568
13067	Batajsk [RUS]	Europe	0,0416	0,1280	0,0866	0,2562
13068	Itaguai [BRA]	Latin America and the Caribbean	0,0866	0,0619	0,1064	0,2550
13069	Ajdabiyah [LBY]	Africa	0,0553	0,0976	0,1008	0,2536
13070	Gaalkacyo [SOM]	Africa	0,0012	0,0324	0,2199	0,2534
13071	Urumqi (Wulumqi) [CHN]	Asia	0,0565	0,0408	0,1560	0,2533
13072	Andria [ITA]	Europe	0,0565	0,0403	0,1547	0,2515
13073	Yaounde [CMR]	Africa	0,0197	0,0306	0,2007	0,2510
13074	Qi Xian [CHN]	Asia	0,0343	0,0627	0,1529	0,2499
13075	Chuzhou [CHN]	Asia	0,0546	0,0634	0,1312	0,2492
13076	Dar'A [SYR]	Asia	0,0188	0,0728	0,1568	0,2485
13077	Miyun [CHN]	Asia	0,1249	0,0424	0,0793	0,2466
13078	Nouakchott [MRT]	Africa	0,0248	0,0441	0,1773	0,2462
13079	Rio Bravo [MEX]	Latin America and the Caribbean	0,0883	0,0814	0,0760	0,2458
13080	Heze [CHN]	Asia	0,0996	0,0933	0,0521	0,2450
13081	Ahar [IRN]	Asia	0,0469	0,0449	0,1532	0,2449
13082	Ragusa [ITA]	Europe	0,0414	0,0669	0,1355	0,2438
13083	Kutaisi [GEO]	Asia	0,0373	0,0423	0,1641	0,2436
13084	Buzuluk [RUS]	Europe	0,0724	0,1247	0,0464	0,2435
13085	Foggia [ITA]	Europe	0,0421	0,0467	0,1542	0,2430
13086	Karu [NGA]	Africa	0,0232	0,0974	0,1195	0,2401
13087	Nanning [CHN]	Asia	0,0556	0,0290	0,1554	0,2400
13088	Maiduguri [NGA]	Africa	0,0151	0,0381	0,1865	0,2396
13089	Divo [CIV]	Africa	0,0122	0,0480	0,1793	0,2395
13090	Qistaquz [TJK]	Asia	0,0156	0,0690	0,1548	0,2394
13091	Zinguinchor [SEN]	Africa	0,0125	0,0407	0,1848	0,2380
13092	Curitiba [BRA]	Latin America and the Caribbean	0,0104	0,0763	0,1513	0,2380
13093	Dakar [SEN]	Africa	0,0167	0,0286	0,1915	0,2369
13094	Salamanca [MEX]	Latin America and the Caribbean	0,0581	0,0619	0,1148	0,2348
13095	Kherson [UKR]	Europe	0,0172	0,0966	0,1210	0,2348
13096	Duekoue [CIV]	Africa	0,0078	0,0342	0,1926	0,2345
13097	Bouake [CIV]	Africa	0,0185	0,0528	0,1631	0,2344
13098	Wugong [CHN]	Asia	0,0499	0,0599	0,1212	0,2310
13099	Manaus [BRA]	Latin America and the Caribbean	0,0156	0,0521	0,1606	0,2283
13100	Minatitlan [MEX]	Latin America and the Caribbean	0,0680	0,0731	0,0850	0,2261
13101	Morelia [MEX]	Latin America and the Caribbean	0,0600	0,0566	0,1080	0,2246
13102	Yining [CHN]	Asia	0,0436	0,0512	0,1279	0,2227
13103	Turakurgon [UZB]	Asia	0,0132	0,1000	0,1091	0,2223
13104	Dushanbe [TJK]	Asia	0,0160	0,0500	0,1548	0,2208
13105	Brynthuraichenai [LKA]	Asia	0,0369	0,0565	0,1251	0,2185
13106	Shijiazhuang [CHN]	Asia	0,0657	0,0108	0,1405	0,2170
13107	Panjin [CHN]	Asia	0,0944	0,0546	0,0673	0,2163
13108	Taiyuan, Shanxi [CHN]	Asia	0,0607	0,0269	0,1273	0,2149
13109	Tuxtla Gutierrez [MEX]	Latin America and the Caribbean	0,0386	0,0555	0,1202	0,2142
13110	Lhasa [CHN]	Asia	0,0387	0,0833	0,0919	0,2139
13111	Merida [MEX]	Latin America and the Caribbean	0,0795	0,0742	0,0597	0,2134
13112	Baghdad [IRQ]	Asia	0,0875	0,0691	0,0568	0,2134
13113	Delhi [IND]	Asia	0,1222	0,0063	0,0827	0,2112
13114	Baoding [CHN]	Asia	0,0637	0,0586	0,0875	0,2098
13115	Xinxiang [CHN]	Asia	0,0545	0,0487	0,1063	0,2095
13116	Suzhou, Jiangsu [CHN]	Asia	0,1477	0,0545	0,0018	0,2039
13117	Changchun [CHN]	Asia	0,0704	0,0257	0,1062	0,2024
13118	Sankt Peterburg (Saint Petersburg) [RUS]	Europe	0,0908	0,0249	0,0856	0,2013
13119	Cartak [UZB]	Asia	0,0183	0,0980	0,0798	0,1962
13120	Idku [EGY]	Africa	0,0324	0,0342	0,1290	0,1956
13121	Kaifeng [CHN]	Asia	0,0583	0,0693	0,0622	0,1897
13122	Majkop [RUS]	Europe	0,0351	0,0955	0,0567	0,1873
13123	Vigevano [ITA]	Europe	0,1074	0,0730	0,0010	0,1814
13124	Bishkek [KGZ]	Asia	0,0246	0,0508	0,0921	0,1675
13125	Suzhou, Anhui [CHN]	Asia	0,0503	0,0430	0,0727	0,1660
13126	Syeverodonets'K [UKR]	Europe	0,0187	0,0816	0,0617	0,1619
13127	Lagos [NGA]	Africa	0,0634	-0,0144	0,1101	0,1591
13128	Jilin [CHN]	Asia	0,0620	0,0274	0,0560	0,1454
13129	Tianjin [CHN]	Asia	0,1778	-0,0043	-0,0298	0,1437
13130	Mazar-e Sharif [AFG]	Asia	0,0105	0,0342	0,0589	0,1035
13131	Dhaka [BGD]	Asia	0,0492	0,1572	-0,1035	0,1029
13132	Kolkata (Calcutta) [IND]	Asia	0,0470	0,0399	-0,0282	0,0587
13133	Krung Thep (Bangkok) [THA]	Asia	0,3456	-0,0878	-0,2422	0,0156
13134	Guangzhou, Guangdong [CHN]	Asia	0,1059	0,0062	-0,3209	-0,2088
13135	Shanghai [CHN]	Asia	0,2741	-0,6387	-0,4498	-0,8143

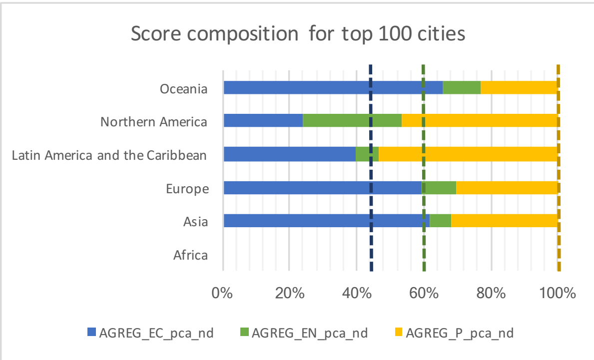
Source: author (2019).

The results have shown that by considering different dimensions of urban resilience – in this case, economic, environmental and physical, due to the lack of data for the dependent variables that represent the social and institutional dimension – can bring an interesting perspective on what it means to be resilient. Regarding the top 100 cities, the average representativeness per dimension on the final score was: 43.43% for the economic, 16.63% for the environmental, and 39.94% for the physical. On the other hand, for the bottom 100 cities those percentages were 25.44%, 22.93% and 51.63%, respectively. Despite these values pointing to the fact that having a strong economic performance – and, more specifically, a high GDP per capita – carries a strong relevance on the final result, some cases contested this assumption. For example, roughly every city in Latin American and the Caribbean had the biggest representativeness for the physical dimension, which occurred because of a high percentage of open spaces in those urban area. Even more interestingly, the cities on positions 35, 44, 55, 65, 89 a 92, all from the United States of America (USA) had the largest share of the final score attributed to the environmental indicator, due to a combination of a high green area per capita and low emissions of CO_2 and PM2.5. In fact, when analyzing the position attributed to Shanghai (China), the importance of an integrated assessment of urban resilience is even more reinforced. As a result of low green area per capita and the highest emissions of CO_2 and PM2.5, on the environmental dimension, and a high area exposed to floods and low percentage of open spaces, on the physical dimension, this urban area occupies the last place on the ranking – despite having a high GDP PPP and GDP per capita.

As Graph 14 shows (the dotted lines are marking the average representativeness on this range of cities), in general, for Asia, Europe and Oceania, the economic dimension was indeed the prevalent and, in reality, the main reason for why African cities did not reach the first 100 urban areas. However, looking for both Latin America and the Caribbean and Northern America, this was not observed, on those cases the physical dimension accounted for around 50% of the score. Two other observations are important to highlight. First, the physical dimension turned out to be the second most representative on the final composite index and, for that reason, is another indicative that it has to be considered on the assessment of urban resilience. Secondly, the environmental dimension was overall the one with the lowest value for the continents because it penalizes the emission of pollutants. That was not the case for Northern America only due to the fact that it has the largest area and rate per capita of green coverage, which compensated for their high CO_2 emission. Validating this argument by counter positioning, it is possible to evaluate Asian cities, who are also very high emitters of pollution, but because they have a small area and rate per capita of green coverage, the environmental dimension was the least representative for them.

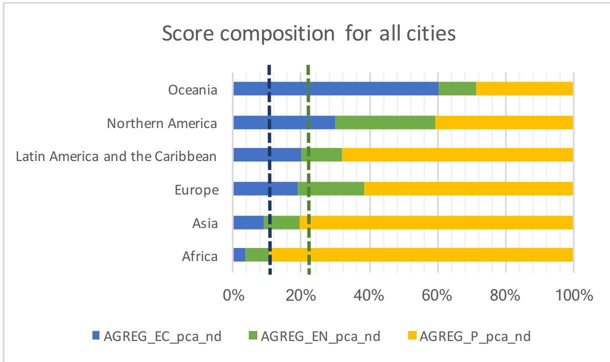
One more interesting analysis is assessing how every continent performs in each perspective of urban resilience, comparing to the worldwide view. Graph 15 shows the composition of the total index for all the urban areas on the dataset. From an initial overview, it can be observed that for urban areas in Oceania and Northern America the results almost did not vary from the top 100 scorers, which means that they are concentrated on higher positions in the ranking. This makes sense because, as previously shown on the boxplot of the range of the final composite index version, indeed the majority of scores for these two continents outperform the others (see Graph 13). Consequently, since Asia, Africa, Latin America and the Caribbean and Europe had more outliers, their average score varied more. With a more in-depth analysis, three other facts come to attention. First, from the global average to the top 100, the aggregated indicator for the economic dimensions almost doubled for Latin America and the Caribbean, tripled for Europe and quintupled for Asia, which shows a higher likeliness of having wealth inequality among these urban areas, because to reduce by that proportion the result of the best performers, there must be a large number of cities with low values for GDP PPP and GDP per capita. Second, the environmental and physical aggregated indicators reduced in an almost inverse proportion (comparing to the economic dimension) for these three continents, which indicates that despite a higher financial influence, those urban areas lack on addressing the challenges such as pollution and control of the land consumption rate compared to population growth. Third, even though for Northern America each aggregated indicator was fairly balanced and for Oceania the economic dominated the score, the physical dimension was the overall the most relevant and, again, it is a reinforcement of how it should be accounted for in urban resilience frameworks.

Graph 14 - Representativeness per dimension for the top 100 cities.



Source: author (2019).

Graph 15 - Representativeness per dimension for all cities.



Source: author (2019)

4.7 Link with other indicators

After presenting the final ranking of cities, it is the moment to understand what are the factors that influence the level of urban resilience, as presented on the operationalization framework. Doing a regression analysis between every independent variable and the total aggregated indicator (final version of the composite index) it is possible to see the main determinants are precipitation, temperature, land use efficiency and development level. A simplified summary of statistics is presented on Table 18 and the full description of the results of the regression analysis is presented on Annex 4. The Income level was included on this analysis with the purpose of check what it would be its R-Squared value, nonetheless, since it not only had a high value, but also is highly correlated to other indicators that compose the aggregated index, it cannot be confirmed that it should belong as the factors or level of urban resilience, and the division proposed initially for this indicator will be considered as adequate for the purposes of this research (in other words, the income level will remain belonging to the dependent variables).

Table 18 - Simplified results of the regression analysis.

Dependent Variable	Statistics	Income	Elevation	Precipitation	Temperature	Land use efficiency	Population density	Development Index
AGREG_Total	**R-Squared**	**0,863*****	**0,328*****	**0,732*****	**0,897*****	**0,940*****	**0,243*****	**0,746*****
	Adj. R-Squared	*0,863*	*0,328*	*0,732*	*0,897*	*0,940*	*0,243*	*0,746*
	Coef.	*0,8566*	*2,0077*	*2,4151*	*0,7147*	*0,8144*	*5,0555*	*0,9212*
	Std. error	*0,003*	*0,025*	*0,013*	*0,002*	*0,002*	*0,078*	*0,005*
	t	*287,050*	*80,042*	*189,455*	*337,618*	*451,657*	*64,912*	*196,472*
	[0,025 - 0,975]	*[0,851 - 0,862]*	*[1,959 - 2,057]*	*[2,390 - 2,440]*	*[0,711 - 0,719]*	*[0,811 - 0,818]*	*[4,903 - 5,208]*	*[0,912 - 0,930]*
Observation: significance level (p) < 0.01 = ***								

Source: author (2019).

Precipitation and temperature are characteristics related to the weather, and that are also affected by anthropogenic actions and climate change. Despite the data still not considering urban heat island effects and being calculated on a three-year interval centred in 2015, as mentioned on the database description (Florczyk et al., 2019), those parameters give an estimative of the climate forecast of the city. They are important to be measured because their lack or excess can have strong impacts. To mention a few examples, low precipitation levels are related to drought and stress to water bodies that cannot be recharged, while abundance usually incurs on flooding events, especially if associated with a large amount of impervious surfaces; and, regarding the temperature, high values can increase energy consumption to keep buildings and houses at comfort conditions for the inhabitants, while very low values (usually below zero and, therefore, associated with the presence of snow and ice) can difficult transportation and provision of services. For the top 100 cities in the ranking, the average temperature was of 16.87 ºC and for the bottom 100 it was 17.24ºC. Despite not being a small variation, comparing the averages of precipitation the effect becomes clearer. The top positions had annual average of 1,228 mm of rain and the lower position only 814 mm, a decrease by almost one third, and around a quarter below the global average of 1,109 mm.

Land use efficiency is calculated with the division of the rate of land consumption by population growth. In other words, this parameter evaluates the sprawl of the urban (built) area and changes of inhabitants (Florczyk et al., 2019). This is an important indicative of how local government is able to plan the development of urban areas and densify the population close to the center, avoiding a unwanted sprawl of the urban area. As a consequence of dense cities, among other characteristics, it is possible to evidence economies of scale on service provision, which is not only of the municipality's interest (since it reduces the costs) but also for the inhabitants (because they will have access to better services). Checking the results of this indicator, the values obtained were 139.55% for the top 100 cities, 30.52% for the global average, and 99.48% for the bottom 100. However, to have a deep understanding about the result, it was necessary to go back to the original data and verify what were the growth rates for both the population and built area for the periods of 1990, 2012 and 2015 measured by the database (Table 19). This information in hands, it is possible to confirm the initial expectation that densifying urban areas have a positive effect on the level of urban resilience.

Table 19 - Increase of the built area and population size between 1990 and 2015.

Interval	Built area		Population	
	1990 to 2012	2012 to 2015	1990 to 2012	2012 to 2015
Top 100	22,53%	12,49%	14,61%	1010,38%
Global average	*22,62%*	*9,52%*	*19,80%*	*22,50%*
Bottom 100	95,68%	45,37%	100,35%	150,28%

Source: author (2019).

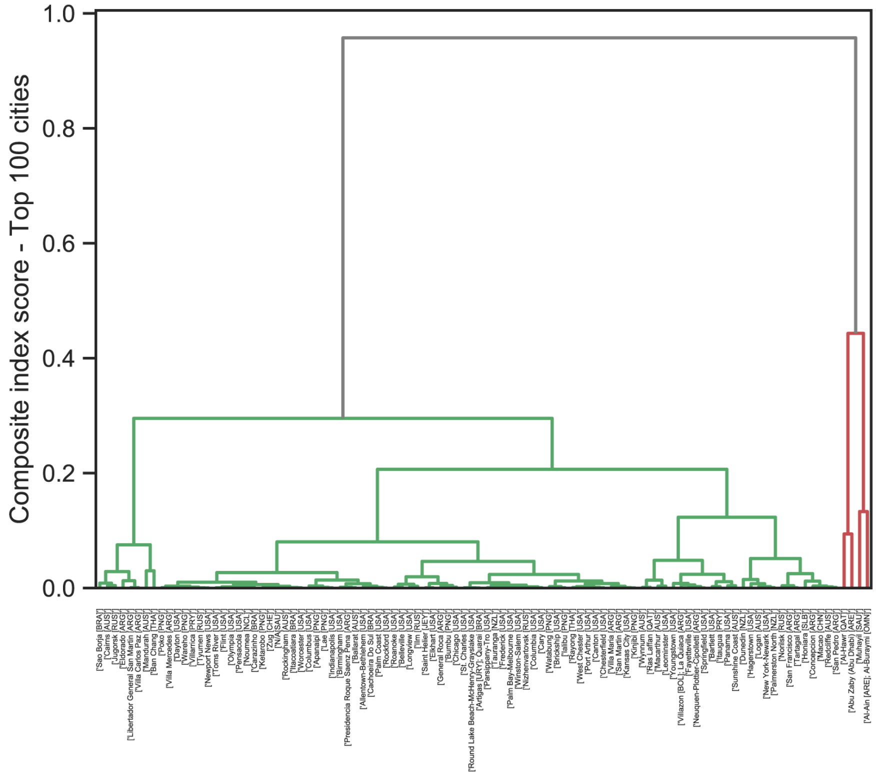
The last main factor of urban resilience is the development level. As previously mentioned, this indicator was transformed from a nominal to a categorical data type, with the categories being: more developed regions; least developed regions, excluding least developed countries; and least developed countries (Florczyk et al., 2019). Despite the R-Squared valued obtained might being biased to the fact the data is not a continuous value, it can still provide a valuable perspective. In fact, the majority of cities on the top 100 positions belong to the first category (higher level of development) and the bottom 100 belong to the second (medium level of development). From this information, it can be inferred that, indeed, a better index of urban resilience is related to a higher level of development.

4.8 Additional analysis

The methodological framework described that supervised and unsupervised learning techniques were going to be used to analyze the dataset and help to answer the research question and sub-questions. Even though the PCA can be considered as both, since it was used with labelled data (measurements related to a particular indicator), so for only the supervised techniques were used. In order to complement the analysis, specifically to visualize the existence or not of groups within the final index ranking, from the unsupervised techniques, the methods of Dendrogram and K-Means clustering were applied. Dendrograms are a type of tree-graph that allows to understand the hierarchy among the data by grouping samples by their proximity. Graphs 16 and 17 show the dendrogram obtained for the composite index total score of the first and last 100 urban areas, respectively. It is worth to notice that the cities on the *x-axis* are not presented necessarily in the ranking order.

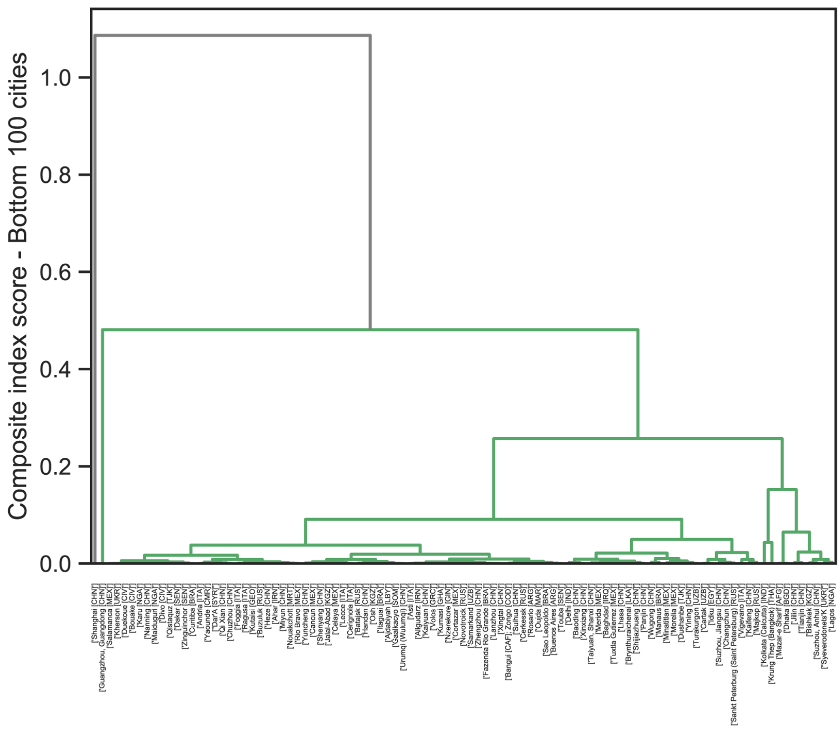
On the top 100 urban areas, four cities are clearly distinguished among the others (marked in red, at right side of the graph). Those cities were grouped together not because they are Asian cities that occupy, coincidently, the first four positions, but indeed for a particular combination of scores on the aggregated indicators. Their score for the economic dimension was very high (above 0.80), their environmental very low (below 0.10) and their physical close or higher to the average of this sample (which is around 0.48). Another small group observed is the one composed by the cities on the positions from 7 to 12. Their similarity was the balance between the economic and physical dimensions (with high values on both) and an environmental indicator better than first four cities, but overall not higher than the average. Lastly, it is important to mention the results obtained for the composite index are quite close from each other and, therefore, only two main groups were observed in the data (colored with green and red on the graph). For the bottom 100 cities, the differences are even harder to be distinguished, however, two main information are important to be highlighted. First, Shanghai (CHN), that occupies the last position in the ranking, is the only city that has high negative values for both the environmental and physical dimensions, as it was already commented on the previous section. Secondly, because the cities have, indeed, results within a small range of values (for the top 100 cities the range was from around 1.0 while for the bottom it was 0.2, without accounting for the last position), there is only one main group identified (marked in green on the graph). Not much information could be derived from the dendrograms, but the next unsupervised techniques, of cluster analysis, is yet to be assessed.

Graph 16 - Dendrogram for the top 100 cities.



Source: author (2019).

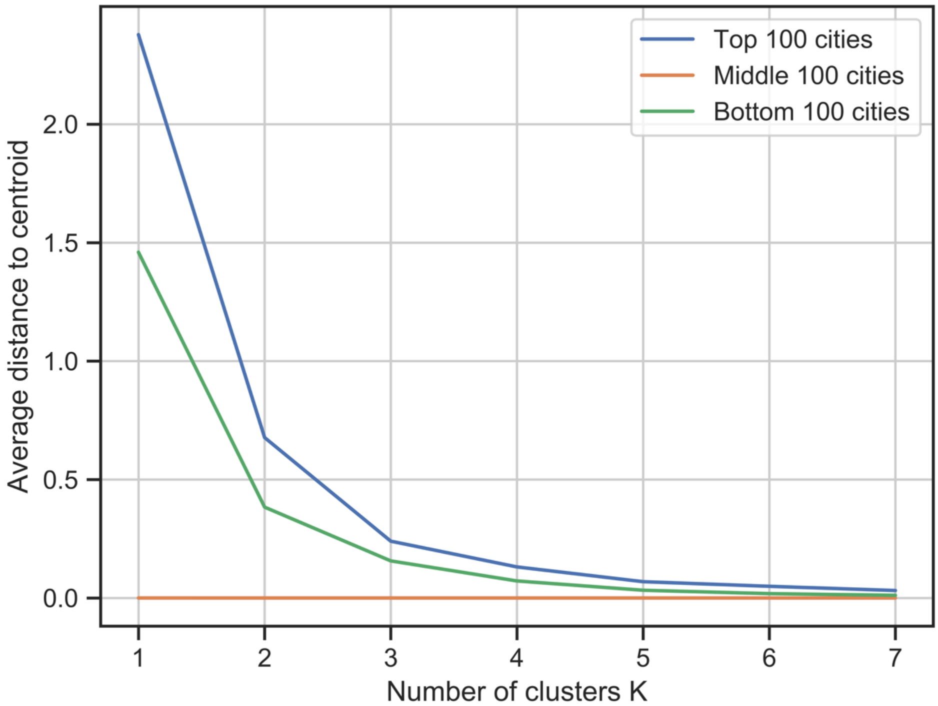
Graph 17 - Dendrogram for the bottom 100 cities.



Source: author (2019).

Similarly to the dendrograms, the *K-means* clustering method also identifies groups of samples. However, in this case the determines a value where, each of a total of 'k' groups are centred, being the centroid calculated based on the cluster average in such way that it optimizes the dispersion (least squares criteria) of the data. To determine the number of clusters more adequate do be considered on the scatter plot of the clusters, an 'elbow visualization' was calculated. This type of graph displays the average distance of the cluster 'k' from the centroid, and the lower that value, the less disperse the data is. Ideally, the aim is to reach a number as close to zero as possible, but the number of clusters is determined by the inflexion point on the graph (nominated as 'elbow') from which a low variation is observed. Graph 18 shows the 'elbow' chart calculated in the range of 1 to 7 clusters, for the top, middle and bottom 100 cities of the final composite index ranking. It is possible to see that, even though different clusters could not be identified for the middle scores, for both the highest and lowest performances the more adequate number of clusters tend to be k=4.

Graph 18 – Elbow visualization to determine the number of clusters for the top, middle and bottom 100 cities.



Source: author (2019).

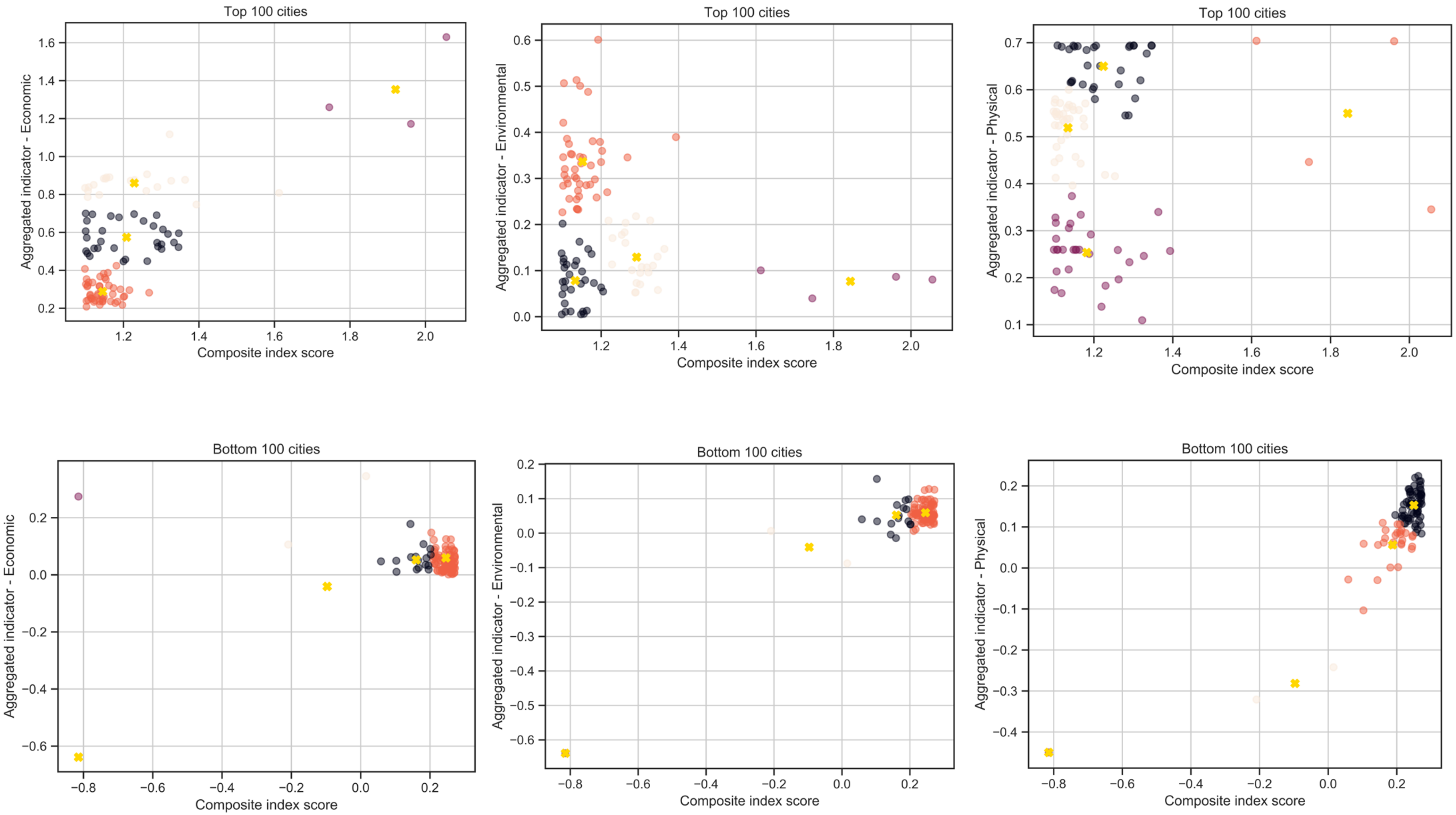
Given that the number of clusters is k=4 and the middle 100 cities only showed to have one cluster, and therefore not much information could be derived from that, Graph 18 shows comparison among the composite index score and each of the its aggregated indicators (economic, environmental and physical). The 'X' plotted on gold yellow refers to the centroid of each cluster. Before analyzing the aggregated indicators individually, a general observation that is possible to made is that, evidently, a cluster that had a good performance on one indicator not necessarily had higher values in the other as well, what also emphasizes the importance of considering different perspectives while evaluating this concept.

Looking first at the top 100 cities, and cross-checking the clusters with the ranking that was generated, it is possible to visualize a few patterns. Cities with lower scores on the economic dimension (orange cluster), tended to have the higher performances on the environmental dimension (orange cluster) and, mostly, medium scores on the physical aspect (crème cluster). In the other hand, cities with the highest scores on the economic dimensions, tended the lowest scores on the environmental and physical. With this information in hands, it can be argued that having a high economic performance in general implies to a less sustainable urban area and in, the other hand, that cities that have lower economic power, which can be a constraint to the implementation of policies, plans and projects towards a more sustainable development, showed to overcome this challenge and still able the address problems related to the pollution and urban space in a satisfactory manner.

In this case, Asian cities tend to be dispersed in all clusters and African cities are not represented among the top 100 as showed on Graph 14. Restricted to only some of the groups, European cities tend to be on the crème cluster for all the indicators; Northern American cities tend to be on the concentrated on the orange cluster for the economic dimensions, the crème and black clusters for the economic dimension, orange for the environmental, and crème or black for the physical; Latin American and the Caribbean cities are concentrated at the black cluster for the economic and environmental indicators, and on the crème and black for the physical; and, finally, cities from Oceania tend to be more concentrated on the black cluster of the economic dimensions, orange for the environmental and purple for the physical.

Now observing the results for the bottom 100 cities, it is not possible to see a pattern the straight away. In fact, only two observations can be made. First, that cities the fall at the lower positions of the ranking did not have a good (or even average) performance in any of the aggregated indicators. Second, that there are some exceptions to that case, specifically the urban areas of Bangkok (THA) and Shanghai (CHN) that had negative scores for the environmental dimensions due to high emission of pollutants and flood exposure.

Graph 19 – Clusters per dimensions of urban resilience for top and bottom 100 cities.



Source: author (2019).

Chapter 5: Conclusion

5.1 Data availability

The availability of data is usually one of the main constraints for local governments, researchers and organizations to develop studies and understand the current scenario of a specific urban area. Further, be able to compare it with the performance of cities worldwide is an even more difficult task. In order to be able to realize those analysis, data should be developed with the same theoretical definitions for the variables and indicators, follow strict technical procedures for collection, and measure the same timespans, just to cite a few criteria. This research proposed on Sub-question 1, to evaluate 'to which extent the dimensions and indicators of urban resilience can be measured' based on existing datasets. By identifying five databases and cross-checking their indicators with the ones proposed on the theoretical framework, as shown on the Graph it is clear that existing information is not able to provide a full picture of the parameters of urban resilience. In fact, it showed that the indicators related to the economic, environmental and physical dimensions are prioritized, while there are more gaps of improvement for the institutional and social dimensions. Actually, the only database that had indicators for all the dimensions was the GHS Urban Settlement Database 2015 (European Commission, 2019), and since it also had the largest samples of cities (of more than 13,000 urban areas) it was the one chosen. Even though the analysis proved itself to result in insightful results, there is still a long way to reach a point where the majority of indicators off all the five dimensions of urban resilience can be measured. It is also important to notice that this does not mean that some of the information needed is not available, but that there must be a process of making sure they follow the same theoretical and technical criteria to be merged and openly shared.

5.2 Composite index, performance of cities and key determinants

To build the composite index that was going to evaluate the performance of the cities in the selected sample, a robust theoretical procedure developed by Nardo et al. (2018) was used to give reliability to the model. Following all the steps of this methodology with supervised learning techniques, besides testing different scenarios and comparing correlation coefficients and relative scores, it can be argued that the composite index obtained is the one that not only the one that better represents the sample of data, but also, because it considers urban areas worldwide in accordance to the proportion of cities and population (as mentioned in Section 4.2), it can be generalized for all other cities that can collect the indicators analyzed. During this thorough process, it was noticed that some indicators initially considered to be part of the dependent variables were actually more suited as independent variables (specifically urban size and flood exposure) and, therefore, both the theoretical and operationalization framework were updated before effectively calculating the performance of cities. With this analysis, it is possible to answer the research sub-question 4 ('Are the indicators of the index proposed adequate to determine a general level of urban resilience?'), given that the model developed proved itself to well represent the dataset with the adjustments that had to be made. More than that, determining the composite index provided the answer to sub-question 2 ('What is the level of urban resilience of a sample of 13,000 cities as measured by an urban resilience index?').

In fact, the ranking of cities showed the relevance of adopting and comprehensive approach to assess urban resilience, given that indicators related to the environmental and physical dimensions showed themselves to be as important as the economic ones. Additionally, having a strong economy does not mean that a local government is able to invest on improvements to adapt to climate change-related effects, such as flooding, contain urban sprawl, keep CO_2 and PM2.5 emissions at a low rate or have an adequate balance between built and green areas. Each continent profile of final scores varied on the top and bottom 100 urban areas, as well on the global average, but, except for cities in Oceania, it was possible to notice that environmental and physical dimensions, together, account for more than 50% of the index.

After the evaluation of the indicators influencing the level of urban resilience, via regression analysis, it was observed that temperature, precipitation, land use efficiency and development level are the main factors. In particular, understanding that the first two have that significance was very important to reinforce the effects caused by climate change, mainly the increase of earth's temperature, that implies on the sea level rise, and strong rains being experienced that, associated with a high percentage of impervious surfaces and lack of drainage infrastructure, causes increases the exposure to flooding events. The third factor is related to how a local government can contain urban sprawl and have a good ratio of land consumption versus population growth, promoting more dense areas that, at the same time, have access to quality services and open (green) spaces. Lastly, the fourth influence is related to a socioeconomic characteristic that provides a perspective of how a city is developed in regard to international standards of classification, which is strongly correlated to factors such as the income level.

5.3 Urban resilience framework

The thorough literature review and summary of variables and indicators was essential to better understand the concept of urban resilience and propose an integrated framework to assess it. Incorporating measurements proposed by researchers and organizations made possible to have an overview of both qualitative and quantitative measurements needed to comprehend the baseline scenario, as well as the determinants of the factors and level of urban resilience. Adopting the five dimensions of urban resilience (economic, environmental, institutional, physical and social), and cross-checking their parameters with information available on existing datasets, provided very useful insights about data availability and the need for improvement on data collection to have a full overview of the concept. Nonetheless, with the robust composite index that was built, the indicators that determine how resilient a city is and the main factors that influence it were, to the limitations of this study, satisfactory determined, consequently achieving the research objectives. In other words, with these comments and the ones that were already presented on Sections 5.1 and 5.2, not only all the research sub-questions were addressed, but complementing the results allows to effectively answer the principal research question (*'Which factors determine the level of urban resilience?'*).

Going back to Chapter 2, the definition of urban resilience adopted by this research was:

> "Urban resilience refers to the ability of an urban system-and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales-to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity" (Meerow, Newell and Stults, 2016, p.39)

This definition was associated with six characteristics important to be considered, espcifically: ‘what’ are the parameters to be considered to build urban resilience; ‘when’, short or long-term action should be implemented and the indicators, measured; ‘where’ if the boundary of the urban; ‘why’ the strategies need to be adopted or, in other words, what is the baseline scenario and what needs to be improved; ‘who’ is the target of the strategies and actions, and here it is important to emphasize that it should be all citizens; and, lastly, ‘how’ institutional aspects can collaborate to ensure the mainstreaming and effectiveness of those actions. In fact, after some corrections that had to be made on theoretical framework, the model of composite index proposed was validated and, consequently, as the concept foundation behind it. The final result is a framework that proposes an integrated perspective over the concept of urban resilience and, also, intends to complement setting the ground for a common definition of this concept. Achieving the purpose of explaining the factors that determine the level of urban resilience, the framework and methodological procedure followed by this research is intended to be used by academia, organizations and local governments to make an assessment of their current performance and understand what factors are the major contributors to it.

5.4 Recommendations

This research is an ongoing analysis in the sense of, as more data become available, the composite index and ranking of urban areas should be updated to provide more insights about the factors determining the level of urban resilience. Tackling the issue of data availability, data collection, openness of information and sharing of databases should be improved the add more value to the analysis. Ideally, a scenario where local government are able to measure, at least, a common set of indicators and realize benchmarking of opportunities and challenges should be reached for a shared-learning process. While calculating the composite index, other techniques can be tested to further extend the validation of the model, given that this study was also limited to a time constraint. For example, other methods of imputation of missing data and weighting and aggregation could enhance the model of composite index proposed. The application of other unsupervised techniques, such as machine learning, would also be interesting to also generate a computational model with high accuracy. And lastly, comparing the measurement of the year 2015, with the data from 2012 and 1990 from the GHS Urban Centre Database 2015, and future time periods that added to the dataset, could also provide an interesting perspective to evaluate how cities’ scores have change overtime and better understand the impact of the plans, policies and projects being implement by them.

References

Agudelo-Vera, C. M., Leduc, Wouter R. W. A., Mels, A. R. and Rijnnaarts, H. H. M. 2012. Harvesting urban resources towards more resilient cities. *Resources, Conservation and Recycling,* 64 pp. 3-12. Available at: https://www-sciencedirect-com.eur.idm.oclc.org/science/article/pii/S0921344912000250 [Accessed 05-06-2019].

ARUP and The Rockefeller Foundation, 2018. City Resilience Index - Resources. Available at: https://www.cityresilienceindex.org/#/resources [Accessed 2019].

Asadzadeh, A., Kötter, T., Salehi, P. and Birkmann, J. 2017. Operationalizing a concept: The systematic review of composite indicator building for measuring community disaster resilience. *International Journal of Disaster Risk Reduction,* 25 pp. 147-162. Available at: https://www.sciencedirect.com/science/article/pii/S2212420917302364 [Accessed 07-04-2019].

Baussan, D., 2015. Social Cohesion: The Secret Weapon in the Fight for Equitable Climate Resilience. Center for American Progress. Available at: https://cdn.americanprogress.org/wp-content/uploads/2015/05/SocialCohesion-report2.pdf [Accessed 27-02-2019].

Béné, C., Mehta, L., McGranahan, G., Cannon, T., et al., 2018. Resilience as a policy narrative: potentials and limits in the context of urban planning. *Climate and Development,* 10 (2), pp. 116-133. Available at: https://www.tandfonline.com/doi/full/10.1080/17565529.2017.1301868 [Accessed 25-03-2019].

Berkes, F. and Folke, C. 1998. Linking social and ecological systems for resilience and sustainability. In: F. Berkes and C. Folke eds., 1998. Linking social and ecological systems management practices and social mechanisms for building resilience. Cambridge: Cambridge University Press. pp. 1-25.

Cai, H., Lam, N. S. N., Qiang, Y., Zou, L., et al., 2018. A systhesis of disaster resilience measurement methods and indices. *International Journal of Disaster Risk Reduction,* 31 pp. 844-855. Available at: https://www.sciencedirect.com/science/article/pii/S2212420918304618 [Accessed 07-04-2019].

Callister, W. D. and Rethwisch, D. G., 2012. Fundamentals of materials science and engineering - An integrated approach. 4th. Hoboken, NJ: John Wiley and Sons.

Carpenter, S. R. and Folke, C. 2006. Ecology for transformation. *TRENDS in Ecology and Evolution,* 21 (6), pp. 309-315. Available at: https://sciences.ucf.edu/biology/king/wp-content/uploads/sites/106/2011/08/Carpenter-and-Folke-2006.pdf [Accessed 05-06-2019].

Chelleri, L., Kunath, A., Minucci, G., Olazabal, M., et al., 2012. Multidisciplinary perspectives on urban resilience. ISBN: 978-84-695-6025-9), Bilbao, Spain: BC3, Basque Centre for Climate Change. Available at: https://s3.amazonaws.com/academia.edu.documents/35043043/Urban_Resilience_978-

84-695-6025-9.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1557844194&Signature=Gzg6iSnOIPR73zV%2Fe%2BEc8UzCkG4%3D&response-content-disposition=inline%3B%20filename%3DReconsidering_Resilience_in_Rapidly_Urba.pdf#page=9 [Accessed 15-05-2019].

Colding, J. and Barthel, S. 2013. The potencial of 'Urban Green Commons' in the resilience building of cities. *Ecological Economics,* 86 pp. 156-166. Available at: https://www-sciencedirect-com.eur.idm.oclc.org/science/article/pii/S0921800912004429 [Accessed 05-06-2019].

Collier, F., Hambling, J., Kernaghan, S., Kovacevic, B., et al., 2014. Tomorrow's cities: a framework to assess urban resilience. *Urban Design and Planning,* 167 (DP2), pp. 79-91. Available at: https://www-icevirtuallibrary-com.eur.idm.oclc.org/doi/10.1680/udap.13.00019 [Accessed 27-03-2019].

Cook, D., Saviolidis, N. M., Davíðsdóttir, B. and Jóhannsdóttir, L. 2017. Measuring countries' environmental sustainability performance - The development of a nation-specific indicator set. *Ecological Indicators,* 74 pp. 463-478. Available at: https://www.sciencedirect.com/science/article/pii/S1470160X16306999 [Accessed 07-04-2019].

da Silva, J., Kernaghan, S. and Luque, A. 2012. A systems approach to meeting the challenges of urban climate change. *International Journal of Sustainable Development,* 4 (2), pp. 125-145. [Accessed 05-06-2019].

Deal, B., Pan, H., Pallathucheril, V. and Fulton, G. 2017. Urban Resilience and Planning Support Systems: The Need for Sentience. *Journal of Urban Technology,* 24 (1), pp. 29-45. Available at: https://www-tandfonline-com.eur.idm.oclc.org/doi/full/10.1080/10630732.2017.1285018 [Accessed 05-06-2019].

ECA, 2009. Shaping climate-resilient development: a framework for decision-making. Economics of Climate Adaptation. Available at: https://media.swissre.com/documents/rethinking_shaping_climate_resilent_development_en.pdf [Accessed 26-02-2019].

Elias-Trostmann, K., Cassel, D., Burke, L. and Rangwala, L., 2018. Stronger than the storm: Applying the urban community resilience assessment to extreme climate events. Washingtion, DC: World Resources Institute. Available at: https://www.wri.org/publication/stronger-than-storm [Accessed 24-02-2019].

Ernstson, H., van der Leeuw, Sander E., Redman, C. L., Meffert, D. J., et al., 2010. Urbans transitions: on urban resilience and human-dominated ecosystems. *AMBIO A Journal of the Human Environment,* 39 (8), pp. 531-545. Available at: https://www.researchgate.net/publication/49667946_Urban_Transitions_On_Urban_Resilience_and_Human-Dominated_Ecosystems [Accessed 05-06-2019].

Euromonitor International, 2019. Passport. Available at: https://go.euromonitor.com/passport.html [Accessed 13-03-2019].

European Comission, 2019. Global Human Settlement - data overview. Available at: https://ghsl.jrc.ec.europa.eu/data.php [Accessed 13-03-2019].

Figueiredo, L., Honiden, T. and Schumann, A., 2018. Indicators for Resilient Cities. 2018/02), OECD iLibrary: OECD Regional Development Working Papers. Available at: https://www.oecd-ilibrary.org/development/indicators-for-resilient-cities_6f1f6065-en [Accessed 10-04-2019].

Florczyk, A.J., Melchiorri, M., Corbane, C., Schiavina, M., et al., 2019. Description of the GHG Urban Centre Database 2015. *Public release 2019, Version 1.0*. Luxemburg: Publications Office of the European Union, 2019. Available at: https://ghsl.jrc.ec.europa.eu/ucdb2018Overview.php. [Accessed 13-03-2019].

Fu, X. and Whang, X. 2018. Developing an integrative urban resilience capacity index for plan making. *Environment Systems and Decisions,* 38 pp. 367-378. Available at: https://link-springer-com.eur.idm.oclc.org/article/10.1007%2Fs10669-018-9693-6 [Accessed 24-03-2019].

Grafakos, S., Trigg, K., Landauer, M., Chelleri, L., et al., 2019. Analytical framework to evaluate the level of integration of climate adaptation and mitigation in cities. *Climatic Change,* Available at: https://link.springer.com/content/pdf/10.1007%2Fs10584-019-02394-w.pdf [Accessed 14-05-2019].

Hernantes, J., Maraña, P., Gimenez, R., Sarriegi, J. M., et al., 2019. Towards resilient cities: A maturity model for operationalizing resilience. *Cities,* 84 pp. 96-103. Available at: https://www-sciencedirect-com.eur.idm.oclc.org/science/article/pii/S0264275117315020?via%3Dihub [Accessed 24-03-2019].

Holling, C. S., 1973. Resilience and Stability of Ecological Ecosystems. *Annual Review of Ecology and Systematics,* 4 pp. 1-23. Available at: http://www.zoology.ubc.ca/bdg/pdfs_bdg/2013/Holling%201973.pdf [Accessed 06-06-2019].

IPCC, 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. In: C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G. -. Plattner, S. K. Allen, M. Tignor and P. M. Midgley eds., 2012. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press. Available at: https://www.ipcc.ch/site/assets/uploads/2018/03/SREX_Full_Report-1.pdf. [Accessed 05-06-2019].

ISO, 2018. ISO37120:2018 - Sustainable cities and communities - Indicators for city services and quality of life. 2nd. Geneva, Switzerland: International Standard Organization. Available at: https://www.iso.org/obp/ui/#iso:std:iso:37120:ed-2:v1:en [Accessed 05-06-2019].

Jabareen, Y. R., 2006. Sustainable Urban Forms: Their Typologies, Models, and Concepts. *Journal of Planning Education and Research,* 26 pp. 38-52. Available at:

https://journals.sagepub.com/doi/pdf/10.1177/0739456X05285119 [Accessed 09-05-2019].

Kaika, M., 2017. '*Don't call me resilient again!*': the New Urban Agenda as immunology ... or ... what happens when communities refuse to be vaccinated with 'smart cities' and indicators. *Environment & Urbanization,* 29 (1), pp. 89-102. Available at: https://journals.sagepub.com/doi/10.1177/0956247816684763 [Accessed 25-03-2019].

Kim, D. and Lim, U. 2016. Urban Resilience in Climate Change Adaptation: A Conceptual Framework. *Sustainability,* 8 (405), Available at: https://www-mdpi-com.eur.idm.oclc.org/2071-1050/8/4/405 [Accessed 25-03-2019].

Kourtit, K. and Nijkamp, P. 2018. Big data dashboards as smart decision support tools for *i*-cities - An experiment on stockholm. *Land use Policy,* 71 pp. 24-35. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0264837717305380 [Accessed 06-04-2019].

Macmillan Dictionary Blog, 2017. Word of the day - resilient. Available at: https://www.etymonline.com/word/resilience [Accessed 05-06-2019].

Meerow, S., Newell, J. P. and Stults, M. 2016. Defining urban resilience: A review. *Landscape and Urban Planning,* 147 pp. 38-49. Available at: https://www.sciencedirect.com/science/article/pii/S0169204615002418 [Accessed 26-02-2019].

Mileti, D., 1999. Disasters by design: a reassessment of natural hazards in the United States. Washington, DC: Joseph Harry Press.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., et al., 2008. Stationary Is Dead: Whiter Water Management? *Science,* 319 (5863), pp. 573-574. Available at: http://science.sciencemag.org/content/319/5863/573 [Accessed 28-02-2019].

MMF, 2018. Global Power City Index 2018. Institute for Urban Strategies, The Mori Memorial Foundation. Available at: http://mori-m-foundation.or.jp/pdf/GPCI2018_summary.pdf [Accessed 06-05-2019].

Mogelgaard, K., Dinshaw, A., Ginoya, N., Gutiérrez, M., et al., 2019. From planning to action: mainstreaming climate change adaptation into development. Washingtion, DC: World Resources Institute. Available at: https://www.wri.org/publication/climate-planning-to-action [Accessed 06-03-2019].

Moghim, S. and Garna, R. K. 2019. Countries' classification by environmental resilience. *Journal of Environmental Management,* 230 pp. 345-354. Available at: https://www.sciencedirect.com/science/article/pii/S0301479718311009 [Accessed 07-04-2019].

Moran, D., Kanemoto, K., Jiborn, M., Wood, R., et al., 2018. Carbon footprints of 13,000 cities. *Environmental Research Letters,* Available at: https://www.researchgate.net/publication/325322301_Carbon_footprints_of_13000_cities [Accessed 13-03-2019].

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., et al., 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD publishing. Available at: https://www.oecd.org/sdd/42495745.pdf [Accessed 27-03-2019].

Ni, P., Kamiya, M. and Ding, R., 2017. Cities Network Along the Silk Road - The Global Urban Competitiveness Report 2017. China Social Sciences Press and Springer Nature Singapore. [Accessed 14-05-2019].

Olazabal, M., Chelleri, L., Water, J. J. and Kunath, A. 2012. Urban resilience: towards an integrated approach. *Paper Presented at 1st International Conference on Urban Sustainability & Resilience, London, UK,* Available at: https://www.researchgate.net/profile/Marta_Olazabal/publication/236236994_Urban_resilience_towards_an_integrated_approach/links/0deec51751b5c21c41000000.pdf [Accessed 14-05-2019].

Opitz-Stapleton, S., Guibert, G., MacClune, K. and Tyler, S. 2011. Only death is certain, yet you still get out of bed in the morning: Communicating Climate Information in Adaptation and Resilience Practice. In: M. Moench, S. Tyler and J. Lage eds., 2011. Catalyzing Urban Climate Resilience: Applying Resilience Concepts to Planning Practice in the ACCCRN Program (2009-2011). Boulder, CO: The Institute for Social and Environmental Transition. pp. 71-122. Available at: http://act-adapt.org/wp-content/uploads/2011/06/ISET_CatalyzingUrbanResilience_allchapters.pdf. [Accessed 28-02-2019].

Picketts, I. M., Déry, S. J. and Curry, J. A. 2014. Incorporating climate change adaptation into local plans. *Journal of Environmental Planning and Management,* 57 (7), pp. 984-1002. Available at: https://doi.org/10.1080/09640568.2013.776951 [Accessed 06-03-2019].

Sellberg, M. M., Wilkinson, C. and Peterson, G. D. 2015. Resilience assessment: a useful approach to navigate urban sustainability challenges. *Ecology and Society,* 20 (1), pp. 43. Available at: https://www.ecologyandsociety.org/vol20/iss1/art43/ [Accessed 05-06-2019].

Sharifi, A. and Yamagata, Y. 2014. Resilient urban planning: Major principles and criteria. *Energy Procedia,* 61 pp. 1491-1495. Available at: https://www-sciencedirect-com.eur.idm.oclc.org/science/article/pii/S187661021403183X?via%3Dihub [Accessed 27-03-2019].

Sharifi, A. and Yamagata, Y. 2018. Resilient Urban Form: A Conceptual Framework. Resilient Urban Form: A Conceptual Framework. 2018. Resilient-oriented urban planning. pp. 167-179. Available at: https://www.researchgate.net/publication/323284961_Resilient_Urban_Form_A_Conceptual_Framework. [Accessed 09-05-2019].

Shaw, R., Razafindrabe, B., Gulshan, P., Takeuchi, Y., et al., 2009. Climate Disaster Resilien: Focus on Coastal Urban Cities in Asia. *Asian Journal of Environment and Disaster Management,* 1 Available at: https://www.researchgate.net/publication/282123042_Climate_Disaster_Resilience_Focus_on_Coastal_Urban_Cities_in_Asia [Accessed 05-06-2019].

Song, M., Cen, L., Zheng, Z., Fisher, R., et al., 2017. How would big data support societal development and environmental sustainability? Insights and practices. *Journal of Cleaner Production,* 142 pp. 489-500. Available at: https://www.sciencedirect.com/science/article/pii/S0959652616317115 [Accessed 05-04-2019].

The Rockefeller Foundation and ARUP, 2014. City Resilience Index: understanding and measuring city resilience. Available at: https://www.arup.com/-/media/arup/files/publications/c/170223_cri-brochure.pdf [Accessed 12-01-2019].

Thiel, S. v., 2014. Research Methods in Public Administration and Public Management: An introduction. London/New York: Routledge.

Towards Data Science, 2018. Understanding Boxplots. Published on 12-09-2018. Available at: https://towardsdatascience.com/understanding-boxplots-5e2df7bcbd51. [Accessed 21-08-2019].

Tromeur, E., Ménard, R., Bailly, J. B. and Soulié, C. 2012. Urban vulnerability and resilience within the context of climate change. *Natural Hazards and Earth System Sciences,* 12 pp. 1811-1821. Available at: https://www.nat-hazards-earth-syst-sci.net/12/1811/2012/ [Accessed 05-04-2019].

Tyler, S. and Moench, M. 2012. A framework for urban climate resilience. *Climate and Development,* 4 (4), pp. 311-326. Available at: https://doi.org/10.1080/17565529.2012.745389 [Accessed 28-02-2019].

Tyler, S., Nugraha, E., Nguyen, H. K., Nguyen, N. V., et al., 2016. Indicators of urban climate resilience: A contextual approach. *Environmental Science & Policy,* 66 pp. 420-426. Available at: https://www.sciencedirect.com/science/article/pii/S1462901116304890?via%3Dihub [Accessed 25-03-2019].

UN, 2015. The Paris Agreement. New York: United Nations Framework Convention on Climate Change (UNFCCC), 2015. Available at: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement [Accessed 23-07-2019].

UN, 2016. Sustainable Development Goals Knowledge Platform - United Nations. Available at: https://sustainabledevelopment.un.org/sdgs [Accessed 2019].

UN, 2017. New Urban Agenda. (A/RES/71/256*), Quito, Ecuador: United Nations Conference on Housing and Sustainable Urban Development (Habitat III). Available at: http://habitat3.org/wp-content/uploads/NUA-English.pdf [Accessed 01-05-2019].

UN, 2018. The World's Cities in 2018 – Data Booklet. (ST/ESA/SER.A/417). United Nations: Department of Economic and Social Affairs, Population, 2018. Available at: http://un.org/en/events/citiesday/assets/pdf/the_worlds_cities_in_2018_data_booklet.pdf [Accessed 02-09-2019].

UN-Habitat, 2014. Planning for climate change: A strategic, values-based approach for urban planners. Barth, Bernard; Cea, Maria Adelaida; Fee, Liam; Gonzalez, Julian; Ohlson, Dan;

Nesbitt, Lorien; Quinlan, Vicky. Nairobi: United Nations Human Settlement Programme. Available at: http://unhabitat.org/wpdm-package/planning-for-climate-change-guide/?wpdmdl=110424 [Accessed 08-03-2019].

UN-Habitat, 2019. UN-Habitat Urban Data: Free and open access to data about countries and cities around the globe. Available at: http://urbandata.unhabitat.org/ [Accessed 13-03-2019].

United Nations, 2017. New Urban Agenda. A/RES/71/256*), Quito: Habitat III. Available at: http://habitat3.org/wp-content/uploads/NUA-English.pdf [Accessed 01-05-2019].

Walker, B., Carpenter, S., Anderies, J., Abel, N., et al., 2002. Resilience Management in Socio-ecological Systems: a Working Hypothesis for a Participatory Approach. *Conservation Ecology,* 6 (1), Available at: http://www.consecol.org/vol6/iss1/art14/ [Accessed 06-05-2019].

WCCD, 2019. World Council on City Data Open Data Portal. Available at: http://open.dataforcities.org/ [Accessed 13-03-2019].

Annex 1: Variables and indicators of the conceptual framework

Annex 1.1 – Dependent variables and indicators (economic dimension).

Dimension	Variables	Indicators	Source
Economic	Employment	> The number of job genereation; > Percentage labor force employed; > Percentage full time employment.	Cai et al., 2018; Fu and Wang, 2018; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Unemployment rate	> Percentage of working age population; > Total unemployment rate, by sex, age and persons with disabilities.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 8).
	Income	> Median household income; per capita; > Percentage of population below 50% median income.	Cai et al., 2018; Fu and Wang, 2018; ISO, 2018; MMF, 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2014; UN, 2017 (SDG 10); UN-Habitat, 2014.
	Municipal revenues	> Annual tax revenues in the area; > Tax collected as percentage of tax billed.	Fu and Wang, 2018; ISO, 2018.
	Poverty rate	> Total inhabitantis living below the (international/national) poverty line; > Number of residents with the income below poverty line (by sex, age, etc.).	Fu and Wang, 2018; ISO, 2018; MMF, 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2014; UN, 2017 (SDG 1); UN-Habitat, 2014.
	Rental prices	> Average household rent; > Percentage of household income spent on rent by the poorest 20% of population.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Price level	> Prices of basic needs	Kourtit and Nijkamp, 2018; MMF, 2018
	Energy intensity of economic activity	> Total primary energy supply (ktoe) per unit of national GDP.	Cook et al., 2017; UN, 2017 (SDG 7).
	Land values	> Assessed value of commercial and industrial properties as percentage of total assessed value of all properties.	ISO, 2018; UN-Habitat, 2014.
	Taxation and fiscal policies	> Annual inflation rate based on the average of the past five years	ISO, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 10,17).
	Debt service ratio	> Debt service expenditure as a percentage of a city's own-source revenue; > Debt service as a proportion of exports of goods and services.	ISO, 2018; UN, 2017 (SDG 17).
	Budgetary system structure	> Capital spending as a percentage of total expenditures; > Gross operating budget per capita; > Gross capital budget per capita.	ISO, 2018; Sharifi and Yamagata, 2014.

Source: author (2019).

Annex 1.2 – Dependent variables and indicators (environmental dimension).

Dimension	Variables	Indicators	Source
Environmental	CO2 emissions	> Total amount of carbon dioxide emissions.	Fu and Wang, 2018; Kourtit and Nijkamp, 2018; Moghim and Garna, 2019; MMF, 2018; Moran et al., 2018; UN, 2017 (SDG 9).
	Energy consumption	> Total energy use for residential, comercial and industrial land use.	Fu and Wang, 2018; ISO, 2018; Moghim and Garna, 2019; Sharifi and Yamagata, 2014.
	Urban tree canopy	> Number of trees per 100,000 population	Sharifi and Yamagata, 2014; ISO, 2018.
	Water demand and consumption	> Water use by households in the area; > Percentage of fresh and groundwater abstraction as proportion of long term average available water; > Level of water stress; > Freshwater withdrawal as a proportion of available freshwater resources.	Cook et al., 2017; Fu and Wang, 2018; ISO, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 6).
	Water quantity and quality	> Protection of water-sensitive lands; > Water contamination levels; > Compliance rate to drinking water quality.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 6); UN-Habitat, 2014.
	Forest conservation	> Current forest area as a percentage of total original area; > Fellings as percentage share of net natural increment (forest increment feelings)	Sharifi and Yamagata, 2014; Cook et al., 2017; UN, 2017 (SDG 15).
	Biodiversity	> Total number of threatened species; > Red List Index; > Percentage change in number of native species.	Cai et al., 2018; Cook et al., 2017; ISO, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 15).
	Green area per capita	> Total green area (hectares) per 100,000 population.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 15).
	Renewable energy generation	> Percentage of renewable energy as a share of total final energy consumption; > Proportion of population with primary reliance on clean fuels and technology.	Cook et al., 2017; Fu and Wang, 2018; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 7).
	Green coverage	> Total green area; > Average percentage of previous surfaces; > Mountains green cover index	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 15).
	Waste generation	> Total amount of municipal waste generated (thousand tones) per year.	Cook et al., 2017; ISO, 2018; Sharifi and Yamagata, 2014.
	Recycling of waste	> Percentage of total municipal waste that is recycled.	Cook et al., 2017; ISO, 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 12).
	Waste in landfills	> Percentage of total municipal waste that is sent to landfill.	Cook et al., 2017; ISO, 2018; Sharifi and Yamagata, 2014.
	PM2.5 emissions	> Total measured in thousands of tonnes of PM2.5 (fine particulate matter with diameter <= 2.5 micrometers).	Cook et al., 2017; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Moghim and Garna, 2019); UN, 2017 (SDG 11).
	PM10 emissions	> Total measured in thousands of tonnes of PM10 (particulate matter with diameter <= 10 micrometers).	Cook et al., 2017; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Moghim and Garna, 2019; UN, 2017 (SDG 11).
	GHG emissions	> Total measured of GHS emissions in million tonnos of CO2 equivalent (MtCO2e)	Cook et al., 2017; Grafakos et al., 2019; ISO, 2018; Moghim and Garna, 2019.
	Land loss	> Proportion of land that is degraded over total land area; > Percentage of wetland loss.	Cai et al., 2018; MMF, 2018; UN, 2017 (SDG 15).
	Environmental risk	> Natural catastrophe exposure; > Number of natural catastrophes; > Number of deaths, missing persons and persons affected by disaster per 100,000 people; > Disaster frequency; > Fire-related, natural-hazard-events and industrial accidents.	Cai et al., 2018; ECA, 2009; Grafakos et al., 2019; ISO, 2018; Kourtit and Nijkamp, 2018; Moghim and Garna, 2019; UN, 2017 (SDG 11, 13).

Source: author (2019).

Annex 1.3 – Dependent variables and indicators (institutional dimension).

Dimension	Variables	Indicators	Source
Institutional	Hazard risk assessment and strategies	> Local strategies for specific hazards; > Hazard analysis and mapping, including emergency facilities and industrial uses; > Adoption and implementation of local disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction; > Number of evacuation routes and population training.	Fu and Wang, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 11, 13).
	Warning systems	> Real-time warning and reporting mechanism; > Multi-hazard emergency and alerts notification system; > High-risk communities with early warning system.	Cai et al., 2018; Elias-Trostman et al., 2018; Fu and Wang, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Consultative planning process	> Comunication system and mechanism; > Participation structure of civil society in urban planning and management that operate regularly and democratically; > Effective mechanisms for communities to engage with government.	Fu and Wang, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 11).
	Data collection	> Common monitoring procedure/framework; > Comprehensive city monitoring and data management.	Grafakos et al., 2019; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Geospatial information	> Volunteered geographic information; > Risk exposure mapping.	Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Data availability	> City open data portal, including budget, organisational structure, plans and projects of different policy sectors; > Adoption and implementation of constitutional, statutory and/or policy guarantees for public access to information; > Availability of basic information, such as population, housing census and birth registration.	MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 16, 17).
	Scenario-based planning	> Establishment or operationalization of an integrated policy, strategy or plan to adapt to the adverse impacts of climate change, and foster climate resilience and low greenhouse gas emissions development; > Local disaster risk reduction strategies; > Proportion of population living in cities that implement urban and regional development plans integrating population projections and resource needs, by size of city.	MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 1, 11, 13).
	Proactive multi-stakeholder collaboration	> Progress report in multi-stakeholder development to support the achievement of the sustainable development goals; > Proportion of population who believe decision-making is inclusive and responsive, by sex, age, disability and population group; > Participation of local communities in decision-making.	Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 6, 16, 17).
	Inter-organizational cooperation	> Existance of formal horizontal mechanisms/incentives between levels of governments; > Effectiveness of mechanisms to ensure co-ordination accross levels of government; > City networking at different levels (regional, national and transnational).	MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Commitment to climate action	> GHGs reduction emission targets; > Alignment with environmental agreements; > Proportion of sustainable development indicators produced at the city level, in accordance with the Fundamental Principles of Official Statistics; > Existance of sustainable consumption and production (SCP) action plans or mainstreaming SCP as a priority or a target into policies.	Cai et al., 2018; Grafakos et al., 2019; MMF, 2018; UN, 2017 (SDG 12, 17).
	Mainstreaming adaptation and mitigation measures	> Percentage of municipal budget for mitigation and adaptation measures; > Existance of integrated mitigation, adaptation, impact reduction and early warning plans.	Cai et al., 2018; Grafakos et al., 2019; UN, 2017 (SDG 13).
	Effective emergency response services	> Average response time of police and fire response from initial call; > Number of residents who have access to emergency numbers; > Number of residents registered in early warning system of total residents in risk areas.	Elias-Trostman et al, 2018; ISO, 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014.
	Incentives for social equality	> Whether or not legal frameworks are in place to promote, enforce and monitor equality and non-discrimination on the basis of sex; > Laws and regulations for women sexual and reproductive healthcare, information and education; > Proportion of people with disabilities and other minorities in public institutions; > Fair and equitable share of rights and benefits.	ISO, 2018; UN, 2017 (SDG 5, 15, 16).

Source: author (2019).

Annex 1.4 – Dependent variables and indicators (physical dimension).

Dimension	Variables	Indicators	Source
Physical	Mixed-use development	> Diversity measurement for land use types; > Diversity/heterogenity of land use mix.	Cai et al., 2018; Fu and Wang, 2018; Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018; UN-Habitat, 2014.
	Built area	> Ratio of impervious surface area over total area; > Percentage of built up land area as a share of total land area; > Density of the built environment.	Baussan, 2015; Cai et al., 2018; Cook et al., 2017; Fu and Wang, 2018; ISO, 2018.
	Medical services	> Number of hospital beds per 100,000 population; > Responsiveness, access and coverage of health systems; > Access to emergency medical care.	Cai et al., 2018; Fu an Wang, 2018; ISO, 2018; MMF, 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Population density	> Ratio of population over total urban area (inhabitants / square kilometer)	Fu and Wang, 2018; ISO, 2018; Kourtit and Nijkamp, 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2018.
	Open spaces	> Area of green and non-green, indoor and outdoor recreation space; > Distance to public space; > Connection of open spaces with public transportation; > Average share of the built-up area of cities that is open space for public use; > Number of cultural institutions and sporting facilities per 100,000 population.	Fu and Wang, 2018; ISO, 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2018; UN, 2017 (SDG 11).
	Accessibility to public transport	> Distance to public transits; > Proportion of population that has convenient access to public transport; > Diverse and affordable transport networks; > Kilometers of public transport system per 100,000 population; > Annual number of public transport trips per capita.	Fu and Wang, 2018; ISO, 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 11).
	Effective public transport	> Frequency of public transportation; > Ponctuality of public transportation; > Adequate maintenance.	Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Vehicle ownership	> Percentage of households with at least one vehicle; > Number of personal automobiles per capita.	Cai et al., 2018; ISO, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Occupancy of hazard prone areas	> Percentage of households in area which are subject to city's identified risks.	Elias-Trostman et al., 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2014.
	Spatial segregation	> Dissimilarity index, or spatial ordinal entropy index; > Degree of equal space distribution; > Distribution pattern of population and employment.	MMF, 2018; Sharifi and Yamagata, 2018.
	Safe housing	> Percentage of population living in dwelling conditions considered inadequate (e.g., leaking roof or damp walls, no bath or shower, or too dark); > Number of persons per dwelling unit; > Percentage of houses which have passed local building code inspections; > Quality of housing materials.	Cai et al., 2018; ISO, 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 11); UN-Habitat, 2014.
	Informal housing	> Percentage of households in informal housing areas; > Proportion of urban population living in slums, informal settlements; > Area size of informal settlements as a percentage of city area	Cai et al., 2018; Elias-Trostman et al., 2018; ISO, 2018; UN, 2017 (SDG 11).
	Access to water supply	> Percentage of households connected to the water supply system; > Proportion of population using safely managed drinking water services; > Average annual hours of water service interruptions.	Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; Moghim and Garna, 2019; Opitz-Stapleton et al., 2011; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 6); UN-Habitat, 2014.
	Access to energy supply	> Percentage of households connected to the electricity grid; > Affordability of energy supply; > Percentage of city population with autorized eletrical service (residential).	Elias-Trostman et al., 2018; ISO, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 7).
	Access to sanitation	> Percentage of households with access to sanitation systems; > Percentage of sewage treatment.	Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; Moghim and Garna, 2019; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 6).
	Access to solid waste collection	> Percentage of households served by municipal waste collection; > Proportion of urban solid waste regularly collected and with adequate final discharge out of total urban solid waste generated.	Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; UN, 2017 (SDG 11).
	Affordable housing	Percentage of population living in affordable housing	ISO, 2018; The Rockefeller Foundation and ARUP, 2014.
	Occupancy of households	> Total number of households; > Number of rental dwelling units as percentage of total; > Percentage of vacant households.	Baussan, 2015; ISO, 2018; Sharifi and Yamagata, 2014.
	Wastewater collection	> Percentage of households linked to wasted water collection and treatment network; > Percentage of informal settlements with storm water system coverage.	Elias-Trostman et al., 2018; ISO, 2018; Opitz-Stapleton et al., 2011; UN-Habitat, 2014.

Source: author (2019).

Annex 1.5 – Dependent variables and indicators (social dimension).

Dimension	Variables	Indicators	Source
Social	Widespread understanding of risks	> Local residents awareness and experience for facing risks; > Percentage of climate risks correctly identified by the residents; > Percentage of school children educated in disaster risk reduction; > Number of schools in high-risk area that have undertaken a resilience simulation; > Number of residents trained in emergency response and resilience.	Elias-Trostman et al., 2018; Fu and Wang, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Education level	> Completion rate of primary school; > Percentage of secondary education completion rate; > Percentage of educational attainment per level; > Number of higher education degrees/university students per 100,000 population.	Cai et al., 2018; Fu and Wang, 2018; ISO, 2018; MMF, 2018; Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 4); UN-Habitat, 2014.
	Demographic distribution	> Percentage of population per age group.	Cai et al., 2018; ISO, 2018; Sharifi and Yamagata, 2014; UN-Habitat, 2014.
	Life expectancy	> Average life expectancy age.	Baussan, 2015; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN-Habitat, 2014.
	Academic performance	> Number of academic researches publish in scientific journals and conferences; > Number of universities among top rankings; > Results in science olympics; > Number of winners of highly-reputed prize (e.g., nobel prize)	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 9).
	Foreign residents	> Percentage of population that is foreign born	Kourtit and Nijkamp, 2018; MMF, 2018; ISO, 2018.
	Medical capacity	> Number of physicians, doctors, nursing and midwifery personnel per 100,000 population.	Kourtit and Nijkamp, 2018; MMF, 2018; ISO, 2018.
	Migration	> Implementation of well-managed migration policies; > Percentage of population that are new immigrants.	Cai et al., 2018; ISO, 2018; UN, 2017 (SDG 10).
	Gender equality	> Proportion of women aged 15-49 years who make their own informed decisions regarding sexual relations, contraceptive use and reproductive health care; > Parity indexes; > Proportion of seats held by women in government and elected for the office; > Proportion of women in managerial positions.	Cai et al., 2018; UN, 2017 (SDG 4, 5); UN-Habitat, 2014.
	Mortality rate	maternal, neonatal, under-five; cardiovascular disease, cancer, diabetes, or chronic respiratory disease; suicide; unsafe water, unsafe sanitation and lack of hygiene	ISO, 2018; UN, 2017 (SDG 3).
	Protection capacity	> Number of firefighters and police-officers per 100,000 population.	Fu and Wang, 2018; ISO, 2018.

Source: author (2019).

Annex 1.6 – Independent variables and indicators (economic dimension).

Dimension	Variables	Indicators	Source
Economic	Savings	> Saving value in bank; > Personal wealth; > Percentage of population with emergency savings.	Baussan, 2015; Elias-Trostman et al., 2018; Fu and Wang, 2018; Sharifi and Yamagata, 2014.
	Single sector dependancy	> Percentage of population not employed in farming, fishing, forestry, and extractive industries; > Herfindahl Index of firm concentration.	Baussan, 2015; Cai et al., 2018; Fu and Wang, 2018; MMF, 2018.
	Economic freedom	> Own-source revenue as a percentage of total revenues; > Level of economic self-sufficiency.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Tourist attraction	> Tourism direct GDP as a proportion of total GDP and in growth rate; > Annual number of visitor stays (overnight) per 100,000 population.	ISO, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 8).
	Business size	> Number of top companies; > Attractiveness to companies; > Number of business per 100,000 population.	Cai et al., 2018; ISO,2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	GDP	> Nominal value of GDP.	Kourtit and Nijkamp, 2018; MMF, 2018; Opitz-Stapleton et al., 2011.
	GDP per capita	> GDP per inhabitant.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 8, 10).
	GDP growth rate	> Annual variation of GDP.	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 8).
	Total maket value	> Market capitalization of listed shares on stock exchanges.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Service industry	> Number of employees in service industry for business enterprises.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Wage level	> Wage by sex, age, occupation; > Percentage of jobs paying in accordance with city/national living wage.	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 8).
	Ease to secure human resources	> Recruitment cost borne by employee as a proportion of yearly income earned in country of destination; > Availability of skilled human resources.	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 10).
	Corporate tax rate	> Average tax rate in loans given to companies.	Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Environment of creative activities	> Number of startups; > Local business development and innovation.	Cai et al., 2018; Kourtit and Nijkamp, 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014.
	Environment of cultural activities	> Number of world heritage sites (within 100km area); > Number of theaters and concert halls; > Number of museums; > Number of stadiums.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Environment of hotel sector	> Number of hotels; > Number of guest rooms of luxury hotels.	Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Environment of commercial sector	> Variety of shopping options; > Variety of dinning options.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Working hours	> Average number of working hours per employee.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Economic risk of natural disaster	> Insured loss and compensation systems of disaster events; > Financial flexibility and stability to disaster losses.	ECA, 2009; MMF, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 11).
	Inclusive labor policies	> Labour share of GDP; > Job diversity of citizens; > Variety of workplace options; > Proportion of informal employment in non-agriculture employment, by sex; > Proportion and number of children aged 5-17 years engaged in child labour, by sex and age.	ISO, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 8, 10).
	Integration with regional economies	> Percentage of GDP generated by regional trading	Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Disaster economic loss	> Direct disaster economic loss in relation to global GDP, including disaster damage to critical infrastructure and disruption of basic services.	Sharifi and Yamagata, 2014; UN, 2017 (SDG 11); UN-Habitat, 2014.
	Material consuption and footprint	> Material footprint per capita and as a percentage of GDP; > Domestic material consumption per capita and as a percentage of GDP.	UN, 2017 (SDG 8, 12).
	Financial support	> Total resource flows for development, by recipient and donor countries and type of flow (e.g. official development assistance, foreign direct investment and other flows); > Foreign Direct Investments (FDI) and official development assistance as a percentage of total domestic budget.	Sharifi and Yamagata, 2014; UN, 2017 (SDG 10, 17).
	Livelihood options	> Average number of residents who indicated likelihood of alternative livelihoods; > Diverse economic protection of livelihoods following a shock.	Elias-Trostman et al., 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.

Source: author (2019).

Annex 1.7 – Independent variables and indicators (environmental dimension).

Dimension	Variables	Indicators	Source
Environmental	Elevation	> Average elevations in the area (meters above sea level).	Fu and Wang, 2018; Sharifi and Yamagata, 2014.
	Proximity to water	> Distance from rivers and other water bodies.	Fu and Wang, 2018; Sharifi and Yamagata, 2014.
	Stewardships of ecosystems	> Monetary measurement for ecosystem service value; > Proportion of national exclusive economic zones managed using ecosystem-based approaches in relation to the total of economic zones.	Fu and Wang, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 14).
	CO emissions	> Total amount of carbon monoxide emissions.	Cook et al., 2017; Fu and Wang, 2018; Moghim and Garna, 2019.
	Erosion rates	> Soil erosion by water and air (tonnes per hectare per year).	Cai et al., 2018; Cook et al., 2017; Sharifi and Yamagata, 2014.
	Temperature	> Average annual temperature (oC); > NHT28; > UDD18; > UDD25.	Grafakos et al., 2019; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Opitz-Stapleton et al, 2011; Trower et al., 2012.
	Business sustainability	> Number of companies with ISO14001 certifcation; > Number of companies publishing sustainability reports; > Proportion of agricultural area under productive sustainable agriculture.	Kourtit and Nijkamp, 2018; UN, 2017 (SDG 2, 12).
	SOx emissions	> Total measured in thousands of tonnes of SOx (sulphate oxides).	Cook et al., 2017; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Moghim and Garna, 2019.
	NOx emissions	> Total measured in thousands of tonnes of NOx (nitrogen oxides).	Cook et al., 2017; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Moghim and Garna, 2019.
	Carbon intensity of economic activity	> Total GHGs emissions (tCO2e) per unit of national GDP.	Cook et al., 2017; ISO, 2018.
	Sustainability of fish stocks	> Average ratio of aggregated stock landings to abundance measured by scientific stock assessments; > Proportion of fish stocks within biologically sustainable levels.	Cook et al., 2017; UN, 2017 (SDG 14).
	Natural protection	> Total land and marine protected areas (km2); mangroves; > Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type; > Conservation of ecologically vulnerable areas.	Cook et al., 2017; Grafakos et al., 2019; ISO, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 14, 15); UN-Habitat, 2014.
	Hazardous waste	> Total volume of hazardous waste in thousand tonnes; > Hazardous waste generated per capita; > Proportion of hazardous waste treated, by type of treatment.	Cook et al., 2017; ISO, 2018; UN, 2017 (SDG 12).
	Precipitation	> Average annual precipitations (mm).	Grafakos et al., 2019; Opitz-Stapleton et al, 2011.
	Wastewater treatment	> Percentage of population connected to urban wastewater receiving at least secondary treatment.	Cook et al., 2017; ISO, 2018; UN, 2017 (SDG 6); UN-Habitat, 2014.

Source: author (2019).

Annex 1.8 – Independent variables and indicators (institutional dimension).

Dimension	Variables	Indicators	Source
Institutional	Incentives to innovation	> Amount of support on research and development for sustainable consumption and production and environmentally sound technologies; > Number of science and/or technology cooperation agreements and programmes, by type of cooperation.	Sharifi and Yamagata, 2014; UN, 2017 (SDG 12, 17).
	Safety	> Survaillance cameras and biometric borders; > Effective systems to deter crime; > Proportion of population that feel safe walking alone around the area they live.	Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 16).
	Land use efficiency and zoning regulations	> Intensity of development in hazard prone areas; > Appropriate zoning and building codes, standards and enforcement; > Control over development type - planned and unplanned, formal and informal; > Land-use plans that have been developed with reference to local hazard risk assessment and that have been subjected to a formal consultation process.	Fu and Wang, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Political and economic stability	> Level of trust in the government; > Political fragmentation; > Strenght of leadership; > Government flexibility, accountability and autonomy; > Level of economic and business risk; > Interorganizational and interagency trust level.	Cai et al., 2018; Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Political engagement	> Number of registered voters as a percentage of the voting age population; > Voter participation in last municipal election > Proportion of members and voting rights in international organizations.	Cai et al., 2018; Fu and Wang, 2018; ISO, 2018; UN, 2017 (SDG 10, 16).
	Capacity-development of citizens	> Extent to which topics such as sustainable development, gender equality and human rights are included in educational policies, curricula, teacher qualification and student assessment; > Strength of institutional, systemic and individual capacity-building to implement adaptation, mitigation and technology transfer, and development actions; > Climate change-related planning and management, including focusing on women, youth and local and marginalized communities.	MMF, 2018; UN, 2017 (SDG 4, 12, 13).
	Municipal investment towards SDGs	> Percentage of municipal budget for sustainable development actions; > Mobilized amount of United States dollars per year starting in 2020 accountable towards the $100 billion commitment.	MMF, 2018; UN, 2017 (SDG 13).
	Municipal investment on basic services	> Percentage of municipal budget for emergency services, fire and police; > Spending on essencial services (health, education and social protection); > Adequate maintanence of critical assets and services.	Cai et al., 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 1, 13, 16).
	Investment in resilience proofing	> Percentage of residents who indicated willingness to invest in resilience-proofing strategies; > Proportion of financial support allocated to the construction and retrofitting of sustainable, resilient and resource-efficient buildings utilizing local materials.	Elias-Trostman et al., 2018; UN, 2017 (SDG 11).
	Supportive finance mechanisms	> Total expenditure (public and private) per capita spent on the preservation, protection and conservation of all cultural and natural heritage; > Total amount of approved funding for promoting the development, transfer, dissemination and diffusion of environmentally sound technologies.	The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 7, 11, 17).
	Proactive corruption prevention	> Proportion of persons/business who had at least one contact with a public official and who paid a bribe to a public official, or were asked for a bribe by those public officials, during the previous 12 months; > Total value of inward and outward illicit financial flows (in current United States dollars); > Number of convictions for corruption and/or bribery by city officials per 100,000 population.	ISO, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 16).
	Effectively managed protective ecosystems	> Proportion of population covered by social protection floors; > Existance of a legal framework (including customary law) that guarantees the right to land ownership and/or control; > Official development assistance and public expenditure on conservation and sustainable use of biodiversity and ecosystems.	The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 1, 5, 15).
	Frameworks to sustainable development	> Management of oceans, forests and fisheries; > Sustainable public procurement policies and actions plans; > Investment in sustainable energy; > Integrated water resources management.	UN, 2017 (SDG 6, 7, 12, 14, 15, 17)
	Land and property acquision	> Secure tenure rights to land; > Percentage of households that exist without registered legal titles; > Housing capital as percentage of homeownership.	Cai et al., 2018; ISO, 2018; Sharifi and Yamagata, 2014; UN, 2017 (SDG 1).
	Evacuation and emergency drills	> Number of evacuation routes and population training; > Percentage of hospitals that have carried out disaster preparedness drills in the last year; > Percentage of population that has received training on first-aid and emergency response skills in past two years.	Fu and Wang, 2018; MMF, 2018; Sharifi and Yamagata, 2014.

Source: author (2019).

Annex 1.9 – Independent variables and indicators (physical dimension).

Dimension	Variables	Indicators	Source
	Shelter capacity	> Number of safe shelters per expected public demand; > Hotels/motels per 10,000 persons; > Provision of open space for sheltering; > Percentage of population that could be served by city's access to stock of emergency shelter for 72 hours.	Cai et al., 2018; Fu and Wang, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Street network connectivity	> Ratio of the number of crossings over the lenght of roads; > Typology of transportation network.	Fu and Wang, 2018; Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018.
	Sidewalk connectivity	> Ratio of sidewalk lenght over total area; > Pedestrian route connectivity.	Fu and Wang, 2018; Sharifi and Yamagata, 2014.
	Evacuation routes	> Number of officialy designated evacuation routes in high-risk area.	Cai et al., 2018; Elias-Trostman et al., 2018; Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018.
	Infrastructure independency	> Robustness, redendancy and protectiveness of infrastructure.	Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Urban form	> Degree of clustering and compacteness; > Disperson from the center; > Number of centralities (monocentric, policentric).	Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018.
	Building configuration	> Density of built area; > Spacing between buildings; > Dimensions and compacteness of building layout.	Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018.
	Urban size	City area (km2)	Opitz-Stapleton et al., 2011; Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018.
	Spatial heterogeinity	> Design and layout of streets; > Priorization of non-motorized modes (cycling and walking).	Sharifi and Yamagata, 2014; Sharifi and Yamagata, 2018.
	Flood coverage	> Area of city exposed to flood; > Use of water efficient landscape techniques; > Existance of storm water drainage systems; > Avoidance of flood plains.	Cai et al., 2018; Sharifi and Yamagata, 2014; UN-Habitat, 2014.
	Access to airports	> Number of passengers on international flights; > Number of internationalfreighter flights; > Number of runways in the airport; > Travel-time to inner-city and international airports.	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 9).
Physical	Commuting conveniance	> Average hours spent on traffic congestions; > Kilometers of traffic.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018.
	Transportation fatalities	> Transportation deaths per 100,000 population; > Death rate due to traffic road injuries.	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 3).
	Taxi fare	> Fare per kilometer.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Communication capacity	> Number of telephone connections (landlines and cell phones) per 100,000 population; > Percentage of population covered by a mobile network; > Percentage of population who own a phone or cellphone.	Cai et al., 2018; Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; UN, 2017 (SDG 5, 9).
	Access to internet	> Number of internet connections per 100,000 population; > Percentage of population with access to broadband internet service; > Number of residents with internet access.	Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; UN, 2017 (SDG 17).
	Sufficient food supply	> Affordable supply of food; > Food reserves wper capita within a city (including supermarket agreements) for 72 hours; > Percentage of population which could be served by the current food production; > Amount of food in urban area; > Prevalance of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale (FIES); > Food loss index	ISO, 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 2, 12).
	Adequate supply of energy	> Average number of eletrical interruptions per customer per year or per household; > Flexibility of the grid.	ISO, 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Information and communication technology (ICT) readiness	> Access to reliable information and communication technologies (ICT); > Security of ICT networks; > Proportion of youth and adults with ICT skills,.	MMF, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 4)
	Access to emergency services	> Percentage of households within 500m distance of school, police station, or civil defense unit	Elias-Trostman et al., 2018; ISO, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 1).
	Access to health services	> Percentage of households within 500m of a hospital or healthcare centre / access to basic services	Cai et al., 2018; Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; The Rockefeller Foundation and ARUP, 2014; UN, 2017 (SDG 1, 3).

Source: author (2019).

Annex 1.10 – Independent variables and indicators (social dimension).

Dimension	Variables	Indicators	Source
Social	Adaptive strategy	> Proactive strategies and plans for adaptation during disaster; > Posession of backup copies of documents; > Number of resilience habits practiced; > Number of resilience kits items correctly identified.	Fu and Wang, 2018; Elias-Trostman et al., 2018; The Rockefeller Foundation and ARUP, 2014.
	Place attachment	> Percentage of population born in a state that still resides in that state; > Number of residents who indicated they intend to live in the neighborhood for the next five years; > Strong city-wide culture and identity.	Cai et al., 2018; Elias-Trostman et al., 2018; Fu and Wang, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Religious bonds	> Number of religious adherents per 10,000 population.	Cai et al., 2018; Fu and Wang, 2018; Sharifi and Yamagata, 2014.
	Social engagement	> Number of social, civic or faith-based advocacy organizations per 10,000 population.	Cai et al., 2018; Fu and Wang, 2018; MMF, 2018.
	Public engagement	> Number of engagements with political activity in the last 6 months (community meeting, protest, or public hearing).	Elias-Trostman et al, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Cultural diversity	> Opportunies of cultural, historical and traditional interaction.	Kourtit and Nijkamp, 2018; MMF, 2018; Sharifi and Yamagata, 2014.
	Social cohesion	> Percentage of neighbourhood with regular association meetings; > Number of residents who indicated they feel part of their neighborhood community; > Percentage of people that say they can count on social/community network support; > Number of regular meetups with informal groups for leisure, hobbies, civic engagement per month.	Cai et al., 2018; Elias-Trostman et al., 2018; MMF, 2018; Sharifi and Yamagata, 2014; The Rockefeller Foundation and ARUP, 2014.
	Self-organization	> Number of neighbors known by first name; > Number of neighbors' phone numbers saved; > Number of irregular meetups in the neighborhoods (meet friends, church engagements, relax, shop) per month.	Elias-Trostman et al., 2018; Sharifi and Yamagata, 2014.
	Language proficiency	> Percentage of population with language competency (or proficiency).	Cai et al., 2018; MMF, 2018; Sharifi and Yamagata, 2014; UN-Habitat, 2014.
	Innovation	> Research and development expenditure as percentage of GDP; > Number of registered property rights (patents).	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 9).
	Events held	> Number of international conferences; > Number of cultural events per 100,000 population (e.g., exihibitions, festivals, concerts).	ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018.
	Travel experiences	> Number of visitors abroad.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Educational openess	> Number of international students.	Kourtit and Nijkamp, 2018; MMF, 2018.
	Work satisfaction	> Level of satisfaction of employees with their lives.	Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 3).
	Ethinical diversity	> Number of different races/ethinical groups on the population.	Baussan, 2015; Cai et al., 2018.
	Crime	> Incidents of violent crimes per 100,000 residents; > Crimes agains property per 100,000 population; > Proportion of population subjected to physical, psychological or sexual violence in the previous 12 months; > Proportion of population victim of physical or sexual harassment.	Cai et al., 2018; Elias-Trostman et al., 2018; ISO, 2018; Kourtit and Nijkamp, 2018; MMF, 2018; UN, 2017 (SDG 11, 16).
	Violence against women	> Number of violent crimes agains women per 100,000 population; > Proportion of ever-partnered women and girls aged 15 years and older subjected to physical, sexual or psychological violence in the previous 12 months.	ISO, 2018; UN, 2017 (SDG 5).
	Homelessness	> Number of homeless people per 100,000 population	ISO, 2018; MMF, 2018.
	Community preparedness	> Community resilience task force established in neighborhood (NUDECs); > Percentage of neighbourhoods with emergency groups.	Elias-Trostman et al., 2018; MMF, 2018.
	Level of development	> Human Development Index (HDI) for neighborhood; > GINI Index	Elias-Trostman et al., 2018; ISO, 2018; MMF, 2018; UN-Habitat, 2014.
	Prevalance of undernourshiment	> Prevalance of malnutrition among children under 5 years of age by type (wasting and overweight); > Percentage of city population undernourished.	ISO, 2018; UN, 2017 (SDG 2).

Source: author (2019).

Annex 2: Missing data information

Annex 2.1 – Number of non-existing and null values for each indicator.

Indicator	Description	Number of 'NAN'	Percentage of total (%)	Meaning of '0'values	Number of '0'	Percentage of total (%)
AREA	Area of the urban center (km2)	-	-	There is no urban center (**not possible**)	-	-
EL_AV_ALS	Elevation (meters above sea level)	4	0,03%	Same level as the sea	-	-
E_WR_P_14	Average annual precipitation (mm)	15	0,11%	No precipitation (**not possible**)	6	0,05%
E_WR_T_14	Average annual temperature (oC)	15	0,11%	Average temperature equal to 0oC	-	-
B15	Built area (km2)	-	-	No built area or, even, no urbanization (**not possible**)	8	0,06%
P15	Population (number of inhabitants)	-	-	No inhabitant (**not possible**)	-	-
BUCAP15	Built area per capita (km2 / inhabitant)	-	-	Area divided by population tend to zero (**not possible**)	8	0,06%
GDP15_SM	GDP PPP (USD 2007)	-	-	No generation of GDP PPP (**not possible**)	317	2,41%
INCM_CMI	Level of income (nominal)	-	-	Not classified on the income levels	-	-
DEV_CMI	Level of development (nominal)	-	-	Not classified on the development levels	-	-
E_GR_AT14	Total greeness (km2)	-	-	Non-existing green areas	1	0,01%
E_EC2E_E12	Non-short cycle CO2 emissions from the energy sector	9617	73,22%	No emissions of CO2	-	-
E_EC2E_R12	Non-short cycle CO2 emissions from the residential sector	5	0,04%	No emissions of CO2	-	-
E_EC2E_I12	Non-short cycle CO2 emissions from the industry sector	3	0,02%	No emissions of CO2	-	-
E_EC2E_T12	Non-short cycle CO2 emissions from the transport sector	327	2,49%	No emissions of CO2	-	-

Indicator	Description	Number of 'NAN'	Percentage of total (%)	Meaning of '0'values	Number of '0'	Percentage of total (%)
E_EC2E_A12	Non-short cycle CO2 emissions from the agriculture sector	725	5,52%	No emissions of CO2	-	-
E_EC2O_E12	Short cycle CO2 emissions from the energy sector	11312	86,12%	No emissions of CO2	-	-
E_EC2O_R12	Short cycle CO2 emissions from the residential sector	71	0,54%	No emissions of CO2	-	-
E_EC2O_I12	Short cycle CO2 emissions from the industry sector	6597	50,22%	No emissions of CO2	-	-
E_EC2O_T12	Short cycle CO2 emissions from the transport sector	6067	46,19%	No emissions of CO2	-	-
E_EC2O_A12	Short cycle CO2 emissions from the agriculture sector	837	6,37%	No emissions of CO2	-	-
E_EPM2_E12	PM2.5 emissions from the energy sector	9599	73,08%	No emissions of PM2.5	-	-
E_EPM2_R12	PM2.5 emissions from the residential sector	3	0,02%	No emissions of PM2.5	-	-
E_EPM2_I12	PM2.5 emissions from the industry sector	4014	30,56%	No emissions of PM2.5	-	-
E_EPM2_T12	PM2.5 emissions from the transport sector	327	2,49%	No emissions of PM2.5	-	-
E_EPM2_A12	PM2.5 emissions from the agriculture sector	5	0,04%	No emissions of PM2.5	-	-
EX_FD_AREA	Total area exposed to flood (km2)	-	-	No area is exposed to flooding	9176	69,86%
SDG_LUE9015*	Land consumption per population growth (1990-2015)	251	1,91%	No increase on land consumption	-	-
SDG_OS15MX	Open spaces	4212	32,07%	None open space	-	-
LEGEND: *in this case 'INF' values were also considered as missing information						

Source: author (2019).

Annex 3: Normalization methods

Annex 2.1 – Examples of normalization methods available.

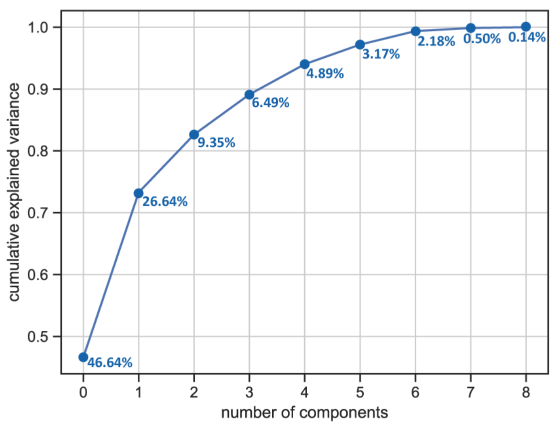
Method	Equation	Description
Z-Scores	$I_{q,c} = (x_{q,c} - \overline{x}_q) / \sigma_q$	Transforms the indicators in a range with standard deviation of one and mean of zero. In this case, extreme measurement have a higher influence on the composite index.
Min-Max	$I_{q,c} = (x_{q,c} - x_{q,min}) / (x_{q,max} - x_{q,min})$	Indicators are transformed to a range between 0 and 1. Extreme values can also distort the composite index, since it widens the range of indicators in a small interval.
Distance to a reference	$I_{q,c} = x_{q,c} / x_{q,ref}$	Measurement of how disperse an indicator is from a reference value, which depends on benchmarks to be determined or be set to the higher value. In the last case, unreliable outliers could provide a wrong comparison of the data.
Above or below the mean	$I_{q,c} = \begin{cases} 1 \text{ if } w > (1+p) \\ 0 \text{ if } (1-p) \leq w \leq (1+p) \\ -1 \text{ if } w < (1-p) \end{cases}$ where $w = x_{q,c} / \overline{x}_q$	This method is not affected by outliers, but the definition of an arbitrary threshold is questionable.

Observation: $\mathbf{I_{q,c}}$ – normalized value for the indicator *q* for urban area *c*; $\mathbf{x_{q,c}}$ – value for the indicator *q* for urban area *c*; $\mathbf{x_{q,max}}$ – maximum value for the indicator *q* for urban area *c*; $\mathbf{x_{q,min}}$ – minimum value for the indicator *q* for urban area *c*; $\overline{x}_q$ – average value for the indicator *q*; σ_q – standard deviation for the indicator *q*; $x_{q,ref}$ – reference value for the indicator *q*; p – arbitrary threshold around the average.

Source: adapted from Nardo et al. (2008).

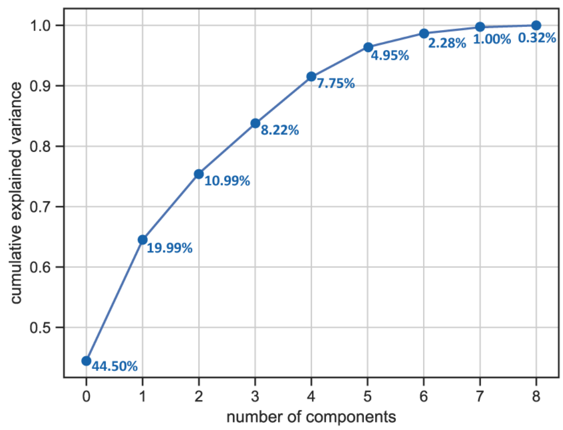
Annex 4: Weighting and aggregation details

Annex 3.1 – Explained cumulative variance of each principal component (partial dataset).



Source: author (2019).

Annex 3.2 – Explained cumulative variance of each principal component (full dataset).



Source: author (2019).

Annex 3.3 – Coefficients of each indicator per principal component (partial dataset).

	GDP_mm	GDPpc_mm	TotalCO2_mm	TotalPM25_mm	Totalgreen_mm	Greenpc_mm	Builtarea_mm	PDENS_mm	Openspace_mm
0	0,051666	0,642865	0,041139	0,000557	0,100198	0,426541	0,093961	-0,282680	-0,549227
1	-0,057353	0,357371	-0,053620	-0,057855	-0,074557	0,429053	-0,057597	-0,162366	0,802153
2	0,367993	0,171545	0,336701	0,264605	0,585842	-0,180865	0,446056	0,179788	0,211088
3	-0,063768	0,639026	-0,101994	-0,091758	-0,226610	-0,491743	-0,175289	0,494119	0,026698
4	-0,034314	-0,134602	-0,019823	0,030338	0,022059	0,594363	0,018810	0,784741	-0,097291
5	0,008907	0,033121	0,055407	0,914076	-0,161126	0,027067	-0,363555	-0,036036	-0,007340
6	0,625397	-0,037965	0,576111	-0,213142	-0,400669	0,070938	-0,253855	0,006334	-0,007363
7	0,627581	-0,022025	-0,659221	-0,045789	0,261949	0,020264	-0,316077	-0,006755	-0,003239
8	0,261382	-0,009352	-0,318941	0,185029	-0,578133	0,003219	0,679183	-0,007011	0,006771
∑ 0 to 4	0,264225	1,676205	0,202402	0,145887	0,406931	0,777348	0,325942	1,013603	0,393421

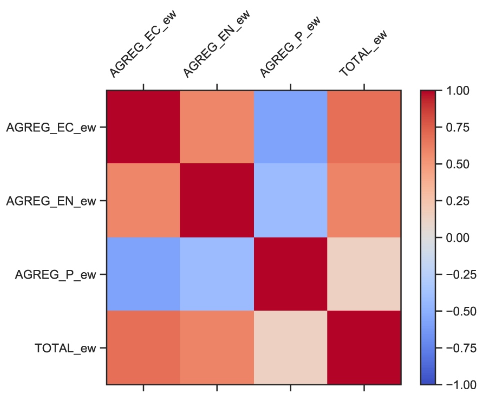
Source: author (2019).

Annex 3.4 – Coefficients of each indicator per principal component (full dataset).

	GDP_mm	GDPpc_mm	TotalCO2_mm	TotalPM25_mm	Totalgreen_mm	Greenpc_mm	Builtarea_mm	PDENS_mm	Openspace_mm
0	0,017147	0,114363	0,009403	0,004580	0,030593	0,170383	0,031480	-0,041620	-0,976641
1	0,011986	0,291560	0,002629	-0,002764	0,046694	0,887819	0,038311	-0,285143	0,204100
2	0,094141	0,871928	0,037691	0,018966	0,085209	-0,172607	0,079370	0,426624	0,061140
3	0,401712	-0,060638	0,256530	0,157492	0,619644	-0,134539	0,516902	-0,272659	0,027380
4	0,083111	-0,369683	0,063424	0,037437	0,179170	0,365259	0,158194	0,812687	-0,001243
5	0,264399	-0,007164	0,583651	0,630945	-0,296819	0,031628	-0,319567	0,008513	-0,002062
6	0,816130	-0,034647	-0,080120	-0,451943	-0,346629	0,020245	-0,038582	0,002678	-0,001303
7	0,250921	-0,006032	-0,407229	0,177398	0,529986	0,005163	-0,677279	0,007870	-0,004053
8	-0,153243	0,005033	0,644787	-0,582745	0,290560	-0,001270	-0,369743	0,002967	-0,001790
∑ 0 to 4	0,608097	0,847529	0,369677	0,215710	0,961309	1,116315	0,824257	0,639889	-0,685264

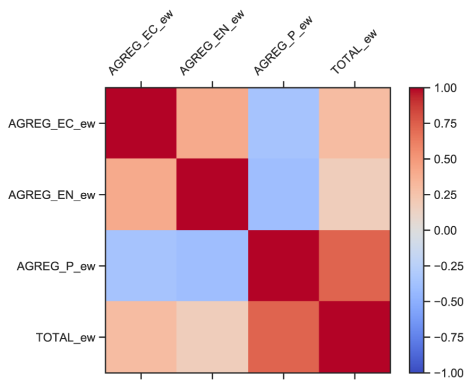
Source: author (2019).

Annex 3.5 – Correlation of aggregated indicators with equal weighting (partial dataset).



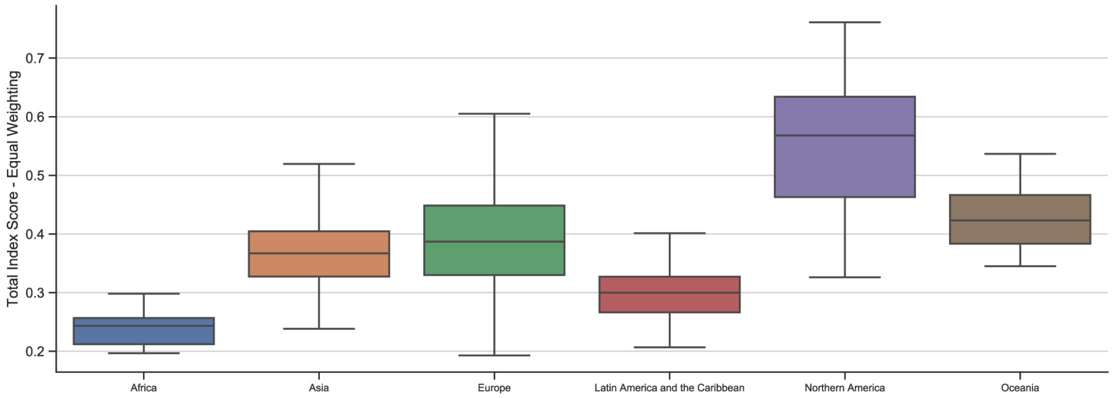
Source: author (2019).

Annex 3.6 – Correlation of aggregated indicators with equal weighting (full dataset).



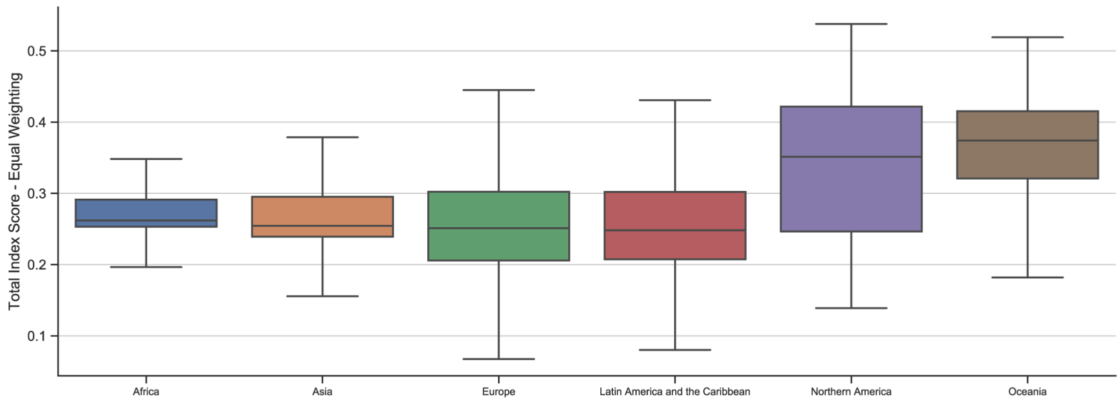
Source: author (2019).

Annex 3.7 – Final range of scores for the equal weighting method (partial dataset).



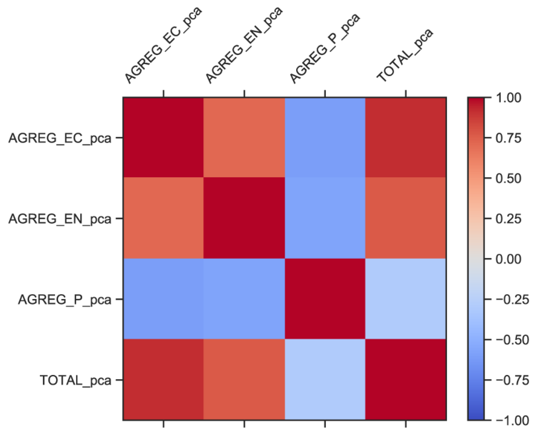
Source: author (2019).

Annex 3.8 – Final range of scores for the equal weighting (full dataset).



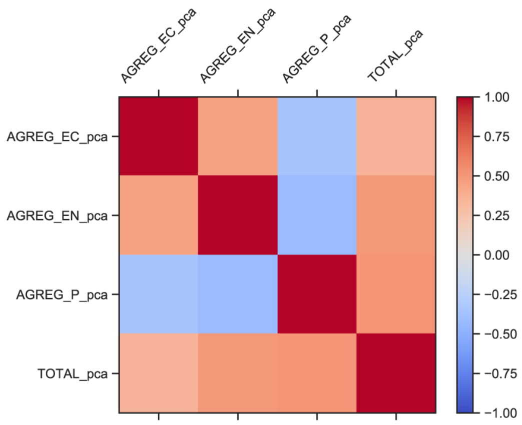
Source: author (2019).

Annex 3.9 – Correlation of aggregated indicators with principal component analysis (partial dataset).



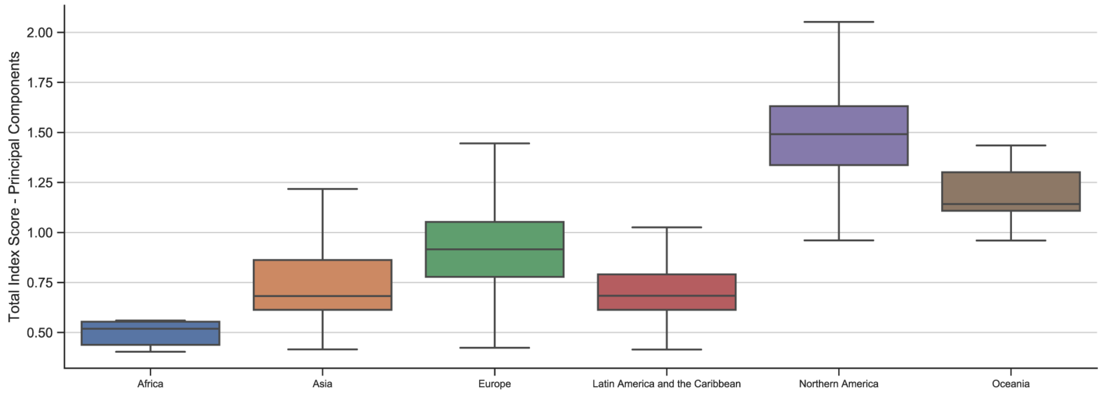
Source: author (2019).

Annex 3.10 – Correlation of aggregated indicators with principal component analysis (full dataset).



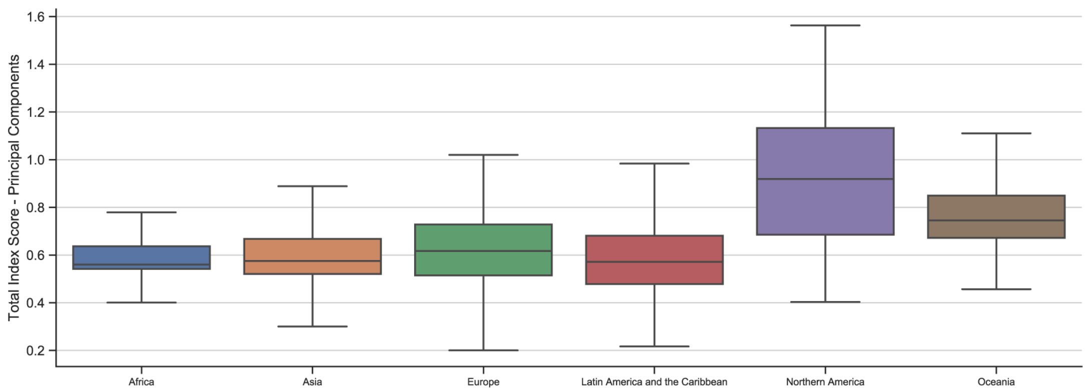
Source: author (2019).

Annex 3.11 – Final range of scores for the principal component analysis (partial dataset).



Source: author (2019).

Annex 3.12 – Final range of scores for the principal component analysis (full dataset).



Source: author (2019).

Annex 4: Regression analysis results

Annex 4.1 – Regression analysis – Income level.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.863
Model:                             OLS   Adj. R-squared:                  0.863
Method:                  Least Squares   F-statistic:                 8.240e+04
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:05:32   Log-Likelihood:                 1521.7
No. Observations:                13135   AIC:                            -3041.
Df Residuals:                    13134   BIC:                            -3034.
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Income_mm      0.8566      0.003    287.050      0.000       0.851       0.862
==============================================================================
Omnibus:                        67.036   Durbin-Watson:                   0.573
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               68.100
Skew:                           -0.171   Prob(JB):                     1.63e-15
Kurtosis:                        3.090   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

Annex 4.2 – Regression analysis – Elevation.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.328
Model:                             OLS   Adj. R-squared:                  0.328
Method:                  Least Squares   F-statistic:                     6407.
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:07:04   Log-Likelihood:                -8900.6
No. Observations:                13135   AIC:                         1.780e+04
Df Residuals:                    13134   BIC:                         1.781e+04
Df Model:                            1
Covariance Type:             nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Elevation_mm     2.0077      0.025     80.042      0.000       1.959       2.057
==============================================================================
Omnibus:                      2832.478   Durbin-Watson:                   0.551
Prob(Omnibus):                   0.000   Jarque-Bera (JB):             6746.180
Skew:                           -1.205   Prob(JB):                         0.00
Kurtosis:                        5.553   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

Annex 4.3 – Regression analysis – Precipitation.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.732
Model:                             OLS   Adj. R-squared:                  0.732
Method:                  Least Squares   F-statistic:                 3.589e+04
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:09:32   Log-Likelihood:                -2859.4
No. Observations:                13135   AIC:                             5721.
Df Residuals:                    13134   BIC:                             5728.
Df Model:                            1
Covariance Type:             nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Precipitation_mm     2.4151      0.013    189.455      0.000       2.390       2.440
==============================================================================
Omnibus:                     1076.013   Durbin-Watson:                   1.211
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3175.804
Skew:                          -0.437   Prob(JB):                         0.00
Kurtosis:                       5.245   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

Annex 4.4 – Regression analysis – Temperature.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.897
Model:                             OLS   Adj. R-squared:                  0.897
Method:                  Least Squares   F-statistic:                 1.140e+05
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:09:54   Log-Likelihood:                 3397.9
No. Observations:                13135   AIC:                            -6794.
Df Residuals:                    13134   BIC:                            -6786.
Df Model:                            1
Covariance Type:             nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Temperature_mm      0.7147      0.002    337.618      0.000       0.711       0.719
==============================================================================
Omnibus:                     2921.667   Durbin-Watson:                   0.658
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7651.293
Skew:                           1.202   Prob(JB):                         0.00
Kurtosis:                       5.864   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

Annex 4.5 – Regression analysis –Land use efficiency.

```
|                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.940
Model:                             OLS   Adj. R-squared:                  0.940
Method:                  Least Squares   F-statistic:                 2.040e+05
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:10:26   Log-Likelihood:                 6913.8
No. Observations:                13135   AIC:                        -1.383e+04
Df Residuals:                    13134   BIC:                        -1.382e+04
Df Model:                            1
Covariance Type:             nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Landuseef_mm     0.8144      0.002    451.657      0.000       0.811       0.818
==============================================================================
Omnibus:                     3895.794   Durbin-Watson:                   0.864
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            21692.114
Skew:                           1.313   Prob(JB):                         0.00
Kurtosis:                       8.722   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

Annex 4.6 – Regression analysis – Population density.

```
|                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.243
Model:                             OLS   Adj. R-squared:                  0.243
Method:                  Least Squares   F-statistic:                     4214.
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:13:00   Log-Likelihood:                -9682.4
No. Observations:                13135   AIC:                         1.937e+04
Df Residuals:                    13134   BIC:                         1.937e+04
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
PDENS_mm       5.0555      0.078     64.912      0.000       4.903       5.208
==============================================================================
Omnibus:                    11820.009   Durbin-Watson:                   0.494
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1069360.859
Skew:                          -3.963   Prob(JB):                         0.00
Kurtosis:                      46.487   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

Annex 4.1 – Regression analysis – Development level.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            TOTAL_pca_nd   R-squared:                       0.746
Model:                             OLS   Adj. R-squared:                  0.746
Method:                  Least Squares   F-statistic:                 3.860e+04
Date:                 Fri, 30 Aug 2019   Prob (F-statistic):               0.00
Time:                         23:15:12   Log-Likelihood:                -2506.2
No. Observations:                13135   AIC:                             5014.
Df Residuals:                    13134   BIC:                             5022.
Df Model:                            1
Covariance Type:             nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Development_mm     0.9212      0.005    196.472      0.000       0.912       0.930
==============================================================================
Omnibus:                      116.156   Durbin-Watson:                   0.554
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              176.879
Skew:                           0.074   Prob(JB):                     3.90e-39
Kurtosis:                       3.549   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Source: author (2019).

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