Planning for Urban Ecosystem Services:

Generating Actionable Knowledge for Reducing Environmental Inequities

in Santiago de Chile

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved November 2017 by the
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ARIZONA STATE UNIVERSITY

December 2017

ABSTRACT

Cities are hubs for economic and social development, but they are increasingly becoming hotspots of environmental problems and socio-economic inequalities. Because cities result from complex interactions among ecological, social, and economic factors, environmental problems and socio-economic inequalities are often spatially interconnected, generating emergent environmental inequity issues due to the unfair distribution of environmental quality among socioeconomic groups. Since urban environmental quality is tightly related to the capacity of urban landscapes to provide ecosystem services, optimizing the allocation of ecosystem services within cities is a main goal for moving towards more equitable and sustainable cities. Nevertheless, we often lack the empirical data and specific methods for planning urban landscapes to optimize the provision of ecosystem services. Therefore, the development of knowledge and methods to optimize the provision of ecosystem services is essential for tackling urban environmental problems, reducing environmental inequities, and promoting sustainable cities. The main goal of this dissertation is to generate actionable knowledge for helping decision-makers to optimize the allocation of urban vegetation for reducing environmental inequities through the provision of ecosystem services. The research uses the city of Santiago de Chile as a case study from a Latin-American city. To achieve this goal, I framed my dissertation in four linked research chapters, each of them providing methodological approaches to help link environmental inequity problems with the development of urban planning interventions promoting an equitable provision of urban ecosystem services. These chapters are specifically aimed at providing actionable

knowledge for: (1) Identifying the level, distribution, and spatial scales at which environmental inequities are more relevant; (2) Identifying the areas and administrative units where environmental inequities interventions should be prioritized; (3) Identifying optimal areas to allocate vegetation for increasing the provision of urban ecosystem services; (4) Evaluating the role that planned urban vegetation may have in the long-term provision of ecosystem services by natural remnants within the urban landscape. Thus, this dissertation contributes to urban sustainability science by proposing methods and frameworks to address urban environmental inequities through the provision of ecosystem services, but it also provides place-based information that can be readily used for planning urban vegetation in Santiago.

DEDICATION

To my family, and particularly to my wife Carlita, for all her love, support, friendship, and understanding during these years of hard work.

To all the people that suffer the environmental, cultural, and economic injustices of this profoundly unfair world.

ACKNOWLEDGMENTS

I would like to thank my advisor, Jingle Wu, for all his support and guidance during the five and a half years of my PhD program at ASU. I really appreciate his always positive attitude in providing advice not only on the research I was doing, but also on other topics and dimensions that are relevant for developing a successful career in academia. I am also thankful for the guidance and suggestions provided by my other committee members: Professors Charles Perrings, Osvaldo Sala, and Javier Simonetti. All of them were always there to meet with me, listen to my ideas and provide insightful feedback, despite their busy schedules. I am grateful to have had such a wonderful dissertation committee.

I also like to thank to all my lab mates at the Landscape Ecology and Sustainability Laboratory at ASU, particularly to Max Wilson and Bingbing Zhou, who were always willing to hear my ideas, join in very interesting discussion, and providing with essential feedback for solving some technical challenges I faced during my research.

I thank to my Chilean friends for keeping in touch and providing emotional support despite being on the other side of the world, and also to the many wonderful friends I made during my stay in Arizona.

My studies would not have been possible without the support of the Fulbright Scholarship Program, the “Becas Chile” Scholarship Program, and the Arizona State University Graduate College Completion Fellowship.

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CHAPTER 1:

INTRODUCTION

1.1 Background information and research justification

We are living in the urban era. While in 1950 less than 30% of human population lived in urban areas, currently this proportion has increased to more than 54%, and is expected that more than 66% of human population will be urban by the middle of this century (United Nations 2015). The large proportion of this urbanization process is taking place in developing countries, with millions of people migrating from rural to urban areas seeking for a better quality of life (Henderson 2010, United Nations 2015). However, while cities have become in main hubs for economic and social development, they are also becoming hotspots of environmental problems and increasing levels of socio-economic inequalities (Grimm et al. 2008, Wu 2010, UN-Habitat 2014). Furthermore, as cities result from complex interactive dynamics between ecological, social, and economic factors (Pickett et al. 2011), environmental problems and socio-economic inequalities are often spatially interconnected, generating additional emergent environmental inequality issues due to the uneven distribution of environmental problems among socioeconomic groups (Daniels & Friedman 1999, Mohai et al. 2009, Pearce & Richardson 2010).

Although the existences of environmental inequalities could be signaling potential environmental injustice issues, is relevant to note that not all environmental inequalities can be judged as socially unfair, and therefore considered as environmental inequities (Kawachi et al. 2002, Fernández & Wu 2016). For example, in several coastal cities the areas near the shore tend to be inhabited by high income people that can afford the high prices of oceanfront properties. Even though these may generate environmental inequalities by making richer people disproportionately susceptible to tsunami hazards, this could be hardly judged as socially unfair (i.e. environmental inequity). Hence, the concept of environmental inequality relates to the "unequal social distribution of environmental risks and hazards and access to environmental goods and services" without a normative judgment (Sustainable Development Research Network 2007), whereas the concept of environmental inequity focuses on the social fairness of that environmental distribution, and therefore if the observed inequality patterns relates to a distributional environmental (in)justice issue (Pope et al. 2016).

Urban environmental inequities can have negative impacts on the quality of life of all urban residents, independent of their socioeconomic status. While the health of more disadvantaged people is directly affected due to a higher exposure to environmental hazards and lack of environmental amenities (Pearce & Richardson 2010), wealthy sectors can be indirectly affected by the emergence of antisocial behaviors in deprived sectors due to the psychological impacts that a perceived unfair distribution of environmental quality may have on them (van Kamp et al. 2003). In fact, there is increasing evidence that perceived inequities could generate antisocial behaviors in both richer and poorer sectors (DeCelles & Norton 2016, Sands 2017), therefore negatively affecting urban sustainability.

Thus, for moving towards more sustainable cities, decision-makers are not only challenged to develop strategies for increasing urban environmental quality, but also to adequately assess the patterns and drivers of environmental inequality to identify potential environmental inequity issues, and based on that information, decide on the areas where planned environmental interventions should be prioritized.

There is increasing evidence that natural and semi-natural ecosystems within urban regions can play a key role in increasing urban environmental quality, as they can provide several ecosystem services for tackling common urban environmental problems (TEEB 2011, Gómez-Baggethun et al. 2013, Gaston et al. 2013). Urban ecosystem services are the "benefits that urban society and each single resident of a city gain from natural processes and ecological functions provided by urban ecosystems" (Breuste & Qureshi 2011). For example, urban vegetation can be used as an effective strategy for reducing air pollution and urban heat island effect (Bowler et al. 2010, Janhäll 2015, Willis & Petrokofsky 2017), which are two prevalent environmental problems in cities around the world. Thus, considering the current and projected trends of urbanization (United Nations 2015), it is not surprising that provisioning urban ecosystem services has been recognized as an essential goal for improving urban sustainability (Lovell & Taylor 2013, Gaston et al. 2013, Wu 2014, Andersson et al. 2015, McPhearson et al. 2015). In fact, urban sustainability can be seen as "an adaptive process of facilitating and maintaining a virtuous cycle between ecosystem services and human well-being through concerted ecological, economic, and social actions in response to changes within and beyond the urban landscape" (Wu 2014).

However, despite the growing evidence that society benefits from ecosystem services provided within and beyond urban boundaries, we often lack the empirical data, specific tools, and guiding principles for planning and managing urban landscapes to optimize the provision of ecosystem services (Ernstson 2013, Lovell & Taylor 2013, Ahern et al. 2014). Indeed, there is often a spatial mismatch between areas that provide ecosystem services and areas that require them (Burkhard et al. 2012, Larondelle & Lauf 2016), which can reinforce environmental inequities generated by the uneven spatial distribution of environmental problems.

While the topics of urban environmental inequity and urban ecosystem services have been extensively covered by the literature, studies linking these two relevant urban issues are uncommon, and have only recently been started to be covered by researchers (Fig. 1.1). Furthermore, most of the current literature on urban environmental inequity comes from developed countries of North America and Europe (Fig. 1.2), and except from a few exceptions (e.g. China, South Africa, Brazil), the same bias towards developed countries exists for studies on urban ecosystem services (Fig. 1.3).

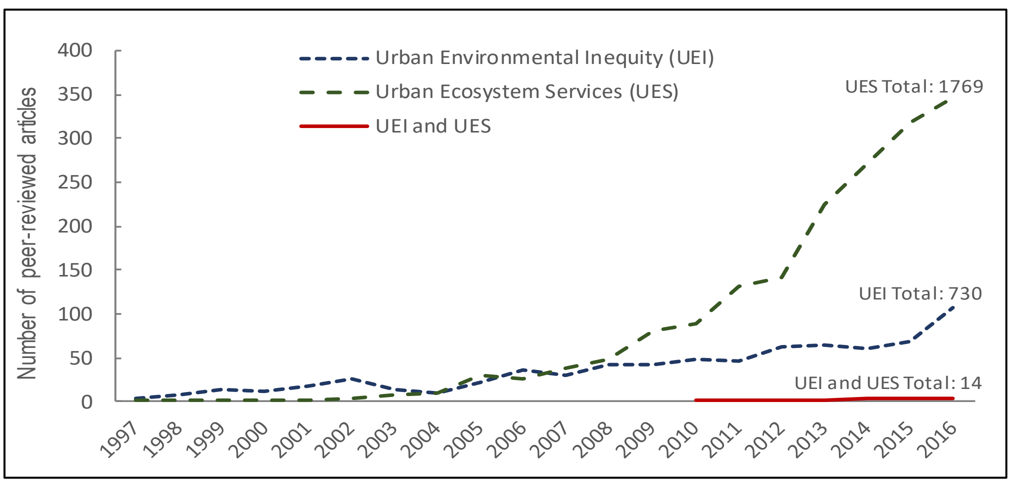

Figure 1.1. Number of peer-reviewed articles published during the 1992-2016 period covering the topics of Urban Environmental Inequity (UEI) and Urban Ecosystem Services (UES), and published articles integrating these two topics during the same period. The search was done on October 2017 through the Scopus database by searching only articles and reviews on the “Article title, Abstract, Keywords” search field. Search strings used were: UEI: ("environmental ineq*" OR "environmental *justice") AND (urban OR city); UES: "ecosystem services" AND (urban OR city); UEI and UES: "ecosystem services" AND ("environmental ineq*" OR "environmental *justice") AND (urban OR city). Total values near lines are the accumulative total for the period.

This bias could be generating a gap of knowledge regarding the intrinsic characteristics of environmental inequity and urban ecosystem services in cities from the developing world, therefore also limiting our understanding for developing place-based strategies to reduce urban environmental inequities through the provision of ecosystem services. Thus, increasing our understanding on the specific characteristics of urban environmental inequities and urban ecosystem services in highly urbanized regions from the developing world is fundamental for reducing the knowledge bias towards developed countries, and also necessary for generating key actionable knowledge to help local decision-makers on how to plan urban ecosystem services for moving towards more sustainable and equitable cities.

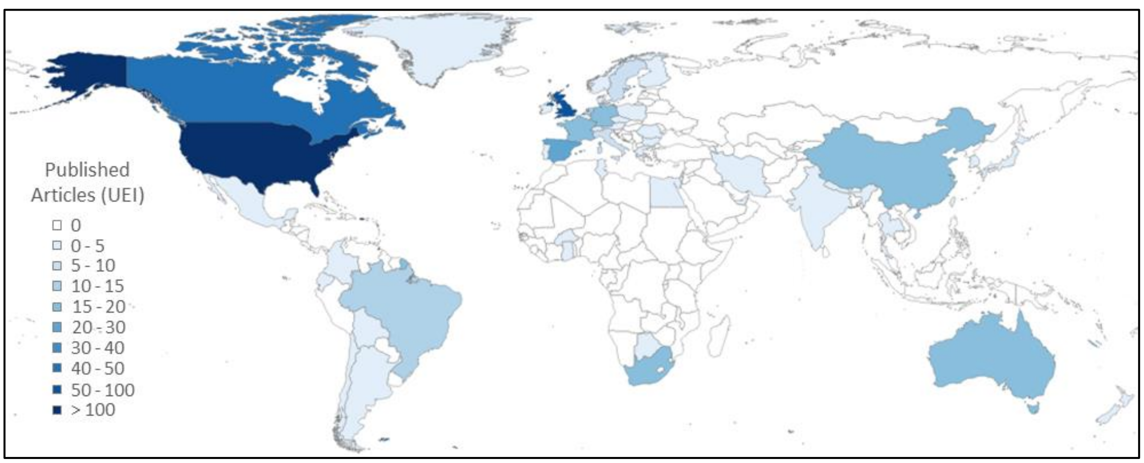

Figure 1.2. Number of articles published per country on the topic of urban environmental inequity. Map was generated based on the country/territory analysis tool available in Scopus, using the same set of articles gathered for generating Figure 1.1.

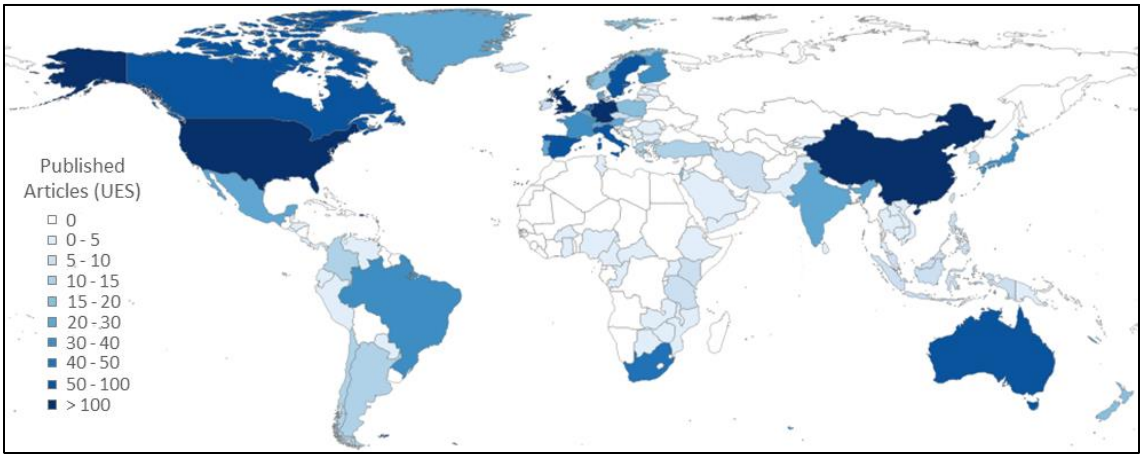

Figure 1.3. Number of articles published per country on the topic of urban ecosystem services. Map was generated based on the country/territory analysis tool available in Scopus, using the same set of articles gathered for generating Figure 1.1.

1.2 Research Goal

The main goal of this dissertation is to generate actionable knowledge for helping decision-makers optimizing the spatial allocation of urban vegetation as a strategy to reduce environmental inequities through the provision of key urban ecosystem services, using the city of Santiago de Chile as a case study from a developing country. Based on this goal, this research has two specific objectives:

(1) To provide a set of methodological approaches that can be used for increasing our understanding on the spatial patterns of urban environmental inequalities and urban ecosystem services, and use this information for better planning the allocation of urban vegetation to increase urban sustainability.

(2) To provide place-based information for Santiago´s policy-makers that can be readily used for planning ecosystem services to reduce environmental inequity issues affecting this city.

1.3 Dissertation Framing

To achieve my objectives, I framed my dissertation based on a sustainability research framework I developed for this purpose (Fig. 1.4). Because sustainability science is a problem-to-solution driven endeavor (Clark & Dickson 2003), this framework not only focuses on understanding the problems from the environmental, social, and economic dimensions, but also on generating the necessary knowledge for developing integrated solutions for a transition towards sustainability. In fact, this framework (Fig. 1.4) conceives sustainability research as an integrated and iterative problem-to-solution process, in which the generation of knowledge is not the main goal, but rather an essential component for linking problems to solutions.

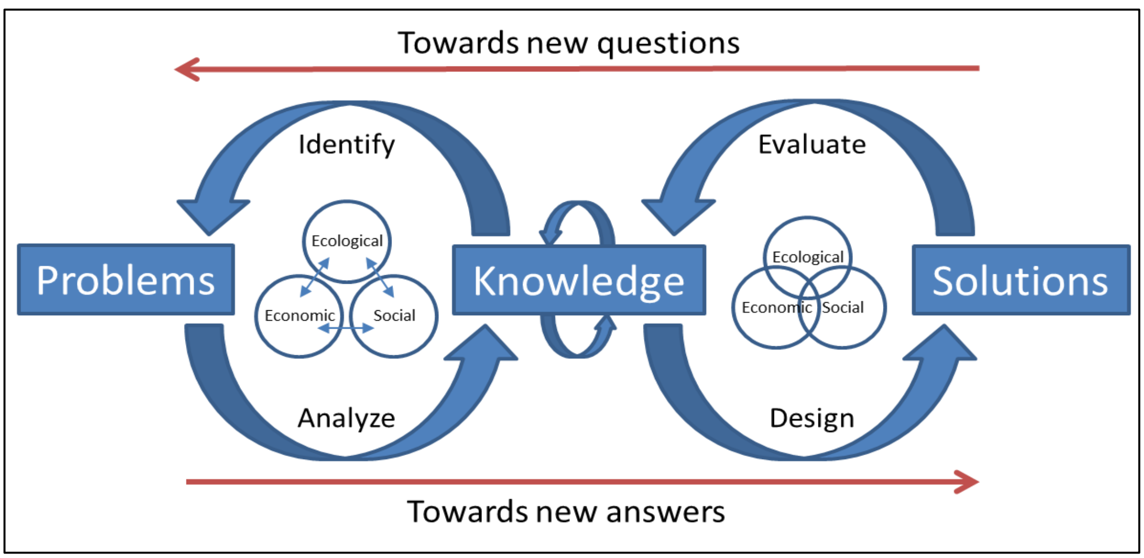

Figure 1.4. Sustainability Research Framework used in this study. This framework conceives sustainability science as an iterative continuous learning process where the generation of knowledge is as a central step for linking problems to solutions.

This framework explicitly recognizes that the generation of potential solutions for any sustainability problem will require:

(1) Developing the foundational knowledge for setting the main questions and objectives of the research.

(2) Identifying ecological, social and/or economic problems that need to be targeted, explicitly considering potential linkages among the ecological, social, and economic dimensions.

(3) Analyzing identified problems in order to increase our knowledge regarding their causes, characteristics, and inter-dimensionality.

(4) Designing potential solutions based in gathered knowledge that explicitly integrates the role of the ecological, social, and economic dimensions in the desired outcomes.

(5) Evaluating proposed solutions, and translating the results into knowledge for policies, solution improvements, and further researches.

1.4 Dissertation Structure

Following the sustainability research framework presented in Fig. 1.4, I have structured this dissertation in a total of 6 chapters: one introductory chapter (current chapter), four linked research chapters (Chapters 2 to 5), and a final synthesis chapter. The four research chapters are the core and more relevant part of my dissertation as they navigate the framework bridging economic, social, and environmental problems (i.e. environmental inequity) with integrated sustainability solutions (i.e. equitable provision of ecosystem services through urban vegetation). Thus, the six chapters of my dissertation are focused on:

- Chapter 1: Providing the fundamental background information to justify identifying urban environmental inequity as a sustainability problem that is needed to be solved.
- Chapter 2: Analyzing urban inequality patterns of Santiago to increase our knowledge on their spatial characteristics, and their social, economic, and environmental drivers.
- Chapter 3: Designing and evaluating a GIS-based methodological framework that could be used as a solution for identifying priority areas to reduce detected urban environmental inequities.
- Chapter 4: Analyzing the distribution of ES provision and deficits in Santiago, and designing and evaluating a GIS-based methodological framework to optimize the allocation of urban vegetation to reduce environmental inequities through the provision of ecosystem services.
- Chapter 5: Analyzing the role of urban vegetation on the potential provision of ecosystem services by urban natural remnants to generate knowledge that can be used for identifying further problems and/or generating potential solutions.
- Chapter 6: Summarizing the contribution of my dissertation to current knowledge for increasing urban sustainability through the equitable provision of ecosystem services.

CHAPTER 2:

ASSESSING ENVIRONMENTAL INEQUALITIES IN THE CITY OF SANTIAGO DE CHILE WITH A HIERARCHICAL MULTISCALE APPROACH

2.1 Introduction

Urban areas are home to more than 50% of the world population, and this number is expected to go beyond 65% by the middle of this century, with most of this growth taking place in the developing world (United Nations 2015). Urban areas are hubs for human development, but also places of increasing environmental problems and socioeconomic inequalities (Wu et al. 2013). Furthermore, as cities are the result of complex socio-ecological interactions operating at different spatial scales, environmental quality, ecosystem services, and social groups are seldom homogenously distributed across the landscape, often leading to environmental inequalities (Bowen et al. 1995, Daniels & Friedman 1999, Heynen et al. 2006, Mitchell & Chakraborty 2014, Pope & Wu 2014).

The concept of environmental inequality refers to "the unequal social distribution of environmental risks and hazards and access to environmental goods and services" (Sustainable Development Research Network 2007). Thus, environmental inequality relates to the statistical relationship between social and environmental variables, and should not be confounded with the normative concept of environmental inequity or distributive environmental justice (Kaswan 2003). Whereas the inequality concept does not entail a normative judgment about the resource distribution, the inequity concept implies that the resource distribution is judged as socially unfair (Kawachi et al. 2002).

Although environmental inequalities may have long characterized urban settlements, they only started to gain attention from researchers and policy-makers in the 1980's, when studies in U.S.A found that disadvantaged people tended to be exposed to higher levels of environmental hazards (Szasz & Meuser 1997). This inequitable distribution of environmental hazards triggered the environmental justice movement, as well as the environmental justice studies as an interdisciplinary body of research (Mohai et al. 2009). Since the pioneering studies in the 1980's, environmental justice research has increased substantially in the developed world, but it was not until the 2000´s that these topics started to gain attention from academics and decision-makers in developing countries (Mohai et al. 2009, Walker 2009). This has limited the generation of locally-based knowledge on environmental inequalities/inequities in developing countries, whose underlying causes, key drivers, scales, and patterns may differ greatly from those in the developed world (Carruthers 2008).

Numerous studies have shown that statistical analyses based on spatial data can be affected by the scale of observation and analysis (Turner et al. 1989, Jelinski & Wu 1996, Wu et al. 1997, Buyantuyev et al. 2010). Different scales of observation/analysis may lead to different or sometimes conflicting results, and the same phenomenon may manifest itself variably across scales (Wu 2007). As environmental inequalities are inherently a spatial matter, therefore, the choice of scale is essential for correctly detecting and quantifying inequity issues, and for designing proper and effective policies to deal with them (Cutter et al. 1996, Baden et al. 2007, Noonan 2008, Pope et al. 2016).

Nevertheless, potential scale effects have rarely been examined explicitly for assessing environmental inequalities, leading to contradictory results from different studies (Anderton et al. 1994, Baden et al. 2007).

Two scale-related issues are particularly important for assessing and interpreting environmental inequalities: The modifiable areal unit problem (MAUP) and the ecological fallacy (Wu 2007). MAUP arises from the fact that units of analysis are modifiable in the sense that they can be aggregated into different sizes or spatial arrangements for statistical analysis (Openshaw 1989, Fotheringham & Wong 1991). MAUP has two related but different components: the scale effect and the zoning problem (Jelinski & Wu 1996). The scale effect is the variation in statistical results in response to aggregation of data into fewer and larger areal units, whereas the zoning effect is the variation in results due to different delineation of areal units at a given scale (Wu 2007).

An ecological fallacy may occur when the inferences made at the aggregated-level data are directly extrapolated to the individual level, or in other words to assume that the relationships observed for aggregated units necessarily hold for individual units (Freedman 2001). In some cases, correlations at the aggregate and individual levels may have opposite signs (Wu et al. 1997, Jargowsky 2005, Buyantuyev et al. 2010). Also, an "individualistic fallacy" or "atomistic fallacy" – the reverse problem of ecological fallacy – may also occur as a result of improperly inferring aggregate-level relationships from individual-level results (Diez Roux 2002). Thus, cross-level or cross-scale inferences using spatial data must be done with caution (Wu 2007).

The MAUP and inference fallacies need to be considered explicitly in designing research projects and interpreting analysis results in environmental inequality assessments. Otherwise, policies and management actions will not be effective or justified when they are based on erroneous inferences. To overcome these scale-related problems, the assessment of environmental inequalities should take a hierarchical multiple scale approach that evaluates the occurrences of inequities, as well as their spatial patterns and drivers, on a range of scales (Wu et al. 1997, Wu 2007, Buyantuyev et al. 2010).

The main objective of this chapter is to assess the patterns of environmental inequalities and associated scale issues in the city of Santiago (Chile) using a hierarchical multiscale approach. This approach focused on the analysis of spatial relationships between three environmental and two socio-demographic variables on multiple nested scales. The three assessed environmental variables are: vegetation coverage, summer surface temperatures, and winter air pollution. I selected these environmental variables because the shortage of green infrastructure, summer heat risk, and winter air pollution are among the most important environmental problems currently affecting the quality of life of Santiago's residents (Krellenberg et al. 2013, Toro et al. 2014, de la Barrera et al. 2016a). The two socio-demographic variables I used are: household wealth and population density. I selected household wealth as the main socioeconomic indicator to evaluate environmental inequalities and inequities in Santiago. I used population density as a supporting variable to analyze if wealth-environmental relation patterns could be associated to other underlying factors, but also as an additional socio-demographic variable to evaluate the scale effect on spatial relationship assessment.

In this chapter I aimed to address the following specific questions: Does the spatial relationship between environmental and socio-demographic variables suggests the occurrence of environmental inequalities in Santiago? How does the scale of analysis affect the degree and spatial pattern of environmental inequalities? What may be the potential drivers for these inequalities at different scales? What are some policy-relevant implications?

2.2 Methods

2.2.1 Study area

The city of Santiago (33°26’15’’S; 70°39’01’’W) is located in the Maipo river basin, bounded on the east by the Andes Mountain Range and on the west by the Coastal Mountain Range. The city covers a surface of about 617 km2 (Romero et al. 2012) with elevation ranging from 450 to 1000 m above the sea level. The climate is Mediterranean, characterized by cold and rainy winters months, and warm and dry summers (Cruz & Calderón 2008). With a projected population of 6.4 million by the year 2015, Santiago has almost doubled the number of residents in the last 30 years, and currently harbors about 37% of Chile’s total population (Instituto Nacional de Estadísticas 2015).

This population growth has been coupled with urban expansion that has doubled the spatial extent of the city since 1975, mostly replacing agricultural land and surrounding natural habitats (Romero et al. 2012). The transformation of agriculture and natural areas to urban infrastructure has negatively impacted the environmental quality of the city, including a decrease in vegetation cover, and an increase in temperatures and air pollution (Romero et al. 1999, Romero & Vásquez 2005, Krellenberg et al. 2013). In addition, the lack of appropriate urban planning and a highly liberalized real-estate market have led to high levels of spatial segregation between social classes (Borsdorf & Hidalgo 2008). These factors are possibly key ingredients for high levels of environmental inequities. Previous studies have reported that lower socioeconomic groups tend to live in areas of lower environmental quality (Escobedo et al. 2006, Reyes-Packe & Figueroa 2010, de la Barrera et al. 2016a) and higher environmental risks (Vásquez & Salgado 2009, Romero et al. 2012, Krellenberg et al. 2013).

2.2.2 Hierarchical multiscale approach

My research design is depicted in Fig. 2.1. This design is based on a hierarchical multiple-scale approach that uses a set of nested areas of analysis (i.e. extent) for which environmental inequalities are assessed with different basic areal units (i.e. grain sizes). While this design can be applied to vector- or raster-based analysis, I decided to use a raster-based approach because it allowed to standardize the size and shape of the extents and areal units when performing the multiple-scale analysis. This reduces potential confounding factors in multiple-scale analysis due to aggregating (or disaggregating) spatial data using polygons of different shape and size (e.g. counties, municipalities, ZIP-codes). Furthermore, if the raster target grain is relatively smaller than vector polygons, the rasterized data can retain the information and spatial accuracy of original vector layer (Congalton 1997). Therefore, I transformed all spatial layers that were in vector format (e.g. census data) to raster format before the analyses.

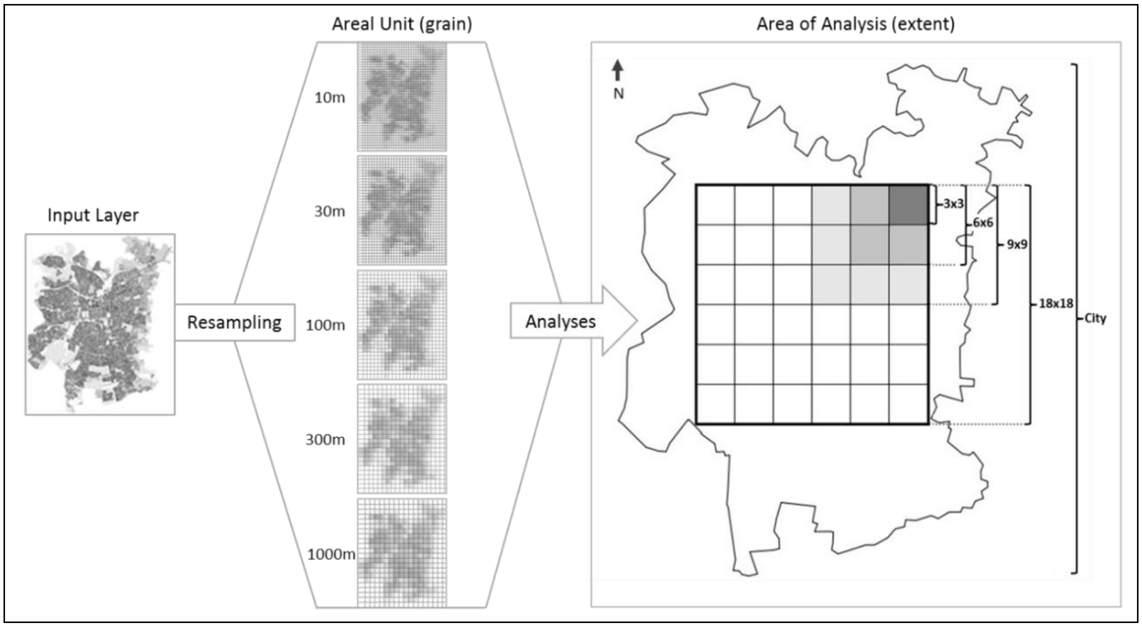

Figure. 2.1. Illustration of the hierarchical multiple-scale approach used to evaluate environmental inequalities in Santiago, Chile. All original input layers were resampled to raster layers of five different grain sizes (10 to 1000 m/pixel), representing the areal units of analysis. Correlation analysis was conducted to evaluate the spatial relationship between environmental and socio-demographic variables at five different nested extents (City to 3x3km), totaling 51 areas of analysis.

I generated five raster layers as inputs for the assessments (See preparation of these layers in section 2.2.3): three environmental (i.e. surface temperature, air pollution, vegetation coverage) and two socio-demographic (i.e. household wealth, population density). I resampled each of these five layers into five raster layers with pixel resolutions of 10, 30, 100, 300, 1000m, which represent the five areal units used for analysis (Fig. 2.1). I chose these grain sizes to have an ample range of areal units that fits perfectly within the different nested extents for the analysis. For resampling I used the bilinear interpolation method because it better retains original spatial patterns than other commonly used resampling methods, such as nearest neighbor and averaging (McInerney & Kempeneers 2015). I performed all data resampling using QGIS Wien 2.8.

I visually inspected each of the 25 generated raster layers (five per input layer) to ensure a spatial match among layers with same resolution. From each of these raster layers I then generated a nested subset of layers by cropping the layer to predefined extents. The largest of these sub-extents was 18x18km, which was the largest square fitting into the convoluted shape of Santiago (Fig. 2.1). This 18x18km square was then subdivided into four 9x9km, nine 6x6km, and thirty-six 3x3km nested extents. Including the city extent, the total number of spatial extents for analysis was 51 (Fig. 2.1). Table 2.1 shows main descriptive statics of the five raster layers for the five grain sizes at the two larger extents (city and 18x18km).

Table 2.1. Main descriptive statics of the raster layers used for the analyses. Mean values and standard deviation are shown. Morans 'I is an indicator of within layers spatial autocorrelation.

Extent	Grain	ST			AP			VC			HW			PD		
		Mean	SD	Morans'I	Mean	SD	Morans'I	Mean	SD	Morans'I	Mean	SD	Morans'I	Mean	SD	Morans'I
City	10m	34.626	2.670	0.996	80.218	8.156	0.998	0.146	0.080	0.981	2.997	1.010	0.986	1.164	0.943	0.749
City	30m	34.626	2.677	0.981	80.219	8.154	0.996	0.146	0.083	0.847	2.997	1.010	0.961	1.166	0.943	0.643
City	100m	34.620	2.670	0.880	80.202	8.161	0.987	0.146	0.079	0.683	2.998	1.000	0.910	1.161	0.844	0.626
City	300m	34.621	2.663	0.648	80.234	8.143	0.961	0.145	0.078	0.510	2.997	1.004	0.792	1.153	0.847	0.471
City	1000m	34.637	2.564	0.416	80.334	8.068	0.883	0.146	0.081	0.292	2.994	1.001	0.614	1.138	0.835	0.263
18x18km	10m	35.001	2.194	0.998	83.670	5.127	0.999	0.128	0.068	0.976	2.916	0.899	0.986	1.361	0.958	0.705
18x18km	30m	35.000	2.200	0.985	83.673	5.122	0.998	0.128	0.072	0.806	2.917	0.900	0.949	1.362	0.957	0.579
18x18km	100m	35.002	2.190	0.889	83.673	5.122	0.993	0.127	0.068	0.633	2.916	0.886	0.885	1.360	0.836	0.542
18x18km	300m	34.990	2.197	0.685	83.673	5.122	0.978	0.127	0.065	0.469	2.921	0.897	0.752	1.354	0.836	0.387
18x18km	1000m	35.027	2.056	0.503	83.792	4.915	0.910	0.126	0.074	0.271	2.884	0.883	0.575	1.285	0.845	0.197

2.2.3 Preparation of data layers

I estimated Surface Temperatures (ST) from a Landsat-8 satellite image taken at 11:35 local time by the TIRS sensor (Band 10) on February 10, 2014. The original image had a spatial resolution of 30m/pixel, with no cloud cover for the study area. I decided to work with only one image representing the distribution of surface temperatures of a typical sunny day of Santiago's summer season. I calculated land surface temperatures using the Normalized Difference Vegetation Index (NDVI)-threshold method (Sobrino et al. 2004). Resulting ST raster layer is shown in Fig. 2.2a.

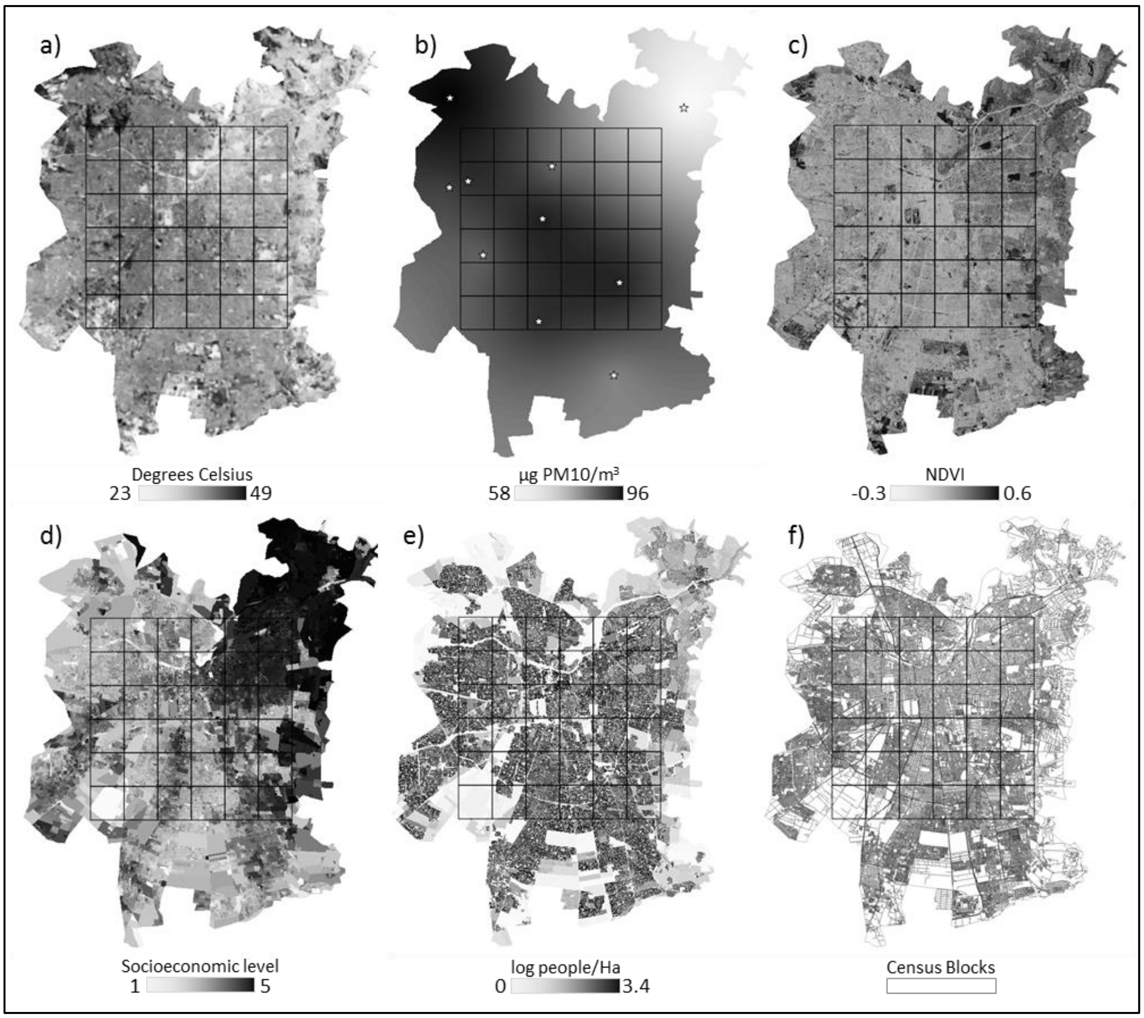

Figure 2.2. Generated raster layers (a-e) and original census vector layer showing the block sizes (f). Raster layers are shown in the resolution at which they were generated. Layers and resolution are: a) ST, 30m/pixel; b) AP, 10m/pixel (location of PM10 monitoring station are shown as white stars); c) VC, 30m/pixel; d) HW, 10m/pixel, e) PD, 10m/pixel. The grid used to define the different extents of analysis (see Fig. 2.1) is shown to facilitate visual comparisons between layers.

I generated the Air Pollution (AP) via Kriging interpolation, from particular matter (PM10) data obtained from 10 public monitoring stations distributed across Santiago (Fig. 2.2b). I built a single raster layer of 10m/pixel resolution based in the daily average concentration of PM10 for the April-August period from the years 2012, 2013, and 2014. I decided to use these autumn-winter months because these are times when air pollution often becomes a serious problem in Santiago (Muñoz & Alcafuz 2012). I used the values of three consecutive years to smooth out potential yearly variability due to climatic variations. I used Kriging for the spatial interpolation, as this is a geostatistical interpolation method that provides an effective way of mapping the spatial pattern of air pollutant based on the spatial autocorrelation structure of point-based sampling (Jerrett et al. 2005, Pope & Wu 2014). This technique has been previously used to estimate the distribution of air pollution in Santiago (Romero et al. 2010). However, as the number of monitor station is relatively small for the area of Santiago, here I acknowledge that this raster layer was produced only for this research purpose, and may not be accurate enough at fine resolutions for decision making.

I estimated Vegetation Coverage (VC) from the NDVI, which is a reliable indicator of vegetation cover in semi-arid regions like Santiago (Elmore et al. 2000). As summer season in Santiago is characterized by an extended hot and dry period (Cruz & Calderón 2008), not managed vegetation drastically decreases the photosynthetic rates (Gerstmann et al. 2010), making summer NDVI a useful indicator to discriminate vegetation coverage associated to urban green infrastructure. I calculated the NDVI from the same Landsat image from which I obtained surface temperatures. Resulting VC raster layer is shown in Fig. 2.2c.

I gathered Household Wealth (HW) data from the 2012 updated version of the 2002 Chilean Official Census Data developed by Norel et al. (2013). The HW data layer was in vector format, representing several kinds of socioeconomic and demographic information at the city block level. The original lumped variable from which I derived HW was called "nivel socio-económico" (i.e. socio-economic level), which consisted of five socioeconomic categories ranked from low to high based on the educational level of the household head and a list of assets potentially present at home (Adimark 2004). Each census block had information on the percentage of households pertaining to each of the five socio-economic categories. I converted this categorical data into a continuous variable by ranking the five categories into five numerical values from 1 to 5 (i.e. low to high) and then calculating the sum of the product between each ranking value and its percentage per pixel. I then converted the generated HW vector layer into a 10m/pixel resolution raster layer (Fig. 2.2d).

I also gathered Population Density (PD) from the 2012 Census Data generated by Norel et al. (2013). The original data set provided the number of people per census block, but not density. Thus, I used this information to calculate population density at the census block based on population/hectare. I then log-transformed resulting PD values to remove the huge skewness towards smaller population densities. The resulting PD vector layer was then rasterized to a 10m/pixel resolution layer (Fig. 2.2e).

2.2.4 *Data analysis*

I analyzed the spatial relationships between the three environmental variables (ST, VC, AP) and the two socio-demographic variables (HW, PD) through Pearson spatial correlation analysis by using all the pixels within each sampled extent. I performed these correlation analyses for each of the areas of analysis (n=51) and areal units (n=5), resulting in a total of 1530 correlations. All statistical analyses were performed using the R-raster package (www.r-project.org) in R-Studio v.0.98 (www.rstudio.com).

2.3 Results

2.3.1 *Environmental inequalities in Santiago: the big picture*

Correlation analyses performed at the city extent (at the grain size of 100m/pixel) indicate the existence of important levels of environmental inequalities in Santiago, evidenced by statistically significant relationships between household wealth and the three environmental variables (Fig. 2.3). Results show that, in general, people living in wealthy areas tend to be exposed to lower temperatures ($R = -0.389$, $p = <0.001$), higher vegetation coverage ($R = 0.300$, $p = <0.001$), and lower air pollution ($R = -0.590$, $p = <0.001$). Indeed, people living in the wealthiest areas experienced substantially lower levels of air pollution than the rest of the population (Fig. 2.3).

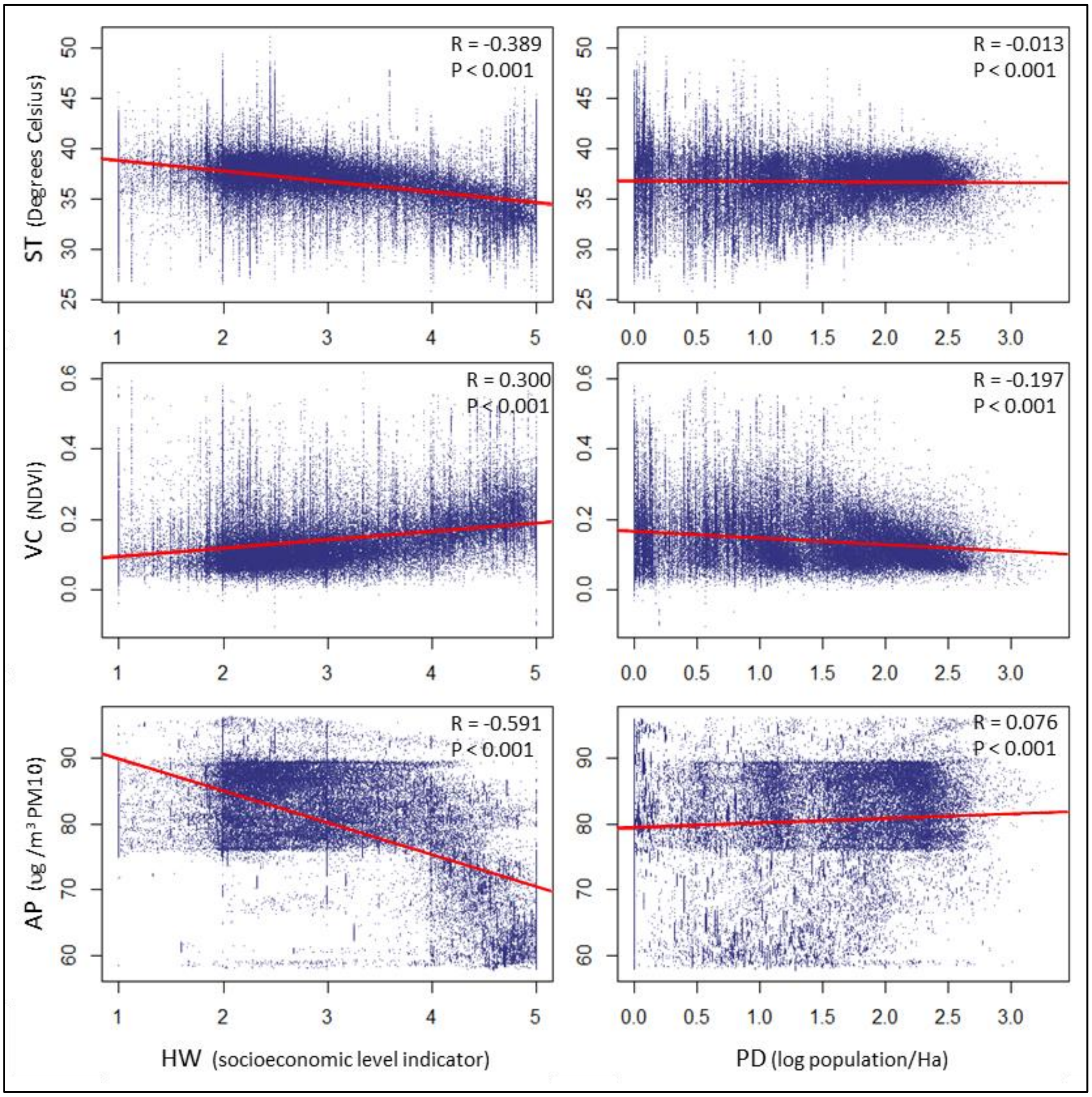

Figure 2.3. Scatterplots showing the relationship between three environmental (ST; surface temperature, VC; vegetation coverage, AP; air pollution) and two socio-demographic variables (HW; household wealth, PD; population density) for the city of Santiago. Pearson correlation coefficient (R), p-value, and fitted lines are shown. Analyses were done at the city extent using the 100m/pixel raster layers.

Population density was rather weakly associated with surface temperature (R = -0.013, p = <0.001) and air pollution (R = 0.076, p = <0.001), and moderately associated with vegetation cover (R = -0.197, p = <0.001). Whereas all these relationships are statistically significant, scatterplots do not show consistent patterns of associations between population density and environmental variables, except for a negative association with vegetation cover at the highest ranges of population density (Fig. 2.3).

2.3.2 Scale effects on correlation results

Spatial relationships between the socio-demographic and environmental variables show a strong dependency on the extent and grain size used for correlation analysis (Fig. 2.4). With regards to changing the extent of analysis, correlation coefficients computed at the two largest extents (i.e. City and 18x18km) show a high degree of similarity, with only a minor reduction in the strength of the correlation for two of the six relationships (i.e. HW-AP, PD-VC; Figs. 2.4b, f). However, when the 18x18km extent was decomposed into smaller areas of analysis, the relationships at the city and 18x18 extents diverged to a range of correlation coefficients, scattering increasingly as the areas of analysis decreased in extent. Although all relationships exhibited a scattering pattern with decreasing extent of analysis, there was a gradient of response to changing extent, ranging from drastic changes in the strength and changing signs of correlation (e.g. HW-AP; Fig. 2.4b) to smoother variations and relatively consistent patterns over all extents (e.g. PD-VC; Fig. 2.4f). For all the assessed relationships, the mean values of correlation coefficients became smaller with decreasing extent of analysis. VC tended to be positively associated with HW but negatively associated with PD for all the extents examined (Figs. 2.4c, f).

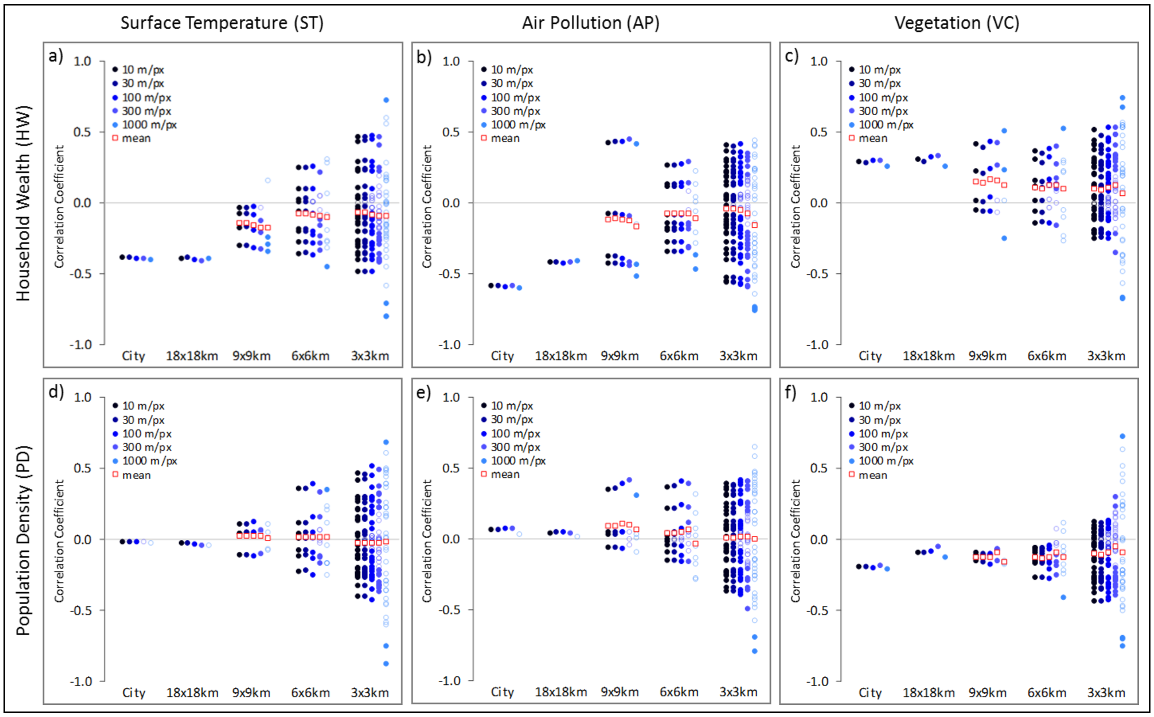

Figure 2.4. Pearson correlations between three environmental quality and two socio-demographic variables at five grain sizes (10, 30, 100, 300, 1000 m/pixel) and five nested extents (City, 18x18km, 9x9km, 6x6km, 3x3km). Filled dots represent correlation coefficients statistically different from 0 at p<0.05, whereas open squares are the means of correlation coefficients at a given extent.

The effects of modifying the grain size (i.e. areal unit) were highly dependent on the extent used for the analysis (Fig. 2.4). At the two largest extents (i.e. City, 18x18km), changing grain size from 10 to 1000m/pixel did not generate major changes in correlation results. In general, correlation results were relatively independent of grain size on larger extents, but tended to vary with grain size over smaller extents. The variations followed a similar general pattern for all the relationships, i.e. the range of variation expanded substantially with increasing grain size and decreasing extent, with some relationships less sensitive to changing grain size than others (e.g. HW-AP; Fig. 2.4b, compared to HW-VC; Fig. 2.4c). Increasing the grain size at smaller extents not only increased the variability in correlation coefficients, but also the proportion and distribution of statistically significant results (Fig. 2.4).

2.3.3 Scale effects on spatial patterns of environmental inequalities

Correlation coefficients between socio-demographic and environmental variables showed increasing spatial heterogeneity as the extent of analysis was reduced (Fig. 2.5). Decomposing larger extents into progressively smaller areas revealed new spatial patterns of relationships that were not detected at larger extents. Even spatially contiguous areas of the city could have relationships on small extents that were opposite to those at the immediately adjacent range of extents. Some relationships showed drastic changes when analyzed on smaller extents (e.g. HW-AP), while others change gradually (e.g. VC-PD).

2.4 Discussion

2.4.1 Methodological approach

This is the first study assessing environmental inequalities in the city of Santiago from a multiscale approach. Although my main objective with the hierarchical multiscale approach was to evaluate the effects of the scale of analysis on Santiago's observed environmental inequality patterns, results from this work may also provide insightful knowledge on the particular level and spatial distribution of environmental inequalities in Santiago.

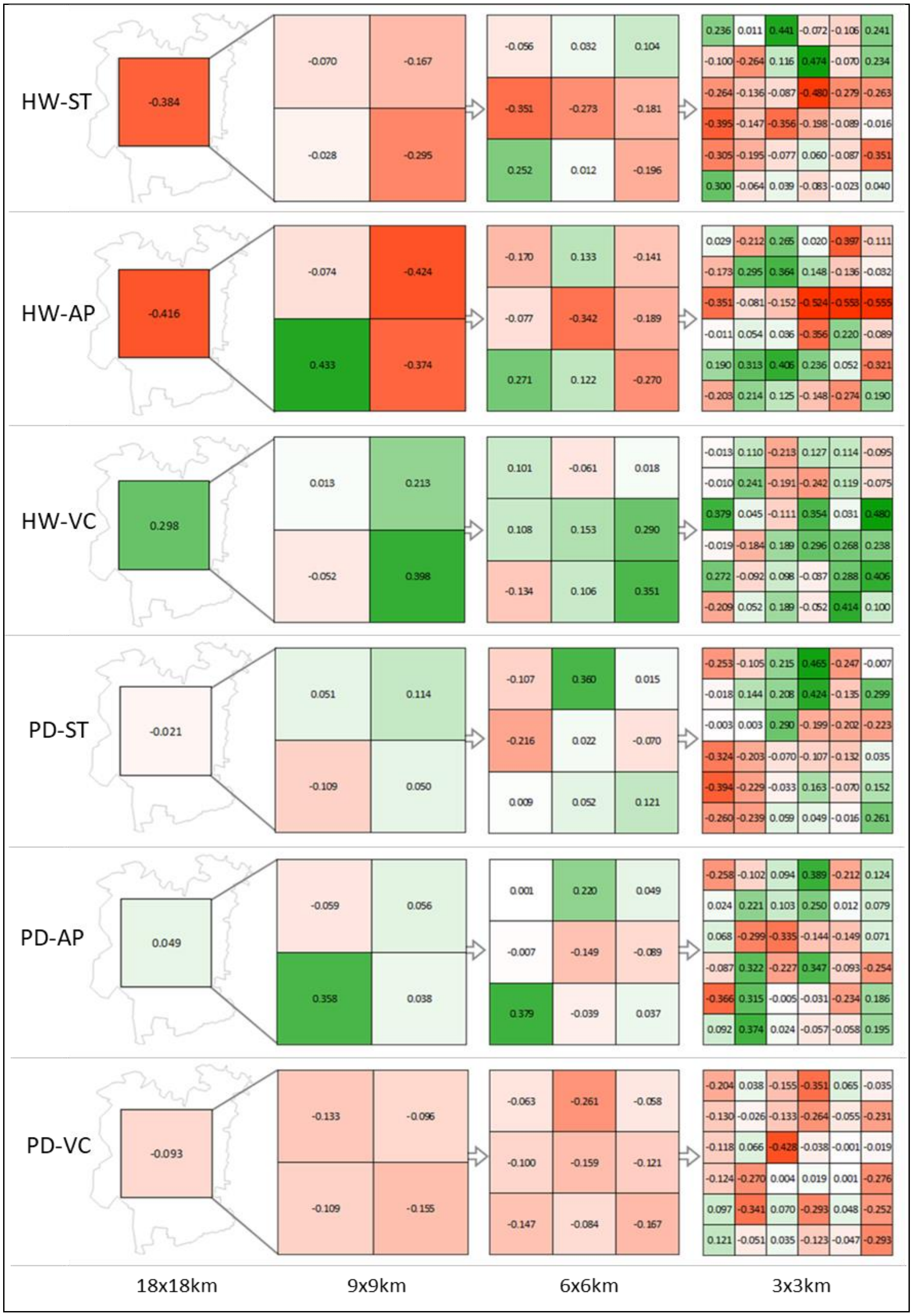

Figure 2.5. Spatial distribution of Pearson correlation coefficient for assessed relationships at the four assessed nested extents, with a grain size of 30m/pixel. Colors represent the strength of the correlation; from green (positive) to red (negative). Correlation coefficients for each extent of analysis are shown. HW: Household Wealth; PD, Population Density; ST, Surface Temperature; AP, Air Pollution; VC, Vegetation Coverage.

However, results from this study have to be carefully used if ought to be compared with other studies, because I based the analysis in raster grids and not in polygons, which has been the most common used method in previous environmental inequalities studies (Ringquist 2005, Baden et al. 2007).

An advantage of using the raster-based approach is the possibility to standardize the sizes of extents and grains to perform the multiple-scale analysis and compare their results, reducing potential confounding factors due to aggregation/disaggregation of polygons with different shapes and sizes. However, a tradeoff of my approach is that because some polygons are represented by pixels of identical values when rasterized, this process may artificially inflate the number of areal units for which information is assumed to be known (a sort of ecological fallacy), which could increase variables native spatial autocorrelation (Downey 2006). Autocorrelated variables may produce biased correlation coefficients towards larger values, and increase the probabilities of false positives (type I error) when analyzing the statistical significance of the observed relationships (Legendre 1993, Lennon 2000).

Several methods have been proposed to deal with spatially autocorrelated variables (Dormann et al. 2007). Nevertheless, removing or controlling for autocorrelation could hamper finding spatial relationships between variables that are truly associated through endogenous spatial processes (Wagner & Fortin 2005). This is particularly relevant for Santiago, because the spatial autocorrelation of variables may result from endogenous processes leading to high levels of social and environmental segregation in space (Romero et al. 2012, Aquino & Gainza 2014, Fernández et al. 2016). I certainly acknowledge that autocorrelation is an important spatial issue that could have affected results from this work. However, if spatial autocorrelation would have had a significant effect in the analysis, I should have observed a trend of larger correlation coefficients at smaller grains, because spatial autocorrelation decreases with grain size (Qi & Wu 1996, Table 2.1). But my data show no evidence of that for any assessed pair of variables, and on the contrary, it seemed to show the opposite pattern for all but the smaller extent (Fig. 2.4). This suggests that the observed changes in correlation values are strongly related to the scale of analysis, not to spatial autocorrelation. Thus, a hierarchical multiscale approach like the one used here can be an additional option to deal with potentially autocorrelated spatial variables without losing key information for exploring the spatial patterns of inequalities.

2.4.2 Patterns and drivers of environmental inequalities in Santiago

Results from my work reveal that environmental inequalities are a prevalent phenomenon in the city of Santiago, and that the details of these inequalities are scale dependent. Changing the grain size and extent of analysis did not only affect the strength of relationships between socio-demographic and environmental variables, but also their spatial distribution across the urban landscape. The dependency of these relationships on the extent used for the analysis, as well as the spatial patterns of their variability, suggests that the underlying drivers for the observed environmental inequalities in Santiago are diverse and operating at different scales. This should not be surprising considering that cities are one of the most heterogeneous landscapes (Wu et al. 2013) and that urban landscapes are shaped by complex socio-ecological interactions operating at different temporal and spatial scales (Pickett et al. 2011). Therefore, in a city of the size of Santiago, it would be expected to find spatial differences in the sign and strength of correlations between environmental and socio-demographic variables.

There are several drivers that may explain the high levels of environmental inequalities observed in Santiago at the city extent, including ecological and human factors. On the one hand, the presence of the Andes Mountain at the east of the city, coupled with large-extent meteorological factors and a complex topography, generates a natural gradient of low-to-high vegetation cover, high-to-low temperatures, and high-to-low air pollution towards the north-eastern part of the city (Romero et al. 1999, Romero & Vásquez 2005). On the other hand, the historical social dynamics of Santiago has resulted in high-level social segregation that is characterized by a concentration of richer neighborhoods also in the north-eastern area of the city (Aquino & Gainza 2014). These uneven socio-environmental spatial patterns may also be reinforced by the biased distribution of urban green infrastructure towards north-eastern municipalities due to the differences in financial investments between rich and poor municipalities (Escobedo et al. 2006, Reyes-Packe & Figueroa 2010), and also because the relatively larger and highly vegetated residential yards maintained by richer neighborhoods (Reyes-Packe & Meza 2011). The dominance of this wealth-driven large-extent spatial pattern is also corroborated by the weak relationships between population density and environmental variables, suggesting that independently of population density, wealth provides access to better environmental quality in Santiago.

While environmental inequalities of Santiago at the city scale may largely be wealth-driven, my results show that this driver does not necessarily dominate at finer scales. Indeed, there are sectors where wealth is inversely associated with environmental conditions, which opposes to results from previous studies. These contradictory results suggest that drivers dominating environmental inequalities at finer scales are diverse, and not the same throughout the city. In this regard, population density could provide some insights about these patterns because it has been reported to be related to air pollution, temperature, and vegetation cover (Hoek et al. 2008, Merbitz et al. 2012, Aquino & Gainza 2014). However, my analysis only showed relative consistent results for the relationship of population density with vegetation cover, indicating that population density is an important factor related to the level of vegetation cover at finer scales, but not for pollution and temperature. The lack of consistent results from assessed relationships does not necessarily mean that other crucial dominating factors not assessed in this study are driven the observed inequalities, because some of the observed patterns could simply be the results of spurious associations, unreliable data, or methodological artifacts. My results indeed suggest that relationships between environmental inequalities and related drivers in the city of Santiago may be highly complex, which highlights the need to be judicious when interpreting results from spatial studies of environmental inequalities.

2.4.3 Scale effects

Many studies have shown that the results of spatial analysis are affected by the scale of analysis, including grain size and extent (Turner et al. 1989, Jelinski & Wu 1996, Wu et al. 1997, Wu 2004, 2007). And there is increasing evidence that these scale issues may also manifest in environmental inequality studies (Cutter et al. 1996, Baden et al. 2007, Noonan 2008). My results support previous studies, but they also show that the effects of changing grain size on correlation analysis depends on the extent used for analysis. In general, the effects of grain size tend to be weakened by increasing spatial extents. This suggests that MAUP may be a function of the extent used for analysis, and there may be particular extent-to-grain ratios at which MAUP is less or more pronounced. Nevertheless, my results suggest that this ratio could be specific for each of the assessed relationships, and may be related to the intrinsic scales on which driving processes operate. In this case, if the analyzed spatial relationship is dominated by factors operating at coarser scales, correlation results should be more sensitive to changes in extent than grain size, as in the case of the HW-AP relationship. By contrast, if the relationship is dominated by finer-scale factors, correlation results should be more sensitive to changes in grain size than extent, as in the case of the PD-VC relationship. There may also be some relationships that are sensitive to both grain and extent, such as the HW-VC relationship in my study, which may imply that coarse- and fine-scale factors interactively influence environmental inequalities.

These findings are interesting and important because comparing and contrasting grain size and extent effects, as discussed above, may provide critical information on the dominant scales at which key drivers for environmental inequalities operate. To do this systematically, scalograms can be used in a similar way for identifying the characteristic scales of landscape patterns (Wu et al. 2002, Wu 2004). Further studies are needed for better understanding the effects of grain size and extent, particularly in the context of environmental inequalities and justice. Of particular relevance is to develop further analysis with higher resolution environmental and demographic data to allow exploring potential drivers of environmental inequalities at very fine scales for which information is hardly available, such as within census block level. Here I used the smallest grain size of 10m, which was only for exploring the effects of MAUP. The results at this scale may not be used for decision-making as this grain size represents a downscaling of coarser resolution data (e.g. Landsat 30m) which was not empirically validated.

2.4.4 Implications for policy making

Results from this study highlight the spatial variability and scale multiplicity of environmental inequalities in Santiago. Due to the scale-dependence of assessment results, researches and decision-makers should be extremely careful when interpreting the findings or translating them into actions. In this regard, my findings are particularly important for improving the understanding of environmental inequalities in Santiago, because the limited published literature on this respect has usually been focused on single scale assessments of particular areas within the city, which may represent a biased view of a more complex multiple scale phenomenon (e.g. Vásquez & Salgado 2009, Reyes-Packe & Figueroa 2010, Romero et al. 2010, 2012).

Policy interventions may be ineffective if the policy scale and the environmental inequality scale are not commensurable. For example, a policy aiming to increase tree coverage through the implementation of large urban parks in low income sectors of Santiago would be effective for reducing city-scale environmental inequalities, but not for reducing local-scale inequalities due to the scarcity of street- or household-level vegetation amenities. Furthermore, because of the great spatial variability of environmental inequalities across the urban landscapes, results obtained for a particular area is not likely to be representative of the entire city. Thus, if decision-makers are to design specific policies for tackling environmental inequalities, it is crucial to ensure that the area for which the analysis is done matches the area for which the policy intervention is intended.

In addition, due to the complex social and environmental spatiotemporal dynamics of urban areas, observed environmental inequalities patterns may probably change over time (Pickett et al. 2011). Although the recent literature suggest that large-extents environmental inequality tend to be consistent over time (Padilla et al. 2014, Ard 2015), there is no evidence to suggest that the same may hold for small-extents inequality patterns. Therefore, decision-makers not only have to be aware of spatial issues when planning the interventions, but they also need to carefully analyze if the data used for the diagnostic represent current environmental and social patterns, and consider how these patterns may change before the interventions are implemented.

Finally, not all environmental inequalities observed in Santiago are driven by socioeconomic factors, and not all environmental inequalities must be judged as socially unfair. Thus, for developing policies to tackle environmental inequalities in general and particularly in Santiago, it is imperative to adequately understand the underlying drivers of observed inequality patterns. Such understanding is absolutely necessary before linking environmental inequalities with distributive environmental justice or injustice. If environmental inequalities are associated with an unfair distribution of environmental risks and access to environmental amenities, mitigation policies must be developed.

CHAPTER 3:

A GIS-BASED FRAMEWORK TO IDENTIFY PRIORITY AREAS FOR URBAN ENVIRONMENTAL INEQUITY MITIGATION AND ITS APPLICATION IN SANTIAGO DE CHILE

3.1 Introduction

Global urban population exceeded rural population for the first time in human history in 2007. Since then, the proportion of people living in urban areas has continued growing and it is expected that by the year 2050 almost two thirds of global population will be urban (United Nations 2015). The large proportion of this urban population increase is taking place in the developing world, with millions of people migrating from rural to urban areas searching for better development opportunities (Henderson 2010). The urbanization process experienced by developing regions is occurring very quickly, often faster than the capability of governments to develop and apply proper urban planning strategies (Cohen 2006). While cities are hubs for innovation, economic growth and sociocultural development, they are also becoming places of severe environmental problems, growing economic and social inequalities, and political and social instabilities (Pickett et al. 2011, Wu et al. 2013, Wu 2014, Nassauer et al. 2014, Wolch et al. 2014, Fernández et al. 2016, Pope et al. 2016).

Latin America has the highest urbanization level among developing regions, with almost 80% of its population currently living in urban areas (United Nations 2015). This region has undergone an explosive urbanization process since the middle of the past century. While in 1950 urban areas in Latin America were home to 70 million people, this number increased to nearly 400 million in 2000, and is expected to go over 600 million by 2030 (Cohen 2006). The urbanization processes associated with this increase in urban population has been seldom coupled with appropriate urban planning policies, often resulting in spatially segregated cities with high levels of social, and environmental inequalities (Angotti 1996, Carruthers 2008). Whereas economic and social inequalities have been widely covered in the literature and increasingly included in governmental political agendas (Roberts 2012), environmental inequality and environmental justice issues are still a scarcely addressed topic in Latin America.

Environmental inequality refers to the "unequal social distribution of environmental risks and hazards and access to environmental goods and services" (Sustainable Development Research Network 2007). A related but different concept is environmental inequity, which implies that the observed environmental inequality is judged as socially unfair (Kawachi et al. 2002). Thus, the concept of inequality emphasizes the spatial distribution of environmental resources and risks without a normative judgment, whereas the concept of inequity focuses on the social justice of that environmental distribution (Pope et al. 2016).

Urban environmental inequity has negative impacts on the well-being of urban residents. This is not only because of the direct effects of environmental hazards on people's health (e.g. air pollution causing respiratory diseases), but also because the psychological impacts on disadvantaged people due to the unfair distribution of environmental quality (van Kamp et al. 2003). These negative effects on perceived well-being could be a common phenomenon operating in Latin American cities, because people in the upper socioeconomic sectors usually have disproportionately greater access to areas of better environmental quality, whereas people in lower socioeconomic sectors are relegated to areas of poor environmental quality (Pedlowski et al. 2002, Escobedo et al. 2006, Wright Wendel et al. 2012, Romero et al. 2012, UN-Habitat 2014, Fernández & Wu 2016). As the future of humanity lies in urban areas (United Nations 2015), reducing urban environmental inequity is a major objective to move towards more sustainable cities (UN-Habitat 2014). This will require to prevent inequities by better understanding their underlying factors, but also to develop urban planning strategies to mitigate inequities once they have been generated.

Whereas reducing intra-urban inequities in developing countries has been noted as of primary concern by the United Nations (UN-Habitat 2012), methods and indicators that can inform decision-makers on where to prioritize their actions for mitigating environmental problems and inequities are still in their infancy (Martínez 2009, Sadd et al. 2011, Benmarhnia et al. 2013, Norton et al. 2015).

A challenging question that decision-makers face when attempting to reduce urban environmental inequities, is where to allocate available resources first. This entails a spatial prioritization problem, highlighting that environmental inequity is inherently a spatial issue (Ringquist 2005). Difficulties to solve this problem arise because (1) environmental problems are seldom evenly distributed within cities, (2) their spatial patterns may not be easily identifiable, and (3) the effects of these problems on people's quality of life may greatly differ based on the socioeconomic resources at their disposal (Jenerette et al. 2011). Furthermore, the severity and spatial patterns of environmental inequities are scale-dependent (Fernández & Wu 2016), meaning that multiple scales need to be considered simultaneously for both research and mitigation policies. Therefore, a prioritization approach to identifying target areas for mitigating urban environmental inequities would require multiscale spatially explicit methods, first aiming to identify the areas with severe environmental problems, and then to prioritize these areas based on socioeconomic factors accounting for the unfair social distribution of environmental amenities and hazards.

Although quantitative data on the spatial distribution of socioeconomic factors are often available at relatively fine spatial resolutions through census databases (e.g. census block data), environmental data are usually available at coarser resolutions (e.g. county, city, municipality or other administrative levels), limiting our ability to assess the spatial relationship between socioeconomic and environmental variables at finer scales. This is a key limitation for addressing intra-urban environmental inequities, because cities are highly spatially heterogeneous systems, and therefore environmental, economic, and social issues often present high spatial variability within administrative boundaries (Cadenasso & Pickett 2008, Pickett et al. 2011).

An alternative to overcome the spatial resolution limitation of environmental data is to take advantage of the increasing availability of remote sensing data and spatial software. Remote sensing data could provide high-resolution environmental information that otherwise would be unfeasible to collect at the intra-urban level (e.g. vegetation, temperature), whereas spatial software could transform point-based information into spatially continuous data (e.g. air pollution interpolation from monitoring stations), increasing our availability to assess the spatial variability of environmental issues in urban areas.

Integration of environmental and demographic information into a spatially explicit framework could be a wise approach to identify the areas concentrating environmental problems, and to prioritize efforts among the areas with higher social relevance (i.e. pertinence to society). Based on such an approach, in this chapter I present a GIS-based indicator framework that integrates environmental and demographic data into an “Environmental Improvement Priority Index (EIPI)”, which can help policy-makers to identify priority areas for reducing environmental inequities at different spatial scales and administrative levels.

This framework aims to help: (1) identifying intra-urban areas having the highest levels of environmental problems, (2) identifying intra-urban areas having the highest levels of social relevance, and (3) prioritizing the allocation of resources within the areas concurrently having the highest levels of environmental problems and social relevance. To show the potential use of this framework for identifying priority areas to be targeted with environmental inequity mitigation interventions, I apply the framework to the city of Santiago de Chile at three different scales. I focus the assessment on three main environmental inequity problems reported to be currently affecting the quality of life of this city: urban heat, reduced vegetation coverage, and air pollution (Fernández & Wu 2016). Based on the results from the application of the framework to Santiago, I further discuss how results from the EIPI framework can be used by policy-makers for addressing intra-urban environmental inequities.

3.2 The Environmental Improvement Priority Index (EIPI) Framework

The EIPI framework (Fig. 3.1) is intended to be a relatively simple and flexible spatial prioritization tool that can be applied at different spatial scales and administrative levels. To use the framework in a particular urban area, relevant environmental inequity problems need to be first identified through scientific research, literature review, stakeholder workshops, political decisions, or combinations of the above. Thus, the goal of the EIPI is not to identify the specific environmental inequities to be targeted, as these need to be identified in a previous stage. The goal of EIPI is to provide a step-by-step procedure to help researchers and policy-makers identifying priority areas or administrative units (e.g. districts, municipalities) to be targeted with environmental interventions to reduce environmental inequities. These areas are prioritized based on the assumption that from an environmental inequity perspective, policy interventions ought to be focused in areas or administrative units where more vulnerable people are facing the harshest environmental problems (e.g. Norton et al. 2015). Whereas the structure of the framework allows for simultaneously addressing multiple environmental inequity problems, it is preferable to assess a set of problems that can be tackled with similar environmental interventions (e.g. increasing vegetation coverage to reduce heat and pollution), otherwise potential interventions to be implemented on priority areas can be difficult to identify.

Operationally, the EIPI index works through constructing and integrating two spatial indicators: (1) an environmental stress indicator (ESI) accounting for the spatial distribution and level of assessed environmental problems within the area of analysis, and

(2) a social relevance indicator (SRI) accounting for the spatial distribution and level of social vulnerability within the same area (Fig. 3.1). The integration of these two indicators into the EIPI index provides a spatial prioritization measure for identifying areas with the highest environmental stress and highest social relevance. The procedures to build ESI and SRI, and to integrate them into EIPI include 4 steps: (A) variable selection, (B) data normalization, (C) ESI and SRI computation, and (D) EIPI integration (Fig. 3.1).

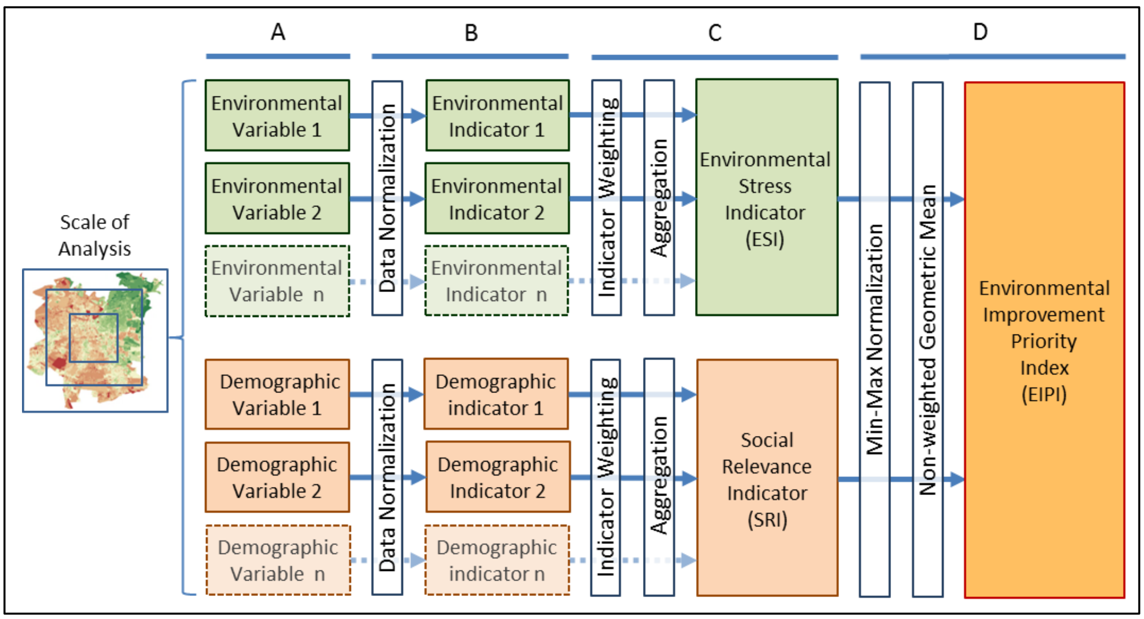

Figure 3.1. Environmental Improvement Priority Index (EIPI) Framework. The four steps involved in calculating the EIPI are denoted by letters A, B, C, D. Scales of Analysis refer to the specific extent (the total study area) and areal unit (grain size) used for the assessment.

Step A of the framework consists on the selection of the variables used to compute ESI, SRI, and EIPI (Fig. 3.1). This is a key step of the procedure because selecting relevant and adequate variables is fundamental for the credibility and usefulness of the framework outputs. The chosen variables not only need to provide accurate spatial data at the scale at which the framework is intended to be applied, but also must match the spatial scale at which environmental improvements are to be implemented. For example, if the framework is intended to be applied for identifying priority neighborhoods, the minimum areal unit of analysis (i.e. resolution in terms of grain size) needs to represent the assessed neighborhoods. Thus, the objective of this step is not to identify the environmental problems to be addressed, but to evaluate and identify the most appropriate available data accounting for the spatial distribution of the environmental problems that have been previously identified as important in the study area. The EIPI framework uses numerical data. If only categorical data for certain variables are available, they need to be transformed into numerical or ranked values to be used as compatible inputs.

Two types of variables are necessary to be defined at this step; environmental and demographic. Environmental variables need to represent relevant spatial information directly related with the environmental problems aimed to be addressed. Demographic variables represent specific characteristics of the population, such as income, education level, ethnicity, and age classes (Lee & Schuele 2010), which can be used to account for the socioeconomic factors related to people's vulnerability to assessed environmental problems (Martínez 2009, Norton et al. 2015, Inostroza et al. 2016). At this point including a measure of population density as an additional spatial variable can be quite useful for helping prioritizing efforts based on the quantity of vulnerable people potentially exposed to environmental problems (Greiving et al. 2006). The total number of demographic variables will depend on the different potential factors accounting for people's vulnerability and exposure to the assessed environmental problems. Nevertheless, it would be preferable to use a relatively small set of key variables that provide specific information to decision-makers, rather than a large set which may hamper posterior interpretation and communication of the results.

Step B is intended to transform the input variables into normalized indicators with compatible units for mathematical computations. There are two main approaches to normalize variables into standardized units, one based on reference or threshold values and the other based on data distribution (e.g. z-scores, max-min rescaling) (See Nardo et al. 2005; OECD 2008 for a review of methods). The reference- or threshold-based approaches involve a normative decision on what the desirable reference or threshold values should be. The data distribution approaches normalize variables based solely on the statistical distribution of their values. Normalization based on references or thresholds is more useful when there are enough empirical data to support the reference or threshold values. On the other hand, normalization based only on data distribution is plausible when information on reference or threshold values is lacking or conflicting. However, for consistency and integration of the results it is recommended to apply the same normalization method for all variables within each set of variables (i.e. environmental and demographic). It is also necessary to analyze the data for potential skewed distribution and outliers to determine whether the data need to be transformed before the normalization process (Dobbie & Dail 2013).

Step C involves the integration of the normalized environmental and demographic indicators (in Step B) into two core composite indicators (i.e. ESI and SRI). This step includes two main processes: to weight the variables according to their relative importance, and then to aggregate them into the respective composite indicators.

There are different methods for weighting indicators (Nardo et al. 2005, OECD 2008, Huang et al. 2015, Gan et al. 2017), including methods based on statistical approaches (e.g. Regression Models, Principal Component Analysis), methods based on expert decisions (e.g. Budget Allocation), and methods based on participatory processes (e.g. analytical hierarchical process, surveys). Methods based on statistical approaches reduce subjective decisions on the final weighting values, which are useful when there is not sufficient knowledge about the drivers and importance of the assessed variables, or if the framework is used mainly for understanding the relationships among variables. On the other hand, methods based on expert knowledge and participatory processes increase the subjectivity on final weight decisions, but they can be desirable because they take account of context-specific political and cultural values not considered by the purely statistical approaches (Nardo et al. 2005). Regardless of the approaches themselves, the process of choosing a particular weighting method will inevitably involve value judgment (Böhringer & Jochem 2007). For the EIPI framework to be used in decision-making, weighting methods combining expert knowledge with participatory processes should be preferable as they integrate technical knowledge from researchers and context-specific values from the stakeholders.

With respect to the aggregation methods, there are two principal approaches; linear (or arithmetic) and geometric aggregation (Dobbie & Dail 2013, Gan et al. 2017). Both aggregation methods imply some degree of compensability between individual indicators (OECD 2008). However, whereas the linear approach allows for a complete compensation between indicators, the geometric method reduces the level of compensation and increases the relevance of spatial interaction between indicators (OECD 2008). Although there is not a specific answer to the question of which aggregation method should be used, in the case of environmental assessment the geometric approach seems more suitable because it decreases the degree of compensability between indicators and increase the relevance of extreme values in final results (Nardo et al. 2005).

Step D aims to integrate the composite indicators constructed in Step C into the EIPI composite index, which is the main output of this framework to help define the priority areas for improving environmental quality. This step requires to first normalize the ESI and SRI built on the previous step, and then to aggregate the ESI and SRI into the EIPI. This step is a key component in this framework, and therefore is less flexible than the previous steps. Normalization of the indicators requires to be done by using the Max-Min rescaling method (eq. 3.1).

$$X_n = \frac{(X - X_{min})}{(X_{max} - X_{min})} \qquad \text{(eq. 3.1)}$$

The Max-Min normalization method rescales the data into values ranging between 0 and 1 through a linear transformation that does not change the relative distribution of original data. The use of the Max-Min method aims to increase the capability of the framework to detect those areas that accumulate the maximum levels of environmental problems and have the maximum social relevance. Normalized ESI and SRI indicators are then required to be integrated through the non-weighted geometric aggregation method (eq. 3.2).

$$EIPI = \sqrt[2]{ESI * SRI} \qquad \text{(eq. 3.2)}$$

The reason for not weighing the indicators is because the objective of this step is to identify the areas with two conditions: high levels of environmental problems and high social priority, and there is no value judgment about which one is more important. The use of the geometric instead of the arithmetic aggregation is to increase the capability of the approach to discriminate the areas that simultaneously hold these two conditions.

3.3 Application of the EIPI framework in Santiago de Chile

The city of Santiago is the largest and most populated urban area of Chile, currently harboring an estimated population of 6.4 million, which represents around 35% of the country's total population (Instituto Nacional de Estadísticas 2015). The Greater Santiago area is composed of 34 municipalities, covering a total area of ~750 km^2. Among the most concerning environmental problems currently affecting the quality of life of Santiago residents are an increasing heat exposure during summer months (Krellenberg et al. 2013, Inostroza et al. 2016), low levels of green infrastructure in most parts of the city (Forray et al. 2012, de la Barrera et al. 2016a), and high levels of air pollution during the winter season (Toro et al. 2014). These environmental problems are not evenly distributed in the city; on the contrary, they tend to be more severe in the areas inhabited by lower-income groups, suggesting the presence of strong environmental inequities (Fernández & Wu 2016). Therefore, identifying the areas of Santiago presenting the highest levels of the assessed environmental problems, and prioritizing them according to their social relevance, can provide essential information for policy-makers to design strategies for reducing environmental inequity and promoting urban sustainability.

3.3.1 Scales of analysis

In the following section I apply the EIPI framework to the city of Santiago, focusing on the three environmental problems discussed above (i.e. urban heat, lack of green infrastructure, and air pollution). I implement the framework through a multiscale approach intending to demonstrate the flexibility of the framework and to generate results that can inform decision-making at different administrative levels. Scale usually refers to both, extent (the total study area or map size) and grain size (the spatial resolution or minimum areal unit of analysis). Specifically, I perform the assessment with three different scale combinations (Fig. 3.2), each having a particular objective:

- *City Extent with municipal-level data (Fig. 3.2a):* At this scale, I analyze the city extent using the municipality as the basic areal unit of analysis. In Santiago, municipalities operate as relatively independent administrative units and therefore several of city-scale policies attempt to allocate resources to most deprived municipalities (Bravo 2014). Information generated as this level can be used by the central government to decide on which of the 34 municipalities of the Greater

Santiago area is more relevant to increase the allocation of resources for enhancing environmental quality.

- *City extent with pixel-based (100m/pixel) data (Fig. 3.2b):* This scale represents a transboundary assessment that treats the city as a whole, without distinguishing between administrative units. The basic areal unit of analysis here is the pixel. The objective at this scale is to capture the detailed spatial patterns of social and environmental variables within the city, which can only be revealed by fine-resolution data. The priority areas identified with the fine-grained pixel-based data may be different from those observed with municipal-based data, but they are complementary to each other, providing multiscale information. This information may be used by the central and regional government to identify particular neighborhoods that have the highest priority for environmental improvements, independently of the municipality in which they are located. This may be particularly useful when an identified priority area crosses the boundaries of different municipalities, or when pocket areas of high priority are located within low-priority municipalities.
- *Municipal extent with block-level data (Fig. 3.2c):* At this scale the assessment is performed within a particular municipality using the city block as the basic areal unit of analysis. The objective at this scale of analysis is to show how the EIPI framework could be used within administrative levels to generate actionable knowledge for municipal policy-makers to prioritize specific neighborhoods or city blocks for environmental interventions. On this scale, I selected the municipality of *Lo Prado* as an example (see highlighted municipality in Fig. 3.2a) because it has severe environmental problems and a large proportion of low income sectors, and is close to

several air pollution monitoring stations, which increases the accuracy of air pollution spatial data for fine resolution analysis.

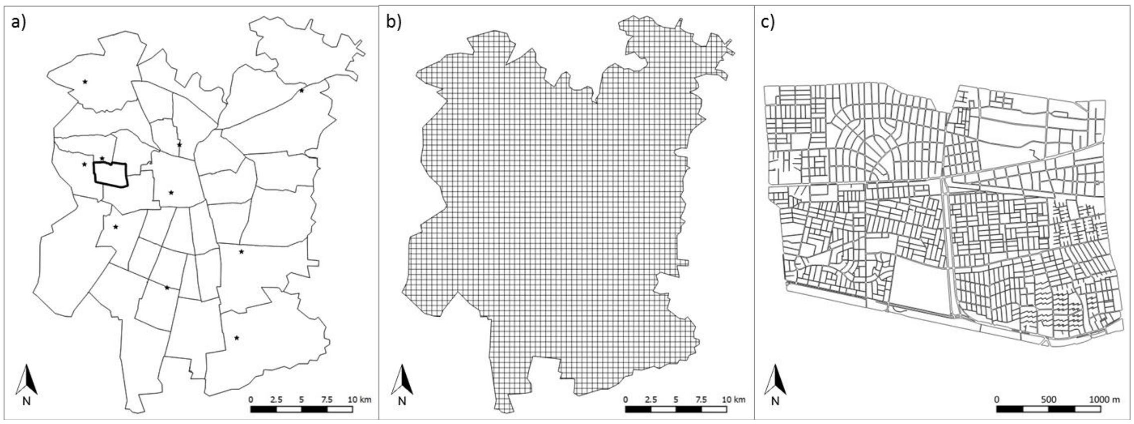

Figure 3.2. Three scales used for the assessment. Extent in a) and b) corresponds to the entire city area, in c) to the municipality of Lo Prado, which is highlighted in a). Areal units of analysis correspond to the municipal level in a), 100m/pixel in b), and census blocks in c). Dots in a) are locations of air pollution monitoring stations. Raster lattice shown in b) is only for visual reference and not at the scale of analysis.

3.3.2 Implementing Step A: Selecting variables and compiling data for calculating ESI, SRI, and EIPI

Following the procedures outlined in section 3.2, I collected and processed the environmental and demographic data at the three different scales. I estimated surface temperature and vegetation cover from a set of four Landsat-8 satellite images acquired on 09 January 2014, 10 February 2014, 12 January 2015, 13 February 2015. Images were gathered through the USGS satellite images database portal (earthexplorer.usgs.gov). Selected images represent the climatic conditions of the warmest and driest period of the summer season in Santiago, which are appropriate for identifying areas with the highest heat risks, and areas with managed green infrastructure (Inostroza et al. 2016, Fernández

& Wu 2016). I estimated surface temperatures from Landsat TIRS sensor Band 10 following the NDVI-threshold emissivity method (Sobrino et al. 2004). For vegetation cover I used the normalized difference vegetation index (NDVI) as an urban vegetation proxy as this index has shown to be a good indicator of vegetation cover in semi-arid climates like Santiago (Elmore et al. 2000), and regarded as a good indicator for measuring vegetation cover associated to managed green infrastructure in Santiago (Fernández & Wu 2016). For both surface temperatures and vegetation cover, I estimated the values for all four satellite images, and then took the averages in order to reduce potential sampling bias due to the use of a single image. I obtained air pollution data through a spatial interpolation (Kriging method) of ten PM-2.5 official monitoring stations distributed in Santiago (see Fig. 3.2a). For the interpolation procedure, I took the daily average PM-2.5 concentrations for the last two officially validated autumn-winter seasons data (01 April to 31 August, years 2013 and 2014). I decide to focus on autumn-winter seasons because is during these months that PM-2.5 pollution becomes hazardous in Santiago (Muñoz & Alcafuz 2012). All environmental variables were originally produced at a resolution of 30m/pixel. For polygon-based analyses the 30m/pixel values were aggregated (arithmetic averaging) into the respective areal unit of analysis (i.e. municipality, block). For raster-based analyses I resampled the data to a 100m/pixel (bilinear interpolation method) to reduce the potential presence of outlier values due to local-scale heterogeneity.

I gathered the demographic variables from the 2012 updated version of 2002 Chilean Official Census Database developed by Norel et al. (2013). From this database, I derived two demographic variables: socio-economic level (SEL), and population density

(PD). The inclusion of SEL aimed to reflect the vulnerability of people to the assessed environmental problems, whereas PD was used to weight this vulnerability based on the number of people experiencing hazardous environmental conditions. Other demographic variables such as age or health condition can also be important for reflecting people vulnerability to particular environmental hazards such as heat stress and air pollution in Santiago (Bell et al. 2008, Oyarzún 2010). However, age and health condition variables are not available in this updated database due to technical reasons (Norel et al. 2013). Therefore, I used SEL as our vulnerability variable, acknowledging that this measure only reflects the educational and economic resources that people may have to cope with these environmental burdens.

SEL has five categorical classes based on the educational level of the household head and a list of properties owned by the household. I transformed this categorical information to ordinal data by assigning numerical values (1 to 5) to the five SEL categories, with higher values corresponding to higher SEL levels. I further transformed the ordinal data to continuous values using equation 3.3 for each census tract, where i represents the ordinal SEL value (between 1 and 5), and p_i the respective proportion of each SEL category.

$$\sum_{i}^{n} i * p_i \qquad \text{(eq. 3.3)}$$

Population density was not directly available in the census dataset, thus, I calculated it as the total number of people per census block divided by block area. Both demographic variables were originally in vector format at the census-block level. To generate the municipal-level data I aggregated block-level data using an area-weighted approach. For pixel-based computation I rasterized the original vector layer at a spatial resolution of 100m/pixel, matching the scale of the raster layer of the environmental variables.

3.3.3 Implementing Step B: Transform input variables into normalized indicators with compatible units

For this step, I transformed all environmental and demographic variables into indicators ranging between 0 and 1 by using a relative value-based normalization approach. With this transformation I intended to capture the spatial distribution of each variable without making normative assumptions of particular desired target or threshold values. Thus, the normalized values of variables are relative importance measures of each area in relation to the others. This type of normalization approach is useful for a city like Santiago where there is ample evidence that the spatial distribution of environmental and social variables reveals an unfair social share of environmental amenities and hazards (Escobedo et al. 2006, Romero et al. 2012, Perez 2015, de la Barrera et al. 2016a, Fernández & Wu 2016).

As for the specific method of normalization, I use the Max-Min method (eq. 3.1) for all the variables, except for the demographic variables at the scale combination of c*ity extent with pixel-based data*, for which I used a ranking-based normalization. I made this decision because population density data showed an extremely skewed distribution with outliers that were not possible to adequately resolve with commonly used transformation methods. Therefore, I decided to normalize these data using a percentile-based ranking of 100 equidistant categories (i.e. from 0.01 to 1). This normalization approach is robust against outliers, and also capable of retaining a high degree of spatial heterogeneity in the original data if the number of categories is relatively high. Furthermore, percentile-based categorization of data is commonly used for designing and implementing social policies, and therefore results from this percentile-normalized data can be easily communicated to decision-makers.

Both Max-Min and percentile ranking normalization methods used in this analysis generate indicators that show the relative position of each area/pixel in relation to the others. Maps built at the three assessment scales following the procedures described in this section are shown in Fig. 3.3.

3.3.4 Implementing Step C: Weight and aggregate indicators to obtain ESI and SRI

To weight the relative importance of environmental indicators I ran an online survey on August 2015 that I share through two social media applications, Facebook and WhatsApp (Fig 3.4). This survey was not aimed to generate an objective representative sample for Santiago's inhabitants, but rather to reduce my personal bias in selecting potential weights for the case of study.

The survey (Fig 3.4). consisted in one main question and one supplementary question used to filter only those answers effectively coming from people residing in Santiago. The main question required ranking four environmental conditions into five categories ranked from less to more important in relation to their relevance for environmental quality at the neighborhood scale. The assessed conditions were: (1) fresh during summer months, (2) abundant trees and gardens in neighborhood, (3) low levels of air pollution, and (4) nearby to green areas and urban parks. I used this last condition as an auxiliary variable to avoid having people responding regarding local scale green infrastructure (condition 3) but thinking in large scale green areas (condition 4). I designed the question in a way that it was possible to evaluate how important is each condition, but also to evaluate the relative importance between conditions.

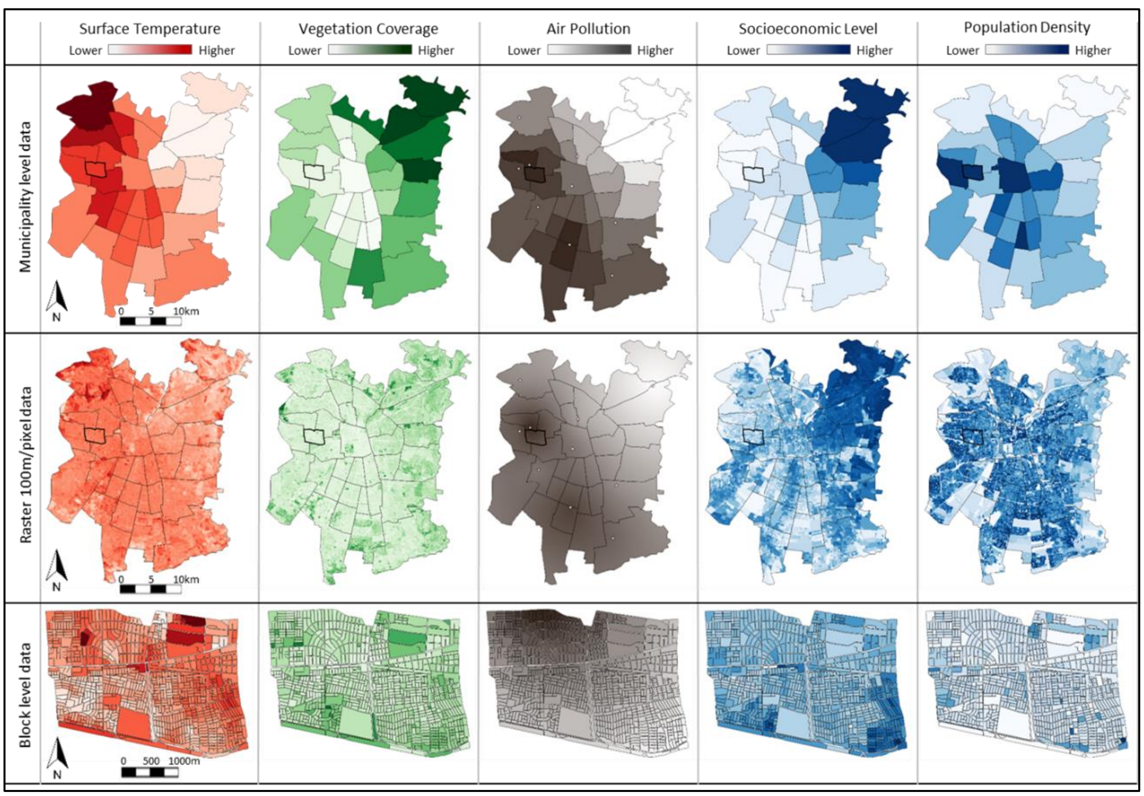

Figure 3.3. Maps of the spatial layers of the three environmental and two socio-demographic indicators on three scales of analysis. Maps represent the spatial distribution of each indicator based on relative values. Top row represents Santiago city Extent with municipal-level data, middle row Santiago city extent with pixel-based data, and bottom row Lo Prado municipal extent with block-level data. Top and middle rows present in bold lines the boundaries of Lo Prado municipality. Dots in Air Pollution maps denote locations of air monitoring stations. In middle row maps boundaries of municipalities are shown to facilitate visual analysis.

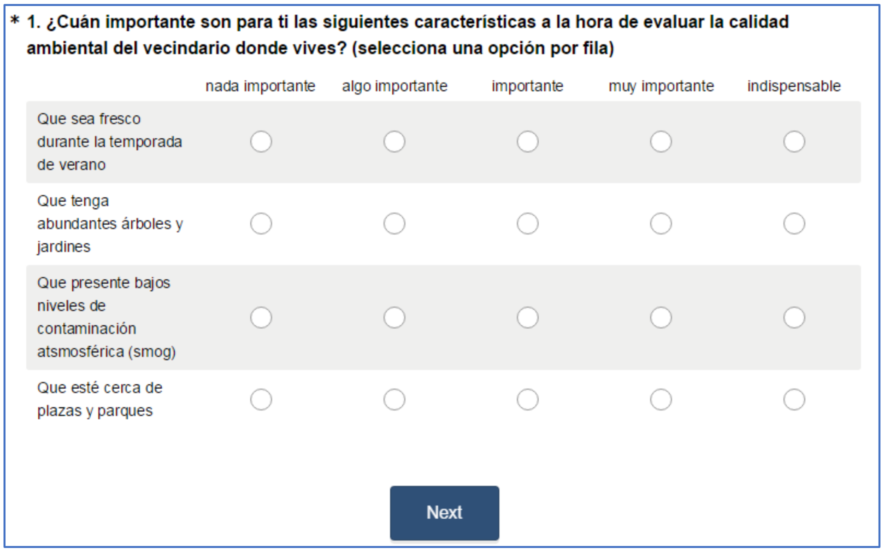

Figure 3.4. Screen caption of the survey used to weight environmental indicators. The four environmental conditions (column on the left) and five ranking alternatives (Row on the top) are shown. Survey is in Spanish.

I left the survey open for 4 days, receiving a total of 112 answers from people living in Santiago, representing a total of 16 municipalities. To generate the weighting values, I ranked each answer into values from 1 to 5 (less to more important), and then used the averaged ranking value for each neighborhood environmental condition as the final weight. Resulting weighting values were: 0.292 for surface temperature, 0.365 for urban green coverage, and 0.343 for air pollution.

In the case of demographic indicators, I used an equal weighting scheme assuming that socioeconomic level and population density are two complementary and equally important indicators for assessing the social relevance of different areas.

Before aggregating variables into the ESI and SRI, I inverted the normalized values for vegetation cover and socioeconomic level indicators of manner to have all the indicators standardized, with higher values representing higher environmental stress and social relevance. To aggregate the variables into the ESI and SRI I used the geometric approach (eq. 3.2) for both environmental and demographic variables. The objective of using the geometric approach was to enhance the capacity of the method to identify the areas presenting an accumulation of environmental problems, and areas concomitantly having low socioeconomic level and high population density.

3.3.5 Implementing Step D: Normalizing ESI and SRI and aggregating them into EIPI

In this step, I directly followed the procedures stated on the framework, which are to first normalize the ESI and SRI indicators using the Max-Min normalization method, and second to aggregate the normalized ESI and SRI values to obtain the composite index, EIPI, through the non-weighted geometric aggregation method.

3.4 Santiago prioritization results

Resulting maps of ESI, SRI, and EIPI on the three assessment scales using the procedures described in steps C and D are shown in Fig. 3.5. The three scales of analysis used in this study provide different, but complementary information for decision-makers. Analysis at the municipal level (Fig. 3.5, top row) provides information regarding the spatial distribution of these indicators among the 34 municipalities making-up the city of Santiago, and the EIPI maps show which municipalities should be targeted first. Analysis with raster-based data at the city scale (Fig. 3.5, middle row) provides information regarding the spatial distribution of these indicators at the neighborhood level, and the EIPI map shows the specific neighborhoods that should be targeted first. Finally, the analysis at the block level (Fig. 3.5, bottom row) provides specific information on the spatial distribution of these indicators as the analysis considers only the distribution of environmental and social variables within the assessed municipality. In this case the EIPI map shows the specific blocks on which interventions should be prioritized.

Figure 3.5. Spatial patterns of ESI, SRI, and EIPI on three assessment scale combinations. In top and middle rows, bold lines are the boundaries of Lo Prado municipality. Letters a) and b) in the bottom right map represent the highest and medium priority blocks, respectively. Street level photos for these blocks are shown in Fig. 3.7.

To show the capability of the framework to detect priority areas, Fig. 3.6 presents street level photographs from middle and high priority areas identified by the EIPI framework using data at the block level.

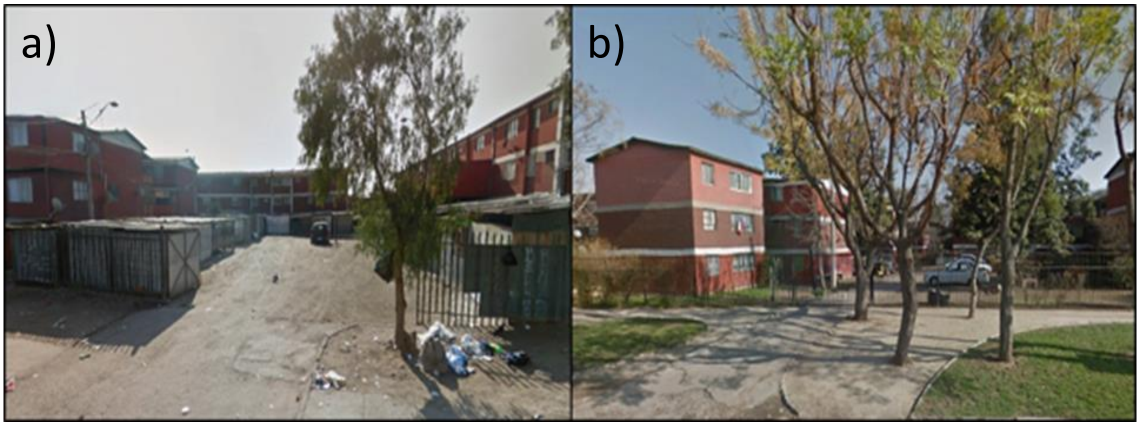

Figure 3.6. Photos from blocks identified as highest (a) and middle (b) priority areas after applying the EIPI framework in Lo Prado Municipality (see Fig. 3.5). Photos were gathered from the Google Street View service. Photos were taken on July 2015.

3.5 Discussion

Urban environmental quality is one of the key factors determining the quality of life of urban residents (van Kamp et al. 2003, Matsuoka & Kaplan 2008). Thus, developing tools to help decision-makers to prioritize environmental improvement efforts is crucial for promoting more equitable and sustainable cities. The EIPI framework presented in this chapter is such a tool that helps to prioritize the areas of interventions for reducing environmental inequities. The aim of the framework is not to measure the patterns of intra-urban environmental quality or inequalities, for which diverse approaches are existent on the literature (Montero et al. 2010, Liang & Weng 2011, Joseph et al. 2014, Pope & Wu 2014, Fernández & Wu 2016), but rather to help identifying the potential areas of the city where environmental improvements could have larger social benefits. A solution framed from the environmental inequity perspective may be particularly relevant for cities having high degrees of socioeconomic segregation, such as Santiago (Fernández et al. 2016), because people in high-income areas may invest to improve their household-level environment or move to a place of high environmental quality, whereas people in low-income neighborhoods do not have the financial resources to do so (Azócar et al. 2007).

Previous studies have integrated environmental and socioeconomic data into GIS-based indicator frameworks to help decision-makers to prioritize available lands (e.g. vacant lots, brownfields) for increasing socioeconomic and environmental benefits (e.g. (Chrysochoou et al. 2012, McPhearson et al. 2013, Kremer et al. 2013). This type of approaches, based on predefined opportunities for intervention, may be useful once the priority target areas have been identified (e.g. Norton et al. 2015). But potential priority areas (e.g. neighborhoods) could be neglected where opportunities for interventions are currently lacking. This is a highly relevant issue in many cities of the developing world, such as Santiago, because the combination of weak urban planning policies and rapid urbanization processes has generally resulted in vulnerable neighborhoods characterized by high residential density, low proportion of green spaces, and a scarcity of available lands for potential environmental interventions (Atisba 2015, de la Barrera et al. 2016a). In this case, therefore, a prioritization approach focused primarily on the availability of areas for interventions would not be adequate. It may even result in unintended worsening of environmental inequity patterns. Thus, the EIPI framework presented here seems a useful tool for helping decision-makers to map and identify priority areas for environmental interventions. Once these areas have been identified, additional methods can be used to help screen potential opportunities for interventions within the area, based on which particular interventions that need to be prioritized can be decided (e.g. Norton et al. 2015).

The EIPI framework is relatively simple, flexible, and easy to communicate, which are desirable characteristics of tools for linking science with decision-making. Implementation of the framework does not only help identify the priority areas, but also map the different variables, and the environmental and social indicators, which can be used as complementary information for final decision-making. Conceptually, the EIPI is framed under the simple but reasonable assumption that policies based on an environmental inequity perspective should prioritize the areas where more vulnerable people are facing more serious environmental problems within a city. This is similar to the "area-based" approach which has been used widely by policy makers to identify deprived urban sectors to be targeted with interventions (Andersson & Musterd 2005, Rae 2011).

The structural flexibility of the framework allows researchers and policy-makers to better fit their objectives by selecting the most relevant environmental and social variables, the most appropriate weighting and aggregation methods, and scale combinations. This flexibility gives the framework the advantages to be used for tackling a variety of environmental inequity-related problems, stimulating direct input from local residents and thus facilitating urban governance for sustainability (Mccall & Dunn 2012). However, this flexibility also increases the possibilities for the framework to be wrongly implemented or populated with inaccurate or low-quality data, which can lead to misleading results. In this regard, for this framework to be correctly used it is fundamental to have an adequate understanding of the problems at hand and clearly justify each and every choice of variables, weighting/aggregation methods, and scales of analysis/policy.

The scale flexibility of the framework is necessary to provide multiple-scale information required for understanding and dealing with the complexity of environmental inequity issues. In most metropolitan areas, including Santiago, decisions are made on multiple hierarchical levels of government or organizations, each of which usually focuses on information at their respective scale of concern (O'Sullivan et al. 2014, Storper 2014). For example, in this case study, results from the *City extent with municipal-level data* analysis provide information on which municipalities of the 34 in the greater Santiago area have the highest priority for improving their environmental quality. This information may be used by the central government or the metropolitan region administration to allocate specific budgets to those municipalities, or to develop specific policies to help people living in prioritized municipalities (Agostini & Brown 2011).

On the other hand, the *City extent with pixel-based data* analysis offers information on the specific neighborhoods that have the highest priority, independently of the municipality in which these neighborhoods reside. This information is crucial for the central government and the metropolitan administration to identify priority neighborhoods that are not necessarily in prioritized municipalities, and based on this develop specific interventions at the neighborhood level (Zapata & Arias 2008). This is highly relevant because results obtained with larger areal units of analysis hide the spatial heterogeneity within smaller areas (Fernández & Wu 2016), and therefore the areas of high priority located in low priority municipalities do not show up.

Finally, the *Municipal extent with block-level data* analysis offer specific information on the particular blocks within a particular municipality that have the highest priority for environmental improvements. Results from this level of analysis can be quite useful because this scale and the associated findings tend to be more actionable in most cities. For example, integrated interventions focused on increasing urban tree coverage at local scales in Santiago could be an effective way to reduce air pollution (Escobedo & Nowak 2009), decrease surface temperatures (Smith & Romero 2016), and increase the overall quality of neighborhood green infrastructure.

While the results from this case study can offer useful information for Santiago's policy makers, the main objective of this case study was to show how the framework can be applied in a city with high levels of environmental inequalities like Santiago. For this purpose, the choices of variables and indicator methods used in this study are justifiable.

Although I met with metropolitan and municipal decision-makers to obtain feedback while designing the framework, and also incorporated local resident opinions into the weighting schemes, results of this study should be taken with caution if they are to be used for policy making in reality, as it would be recommended to perform a more thorough participatory process involving a broader range of stakeholders and decision-makers. Also, these results are constrained by the fact that the data came from a particular period of time, while social and environmental changes in urban areas are pervasive in time and space (Pickett et al. 2011). For this framework to be used in the decision-making arena, the problems, variables, and weighting and aggregation methods should be decided through a continuous and comprehensive participatory process. Including affected people in an equitable and representative participation process is fundamentally important to the fairness and transparency of the procedures, as well as to the legitimacy of the outcomes (Mccall & Dunn 2012).

3.6 Conclusions

Environmental inequity is a prevalent and challenging problem in cities around the world, and particularly in developing regions. Environmental inequity not only affects people's well-being due to the health impacts of a disproportionate load of environmental "bads" on vulnerable sectors, but also due to the ethical and moral implications that this unfair distribution has in the society. Considering the explosive urbanization process occurring during the recent decades, it is not surprising that reducing environmental inequity is becoming a key challenge for urban planners and policy-makers. Addressing this problem requires understanding the spatial patterns and levels of environmental inequities, and to develop tools that help decision-makers to prioritize the allocation of policy interventions in areas of highest needs.

The EIPI framework developed in this chapter can help achieve both objectives. Particularly, it can serve as a tool to bridge the diagnosis of environmental inequities with the production of actionable knowledge necessary for implementing potential solutions. The process of building the ESI and SRI indicators provides a platform for discussion and deliberation of key environmental and demographic variables related to environmental inequities, and produced maps are an effective way to evaluate preliminary outputs and communicate final results. These characteristics made this framework a useful tool that can be adopted and used by decision-makers for identifying priority areas and planning interventions to reduce environmental inequities. However, it is only through a meticulous application that this framework will provide credible, salient, and legitimate results (Cash et al. 2003). It is essential for the decision makers and stakeholders to have a good understanding of the assessed environmental problems, and work together to design proper and feasible interventions. This is not only relevant for designing the intervention policies, but also for ensuring the effectiveness and efficiency of implementing them. Decision-making processes are based in both art and science, and the EIPI framework is designed to help integrate the art of deliberation with the science of producing useful and reliable data.

CHAPTER 4:

AN ECOSYSTEM SERVICES MAPPING FRAMEWORK FOR INFORMING THE SPATIAL ALLOCATION OF URBAN VEGETATION

4.1 Introduction

Cities have become the main habitat for humans. Currently more than 50% of human population live in urban areas and is expected that this number goes beyond 65% by the middle of this century (United Nations 2015). Most of this increase will take place in developing countries, with millions of people migrating from rural to urban areas seeking for better development opportunities (Henderson 2010, United Nations 2015). While cities are main hubs of human development opportunities, they are also hotspots of environmental and socio-economic problems (Grimm et al. 2008, Wu 2010). Although residents of urban areas may have better access to economic opportunities than in rural areas, their quality of life can be negatively affected by poor environmental conditions (van Kamp et al. 2003). Furthermore, environmental quality in urban areas is often positively associated with people economic and social resources, implying that disadvantaged groups are frequently exposed to a disproportionate share of environmental burdens (e.g. Brulle & Pellow 2006, Pearce & Richardson 2010, Padilla et al. 2014, Fernández & Wu 2016). Thus, planners and decision-makers are not only challenged to develop effective strategies for improving urban environmental quality, but also to properly allocate investments and interventions so as to alleviate the problem of urban social unfairness (Wolch et al. 2014).

There is increasing evidence that natural and semi-natural areas play a key role in promoting environmental quality in urban areas. In fact, urban areas are not decoupled from ecological systems; but on the contrary, they strongly depend on the ecosystem services (ES) provided by natural and semi-natural systems that are within and beyond the urban physical boundaries (Tzoulas et al. 2007, Jansson 2013). While a large proportion of ES provided in urban areas are generated outside the urban boundary (Luck et al. 2001), vegetation within cities play a fundamental role providing ES that can be key for solving prevalent urban environmental problems. For instance, the use of urban vegetation has shown to be an effective strategy for mitigating air pollution and reducing the urban heat island effect (Bowler et al. 2010, Janhäll 2015, Willis & Petrokofsky 2017), which are two common environmental problems in cities around the world.

Taking in consideration the current and projected urban population, it is not surprising that providing ES in urban areas has been increasingly highlighted as a key goal for improving urban sustainability (Lovell & Taylor 2013, Gaston et al. 2013, Wu 2014, Andersson et al. 2015, McPhearson et al. 2015).

While there is ample support for implementing urban vegetation to provide ES for increasing urban quality of life, we often lack the empirical data and specific approaches for optimizing the spatial allocation of vegetation within urban areas. Although methods for optimizing the allocation of vegetation are increasingly published in the literature (e.g. Wu et al. 2008, Locke et al. 2010, Morani et al. 2011, Norton et al. 2015, Bodnaruk et al. 2017), these have been largely focused on the provision of ES by vegetation at the local scale (e.g. street level, neighborhoods), often overlooking the capacity of vegetation to provide ES beyond local boundaries. The benefits provided by vegetation to a specific area will depend not only on the ES generated within that area, but also on ES flowing from vegetated areas outside the local boundaries. For instance, there is evidence that the cooling effect of vegetation from urban parks can spread up to several hundred meters into surrounding residential areas (Bowler et al. 2010), and that the level of air pollutants in residential neighborhoods depends on the level of vegetation in surrounding areas (Irga et al. 2015).

Hence, key to planning the allocation of urban vegetation for providing ES is the use of spatial methods capable to integrate the potential flows of ES from services providing areas (SPA) to services benefiting areas (SBA). Here I refer to ES flow as the physical transference of ES from the actual site where the ES are generated (SPA) to the areas where people experience the benefits from these services (SBA) (Bagstad et al. 2013). In other words, ES flows relate to the physical connection between ES provided by SPA, and the benefits yielded at SBA. Thus, the notion of SPA and SBA offers a useful approach to integrate the concepts of ES flows into urban planning (Syrbe & Walz 2012). For example, this approach could be used to map the spatial patterns of current ES provision and ES deficits, assess their spatial mismatch, and use this information to identify the areas where increasing the provision of ES is more necessary (Larondelle & Lauf 2016). Furthermore, as the areas of higher ES deficits are often spatially associated with lower income sectors (Jenerette et al 2011, Wolch et al 2014), such an approach could be also helpful if the objectives include allocating ES from an environmental justice perspective (Ernstson 2013).

However, assessing the flows of ES is still a prevalent challenge for researchers, which may explain why methods to prioritize the allocation of urban vegetation have largely overlooked ES flows. This is not only challenging because of the difficulties of assessing the distance at which a particular ES may flow from SPA (Fisher et al. 2009, Syrbe & Walz 2012, Bagstad et al. 2013, Serna-Chavez et al. 2014), but also because not all vegetation types are equally effective in providing commonly required services within cities (Bowler et al. 2010, Janhäll 2015). Thus, the development of spatial explicit methods to map ES flows generated by urban vegetation are still needed. A method like this can provide more accurate information on the current spatial patterns of ES provision, and with this, better data for assessing the spatial mismatch between ES provision and ES deficits, which is key information for identifying priority areas for planning the allocation of urban vegetation.

In this Chapter I have two main objectives: (1) to develop a general methodological framework that can be used (with or without an ES flow approach) to prioritize the allocation of urban vegetation based on identifying the optimal places to provide ES to reduce the gap between current provision and deficits of ES, and (2) to apply the methodological framework to inform policy-makers on where to provide ES in the city of Santiago de Chile.

In the implementation of the framework, I will first present a method for mapping two regulating ES (i.e. temperature reduction, air pollution mitigation) by using an ES flow approach. Second, I will evaluate the current spatial patterns of provision and deficits of these two ES in this city (for which this information is absent). Third, I will evaluate how the spatial patterns of identified optimal areas for allocating vegetation in Santiago may change with and without an ES flow approach integrated in the proposed framework.

4.2 Methodological framework for allocating vegetation to provide ES

The methodological framework proposed in this work to identify optimal areas for allocating vegetation to provide ES (Fig. 4.1) consists of 6 consecutive steps:

(1) Mapping ES provision; which is intended to map the spatial patterns of current provision of the specific ES under analysis.

(2) Mapping ecosystem services deficits; aimed to map the current spatial patterns of the current deficits for the specific ES under analysis.

(3) Identification of target SBA; aimed to identify SBA with higher gaps on ES provision based on the spatial mismatch between ES provision and deficits.

(4) Identification of required SPA; meant to identify the areas that based exclusively on their location have higher potential to provide ES to target SBA.

(5) Estimation of potential of sites for vegetation; aimed to assess the suitability of required SPA for harboring vegetation.

(6) Identification of optimal areas for vegetation, which is a step intended to integrate results from steps 4 and 5, and other potential factors (e.g. land ownership, land price, zoning maps) to identify optimal places for allocating vegetation to provide ES.

These 6 steps can be used by integrating the effects of ES flow in the process (i.e. flow approach), or by assuming that solely the local provision of ES is relevant (i.e. local approach). Note that the differences between these two approaches (i.e. local vs flow) are only in the specific methods used to map ES provision and required SPA (Fig. 4.1).

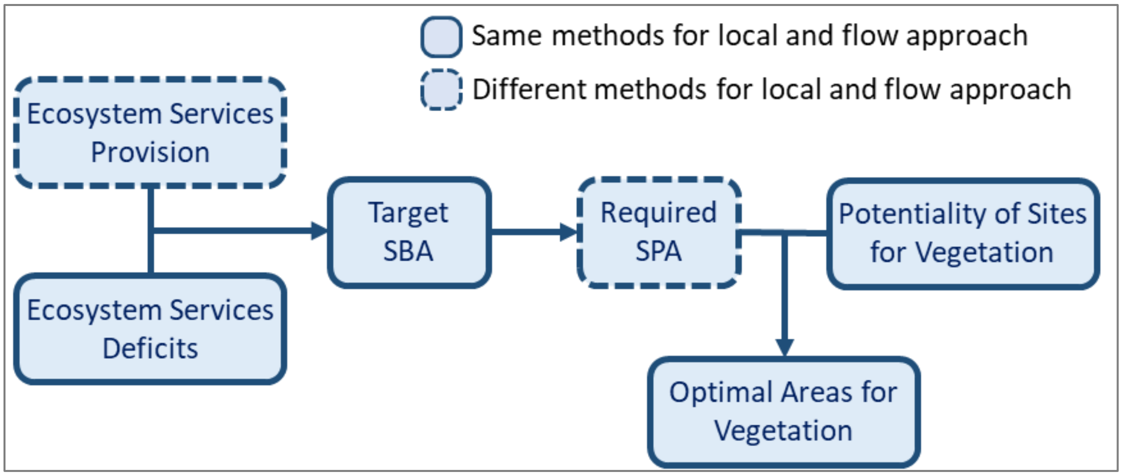

Figure 4.1. Steps of the methodological framework used for identifying the optimal areas for allocating vegetation to provide ES. Note that mapping of ES provision and required SPA are performed differently for the flow and local approach.

In the following section, I apply this methodological framework to the city of Santiago to identify the optimal areas to allocate vegetation for providing temperature reduction and air pollution mitigation ES, and comparing how these prioritization results may change by using the local or flow approach.

4.3 Application of the framework in Santiago de Chile

4.3.1 Area of study

The study area (Fig. 4.2) corresponds to the city of Santiago, which is located in the Maipo River Basin of Central Chile (33°26’15”S; 70°39’01”W), bounded on the east by the Andes Mountain and on the west by the Coastal Mountain Range, covering a total built-up area of near 600km2 (Banzhaf et al. 2013). The climate is Mediterranean, characterized by cold and rainy winters and hot and dry summers. Original vegetation is represented mostly by summer evergreen drought tolerant species, which can form sparse shrublands to dense forests depending on topographic conditions (Jaksic 2001).

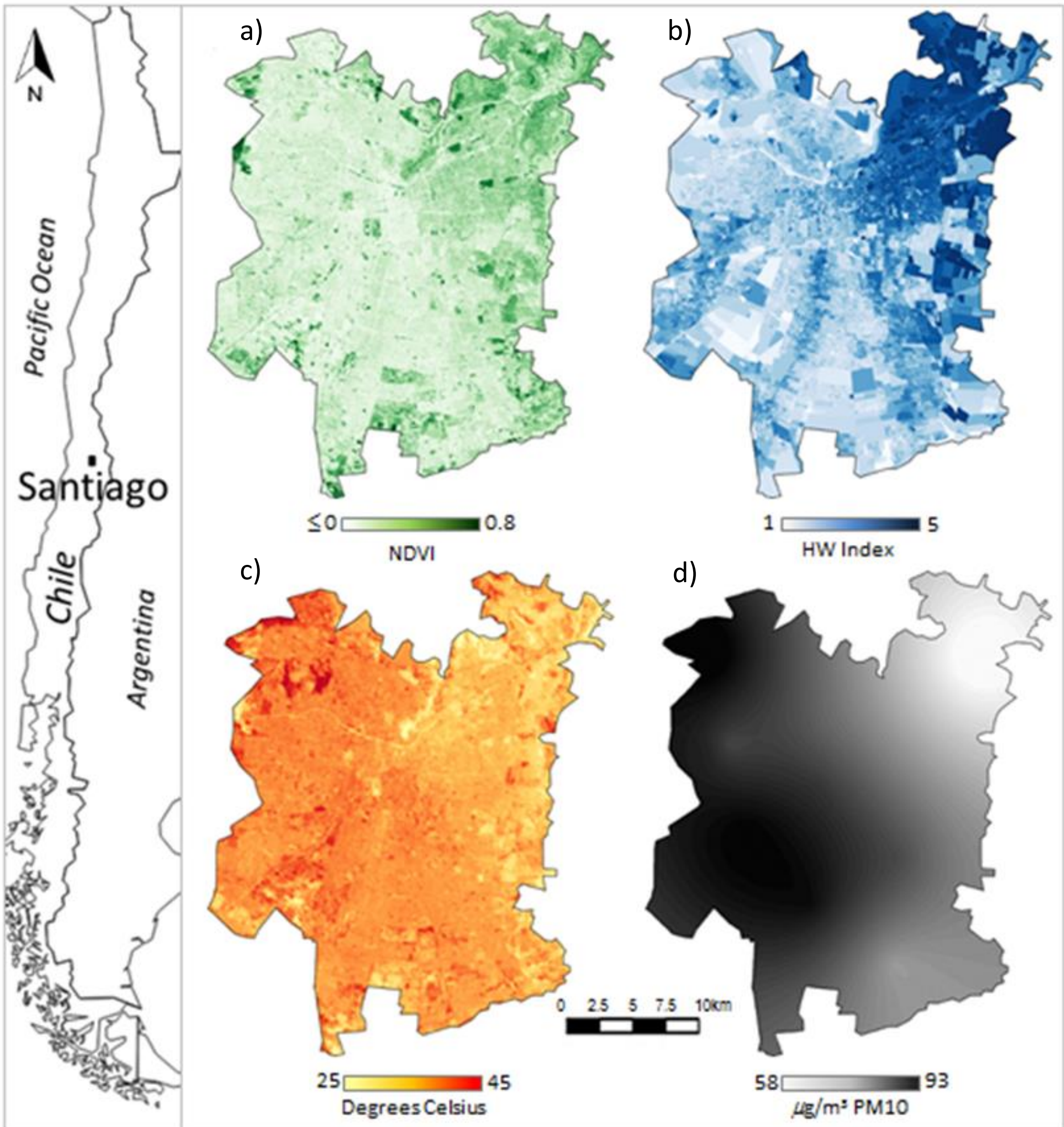

Figure 4.2. Study Area. Maps of the city showing the spatial patterns of (a) normalized difference vegetation index, (b) household wealth Index, (c) land surface temperature, (d) PM10 air pollution. The data and methods used to generate these maps are detailed in section 4.3.3.

Santiago has almost duplicated its population during the last 30 years, and currently is estimated to harbor close to 6.5 million people, representing around 37% of the total population of the country (Instituto Nacional de Estadísticas 2015). This population growth has been associated to a rapid urban expansion that has doubled the spatial extent of the city since 1975, mostly replacing agricultural land and surrounding natural habitats (Romero et al. 2012). The transformation of agriculture and natural areas to urban infrastructure has reduced the vegetation coverage, negatively impacting the provision of ecosystem services and the environmental quality of the city (Romero & Vásquez 2005). Among the most concerning environmental problems currently affecting the quality of life of Santiago residents are an increasing heat exposure during summer months (Inostroza et al. 2016, Smith & Romero 2016), low levels of green infrastructure in most parts of the city (Forray et al. 2012, de la Barrera et al. 2016a), and high levels of air pollution during the winter season (Toro et al. 2014, Perez 2015).

These environmental problems are not evenly distributed in the city; on the contrary, they tend to be more severe in the areas inhabited by lower wealth groups (Fig. 4.2). Therefore, increasing the provision of ecosystem services by urban vegetation is highly relevant for this city, as these are prevalent environmental problems that are unfairly distributed among socio-economic sectors (Fernández & Wu 2016). Furthermore, as available areas for implementing or restoring vegetation in cities can be a limiting factor (Standish et al. 2013), which can be an additional challenge for Santiago due to the lack of potential public available areas (de la Barrera et al. 2016a), in this work I also analyze how the results of the framework may change if only public areas are deemed suitable for allocating vegetation.

4.3.2 Mapping ES provision

I mapped ES provision by taking a three steps approach. First, I used a GIS-based vegetation classification method and remote sensing images to discriminate among different vegetation types, and estimate the relative productivity of each vegetation type, assuming that the level of ES provision depends on the type of vegetation providing the services at SPA (Bowler et al. 2010, Janhäll 2015). Second, I estimated the maximum distances at which each of the two assessed ES may flow from SPA. This step was only applied to the flow approach, as I assumed that for the local approach the provision of ES takes place only within each SPA. Third, I used the information gathered in these two previous steps to map the provision of ES based on the relative weight of each vegetation type for providing the services, and the distances at which services can flow from SPA under the two mapping approaches (i.e. local and flow). The specific methods used for these three steps are detailed on the remaining of this section.

Vegetation classification and productivity levels

To perform the vegetation classification, I used a single-class classification method based on the maximum entropy algorithm available through MaxEnt software (http://biodiversityinformatics.amnh.org/open_source/maxent). While MaxEnt was originally designed as a species distribution modelling software (Phillips & Dudík 2008), its built-in algorithm can be readily used for single-class classification, and has shown to outperform other single-class available methods (Li & Guo 2010, Lin et al. 2014). Furthermore, a single-class classification method is a useful approach when the objective is to identify specific landcovers because it does not require using resources to identify other landcovers which are not of interest.

I discriminated between four vegetation types of interest: permanent grass, winter seasonal grass, evergreen trees, winter deciduous trees. These are the four main vegetation types dominating the Santiago urban area. The objective of discriminating among these vegetation classes was to include the effects of vegetation phenological variations on the provision of the assessed ES. For instance winter deciduous trees may not be efficient for providing air pollution mitigation services during winter, but could be useful for temperature mitigation services during summer (Willis & Petrokofsky 2017).

To run MaxEnt I used 100 sample points for each vegetation type and a set of remote sensing layers gathered from two Sentinel-2 satellite images representing vegetation conditions of late summer (March 06, 2016) and winter (August 02, 2016) for the study area. I selected the vegetation sample points using Google Earth images representing the same period of the satellite images. To ensure that sample points represented the vegetation classes of interest, I used the "time tool" available in Google Earth to identify the phenological changes representative of each vegetation class. Because the analysis required high resolution data, I only used Sentinel bands gathered at a 10m/pixel resolution (i.e. green, blue, red, infrared). I added to this set the respective NDVI for each year, and generated a new band (i.e. NDVI-diff), which was computed as the arithmetic difference of winter and summer NDVI. Because MaxEnt results can be sensible to over-parameterization, I removed layers showing a correlation higher than 0.8. After this depuration, I ended with a set of 7 layers (i.e. red, near infra-red and NDVI for summer and winter, and NDVI-diff.) that I used for running MaxEnt.

MaxEnt logistic output provides a pseudo-probability map with values ranging from 0 to 1 (lowest to highest probability), therefore it is usually necessary to set a threshold value to define the areas effectively covered by the assessed vegetation classes (Li & Guo 2010). MaxEnt provides several threshold values based on data statistics, however deciding for any of those thresholds implies a subjective decision that can bias the results (Lin et al. 2014). Thus, instead of using MaxEnt provided thresholds to build the vegetation maps, I decided to use a different approach that does not rely on predefined thresholds, but rather on the relative proportion of each pixel pertaining to each assessed vegetation class. This reduces a potential subjectivity bias, and better aligns with my objective of estimating ES provided by different vegetation types. The approach consisted in using the probability of each pixel to be classified in each vegetation class to calculate the relative proportion of each vegetation class per pixel. Then I multiplied the proportion of each vegetation class by a "corrected NDVI value", which consisted in the original NDVI values, but with all values lower than 0.15 set to 0. The NDVI value of 0.15 was defined after analyzing the NDVI values of places with and without vegetation (Fig. 4.3), and therefore used as a threshold value to remove pixels with no vegetation.

Thus, by this method I aimed to obtain a proportional measure of each pixel NDVI contribution associated to each of the four assessed vegetation classes (i.e. vegetation-class-NDVI). I used the same approach for summer and winter vegetation classification. As NDVI is related to vegetation productivity, I consider that this approach can provide a good measure of the relative potential of each vegetation type to differentially provide ES in summer and winter. The vegetation-class-NDVI layers generated through the vegetation classification method are shown in Fig. 4.4.

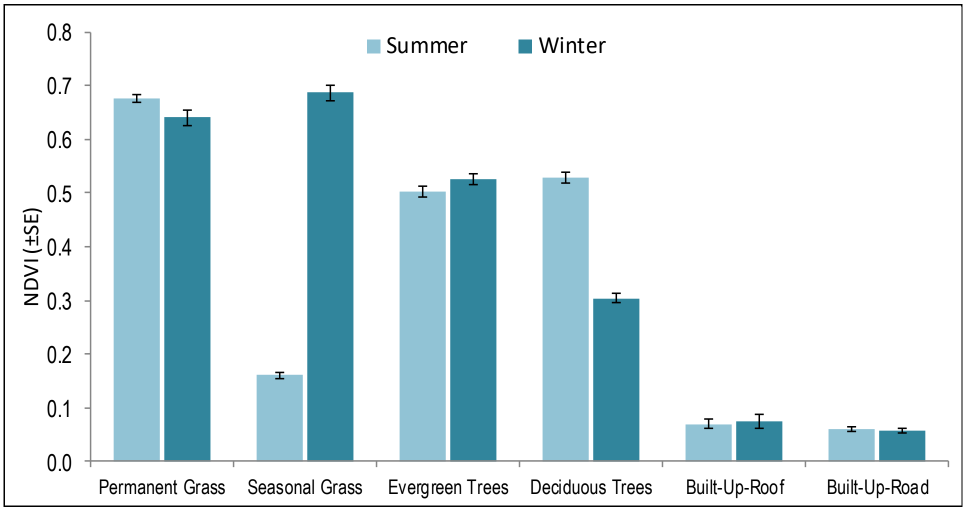

Figure 4.3. Mean NDVI values for vegetation classes and built-up areas in Santiago for winter and summer. Data corresponds to 100 sample points for each vegetation and built-up classes per climatic season.

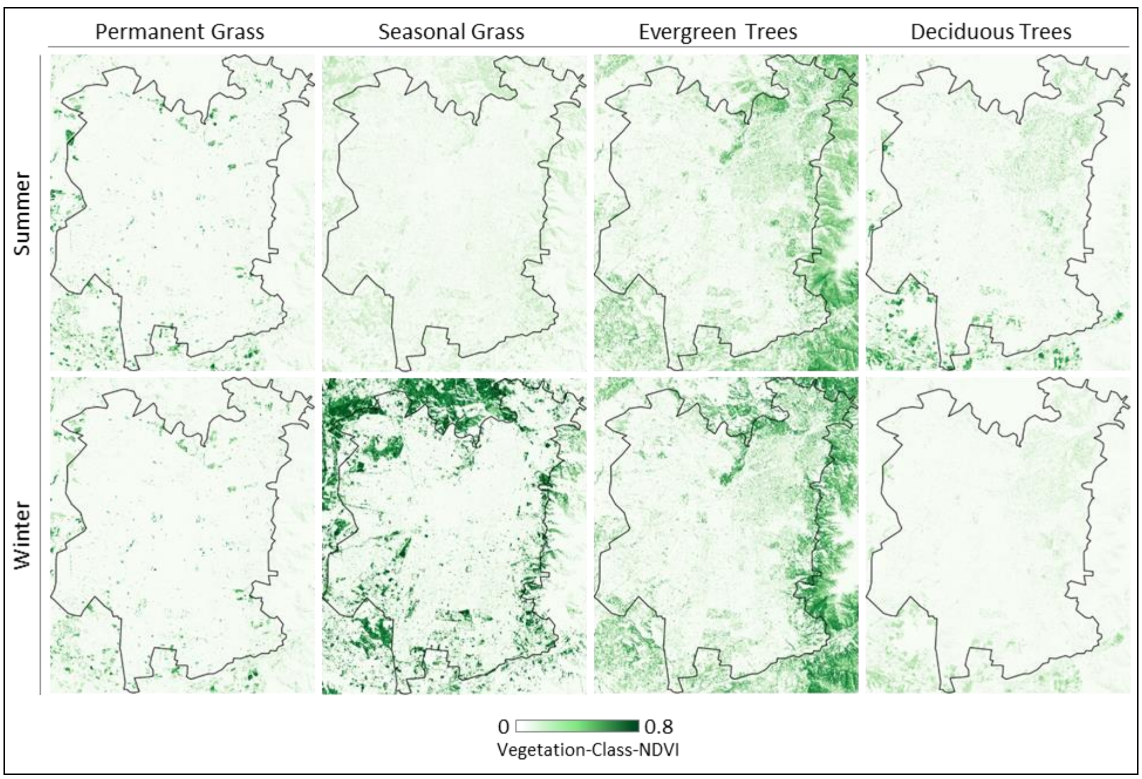

Figure 4.4. Vegetation-class-NDVI values for the four vegetation classes in summer and winter months. Boundaries of Santiago urban area are shown.

Estimating maximum ES flow distance

Because only the flow approach considers the potential additional ES that are physically transferred from vegetation located beyond local boundaries, I only estimated flowing distances for mapping ES provision under the flow approach. This step is not necessary for the local approach. The objective of this step was to estimate the maximum distance at which the services flowing from vegetation can influence surrounding areas. To estimate this distance, I assessed the spatial relationship between the distribution of the assessed environmental problems and the vegetation-class-NDVI at different spatial extents by building a set of "correlation-scalograms" (Fig. 4.5). These correlation-scalograms were generated by plotting the correlation values for the relationship of the environmental problems (Figs. 4.2c, d) and each vegetation-class-NDVI values (Fig. 4.4) at different spatial extents. My approach assumed that if vegetation is actually providing ES, the distance at which these services are provided could be estimated by analyzing how the level of environmental problems at a given pixel is related to the type of vegetation and their respective NDVI values in pixels from neighborhoods of increasing sizes. Thus, the strength of this relationship will reach a maximum when the neighborhood size is large enough to capture all the spatial variability generated by the effects of the ES provided at neighboring pixels. Hence, this neighborhood size could be used as an indicator to estimate a theoretical maximum distance of ES flowing from SPA.

Building the correlation-scalograms required first to calculate, for each pixel, the average vegetation-class-NDVI values of their surrounding pixels at different spatial extents. I did this by using the "r.neighbors" algorithm (circular option) available within the GRASS plugin in QGIS (www.qgis.org). This algorithm reclassifies each pixel to the average value of the pixels surrounding it at a given distance. For each ES, I used the vegetation-class-NDVI values corresponding to the season at which the provision of these services becomes more relevant (i.e. summer vegetation-class-NDVI for temperature reduction, winter vegetation-class-NDVI for air pollution mitigation).

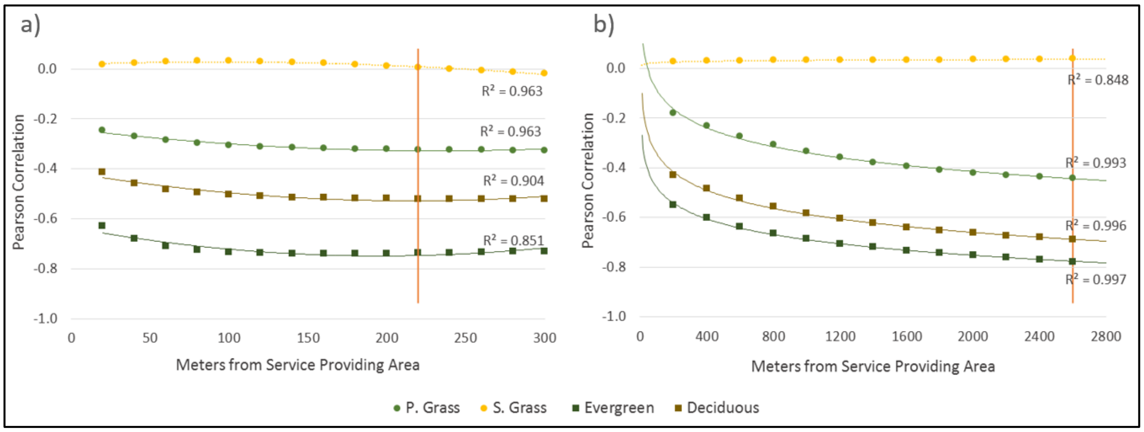

Figure 4.5. Correlation-scalograms for summer temperature and summer vegetation-class-NDVI values (a), and for winter air pollution and winter vegetation-class-NDVI values (b). In (a) curves and R^2 were obtained using polynomial fit of second order. In (b) curves and R^2 were obtained using logarithmic fit. Neighborhood sizes used to set the maximum distance flows of ES are shown by the vertical orange line.

To build the correlation-scalograms I used the same distance-based approach for both assessed ES, but for each case I modified the extent of analysis to better fit the potential flow of the particular service. Thus, for temperature reduction I used neighborhood's summer vegetation-class-NDVI values calculated at neighborhoods with increasing distances of 20 meters from the focal pixel, whereas for air pollution mitigation I used neighborhood's winter vegetation-class-NDVI values calculated at neighborhoods with increasing distances of 200 meters. I used these neighborhood sizes assuming that vegetation effects for temperature reduction would be comparative more localized if compared with the effect of vegetation for pollution mitigation. For both analyzed ES I started by calculating the first 10 neighborhoods to generate the correlation-scalograms, and based on their results I evaluated if it was required to include additional neighborhoods sizes for the analysis. In both cases it was required to increase the size of neighborhoods as I did not find a maximum correlation value within the 10 first neighborhood distances (Fig. 4.5).

The correlation-scalogram for temperature showed that the spatial relationship between vegetation-class-NDVI and temperature starts to decrease in strength at a neighborhood size of 220 meters (Fig. 4.5a). Thus, I used this distance (i.e. 220 meters) as the maximum theoretical extent at which temperature reduction ES provided by vegetation within a SPA may have a significant effect on the surrounding areas.

For air pollution mitigation, the correlation-scalogram did not show an inflection point, but a logarithmic decrease (Fig. 4.5b). Thus, for air pollution I decided to set the maximum distance as the point at which variation between correlation values of two consecutive distances were less than 1%. Using this approach, I set 2,600 meters as the maximum theoretical extent at which vegetation from SPA have a significant air pollution mitigation effect on surrounding areas.

Weighting and mapping ES provision

The final step for mapping ES provision required to weight and integrate the amount of ES provided by the different vegetation classes at each pixel (i.e. the SPA), and for the flow approach, to also include their respective flows to neighboring areas.

To estimate the weights of vegetation-class-NDVI for the flow approach, I first built one layer for each vegetation class and season (i.e. 8 layers) by using a distance decaying function. I built each of these eight layers by computing the arithmetic mean of their respective layers containing the neighborhood vegetation-class-NDVI values within the maximum defined flow distance (i.e. 11 and 13 vegetation-class-NDVI layers for temperature and air pollution, respectively). Because smaller neighborhoods are nested in larger ones, each of the resulting "mean-vegetation-class-NDVI layers" were computed based on the weighted arithmetic mean of neighborhoods sizes, where weights represented an exponential decaying function as distance from SPA increases (Fig. 4.6).

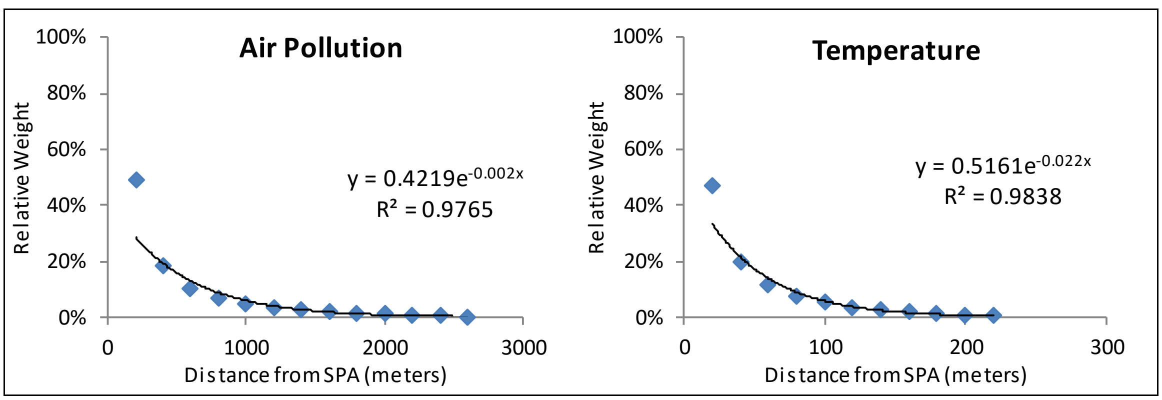

Figure 4.6. Exponential decaying functions representing the relative weights given to the different neighborhoods sizes determined by the distances from SPA. These weights were used only for computing the mean-vegetation-class-NDVI layers for the flow approach.

After building the eight mean-vegetation-class-NDVI layers, I run spatial linear regression analysis for each of the two assessed ES, using these previously generated layers as independent variables, and temperature and air pollution problem layers as their respective dependent variable (Table 4.1). I included X and Y geographic coordinates as covariates in the model to reduce autocorrelation issues and adjust for spatial trends related to other factors not included in the regression model. For selecting the best models, I removed vegetation classes layers showing positive relationships with the assessed problems (as these may represent disservices), and used the coefficients of remaining vegetation classes layers to compute their respective final weights (Table 4.1). I generated the final ES provision map for the flow approach by using these weights to calculate the weighted arithmetic mean of the mean-vegetation-class-NDVI layers computed on the previous paragraph.

Table 4.1. Regression models used for calculating the weights of the respective layers used to build the ES provisioning layers for both mapping approaches. (d) Decaying function layers. (*) These models were built by using the X and Y geographical coordinates as additional covariates. R(w) corresponds to the correlation value between the built weighted layer and the respective environmental problem layer. All included variables are statistically significant with a p-value < 0.001

Ecosystem Service		Regression(*)				Weighted Layer	
		Variable	Coefficient	R	Model R^2	Weights	R(w)
Flow Approach	Temperature Reduction	P. Grass (d)	-6.713	-0.181	0.665	0.183	-0.780
		Evergreen (d)	-16.104	-0.580		0.440	
		Deciduous (d)	-13.772	-0.351		0.376	
	Air Pollution Mitigation	Evergreen (d)	-31.893	-0.251	0.807	0.173	-0.788
		Deciduous (d)	-152.362	-0.482		0.827	
Local Approach	Temperature Reduction	P. Grass	-4.992	-0.181	0.505	0.262	-0.595
		Evergreen	-7.976	-0.422		0.320	
		Deciduous	-6.115	-0.253		0.418	
	Air Pollution Mitigation	Evergreen	-5.782	-0.084	0.721	0.289	-0.383
		Deciduous	-14.199	-0.139		0.711	

For the local approach, I also mapped ES provision based on the weighted arithmetic mean of vegetation layers, where weights were obtained from regression models (Table 4.1). However, at difference from the flow approach, here I did not use the “mean-vegetation-class-NDVI layers” computed through the distance decaying function, but the original vegetation-class-NDVI layers shown in Fig. 4.4. Thus, the main difference between both mapping approaches is the additional step to account for the dispersal of ES from SPA in the flow approach. Resulting ES provision maps for both approaches are shown in Fig. 4.7.

4.3.3 Mapping ES deficits

To map ES deficits, I assumed that areas currently experiencing environmental problems have an implicit “environmental debt”, and that this environmental debt can be translated to a socio-environmental dimension by relating it to the economic and cultural resources that people living in those areas have for coping with the particular environmental problems. Thus, my approach assumed that from an environmental justice perspective the ES deficits are higher for people lacking the resources to cope with environmental problems. Then, for mapping ES deficits I used the environmental problems layers as a measure relative to the exposure to the problems, and household wealth (which include economic and educational factors) as a proxy representing people coping capacities. I also included population density of way to weight the ES deficit level based on the number of people requiring the provision of ES. In the following section I provide the information regarding the data and methods used to build the environmental problems (i.e. surface temperature, air pollution), household wealth, and population density layers. Then I provide the method I used for building the final ES deficits maps.

Data and method for building input layers

I estimated surface temperature from a set of two Landsat-8 satellite images (TIRS sensor Band 10) acquired on January 28, 2015 and January 15, 2016. Selected images had 0% cloud cover for the analyzed area and represent the climatic conditions of the warmest and driest period of the summer season in Santiago, which are appropriate for identifying areas with the highest heat risks (Inostroza et al. 2016, Fernández & Wu 2016). To estimate surface temperature I followed the NDVI-threshold emissivity method (Sobrino et al. 2004) using the Land Surface Temperature Plugin V.03 available in QGIS. I calculated surface temperature for each of the two satellite images, but then took their average to reduce potential sampling bias due to the use of a single image. To generate the final layer, I used a nearest neighbor algorithm to resample the layer from its original 30 m/pixel to a 10 m/pixel resolution. Resulting land-surface temperature layer is shown in Fig. 4.1c.

To build the air pollution layer I used a spatial interpolation (i.e. Kriging) method based on ten PM10 government-official monitoring stations distributed in Santiago. For the interpolation process I took the daily average PM10 concentrations for the last two officially validated autumn-winter seasons data (April 01 to August 31, years 2015 and 2016). I gathered this data from the Chilean National System of Air Quality Database (http://sinca.mma.gob.cl/index.php/region/index/id/M) focusing my analysis on autumn-winter seasons because is during these months that air pollution becomes hazardous in Santiago (Muñoz & Alcafuz 2012). I produced this layer at a 10m/pixel resolution. The PM10 air pollution layers is shown in Fig. 4.1d.

I gathered the Household Wealth (HW) information from the 2012 updated version of 2002 Chilean Official Census Database developed by Norel et al. (2013). In the census database HW is categorized into five categorical classes based on the educational level of the household head and a list of goods existing at the household. I transformed this categorical information to ordinal data by assigning numerical values (1 to 5) to the five HW categories, with higher values corresponding to higher HW levels. Then, I transformed the ordinal data to continuous values by multiplying the proportion of households in each category by their respective values, and then adding these results at each census block. Therefore, the resulting continuous values ranged from 1, for a block having 100% of households in the lowest HW level, to 5, for a block having 100% of households in the highest HW level. The census block vector layer was then converted to a 10 m/pixel resolution raster, which is shown in Fig. 4.1b.

For population density (PD) I also gathered the information from Norel et al. (2013) census database. PD was not directly available in the census dataset. Thus, I calculated PD as the total number of people per census block divided by the respective block area. Because the distribution of PD showed a huge skewedness towards smaller values, I built this layer by using the log-transformed values of PD. As with HW variable, I converted the resulting PD vector layer into a 10 m/pixel resolution raster.

Integrating layers and mapping ES deficits

After building all the required layers, I proceeded to map the deficit level for each of the two assessed ES by using the same approach. I first normalized all the layers into values ranging between 0 and 1 by using a relative value-based normalization approach based in each variable maximum and minimum values. This approach is useful because it does not alter the relative distribution of values within variables, allowing to have compatible computational values representing the relative position of each area for the different variables. For the case of HW, I inverted the values in order to assign the highest values to areas with the lowest HW. Then I computed the geometric mean between HW and PD aiming to have a measure of the spatial distribution of the HW weighted by PD. I then calculated the geometric mean between this layer and each of the two environmental problems layers of way to have an indicator showing the spatial interaction between the problems and the capacity of people to cope with each of them. I assumed that areas showing high levels of environmental problems, low levels of coping resources, and high population density would have the largest deficits for ES. Resulting ES deficits maps are shown in Fig. 4.7.

4.3.4 Identification of target services benefiting areas (TSBA)

In my approach, TSBA represent areas having higher ES provision debt. Thus, I assumed that this ES debt will be higher in areas having high deficits and low provision of ES. In other words, where the spatial mismatches between ES provision and deficits are the largest. To compute TSBA I first normalized the ES provision and deficits layers into values ranging between 0 and 1 by using a Max-Min approach. Then I computed the TSBA by integrating these layers using the following equation:

$$TSBA = ES\ Requirement * (1 - ES\ Provision)$$

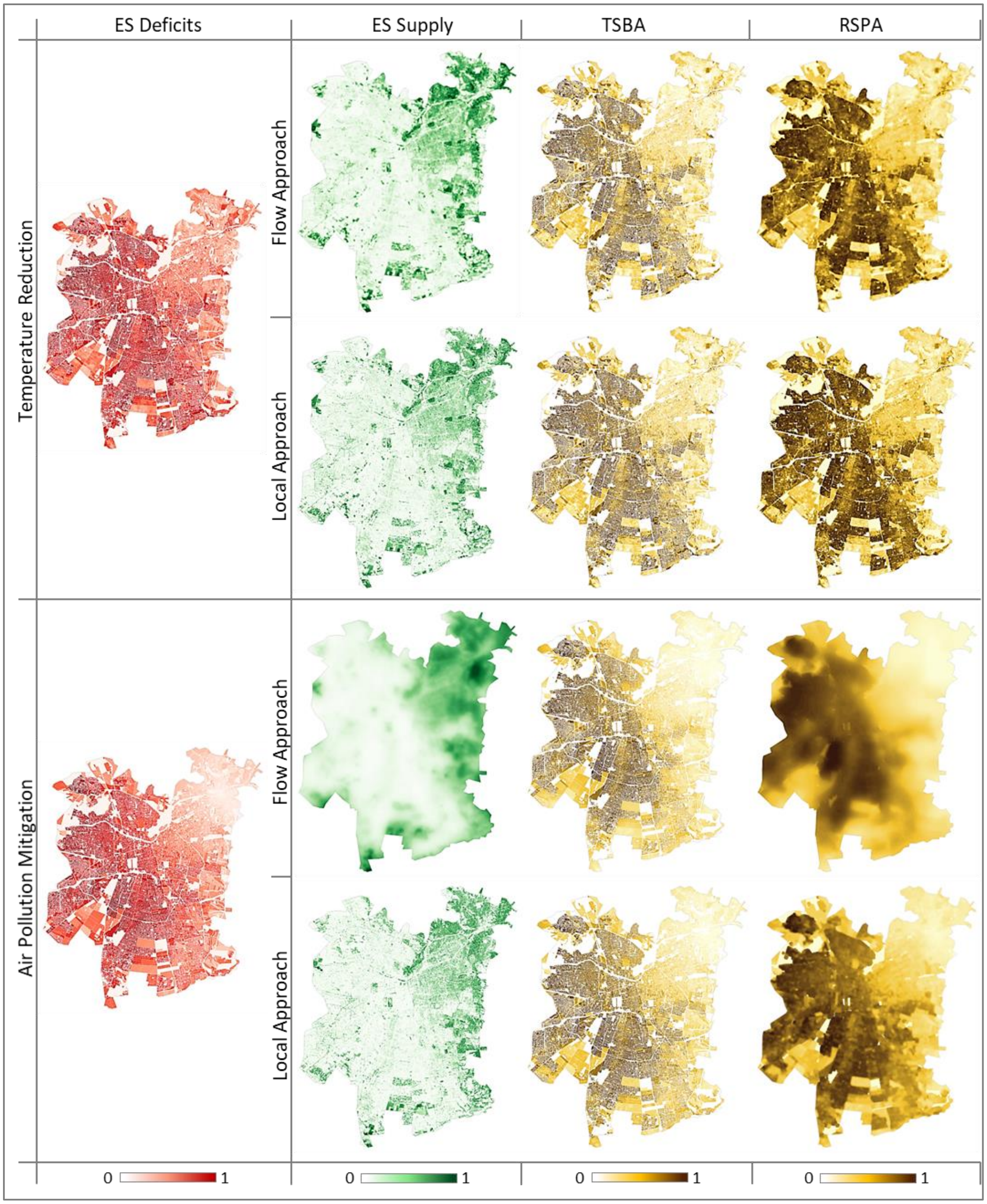

Figure 4.7. Resulting maps for ES deficits, ES provision, TSBA, and RSPA for both assessed ES and both mapping approaches (i.e. flow and local). All maps are based on max-min normalized values ranging between 0 and 1. For ES deficits and provision, these values represent the spatial distribution of areas of lower and higher deficits and provision. For TSBA and RSPA, values represent the spatial distribution of areas of lower and higher priority.

I used the same method for the flow and local mapping approaches. Resulting TSBA layers are shown in Fig. 4.7.

4.3.5 Identification of required services providing areas (RSPA)

To identify RSPA I first applied a residential mask to the four generated TSBA layers, aiming to increase the capability of my analysis to effectively discriminate between areas having people inhabiting them, and areas where the true residential density could be assumed to be 0. This residential mask included public areas (e.g. streets, urban parks, green areas) and other areas (e.g. empty lots, areas outside urban boundaries) that have no dwellings. Thus, this mask assigned a value of 1 to all effective residential areas, and a value of 0 to all areas not having population. I applied this mask by simply multiplying the TSBA layer by this residential mask. Then, I proceed to calculate the RSPA layers using a different method for the flow and local approaches.

Flow approach

For the flow approach, I proceeded to calculate the RSPA layer for each assessed ES by using the same distance decaying function approach I used to compute ES provision under the flow approach (See section 4.3.2). I applied a distance decaying function assuming that services will flow from SPA to SBA; therefore, RSPA need to consider the flow of services from potential SPA to SBA. In other words, RSPA must include all the potential areas surrounding a TSBA that can theoretically produce services that flow to the TSBA, but considering that the flow of services will decay with the distance from TSBA. Thus, to build the RSPA layer I decided to use the same neighborhood analysis function and distances used to map ES provision. Hence, using the TSBA layer for the flow approach as my source data (Fig. 4.7), I built 11 neighborhoods layers (increasing radius of 20 meters) to cover the 220 meters flow distance for temperature reduction, and 13 layers (increasing radius of 200 meters) to cover the 2600 meters flow for air pollution mitigation. Then I averaged the layers for each ES to produce the final RSPA including their respective ES flow decaying function. Finally, I normalized the two generated layers into values ranging between 0 and 1 (higher values representing larger RSPA values) by using the Max-Min normalization method. Resulting layers for the flow approach are shown in Fig. 4.7.

Local approach

For the local approach, I only considered the potential provision of ES that could be generated at the local level. However, to generate results that were methodologically comparable to the ones obtained with the flow approach, I decided to be consistent with the neighborhood sizes used for the flow approach. Thus, to compute the RSPA I defined the local level as the minimum neighborhood size used for the flow approach (i.e. 20 meters and 200 meters from the focal SPA for temperature and air pollution, respectively). Hence, using the TSBA layer for the local approach as the source layer, I built the local RSPA layers by using the" r.neighbors" algorithm using a neighborhood of 5 pixels (20 meters from focal pixel) in diameter for temperature reduction, and one of 41 pixels (200 meters from focal pixel) in diameter for air pollution mitigation. Resulting layers are shown in Fig. 4.7. By using a similar method for mapping RSPA under both approaches, I aimed to reduce methodological confounding factors, and increase the capability of my analysis to detect how mapping results may change if the flows of ES are or not included for the assessment.

4.3.6 Estimation of potential of sites for vegetation

I defined potential of sites for vegetation as the relative capacity of sites for growing additional vegetation. The capacity of urban soils to growth vegetation may depend on several factors, such as the proportion of unpaved surfaces, the coverage and type of current vegetation, level of pollutants, and the quality of available soils (Pavao-Zuckerman 2008). As many of these factors are seldom available at fine resolution, as it was the case for Santiago, I assessed the potentiality for vegetation by taking advantage of the characteristic phenological patterns of vegetation in Central Chile. As not-irrigated vegetation in Central Chile are often water limited, areas that are suitable for an increase in vegetation cover show a large increase on NDVI during the wet season (winter months), but then these NDVI values are reverted to very low values during the dry season (summer months). Thus, I used this winter-to-summer NDVI differences as a proxy to estimate the potentiality of areas for growing new vegetation.

To estimate the potential of sites for vegetation I used the same two Sentinel-2 NDVI-derived images (i.e. winter and summer NDVI) that I used to compute the ES provision maps. To perform this task, I first set all the pixels showing NDVI values below 0 to 0, as negative NDVI values are usually associated to water bodies where terrestrial vegetation cannot be implemented. After applying this filter, I simply calculated a “winter-summer- NDVI-difference” by subtracting summer NDVI from winter NDVI. Then I normalized this final layer to values ranging between 0 and 1 (larger values representing higher potential) using the Max-Min normalization method. Resulting layer for potentiality of sites for vegetation is shown in Fig. 4.8a.

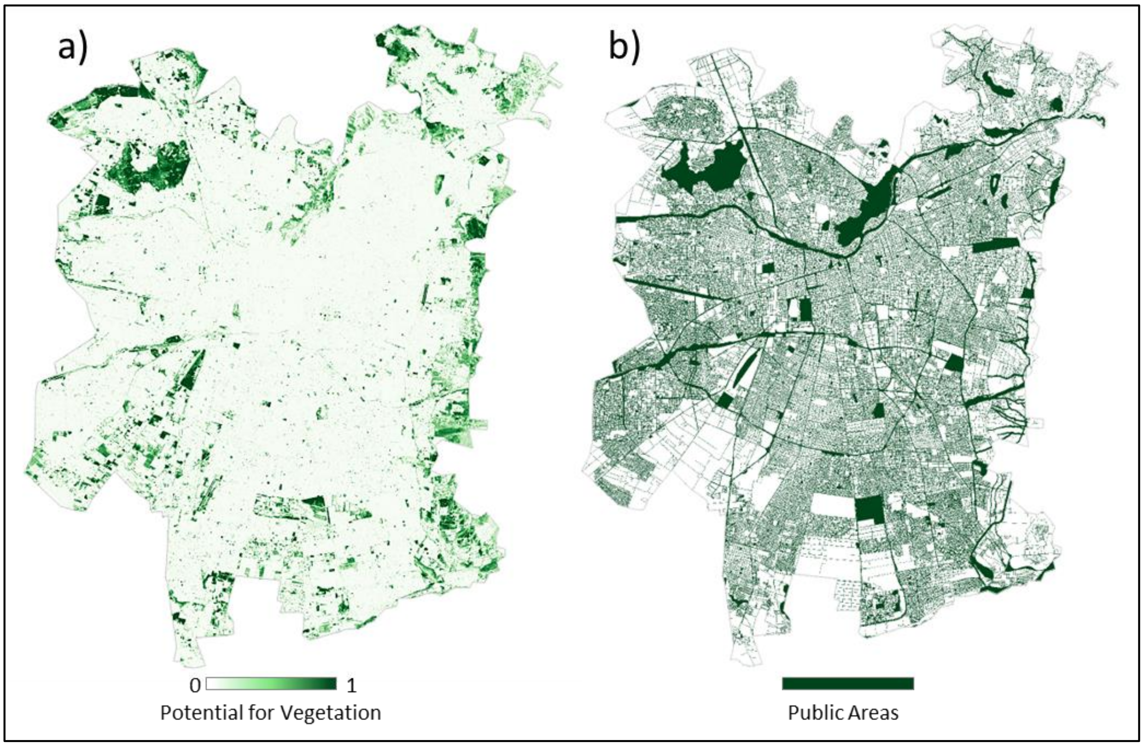

Figure 4.8. Layers of (a) potential of sites for vegetation, and (b) public areas mask.

4.3.7 Identification of optimal areas for vegetation

To identify the optimal areas for allocating vegetation to provide the required ES, I computed the geometric average between the RSPA layers and the potentiality of areas for vegetation layers. I used the same method for each ES and mapping approach. To improve my capability to visually identify optimal areas for vegetation and provide useful information for decision-makers, I transformed the values of the resulting layers to percentiles by using the “sample quantile” function in R-studio (V, 1.0.136), and proceeded to map the results for the 1st and 2nd percentiles (Figs. 4.9, 4.10). To further evaluate how the identified optimal areas for vegetation relates to the availability of public areas, I applied a mask layer representing all public areas suitable for allocating vegetation, including streets, current green areas, planned green areas, and other public areas reserved for development of green infrastructure (Fig. 4.8b). Finally, I computed 5 landscape metrics for each of these generated maps using the SDMTools package in R to evaluate how the two different mapping approaches affect the spatial patterns of the areas identified as optimal for allocating vegetation in Santiago (Fig. 4.11).

4.4 Results of the methodological framework applied to Santiago

To facilitate the visual interpretation of the main maps generated based on the vegetation allocation framework (Fig. 4.1), I have integrated maps of ES provision, ES deficits, TSBA, and RSPA in only one figure showing the results for temperature reduction and air pollution mitigation (Fig. 4.7). These figures show the maps generated by using the flow and local approaches. I have also generated a matrix correlation (Table 4.2) that show the results of spatial correlation analysis between these generated maps for further analytical interpretation. Additionally, in Figs. 4.9 and 4.10 I have integrated the resulting maps showing the optimal areas for planting vegetation to provide the required ES under both mapping approaches, differentiating among all potential areas and those located in public areas. To further analyze these results, I provide a summary of 5 landscape metrics (Fig. 4.11) to evaluate how the different approaches modifies the spatial configuration of the areas identified on the two highest priority ranks (i.e. 1st and 2nd percentiles).

4.4.1 Spatial patterns of ES deficits, provision, TSBA, and RSPA

Deficits for temperature reduction and air pollution mitigation services in Santiago show very similar spatial patterns, which is confirmed by a strong spatial correlation between them (R = 0.907, Table 4.2). In general, deficits for both ES show lower levels in the northeastern areas of the city and higher levels in the southern and western areas. However, the differences on ES deficits between these areas tend to be more drastic for air pollution than for temperature (Fig. 4.7).

The four maps of ES provision show similar patterns, with a clear uneven distribution of services provision towards the northeastern area of the city (Fig. 4.7). However, and similar that what is shown for ES deficits, this uneven distribution seems to be stronger for air pollution, which becomes even more severe when the flow approach is used for ES provision mapping (Fig. 4.7). While for the case of temperature reduction using the flow or local approach does not generate a big difference on ES provision maps (R = 0.800), in the case of air pollution both approaches generate maps that tend to be more different between them (R = 0.552). The differences of using the flow or the local approach to map ES provision is also shown by the spatial relationship between both ES, as correlation between temperature reduction and air pollution mitigation is slightly weaker for the flow than for the local approach (Table 4.2).

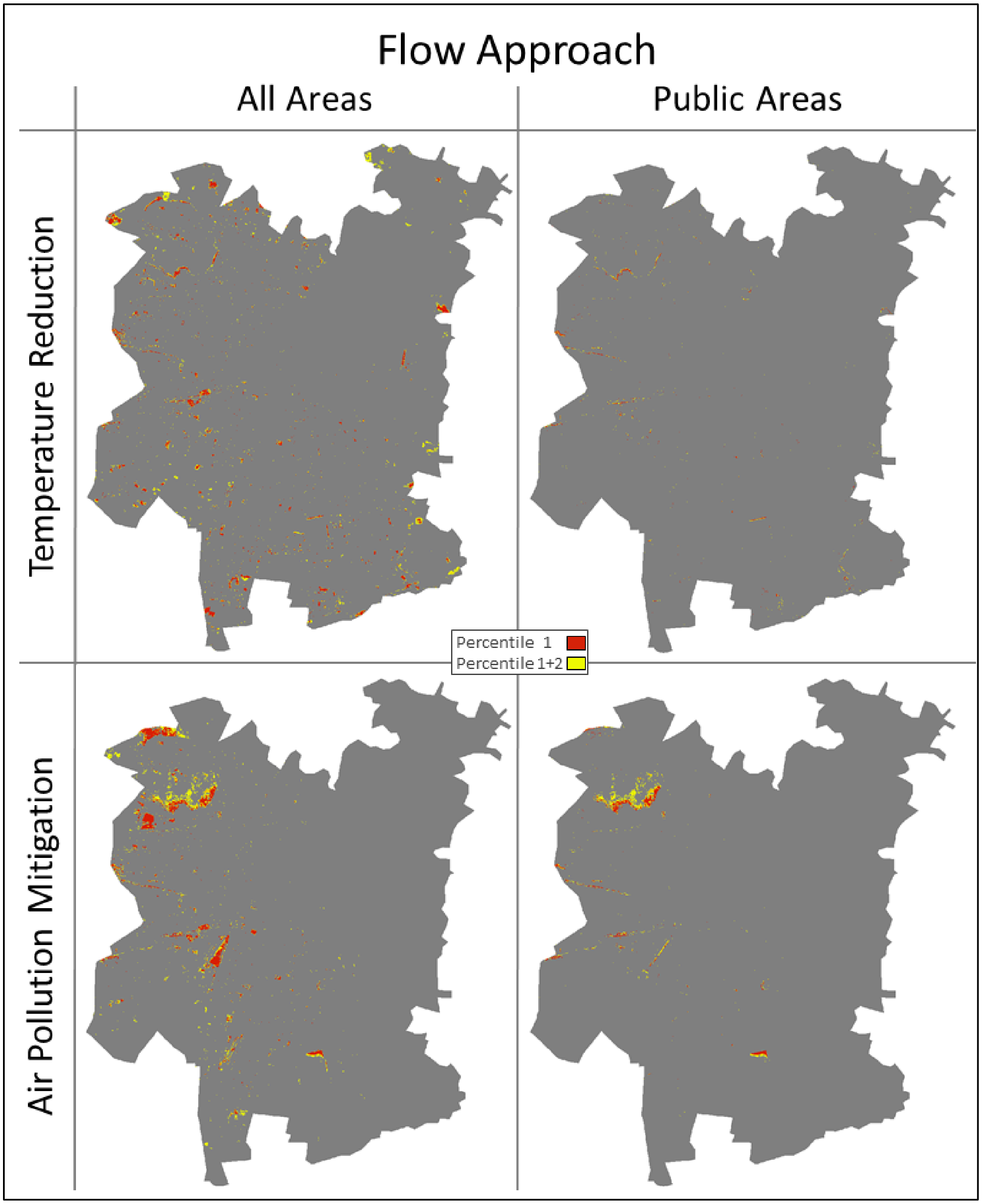

Figure 4.9. Optimal areas for allocating vegetation to provide ES in Santiago under the flow approach. Only areas ranked in the highest 1st and 2nd percentile are highlighted to facilitate decision-making. "All Areas" includes all potential areas suitable for vegetation allocation. "Public Areas" includes only those suitable areas corresponding to public areas (e.g. streets, public spaces, green areas).

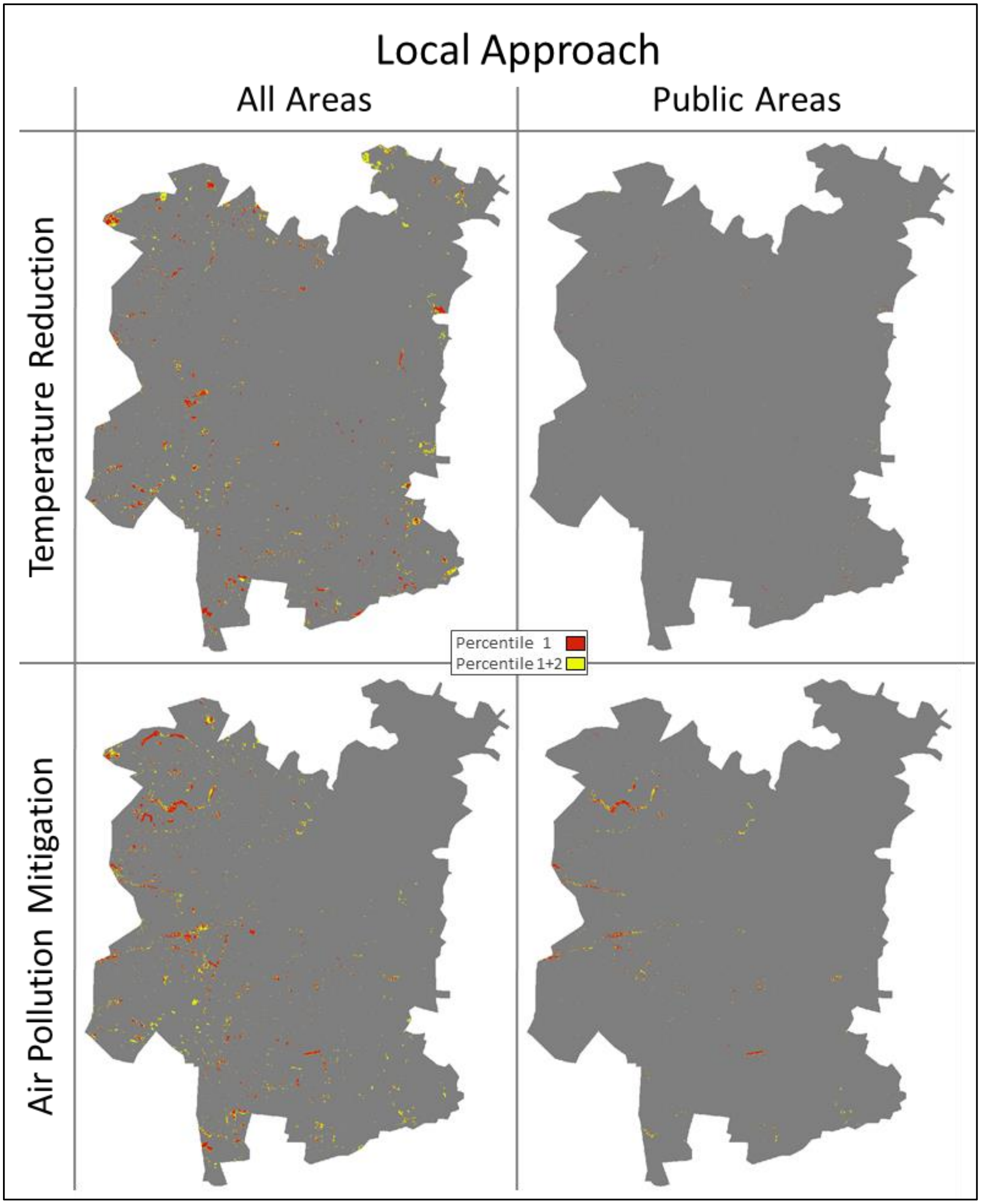

Figure 4.10. Optimal areas for allocating vegetation to provide ES in Santiago under the local approach. Only areas ranked in the highest 1st and 2nd percentile are highlighted to facilitate decision-making. “All Areas” includes all potential areas suitable for vegetation allocation. “Public Areas” includes only those suitable areas corresponding to public areas (e.g. streets, public spaces, green areas).

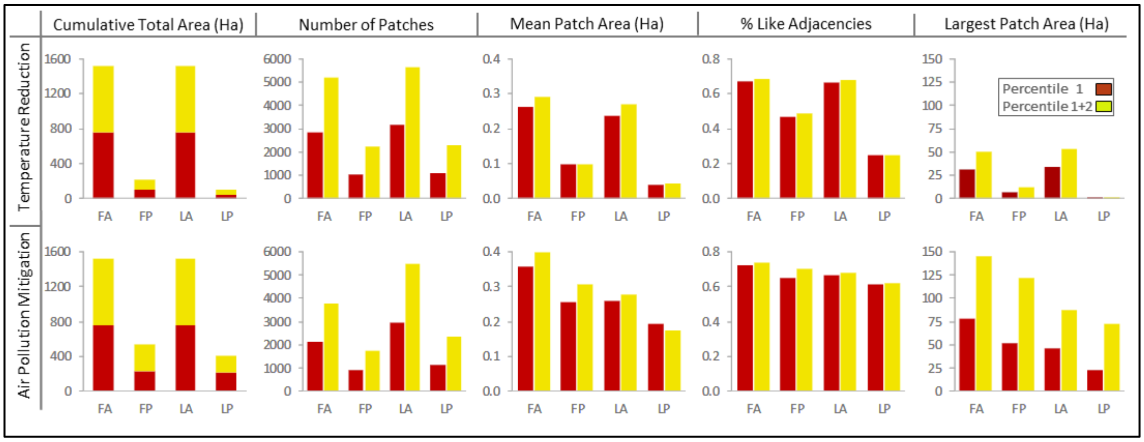

Figure 4.11. Landscape metrics of the areas signaled as optimal and ranked in the highest 1st and 2nd percentile. Acronyms on the X-axis are: FA, flow approach-all areas; FP, flow approach-public areas; LA, local approach-all areas; LP local approach-public areas.

Table 4.2. Pearson correlation values for the spatial relationships of generated map layers. Correlations were calculated using pixels representing residential areas, except for correlations showing the (*) symbol, for which all pixels of the study area were used to run the analyses. ES Deficits (ESD), ES Provision (ESP), Flow (F), Local (L).

		Temperature Reduction							Air Pollution Mitigation						
		ESD	ESP.F	ESP.L	TSBA.F	TSBA.L	RSPA.F	RSPA.L	ESD	ESP.F	ESP.L	TSBA.F	TSBA.L	RSPA.F	RSPA.L
Temperature Reduction	ESD		-0.650	-0.511	0.961	0.929	0.952	0.951	0.907	-0.699	-0.497	0.893	0.912	0.783	0.893
	ESP.F	-0.650		0.800*	-0.815	-0.776	-0.667*	-0.518*	-0.591	0.787*	0.553*	-0.680	-0.669	-0.676*	-0.490*
	ESP.L	-0.511	0.800*		-0.650	-0.769	-0.494*	-0.450*	-0.451	0.719*	0.868*	-0.511	-0.583	-0.482*	-0.436*
	TSBA.F	0.961	-0.815	-0.650		0.962	0.991	0.984	0.873	-0.791	-0.616	0.904	0.909	0.815	0.893
	TSBA.L	0.929	-0.776	-0.769	0.962		0.944	0.984	0.839	-0.733	-0.713	0.858	0.904	0.768	0.851
	RSPA.F	0.952	-0.667*	-0.494*	0.991	0.944		0.853*	0.877	-0.645*	-0.454*	0.914	0.907	0.719*	0.529*
	RSPA.L	0.951	-0.518*	-0.450*	0.984	0.984	0.853*		0.860	-0.572*	-0.407*	0.880	0.910	0.886*	0.668*
Air Pollution Mitigation	ESD	0.907	-0.591	-0.451	0.873	0.839	0.877	0.860		-0.763	-0.456	0.964	0.978	0.901	0.976
	ESP.F	-0.699	0.787*	0.719*	-0.791	-0.733	-0.645*	-0.572*	-0.763		0.552*	-0.874	-0.790	-0.904*	-0.720*
	ESP.L	-0.497	0.553*	0.868*	-0.616	-0.713	-0.454*	-0.407*	-0.456	0.552*		-0.511	-0.609	-0.457*	-0.418*
	TSBA.F	0.893	-0.680	-0.511	0.904	0.858	0.914	0.880	0.964	-0.874	-0.511		0.965	0.957	0.973
	TSBA.L	0.912	-0.669	-0.583	0.909	0.904	0.907	0.910	0.978	-0.790	-0.609	0.965		0.901	0.971
	RSPA.F	0.783	-0.676*	-0.482*	0.815	0.768	0.719*	0.886*	0.901	-0.904*	-0.457*	0.957	0.901		0.844*
	RSPA.L	0.893	-0.490*	-0.436*	0.893	0.851	0.529*	0.668*	0.976	-0.720*	-0.418*	0.973	0.971	0.844*	

The distribution of ES provision is inversely related to the patterns of ES deficits for both assessed ES, independently of the mapping approach (Fig. 4.7). However, for both ES, the flow approach shows a stronger negative association between deficits and provision if compared with the local approach (Table 4.2). This increase on the spatial association also depends on the assessed ES. While for temperature, correlation values between deficits and provision increase from R = -0.511 for the local approach, to R = -0.650 for the flow approach, for air pollution this association increases from R = -0.456 to R = -0.763 (Table 4.2). Thus, for both ES, the flow approach generates ES provision maps that better aligns (inversely) with the spatial distribution of their respective ES deficits. Thus, areas showing the largest ES deficits tend to spatially match with areas of lower level of ES provision.

Maps for TSBA were generated as a function of ES deficits and provision, and therefore it is not surprising that these maps show strong positive correlations with ES deficits, and strong negative correlations with ES provision (Fig. 4.7, Table 4.2). However, my results show that for both ES, the spatial association with TSBA is stronger for ES deficits than for ES provision. These results are consistent for both ES, independently of the approach used for mapping ES provision (Table 4.2), indicating that in general the current spatial patterns of ES provision for both services is poorly performing in terms of offsetting their respective ES deficits. Moreover, TSBA maps are highly similar among them (Fig. 4.7, Table 4.2), implying that there is a strong spatial match between the areas of the city concurrently requiring the provision of ES for temperature reduction and air pollution mitigation.

Resulting RSPA maps show that the spatial distribution of neighboring areas identified as better for providing ES to TSBA differ depending on the approach used for ES mapping, and particularly if the assessed ES may flow from areas farther apart; as for the case of air pollution mitigation (Fig. 4.7). Nevertheless, results from correlations analysis shows that there still a strong correlation between RSPA maps generated by both approaches (Table 4.2). As expected, RSPA maps are strongly positively correlated with ES deficits and TSBA, and negatively correlated with ES provision. Interestingly, using the flow or the local approach for mapping RSPA has only a small impact on its correlation with TSBA and ES deficits, but a relative large impact on its correlation with ES provision. For both ES, using the flow approach to map RSPA strongly increases its negative correlation with ES provision (Table 4.2), suggesting that the flow approach better identifies the locations currently having the largest ES provision debts.

4.4.2 Optimal areas for allocating vegetation

The spatial distribution of optimal areas for allocating vegetation shows important differences between both ES when all areas are considered, and these differences tend to be larger when the flow approach is used for mapping (Fig. 4.9). While for temperature reduction optimal areas are represented by small patches scattered throughout the city, for air pollution these areas tend to be more concentrated and forming larger patches in the western areas of the city (Figs. 4.9, 4.10). The use of the flow approach instead of the local approach generates prioritized locations represented by a smaller number of patches of larger average sizes. This result is consistent for the two ES and both computed percentiles (Figs. 4.9, 4.10, 4.11). However, this difference between both approaches is considerably larger for air pollution than for temperature reduction, implying that the differences between results from both approaches depends on the inherent spatial structure of the assessed ES.

The analysis made to assess the spatial distribution of optimal areas located in public areas show striking results. Only a small fraction of the areas identified as optimal are located within public areas, meaning that the vast proportion of the best areas for providing the required ES are located in private lands (Figs. 4.9, 4.10). However, this scarcity of areas is stronger for temperature reduction than for air pollution mitigation. Interestingly, the number of optimal patches located within public areas is similar for both ES, but the mean patch area, % like adjacencies, and largest patch area is substantially larger for air pollution (Fig. 4.11). These differences between the two ES become more extreme when the local approach is used for mapping. In fact, under the local approach the largest patch for temperature reduction within public areas is smaller than 2 hectares, even if the first and second percentiles are considered (Fig. 4.11).

These results show that while the use of the local, instead of an ES flow approach, could negatively affect the vegetation allocation results by recommending more fragmented spatial patterns, the largest constraint for allocating vegetation in Santiago is currently imposed by the scarcity of public areas suitable for implementing vegetation.

4.5 Discussion

In this work, I have proposed and applied a GIS-based methodological framework that can help decision-makers to identify the optimal areas for providing regulating ES by urban vegetation, based on the spatial mismatches between ES provision and ES deficits, and by taking explicit consideration of the potential flows of ES from SPA to SBA.

Understanding the spatial relationships and mismatches between urban ES provision and deficits is fundamental for adequate planning, management, and governance of urban green infrastructure (Kremer et al. 2016). Nevertheless, accounting for the spatial flows of ES is still a pervasive challenge for the application of the ES concepts in decision-making (Bagstad et al. 2013, Serna-Chavez et al. 2014), which may help explain why ES flows are often disregarded in published methods for deciding optimal places for implementing urban vegetation. Therefore, methods for ES mapping, such as the one presented in this work, can improve our capabilities for mapping the spatial relationship between ES provision and deficits, and to use this information for taking better decisions on the optimal places for allocating vegetation to provide ES. In addition, as I used commonly available spatial data and open source software, I consider that this approach has the potential to be applied elsewhere where this kind of data is available, and may be particularly helpful for cities in the developing world where this type of information is more needed.

4.5.1 Methodological approach

While most of prioritization methods for allocating vegetation in urban areas recognizes the key role of vegetation for mitigating environmental problems through the provision of ES (e.g. Wu et al. 2008, Locke et al. 2010, Morani et al. 2011, Norton et al. 2015), methods explicitly based on the ES conceptual framework have only recently been proposed (Bodnaruk et al. 2017). Nevertheless, none of these methods have approached their analysis based on the spatial mismatch between ES provision and deficits, and what is most relevant, currently no method has considered the potential effect of ES flows for the assessments. Furthermore, procedural frameworks integrating the concepts of ES provision, deficits, and flows from SBA to SPA to identify areas requiring ES in urban areas are largely missing in the literature. In this regard, I consider that this methodological approach has two main contribution to current literature. First, I proposed a simple procedural framework (Fig. 4.1) that can be applied to identify priority areas for ES provisioning, highlighting the potential mismatch between ES provision and deficits, and the relevance of considering ES flows and the potential of sites for vegetation. Second, I provided a novel approach to map the potential flows of regulating ecosystem services by taking explicit consideration of the capacity of different vegetation types to provide specific ES and how this provision decay as distance from SPA increases.

However, I acknowledge that the specific methods I used to develop the assessment may have some limitations that need to be considered for decision-making. For example, because the lack of additional social variables in the 2012 updated Census database, I only used household wealth to account for people resources to cope with the two assessed environmental problems, yet other additional variables such as age, health, and house material could also be important to be considered (Romero-Lankao et al. 2013, Inostroza et al. 2016). Including these types of variable may have increased the capability of my methods to assess the fine spatial variability of ES deficits. However, as in my method coping resources accounted only for 25% of variables contribution to ES deficits, I consider that my results may only slightly change if additional coping variables were included.

Some authors have proposed to estimate ES deficits and provision based in absolute values to identify positive and negative ES budgets, and then translate them to relative indicators to evaluate their spatial mismatch (Burkhard et al. 2012, Larondelle & Lauf 2016). Such an approach could be useful when the objective is to quantify ES budgets, but may not be necessary if the main objective is to map the spatial mismatch between ES deficits and provision (Goldenberg et al. 2017). Furthermore, estimating absolute values requires additional environmental local data that may not be easily available in cities from developing countries, such as Santiago. Thus, I used an alternative approach that estimated ES provision and deficits based on relative, instead on absolute values. Therefore, my TSBA maps are not representing an "absolute level of required ES", but an indicator of the "relative level of required ES" based on the degree of mismatch between spatial indicators of current ES provision and deficits. This approach is particularly useful for my assessment, because in Santiago all areas of the city exceed the pollution norm for PM10 (i.e. 50 $\mu g/m^3$ yearly average), and also present temperatures reaching over 30°C during summer (Toro et al. 2014, Smith & Romero 2016), suggesting that all areas of the city could be still benefited by an increase of ES provision. Thus, as my main objective was to identify priority areas to increase the provision of ES through the implementation of urban vegetation, I consider that analyzing the gap between relative values of ES provision and deficit was an appropriate approach. However, because resulting values are only relative to each other, a shortcoming of this method is the lack of information on the quantity of ES provision potentially required to meet a particular environmental quality standard.

Integrating the potential spatial flows of ES from SPA to SBA still is a pervasive issue for ES mapping. Methods for mapping ES flows have included modeling potential connections between SPA to SBA using agent based models (Bagstad et al. 2013), and methods based on maximum theoretical ES flow distances (Serna-Chavez et al. 2014, Goldenberg et al. 2017). Modeling method may provide more accurate results, but are data and knowledge intensive, limiting its application. At the other hand, methods based in maximum theoretical flow distances are simpler to apply, but because they usually depend on arbitrary predefined theoretical flow distance, they can be less accurate. My approach is also based in maximum ES distance flows, but instead of defining that distance based in theoretical knowledge, I used correlations-scalograms to assess what the maximum distance were for the assessed ES within the study area. This could be highly relevant, because the spatial flows of ES may differ for different urban settings. In addition, instead of averaging the values of provision within ES flowing areas (e.g. Goldenberg et al. 2017), I used a decaying distance function that may better represent how ES flow decreases as distances from SPA increases.

Another novelty of my approach is the use of neighborhood analysis functions (i.e. r.neighbors in Q.GIS) to estimate the provision of ES at each spatial scale. This function allows to calculate for each pixel the average value of ES provided at their surroundings, and therefore can be a useful method to estimate the level of ES that is potentially reaching any given pixel. However, a shortcoming of this approach is that it assumes that ES flows from SPA are omnidirectional (i.e. equal in all directions), which may not be true for all regulating ES (Fisher et al. 2008, Syrbe & Walz 2012, Serna-Chavez et al. 2014). For instance, the spatial patterns of provision of the two ES assessed in this work may be affected by factors such as prevailing wind direction, built-up structure patterns, and urban topography (Bowler et al. 2010, Janhäll 2015). Therefore, while I consider that my approach may help to better map the provision of temperature reduction and air pollution mitigation ES, this method still requires refinement to increase its capability to accurately represent the fine scale spatial heterogeneity of ES provision.

4.5.2 Spatial patterns of ES deficits and provision in Santiago

This is the first study attempting to measure the spatial patterns of provision and deficits of regulating ES generated by urban vegetation in Santiago at the city scale. While previous studies have mapped Santiago's vegetation to relate these patterns to ES provision (de la Barrera et al. 2016b, de la Barrera & Henríquez 2017), these studies have assumed that vegetation may provide a certain level of services, but have not based their analysis in effectively measuring the actual level and patterns of ES provided by vegetation in Santiago.

My results show that the deficits for the two analyzed ES tend to show similar patterns, presenting relatively high deficits for services in most of the city, except for the areas located in the northeastern zone, which is the area concentrating high income population. This was an expected result, because in Santiago areas of higher incomes are exposed to lower levels of air pollution, lower temperature, and higher percentages of vegetation coverage (Fernández & Wu 2016). In fact, Santiago has a long history of unequal socioeconomic development and spatial segregation (Fernández et al. 2016), which has produced high levels of environmental inequities (See Chapter 3).

In relation to ES provision, previous studies have shown that green spaces and urban vegetation coverage are positively associated with areas with higher incomes in Santiago (Aquino & Gainza 2014, de la Barrera et al. 2016a), and therefore it may be expected that the spatial patterns of provision of the two assessed ES closely resemble this uneven spatial structure. However, this may not be always true because the provision of ES for temperature and air pollution mitigation does not depend directly on vegetation cover, but more strictly on the type of vegetation (Bowler et al. 2010, Janhäll 2015). Thus, as I mapped ES provision based on four vegetation types whose spatial patterns do not strictly follow the original patterns of Santiago's vegetation cover (Figs. 4.1, 4.4), it could be expected that my result showed lower level of inequalities for the distribution of the assessed ES provision, than for vegetation cover. But, on the contrary, my data show that the spatial correlations between ES provision and household wealth (HW) are even stronger, meaning that inequalities associated to the ES provided by vegetation are even larger than the ones generated by vegetation cover alone. In fact, while the spatial correlation between summer vegetation cover and HW is $R = 0.311$, this relationship increases to $R = 0.337$ and $R = 0.481$, when the analysis is made for the provision of temperature reduction services using the local and flow approach, respectively. For air pollution mitigation, this increase is even stronger, going from $R = 0.139$ for the spatial correlation between winter vegetation cover and HW, to $R = 0.318$ and $R = 0.587$, for the analysis with ES provision using the local and flow approach, respectively.

The differences between the relationships of HW with vegetation cover and ES provision can be explained because trees tend to be better for providing the assessed ES than grasses (Bowler et al. 2010, Janhäll 2015), and in Santiago trees are highly concentrated in the richest part of the city (Escobedo et al. 2016). This interpretation is supported by the result of the regression models (Table 4.1), as these showed that for temperature reduction, grasses provided less ES than trees, and that for air pollution grasses were not a relevant source of ES. These results highlight the relevance of developing efforts to better map the provision of ES in urban areas, as these can help to better inform decision-makers for planning mitigation strategies, and may also provide stronger support to why is relevant to include the provision of ES in the environmental inequality agendas.

4.5.3 Implications for policy-making

Result from my work have important implications for policy-making, particularly for the development of planning strategies aiming to optimize the provision of regulating ES within urban areas. As results for Santiago show, considering or not the flows of ES is a key decision for identifying optimal areas for implementing urban vegetation. Considering ES flow not only change the spatial distribution of areas identified as optimal for placing vegetation, but also their relative size and spatial configuration. Current approaches for planning the provisioning of regulating services in cities are mostly approached from a local perspective that have overlooked the potential flows of ES to and from neighboring areas (Wu et al. 2008, Locke et al. 2010, Morani et al. 2011, Norton et al. 2015, Bodnaruk et al. 2017). While these approaches have provided insightful knowledge to help linking the ES concept with urban vegetation planning, there is still place for improving the accuracy of these assessment by explicitly incorporating the potential flows of ES. Including ES flows in this type of assessments may not only help to better identify optimal areas to provide specific ES, but may also help to conceptualize urban vegetation as an integrated system of green infrastructure where ES are provided at multiple scales.

Also, if planners ought to implement vegetation in prioritized areas, they have to analyze what are the most relevant ES that are needed to provide on those particular areas, as a single vegetation patch can provide multiple ES (Dobbs et al. 2011). Furthermore, it is not only relevant to identify what are the optimal areas to provide the ES, but also if these are on public or privately-owned lands, because land ownership could be a relevant factor for defining the specific intervention strategies to increase urban vegetation. While government may directly implement vegetation in public areas, increasing vegetation in privately owned lands may require specific incentives or to modify current legislation.

Policy-makers also have to be aware that implementing vegetation in some particular areas may generate disservices (Von Döhren & Haase 2015). Therefore, planners have to design their interventions based on the specific local context. For example, in the city of Santiago winters are cold and cloudy; thus, planting evergreen species on streets could be useful for intercepting winter air pollution, but can block the heat and light provided by the sun. Hence, while this spatial optimization method may provide decision-makers with useful information on where to provide ES, the final decision on how to provide ES also needs to consider people’s preferences and environmental conditions at the local scale.

CHAPTER 5:

THE URBAN MATRIX MATTERS: EFFECTS OF SURROUNDING URBAN VEGETATION ON PRIMARY PRODUCTIVITY WITHIN URBAN NATURAL REMNANTS

5.1 Introduction

Urbanization is among the most drastic human-driven land-use change processes (Foley et al. 2005, Seto et al. 2011, Sushinsky et al. 2013). Urbanization usually results in the loss, degradation, and fragmentation of natural habitats; reduction of native biodiversity and increase of invasive species; loss of agriculture lands; pollution of streams, air and soils; and modification of energy flows and nutrient cycles (Alberti 2005, McKinney 2008, Grimm et al. 2008). These modifications have long-lasting effects on the structure and functioning of ecosystems. Once urbanization takes place, chances to restore urbanized lands to a previous natural stage are severely limited (Lindig-Cisneros & Zedler 2000, Pavao-Zuckerman 2008, Standish et al. 2013).

Urbanization is a dynamic process, often combining periods of slower inner densification and rapid outward expansion (Antrop 2004, Dietzel et al. 2005). As urban areas expand, protected and non-urbanizable areas outside urban boundaries become progressively fragmented, often leading to a system of scattered natural remnants embedded in an urban matrix (Ramalho & Hobbs 2012). Here I refer to these remnants as Urban Natural Remnants (UNRs), defining them as “natural areas that have been partially or completely isolated by an urban matrix, but that still retain compositional and structural characteristics of the original natural habitat".

UNRs can provide multiple ecosystem services (ES) for urban areas, such as carbon sequestration, oxygen provision, air pollution reduction, microclimatic regulation, water infiltration, recreational and educational opportunities, increased city attractiveness, and provision of habitat for biodiversity (La Rosa & Privitera 2013, Lovell & Taylor 2013, Silva de Araújo & Bernard 2016). Nevertheless, the provision of ES cannot be taken for granted, as the long-term provision of ES by UNRs will depend on their capacity to retain the underlying ecosystem processes supporting the delivery of services (de Groot et al. 2002; 2010). As UNRs become progressively fragmented by urbanization, ecosystem processes within UNRs (e.g. decomposition, primary production) could become highly altered, negatively impacting the potential of UNRs for delivering ES.

Urbanization could alter ecosystem processes within UNRs via two main pathways: biotic and abiotic effects. Urbanization fragments and reduces the area of remaining natural habitats, inducing changes in the species composition of UNRs. These changes are often characterized by an increase in richness and abundance of exotic and generalist species, and a reduction in richness and abundance of native species (Soulé et al. 1992, Gibb & Hochuli 2002, Jellinek et al. 2004, Fernández & Simonetti 2013). The changes in species composition are coupled with modification of trophic dynamics, which lead to new system dynamics that may radically alter fundamental ecological processes such as primary productivity and soil formation (Crooks & Soulé 1999, Faeth et al. 2005, Buyantuyev & Wu 2009, Ramalho et al. 2014). At the other hand, abiotic conditions in urban areas often differ from those in natural and rural areas. Therefore, as UNRs become isolated by the urban matrix, they are commonly exposed to higher average temperatures, lower wind speeds, higher levels of air particulate matter, higher atmospheric concentration of inorganic and organic pollutants, and accumulation of these compounds and heavy metals on soils (Grimm et al. 2008, Pickett et al. 2011). These factors could have negative impacts on UNRs ecosystem processes, reducing their ecological functionality, and therefore threatening their capacity to provide ES in the long-term.

Urban ecological studies have provided insightful knowledge regarding the effects of the urban matrix on remnants biodiversity (e.g. Donnelly & Marzluff 2004, Watson et al. 2005, Öckinger et al. 2009, Fitzgibbon et al. 2011, Litteral & Wu 2012, Fernández & Simonetti 2013) as well as fundamental understanding about urban ES (Lundy & Wade 2011, Gómez-Baggethun et al. 2013, Haase et al. 2014). Nevertheless, we still have a gap of knowledge regarding the effects of the urban matrix on the ecosystem processes supporting the provision of services by UNRs. For example, whereas we know that dense vegetated areas on the urban matrix may have positive effects on nearby remnants biodiversity (Mörtberg 2001, Ikin et al. 2012), we have little understanding on the potential effects of urban matrix vegetation on UNRs ecosystem processes. Thus, understanding the role that the urban matrix, and particularly urban vegetation, plays on the ecosystem processes of UNRs is fundamental to design proper urban planning promoting the long-term delivery of ES by these remnants.

Understanding the effects of the urban matrix on UNRs is a challenging task for two main reasons. First, the urban matrix is highly heterogeneous and therefore approaches that treats the matrix as a rather homogenous element, such as those based in landscape fragmentation theories (Fahrig 2003, Ewers & Didham 2006), may fail to identify relevant spatial patterns affecting ecosystem processes within remnants (Ricketts 2001, Murphy & Lovett-Doust 2004, Prevedello & Vieira 2010, Watling et al. 2011, Ruffell et al. 2017). Second, ecosystem processes relate to physical, chemical, and biological variations in time, implying that any attempt to assess ecosystem processes would require using an approach able to measure how any of these components change in time (Ramalho & Hobbs 2012). In this regard, an urban landscape ecological approach may be particularly helpful for understanding and addressing these types of challenges. This approach emphasizes the interrelation between landscape patterns and ecological processes operating at multiple temporal and spatial scales, and encourages place-based research that integrates ecology with urban design and planning (Wu et al. 2013).

In this work, I used a multi temporal and spatial scale approach to evaluate the potential role of vegetation patterns of the urban matrix on the primary productivity of 10 UNRs located in the city of Santiago de Chile. Using a set of 6 remote sensing-derived vegetation indices data (years 1985 to 2010), I analyzed how the temporal changes on primary productivity within UNRs relates to changes of vegetation patterns of the surrounding urban matrix at different temporal and spatial scales. I aimed to answer the following questions: (1) Is primary productivity of UNRs affected by the amount and spatial pattern of vegetation cover in the urban matrix? (2) At what temporal and spatial scales do these effects take place? (3) What factors may be driving these effects at different scales?

5.2 Methods

5.2.1 Study area

The city of Santiago is located in the Maipo River Basin of Central Chile (33°26'15"S; 70°39'01"W), bounded on the east by the Andes Mountain and on the west by the Coastal Mountain Range (Fig. 5.1), covering a total built-up area of near 600km^2 (Banzhaf et al. 2013). Climate is Mediterranean, with a marked cold and rainy winter, and a dry and hot summer season. Original vegetation is represented mostly by summer drought tolerant species, which can form dense or sparse shrublands depending on topographic conditions (Jaksic 2001).

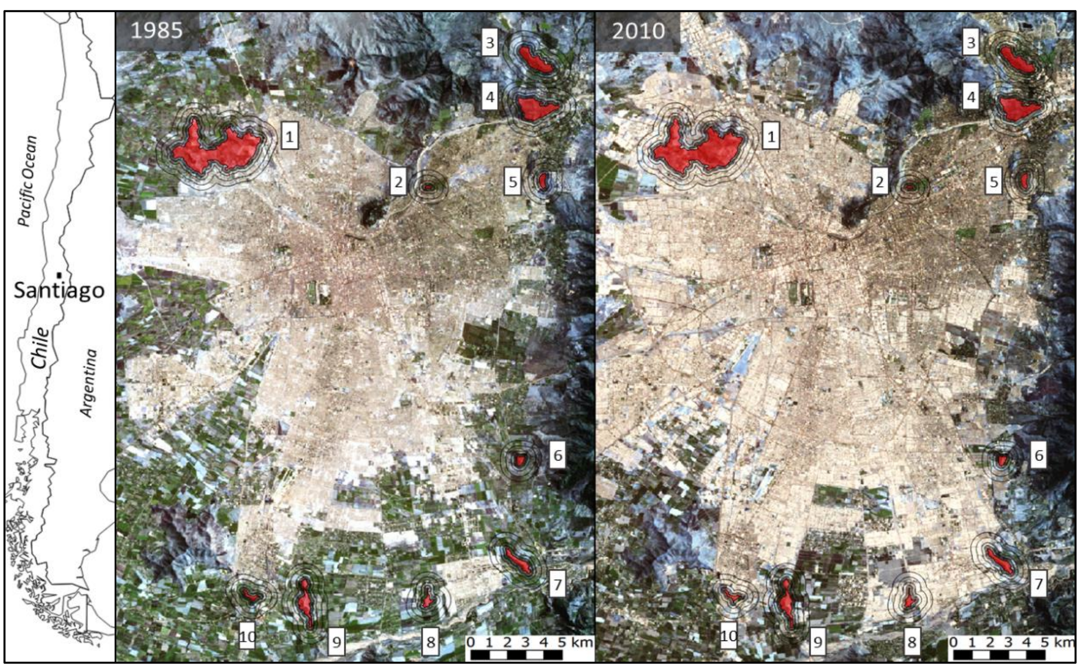

Figure 5.1. Area of Study. Landsat-5 satellite showing Santiago in 1985 and 2010. The 10 assessed UNRs are shown in red and their respective buffers in grey. Numbers near UNRs are to identify them in Table 5.1. Colors of the image have been modified to highlight the expansion of the urban area and changes on vegetation patterns.

Santiago has almost duplicated its population during the last 30 years, and currently is estimated to harbor close to 6.5 million people, representing around 37% of the total population of the country (Instituto Nacional de Estadísticas 2015). This population growth has been associated to a rapid urban expansion that has doubled the spatial extent of the city since 1975, mostly replacing agricultural land and surrounding natural habitats (Romero et al. 2012). The transformation of agriculture and natural areas to urban infrastructure has reduced the vegetation coverage, negatively impacting the provision of ES and the environmental quality of the city (Romero & Vásquez 2005).

5.2.2 The UNRs system

This study focuses on primary productivity trends of 10 UNRs (locally known as *Cerros Isla;* Island Hills in English) and vegetation cover patterns of their respective surrounding matrix at five different nested extents (Fig. 5.1). These 10 UNRs are a subset of 22 hilly natural areas, ranging from 2 to more than 1,000 Ha, which have been partially or completely surrounded by Santiago's urbanization processes (Fernández 2011). These hills were officially declared as protected green spaces by the Santiago Metropolitan Government in the year 1994; nevertheless from these 22 remnants, only few have been managed for this purpose, particularly through their reforestation with exotic species (Forray et al. 2012). The ecological conditions of the hills that have not been managed is diverse, as several of them have been degraded by direct impacts of anthropogenic activities (Fernández 2011, Forray et al. 2012). However, the large proportion of unmanaged hills still present representative vegetation from the original natural communities, and therefore can be considered as natural remnants (Fernández 2011). Yet, not all these hills are isolated from natural areas, therefore from the total of 22 hills, I only selected those remnants presenting two main conditions: (1) dominance of native vegetation representative from original natural habitats, and (2) remnants that by 2010 were partially or totally embedded in the urban matrix, and completely disconnected from any natural habitat. Geographic coordinates and main descriptive statics for the 10 UNRs assessed in this study are shown in Table 5.1.

Table 5.1. Name, identification ID in figure 5.1, geographical coordinates, area and NDVI values for years 1985 to 2010 of the 10 UNRs assessed in the study.

UNR (Hill)	ID	Geo. Coordinates		Area	Hills NDVI Mean ± (SD)					
		Lat S	Lon W	(Ha)	1985	1990	1995	2000	2005	2010
Renca	1	33°23'30"	70°43'29"	662.89	0.21 (0.03)	0.18 (0.04)	0.15 (0.04)	0.21 (0.04)	0.14 (0.04)	0.13 (0.04)
San Luis	2	33°24'35"	70°35'57"	3.63	0.40 (0.09)	0.32 (0.09)	0.34 (0.10)	0.37 (0.09)	0.32 (0.08)	0.30 (0.07)
Del Medio	3	33°20'43"	70°32'03"	110.96	0.39 (0.08)	0.30 (0.06)	0.29 (0.06)	0.36 (0.06)	0.30 (0.06)	0.29 (0.05)
Alvarado	4	33°22'13"	70°32'07"	166.54	0.34 (0.05)	0.27 (0.04)	0.26 (0.05)	0.32 (0.05)	0.28 (0.05)	0.28 (0.05)
Apoquindo	5	33°24'26"	70°32'49"	23.48	0.31 (0.05)	0.18 (0.04)	0.19 (0.04)	0.27 (0.03)	0.24 (0.04)	0.22 (0.02)
Santa Rosa	6	33°33'05"	70°32'49"	18.45	0.35 (0.06)	0.27 (0.05)	0.28 (0.06)	0.32 (0.05)	0.26 (0.05)	0.25 (0.07)
La Ballena	7	33°36'18"	70°32'51"	55.65	0.36 (0.07)	0.28 (0.07)	0.27 (0.07)	0.34 (0.08)	0.26 (0.06)	0.25 (0.04)
Las Cabras	8	33°37'25"	70°36'12"	24.24	0.33 (0.09)	0.23 (0.04)	0.20 (0.04)	0.26 (0.05)	0.20 (0.03)	0.21 (0.04)
Negro	9	33°37'28"	70°40'34"	83.79	0.31 (0.08)	0.24 (0.07)	0.22 (0.06)	0.28 (0.07)	0.20 (0.07)	0.23 (0.07)
Adasme	10	33°37'16"	70°42'22"	16.90	0.37 (0.07)	0.30 (0.05)	0.29 (0.06)	0.30 (0.05)	0.20 (0.04)	0.21 (0.03)

5.2.3 UNRs primary productivity and urban matrix vegetation cover indicators

I used the Normalized Difference Vegetation Index (NDVI) as a proxy for primary productivity of UNRs and the Soil Adjusted Vegetation Index (SAVI) as a proxy for vegetation cover on the surrounding urban matrix. These two indices are derived from a similar equation and therefore are strongly correlated between them. Nevertheless NDVI has been widely used as a surrogate for primary productivity and could perform particularly good for this purpose in lower vegetation cover areas (Xu et al. 2012), such as in Santiago's UNRs. At the other hand, SAVI is more suitable for intermediate vegetation cover and highly heterogeneous areas (Huete 1988), and therefore could be a better indicator for estimating vegetation cover on a heterogenous urban matrix.

Although these two vegetation indices are based on the ratios of red and infrared wavelengths reflected by photosynthetic tissues, their interpretation for this analysis differ. Vegetation within remnants is not managed nor watered, thus during summer months NDVI can be directly related with the capacity of native drought tolerant species to maintain photosynthetic activity, and therefore could be a good measure of the conservation status and primary productivity of the natural remnant system (Gerstmann et al. 2010). On the other hand, vegetation in the matrix is generally managed and watered, implying that during summer, managed vegetation will remain photosynthetically active and therefore, their spatial patterns (i.e. vegetation cover level and configuration) could be effectively assessed by NDVI derived indicators, such as SAVI (de la Barrera & Henríquez 2017)

5.2.4 Data gathering

I estimated UNRs NDVI and urban matrix SAVI from a set of six Landsat-5 satellite images taken during the summer period of years 1985, 1990, 1995, 2000, 2005 and 2010. These raster images have a 30m/pixel resolution, and all of them were taken in mid-January at ~11.30am local time with a 0% cloud cover. I used Landsat-5 images as this satellite provides the longest temporal coverage for our study area. All images were atmospherically corrected and radiometrically calibrated using the Semi-Automatic Classification Plugin (Ver.4.9.4) available in Quantum GIS (www.qgis.org). I calculated NDVI for each UNR and year by averaging all pixel values within each remnant for the respective year (Table 5.1). I estimated urban matrix SAVI for 5 nested buffer zones (i.e. 90, 150, 300, 600, 900m from remnants border) by averaging the SAVI values of all pixels pertaining to each buffer for the respective year. UNRs NDVI and matrix SAVI values for all years and buffers are shown in Fig. 5.2.

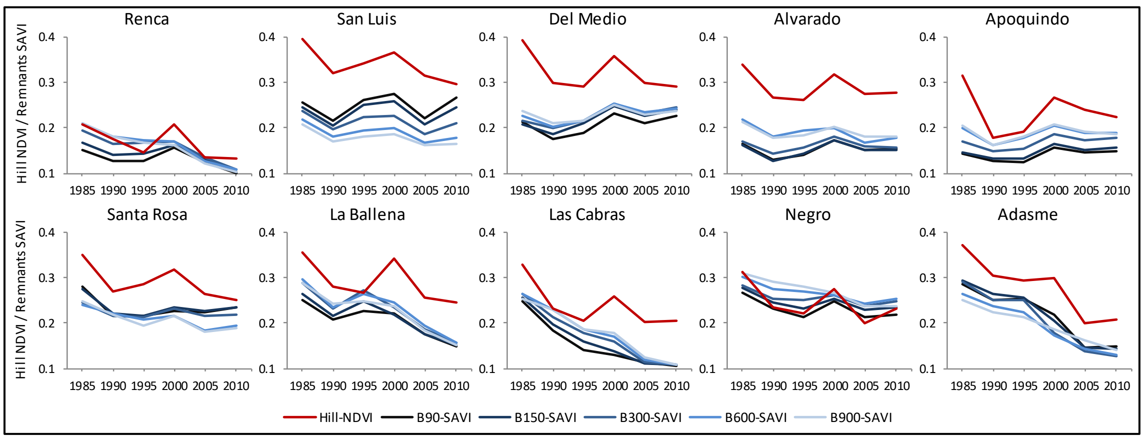

Figure 5.2. UNRs (Hills) NDVI and their respective urban matrix SAVI values at the 5 nested buffers.

5.2.5 Data processing and analysis

Spatial association between changes on UNRs primary productivity and matrix vegetation cover level

To assess the degree of spatial association between temporal changes of primary productivity within UNRs and changes in vegetation cover level at their respective surrounding matrix, I used the satellite image from 1985 as the baseline year, and calculated the changes (i.e. delta: Δ) on UNRs NDVI and matrix SAVI from baseline year to years 1990, 1995, 2000, 2005, 2010. These deltas were calculated as the absolute difference between baseline values and the respective analyzed year. Thus, the generated dataset represents the absolute change of NDVI (i.e. ΔNDVI) and SAVI (i.e. ΔSAVI) for each UNRs and their respective buffers, for an elapsed time of 5, 10, 15, 20 and 25 years since the baseline year (Fig. 5.3). With this approach, I aimed to evaluate if the temporal changes of UNRs NDVI are spatially associated with the changes of matrix SAVI, independently of the temporal variability of NDVI and SAVI due to external factors, such as inter-annual precipitation variability. In other words, my analysis focuses on evaluating if the increase or decrease of NDVI on UNRs could be spatially associated with changes on the level of vegetation cover (i.e. SAVI level) in the surrounding urban matrix. To assess for this spatial association, I assessed the spatial correlation (Pearson correlation) between UNRs ΔNDVI and their respective matrix ΔSAVI for each of the five elapsed times, and for each of the five buffers extent. Then, I integrated resulting correlation coefficients into a single graph for facilitating visual interpretation (Fig. 5.3, top graph).

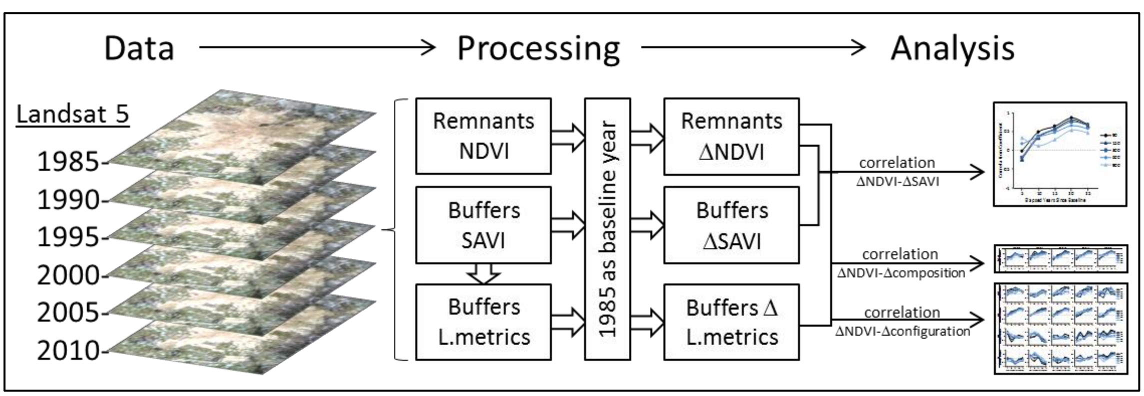

Figure 5.3. Schematic representation of the methodological approach used for data processing and analysis.

Spatial association between changes in UNRs primary productivity and changes in matrix vegetation cover metrics

To assess the degree of spatial association between temporal changes of UNRs primary productivity and changes on vegetation cover metrics, I first categorized matrix vegetation cover into five classes based in five SAVI range values (i.e. 0.10-0.15, 0.15-0.20, 0.20-0.25, 0.25-0.30, >0.30). I selected these values after analyzing the distribution of SAVI values within the area under analysis (i.e. within the 900meters buffer), taking the lowest and upper values from boxplot graphs to set SAVI classes ranges (Fig. 5.4).

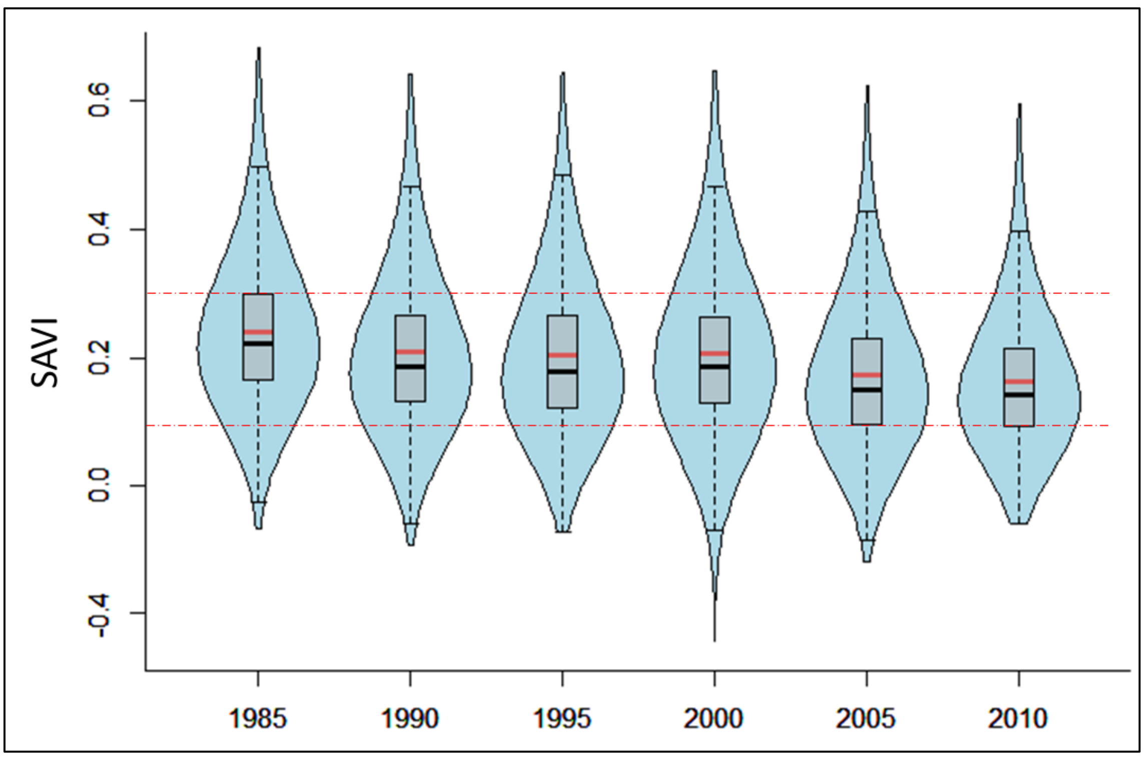

Figure 5.4. Vioplots combining probability densities of data distribution with boxplots for SAVI values for the 10 UNRs and six assessed years using the 900 meters buffer extent. Boxplots are based on the 25th and 75th percentile. Red and black lines within boxplots show the median and mean, respectively. The two horizontal dashed lines show the maximum and minimum values for the boxplots, which were used for deciding on SAVI values classes.

I did not include SAVI values below 0.10 as I assumed that these represented areas lacking vegetation cover. I used these SAVI classes to calculate one compositional (i.e. %landscape) and four configurational class metrics (i.e. mean patch area, largest patch index, landscape shape index, patch density) for each of the five vegetation classes, buffer sizes and years. I computed the absolute change of matrix vegetation cover class metrics since the baseline year (i.e. 1985) for each vegetation class and buffer size per UNR. I analyzed the spatial relationship between UNRs ΔNDVI and changes in buffers vegetation metrics through correlation analysis. Then, I integrated resulting correlation coefficients into a multiple graph for visual interpretation (Fig. 5.3, bottom graphs).

5.3 Results

5.3.1 Spatial association between UNRs ΔNDVI and matrix vegetation ΔSAVI

Pearson correlation analysis shows that UNRs ΔNDVI and matrix vegetation ΔSAVI tend to be spatially positively correlated for all assessed periods (i.e. years elapsed since the baseline year), except for the shortest period (Fig. 5.5). These associations become stronger in time, and weaker as distance from UNRs edge increases (i.e. increasing buffer size). Although most of correlation values are not statistically significant ($p<0.05$), the spatial and temporal trends are consistent, showing peak correlation values for all assessed buffers at 20 years since baseline. For this period (i.e. 20 years), except for the 900m buffer, all correlations are statistically significant, showing consistent weaker association as buffer size increases (Fig. 5.5).

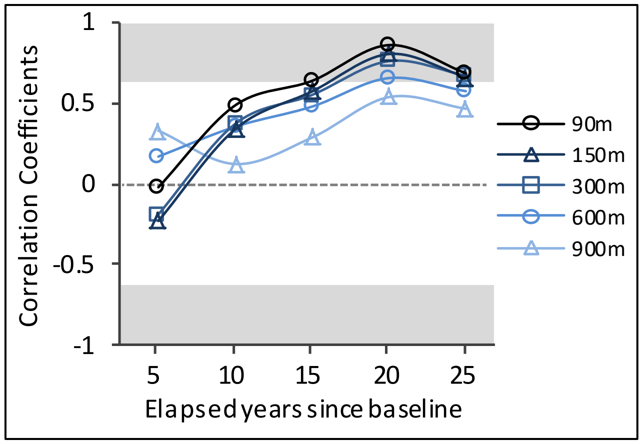

Figure 5.5. Pearson correlation analyses between UNRs ΔNDVI and matrix vegetation ΔSAVI for the five assessed periods and buffer sizes. Shaded areas show statistically significant correlation values at $p<0.05$.

5.3.2 Spatial association between UNRs ΔNDVI and changes on %landscape covered by the five assessed vegetation classes

Correlation coefficients for the spatial relationships of UNRs ΔNDVI and temporal changes on the percentage covered by each vegetation class for the five analyzed vegetation classes at the five buffer sizes are shown in Fig. 5.6. Results show that temporal dynamics of lower SAVI classes tend to be negatively correlated with UNRs NDVI, whereas larger SAVI classes tend to be positively correlated with UNRs NDVI. In general, for all the assessed vegetation classes correlations tend to be stronger and statistically more significant as elapsed years since the baseline increases. Also, and in particular for the longest time periods, correlations tend to become weaker as the buffer size increases (Fig. 5.6). The strongest statistically significant correlations values are obtained for the highest vegetation class (SAVI > 0.30), whose resulting graph is highly consistent to the graph of the spatial relationship of remnants ΔNDVI and matrix ΔSAVI (Figs. 5.5, 5.6).

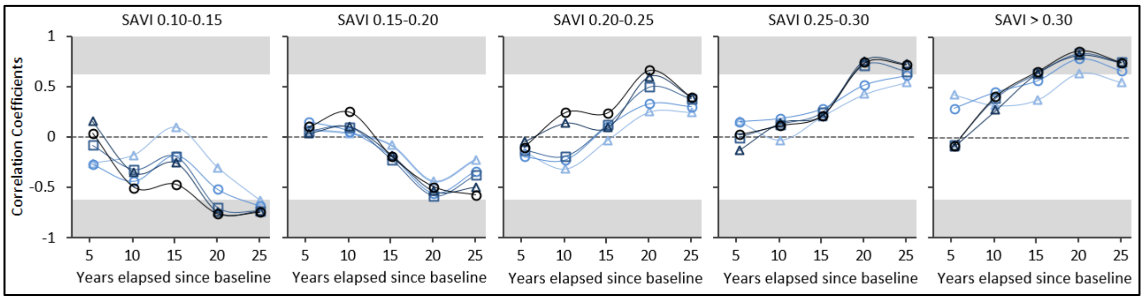

Figure 5.6. Pearson correlation analyses between UNRs ΔNDVI and changes on the %landscape covered by each vegetation class for the five assessed periods and buffer sizes. Shaded areas show statistically significant correlation values at $p<0.05$.

5.3.3 *Spatial association between UNRs ΔNDVI and changes on configuration of the five assessed vegetation classes.*

Correlation coefficients for the spatial relationships of UNRs ΔNDVI and temporal changes on the four assessed configuration metrics for the five analyzed matrix vegetation classes are shown in Fig. 5.7. None of the four configuration metrics shows consistent correlation patterns that can suggest an association between UNRs ΔNDVI and changes on the configuration of matrix vegetation classes. Nevertheless, although there is a great variability of correlation results between metrics, and between and within analyzed vegetation classes, there are three main general patterns that can be highlighted from the configuration analyses (Fig. 5.7). First, for the two smallest vegetation classes, correlation coefficients seem to decrease in time; whereas at the two highest vegetation classes this trend seems to be inverted. Second, the intermediate vegetation class (i.e.

SAVI 0.20-0.25) seems to represent a threshold value where the slope of the temporal patterns of correlation tends to shift from negative to positive. Third, the strength of correlations seems to increase with time and decrease with buffer sizes.

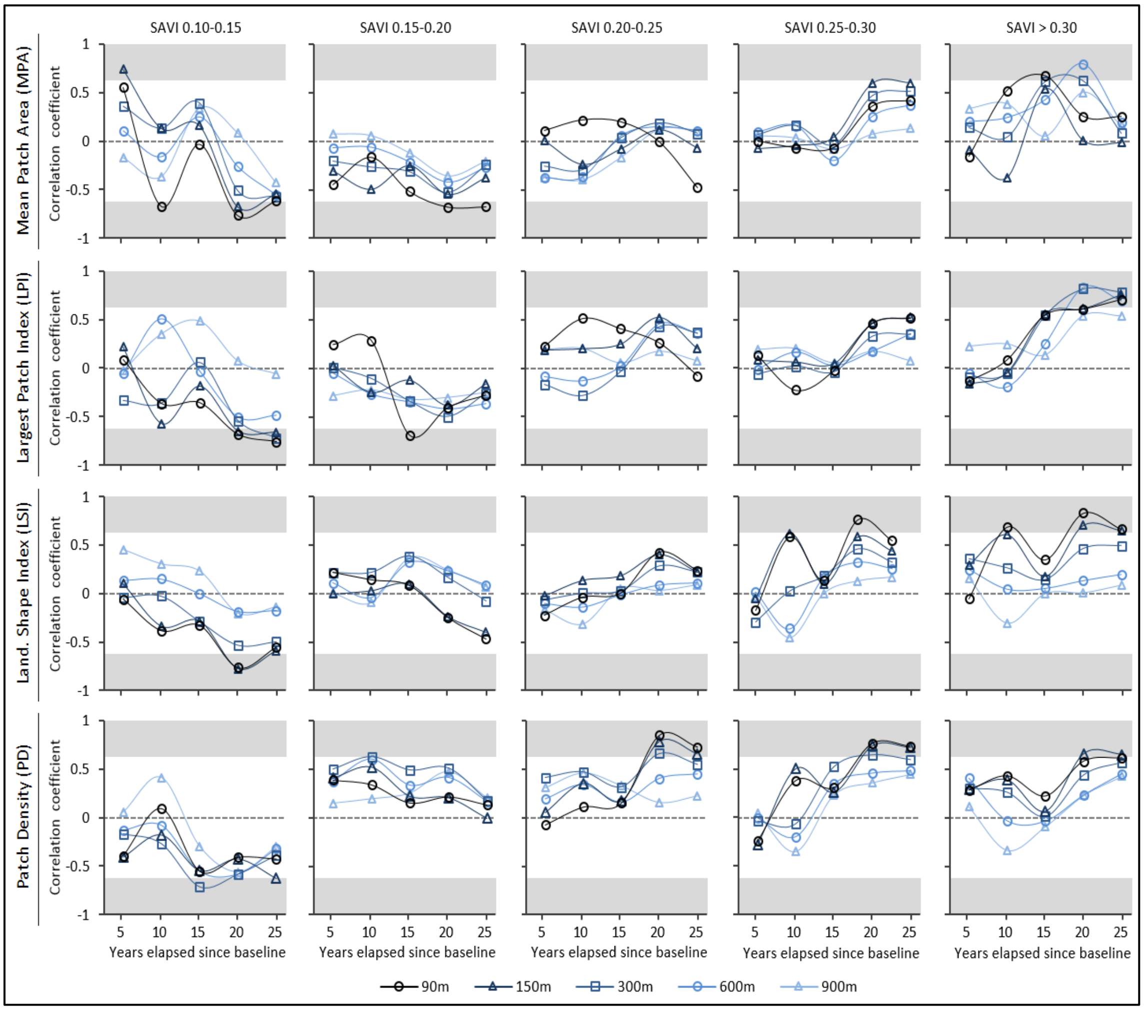

Figure 5.7. Pearson correlation analyses between UNRs ΔNDVI and changes on the four assessed configuration metrics calculated for each vegetation class for the five assessed periods and buffer sizes. Shaded areas show statistically significant correlation values at $p<0.05$.

5.4 Discussion

The main objective of this study was to evaluate if the temporal trends of primary productivity of 10 UNRs were spatially associated with the changes in the amount and configuration of vegetation cover in the surrounding urban matrix. If well managed, UNRs can provide several ES to urban areas (Ramalho & Hobbs 2012, Standish et al. 2013). Nevertheless their potential to provide ES will depend on their capacity to retain the underlying ecosystem process supporting these services (de Groot et al. 2002; 2010). Thus, efforts to understand the potential role of vegetation at UNRs surrounding urban matrix, such as this study, are key for evaluating potential novel strategies targeting UNRs neighboring areas.

Results show that Santiago's UNRs have been increasingly isolated by the urbanization process, which may be negatively affecting their ecological dynamics, and therefore, their potential to provide ES in the long-term (Fernández 2011). In fact, our NDVI data (Table 5.1) shows that the primary productivity levels for all assessed UNRs decreased between years 1985 and 2010, suggesting that the urbanization process has had a negative effect on UNRs productivity. But, it is also possible that other external factors, such as precipitations, may also be related to the observed reduction of UNRs NDVI. Primary productivity of natural vegetation in Central Chile is strongly limited by water availability (Gutiérrez & Jaksic 2000), and Santiago's region experienced decreasing rates of precipitation during the analyzed period (Boisier et al. 2016). Thus, this apparent reduction of UNRs NDVI due to urbanization could be simply an artifact of the decreasing precipitation patterns during the analyzed period. However, Table 5.1 also shows that UNRs having large decrease on NDVI (e.g. La Ballena, Adasme, Las Cabras) are coupled to large reduction on SAVI values at their surrounding matrix. Whereas UNRs showing small decrease on NDVI (e.g. Alvarado, Apoquindo, Negro) are associated with rather stable or increasing levels on SAVI values on the matrix (Fig. 5.2). Thus, although water limitation may have a preponderant effect on UNRs NDVI temporal trends, the effect of precipitation variability may be amplified or mitigated depending on vegetation levels in their surrounding matrix.

The potential association between UNRs primary productivity and matrix vegetation observed in Table 5.1 is supported by the correlation analyses between ΔNDVI and ΔSAVI (Fig. 5.5). Indeed, results from correlation analyses not only provide statistical support to this association, but also show that this relationship tend to become stronger in time and weaker as buffer distance increases. Because changes in matrix vegetation patterns are mostly mediated by human-driven landscape modifications (de la Barrera & Henríquez 2017), a logical conjecture is that this association is caused by the effect of matrix vegetation on UNRs primary productivity.

A potential mechanism mediating the effects of matrix vegetation on UNRs primary productivity could be related to the microclimatic changes induced by vegetation surrounding UNRs. Urban vegetation can reduce local temperatures (Bowler et al. 2010) and there is ample evidence showing that in Santiago residential areas having higher vegetation cover present lower temperatures (Romero et al. 2012, Inostroza et al. 2016, Smith & Romero 2016, Fernández & Wu 2016). Moreover, as vegetation from residential and recreational areas are usually watered, high-cover vegetated areas may also present higher levels of moisture during summer (Peña 2008, Peters et al. 2011). Thus, high-cover vegetated areas could generate microclimatic conditions of lower temperature and higher moisture that may reduce the summer water stress of vegetation located in nearby not irrigated areas, such as the analyzed UNRs. This potential mechanism is supported by the matrix vegetation composition results (Fig. 5.5), because the positive association between matrix vegetation and UNRs primary productivity is only seen for the three highest SAVI classes and is stronger for smaller buffers, which suggests that this effect is mostly mediated by high-cover vegetated areas located close to UNRs.

However, results from this work suggests that the effect of matrix vegetation on UNRs primary productivity is not immediate, but it only becomes relevant after 10 to 15 years since the baseline year (Figs. 5.5, 5.6). Thus, UNRs primary productivity seems to not be responding to short-term fluctuations on matrix vegetation cover, but to the general long-term trends of vegetation cover in their immediate surrounding matrix. As summer NDVI in Santiago's UNRs is mostly associated to slow-growing drought-resistant shrubs and trees species (Armesto & Martínez 1978), this result may indicate that changes induced by matrix vegetation does not affect the primary productivity of UNRs by modifying photosynthetic rates of stablished vegetation, but rather by modifying shrubs and trees cover through changes on recruitment and mortality rates. This differential effect on plants recruitment and mortality rates have been reported for forest fragments surrounded by agricultural landscapes with different vegetation cover (Mesquita et al. 1999, Laurance et al. 2007), which can provide support to this potential explanation. Nevertheless, further researches assessing plants recruitment and mortality rates are needed to evaluate if this mechanism is effectively occurring in Santiago's UNRs.

Primary productivity of UNRs can also be affected by biotic-mediated effects. Colonization by exotic plant species frequent on the urban matrix has been reported for UNRs in Mediterranean urban areas of California and Spain (Soulé et al. 1992, Guirado et al. 2006), and Santiago's UNRs are not the exception. Nevertheless, the few studies measuring vegetation coverage and richness in Santiago's UNRs (Mella & Loutit 2007, Fernández & Simonetti 2013) have found that while colonization of plants species from the matrix occurs, the relative contribution of these to UNRs total vegetation coverage is small. This can be due to the severe conditions imposed to seed germination and seedlings survivals by the long dry summer season of Central Chile (Becerra et al. 2011, 2013), which may preclude the colonization from drought-sensible species that dominates Santiago's urban matrix (de la Maza et al. 2002). Thus, plant colonization from the matrix may not be a relevant factor modifying primary productivity in Santiago's UNRs.

Matrix vegetation patterns could also have indirect effects on UNRs primary productivity by providing supplementary habitat to animal species supporting key plant-animal interactions in UNRs. Several trees and shrubs composing the native vegetation of Santiago's UNRs requires birds to disperse their seeds (Jaksic 2001), and there is also evidence that for some shrubs species the ingestion of seed by birds can play a key role increasing seed germination rates (Reid & Armesto 2011). Areas of Santiago with higher vegetation cover could provide supplementary habitats to native bird species inhabiting UNRs (Urquiza & Mella 2002, Díaz & Armesto 2003), which may help to support native plant species recruitment within UNRs. As birds are more sensitive to habitat quantity than to habitat spatial configuration (Donnelly & Marzluff 2006), their potential role mediating the effect of matrix vegetation on UNRs is not contradictory to the fact we did not find a consistent relationship between UNRs primary productivity and matrix vegetation configuration. While other animal species, such as native small mammals, may also be relevant for controlling vegetation recruitment (Fuentes et al. 1983), results from a previous study suggests that these remnants are not able to support native small mammals populations because they cannot use or disperse through the surrounding urban matrix (Fernández & Simonetti 2013). This potential barrier to dispersal between UNRs and surrounding matrix vegetation patches is also supported by the fact that while these remnants harbor an important diversity of native birds, they seems to lack bird species with poor flying capacity (Mella & Loutit 2007). Therefore, it is possible that the positive correlations I found between UNRs NDVI and matrix vegetation SAVI levels could be mediated by the interaction of abiotic effects through microclimatic changes, and biotic effects through plant-animal interactions mediated by birds.

5.5 Conclusions

Increasing the provision of ES within urban areas is as a fundamental goal for moving towards more resilient and sustainable cities (Jansson 2013, Wu 2014, McPhearson et al. 2015). Nevertheless, while there is ample knowledge on the direct role of urban vegetation in providing urban ES (Niemelä et al. 2010, Gómez-Baggethun & Barton 2013, Lovell & Taylor 2013), there is scarce evidence on the additional role that urban vegetation may have on sustaining the provision of ES by UNRs. Apparently, most of urban ecological studies still conceives the urban matrix as a homogenous inhospitable habitat, therefore focusing in their negative effects, but disregarding a potential positive effect on UNRs ecological processes. While fragmentation by urbanization has an overall negative effect on UNRs ecological processes, results from this work suggests that in urban ecosystems of Central Chile these effects could be mitigated by the level of vegetation in their surrounding urban matrix. Therefore, increasing the vegetation cover in areas surrounding UNRs can be a suitable urban planning strategy to mitigate the negative impacts of fragmentation. This can be considered as a win-win strategy, because an increase of matrix vegetation cover will directly provide ES to local residential areas and will also increase the chances of UNRs to keep providing ES at larger scales. An approach like this require changing the way we conceptualize UNRs, from the "island hills" surrounding by an inhospitable urban matrix perspective, to one where these remnants are part of a system of interactive and highly dynamic heterogenous patches.

CHAPTER 6:

SYNTHESIS

The main goal of my dissertation was to generate actionable knowledge to help decision-makers optimizing the spatial allocation of urban green infrastructure as a strategy to reduce unfair environmental inequalities (i.e. environmental inequities) through the provision of ecosystem services. These two concepts (i.e. urban environmental inequality/inequity, urban ecosystem services) have been extensively covered in the literature. Nevertheless, efforts to understand the role of ecosystem services in solving or generating urban environmental inequalities/inequities are still scarce, and therefore necessary (Ernstson 2013). In this regard, my research contributes to both the environmental inequality/inequity and ecosystem services literature by providing empirical knowledge and methodological frameworks that help decision-makers to develop planning strategies focused on the equitable (but not necessarily equal) distribution of ecosystem services within urban areas. Furthermore, I focus my analyses and case study in a Latin-American city (Santiago de Chile), which also helps to fill the large knowledge gap for cities from the developing world.

I consider important to note that while each of my four research chapters (chapters 2 to 5) was conceived as standalone paper, they are logically linked, as previous chapters provide the empirical and conceptual building blocks for the ensuing chapters. Also, while planning my research I was particularly focused on developing novel methodological approaches in a way that my research would not only contribute to local actionable knowledge for Santiago, but also to the general body of knowledge of urban sustainability by proposing new methods and frameworks that can be applied elsewhere. Thus, in the following four paragraphs I will refer to each of these chapters by briefly discussing how each of them contributes to: (1) increasing the body of knowledge of urban sustainability science, (2) developing new methodological approaches for addressing urban sustainability challenges, (3) generating actionable knowledge to inform decision-makers on how to improve Santiago's sustainability. In Table 6.1 I provide a summary with the contribution of each of the four research chapters of my dissertation.

Table 6.1. Scientific contributions from the research chapters of my dissertation

Chapter	Body of Knowledge	Methodological Knowledge	Local Knowledge
2	-Spatial scale issues (i.e. MAUP) -Environmental inequalities	-Hierarchical multi-scale approach for assessing bivariate spatial relationships	-Spatial patterns and levels of environmental inequalities in Santiago
3	-Environmental inequities -Spatial decision-making -Spatial prioritization	-A GIS-based framework: Environmental Improvement Priority index (EIPI)	-Identification of priority areas for reducing environmental inequities in Santiago
4	-Urban vegetation planning -Spatial prioritization -Ecosystem services mapping and planning	-Methodological Framework for green infrastructure prioritization -Method for mapping provision of ecosystem services including spatial flows	-Maps of ecosystem services deficits and provision -Identification of optimal areas for implementing vegetation in publicly- and privately-owned areas of Santiago
5	-Spatial patterns and ecological processes -Fragmentation by urbanization -Ecosystem services management	-Methodological approach for evaluating landscapes spatio-temporal relationships	-Results suggest that in Santiago, vegetation on the urban matrix can be managed to favor the long-term provision of ecosystem services by natural remnants

Chapter 2 contributes to the general body of knowledge of environmental inequality by focusing on how the spatial scale at which analyses are done in Santiago may modify inequality assessments results, and therefore, interpretations. This effect, known as the modifiable areal unit problem (MAUP) has been long known by geographers (Openshaw 1989, Wu 2007), nevertheless scale effects have rarely been examined explicitly in environmental inequality assessment, leading to contradictory results from different studies (Baden et al. 2007, Noonan 2008). To test for potential scaling issues in assessing environmental inequalities in Santiago, I developed a hierarchical multiple-scale methodological approach that allowed me to evaluate the effects of both, extent and grain size (and their interactive effects), on the observed patterns and levels of environmental inequalities related to three environmental variables, i.e. surface temperature, air pollution, and vegetation cover. My results showed that the level and spatial patterns of environmental inequalities in Santiago are highly scale dependent, therefore providing new evidence on the importance to explicitly address potential issues due to the MAUP effect when assessing environmental inequalities. This method could be used elsewhere and with different environmental and social variables, and therefore can be a relevant contribution to the current methods for dealing with scaling effects when assessing for environmental inequalities. In addition, results from my assessment for Santiago can inform locally policy-makers on the specific scales and areas where environmental inequalities become more severe.

In chapter 3 I built from the evidence of environmental inequalities in Santiago and the scale dependency of these, to generate a spatial explicit methodological framework (i.e. Environmental Improvement Priority Index, EIPI) that could help decision-makers to identify priority areas for reducing environmental inequalities that are judged as socially unfair (i.e. environmental inequities). Therefore chapter 3 acts as a bridge linking the problem diagnosed in chapter 2 with potential intervention solutions which I addressed in chapter 4. This framework may have an important contribution for urban sustainability, because whereas reducing urban inequities in developing countries has been signaled as of primary concern by United Nations (UN-Habitat 2014), methods to inform decision-makers on where to prioritize interventions for reducing environmental inequities are still needed. I built the EIPI as a relatively simple, flexible, and easy to communicate tool, which are desirable characteristics for linking scientific assessment with decision-making processes. Furthermore, this framework does not only help identifying priority areas for interventions, but also to map social and environmental indicators at different scales, which can be used as complementary information for final decision-making. Finally, by applying this framework to the city of Santiago I generated valuable information that could be readily used by local policy-makers to prioritize the areas where environmental interventions are more urgent.

In chapter 4 I developed a methodology aimed to help identifying the optimal areas for implementing green infrastructure to provide ecosystem services for reducing environmental problems in areas of higher need. The proposed method is highly relevant, because while there is ample evidence on the role of green infrastructure in providing ecosystem services within cities (Wu 2014, Wolch et al. 2014), we often lack the empirical data, specific tools, and guiding principles for planning and managing green infrastructure to optimize the provision of ecosystem services (Lovell & Taylor 2013). Thus, chapter 4 is aimed to provide the actionable knowledge necessary to start developing solutions (based on provisioning ecosystem services by green infrastructure) to mitigate the unfair inequality problems diagnosed in chapter 2 and then prioritized in chapter 3. This chapter provide conceptual, methodological, and empirical knowledge that may help to: (1) better understand the spatial flows of ecosystem services within cities, (2) planning green infrastructure based on an equitable provision of ecosystem services prioritization perspective, and (3), better mapping the provision of ecosystem services by including the potential spatial flows (i.e. dispersal) of services from areas where these are produced. In addition, the application of this methodological approach to the city of Santiago provided valuable place-based knowledge that can be directly taken by local decision-makers for planning where to allocate vegetation.

Finally, chapter 5 complement the information provided in previous chapters by generating additional knowledge focused on the effects of spatial patterns of urban vegetation on the ecosystem services delivered by natural remnants fragmented by urbanization. In this regard, while previous chapters were focused in planning urban vegetation for provisioning ecosystem services, chapter 5 add to this information by evaluating how by correctly planning vegetation in the urban matrix is it also possible to support the provision of ecosystem services by surrounding natural areas. Although there is ample knowledge on the direct role of urban vegetation in providing urban ecosystem services (Niemelä et al. 2010, Gómez-Baggethun & Barton 2013, Lovell & Taylor 2013), there is scarce evidence on the additional role that urban vegetation may have on sustaining the provision of ecosystem services by urban natural remnants. Reducing this knowledge gap is highly relevant for Santiago, because a large proportion of available areas that can be managed for providing ecosystem services are constituted by urban natural remnants.

Thus, understanding the role that urban vegetation plays on the ecosystem processes of urban natural remnants is not only relevant to reduce our knowledge gap, but is also fundamental for designing better urban planning strategies focused in managing urban matrix vegetation to promote the long-term delivery of ecosystem services by Santiago's natural remnants. In fact, my results show that whereas fragmentation by urbanization have a negative effect on Santiago's natural remnants, to increase the vegetation cover in the urban matrix can be a suitable strategy to promote the long-term delivery of ecosystem services by these remnants. This information can be used by local urban planners to design novel win-win vegetation planning strategies focusing on increasing matrix vegetation cover near urban natural remnants to: (1) directly provide ecosystem services to local residential areas, and (2), increase the chances of natural remnants to keep providing ecosystem services in the long-term.

In conclusion, my research provides conceptual background and methodological approaches that help researchers and decision-makers to navigate the different steps necessary to develop strategies to mitigate urban environmental problems through the equitable provision of ecosystem services by urban vegetation. This research is a truly sustainability-based endeavor, where the generation of knowledge plays a central role, but where the design of integrated solutions for increasing human well-being is taken as the ultimate goal.

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