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A GIS-based framework to identify priority areas for urban environmental inequity mitigation and its application in Santiago de Chile

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ABSTRACT

Environmental inequity is a common phenomenon of modern cities, particularly in the developing world where the high rates of urbanization often surpass the capacity of local governments to develop proper urban planning. In these cities the spatial distribution of environmental quality is frequently associated with socioeconomic characteristics, with vulnerable sectors often having a disproportionately larger share of environmental problems. While reducing environmental inequity is widely recognized as an important step towards more sustainable cities, decision-makers usually lack the tools and information for designing effective and efficient intervention strategies. A challenging decision is to resolve on where, among all the areas having environmental problems, efforts should be allocated first. Here we present a GIS-based framework that can help decision-makers to prioritize the spatial allocation of policy interventions at different spatial scales or administrative levels. The framework focuses on (1) identifying areas having the highest levels of environmental problems, (2) identifying 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 the framework we apply it to the city of Santiago de Chile at three different scales. Our assessment focuses on three main environmental problems currently affecting this city: urban heat, lack of green infrastructure, and air pollution. Based on the results from Santiago, we discuss how the framework can be used to help policy-makers to identify priority areas for policy intervention at their respective administrative level.

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 2050 almost two thirds of global population will be urban (UNDESA, 2014). 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 living conditions and development opportunities (Henderson, 2010). The urbanization process experienced by developing regions is happening 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 (Nassauer, Wu, & Xiang, 2014; Pickett et al., 2011; Wolch, Byrne, & Newell, 2014; Wu, 2014; Wu, He, Huang, & Yu, 2013).

Latin America has the highest urbanization level among developing regions, with almost 80% of its population currently living in urban areas (UNDESA, 2014). 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 socioeconomic and environmental inequalities (Angotti, 1996; Carruthers, 2008; Fernández, Manuel-Navarrete, & Torres-Salinas, 2016). Whereas socioeconomic inequality has been widely covered in the literature and increasingly included in governmental political agendas (Roberts, 2012), environmental inequality is 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

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related but different concept is environmental inequity, which implies that the observed environmental inequality is judged as socially unfair (Kawachi, Subramanian, & Almeida-Filho, 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 fairness of that environmental distribution (Pope, Wu, & Boone, 2016). In this work we focus on environmental inequity, as this plays a key role for bridging environmental inequalities with the broader concept of environmental justice. In this regard, environmental justice goes beyond the unfair spatial distribution of environmental resources (i.e. inequities), by covering other dimensions such as power relations, politics and social movements (Schlosberg, 2013).

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, Van, Leidelmeijer, Marsman, & de Hollander, 2003). For example, people in environmental disadvantaged neighborhoods could be more prone to experience feelings of personal powerlessness and develop depression (Downey & Van Willigen, 2005). 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 lower environmental quality (Escobedo et al., 2006; Fernández & Wu, 2016; Pedlowski, Silva, Adell, & Heynen, 2002; Romero et al., 2012; UN-Habitat, 2014; Wright Wendel, Zarger, & Mihelcic, 2012).

As the future of humanity lies in urban areas (UNDESA, 2014), 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 (Benmarhnia, Laurian, & Deguen, 2013; Martínez, 2009; Norton et al., 2015; Ribeiro, de Fátima Pina, & Mitchell, 2015; Sadd, Pastor, Morello-Frosch, Scoggins, & Jesdale, 2011).

A challenging question that decision-makers may 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, Harlan, Stefanov, & Martin, 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 these problems.

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 infeasible 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 is a helpful 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, we present a GIS-based indicator framework that integrates environmental and demographic data into an "Environmental Improvement Priority Index (EIPI)", which can be used by 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, we apply the framework to the city of Santiago de Chile at three different scales, focusing our study on three main environmental inequity problems currently affecting this city: urban heat, low vegetation coverage, air pollution (Fernández & Wu, 2016). Based on the results from our case study, we further discuss how results from the EIPI framework can be used by policy-makers for addressing intra-urban environmental inequities.

2. The Environmental Improvement Priority Index (EIPI) framework

The EIPI framework (Fig. 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 particular 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 procedural framework to help researchers and policy-makers identify 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 severe 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, 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

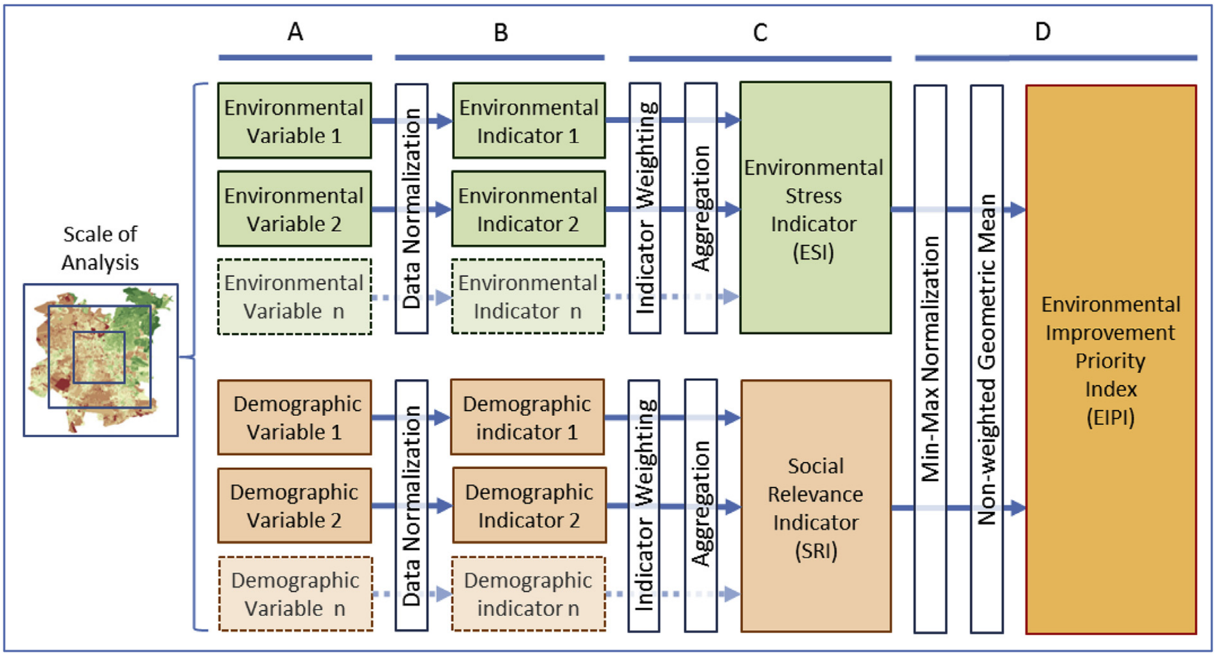

Fig. 1. Environmental Improvement Priority Index (EIPI) Framework. The four steps involved in calculating the EIPI are denoted by letters A, B, C, D. Scales of Analysis refer to the specific extent (the total study area) and areal unit (grain size) used for the assessment.

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. 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. 1).

Step A of the framework consists on the selection of the variables used to compute ESI, SRI and EIPI (Fig. 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 need to 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 within the study area. The EIPI framework uses numerical data. If only categorical data for certain variables are available, they must be transformed into numerical or ranked values to be used as valid 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 the vulnerability of people to the assessed environmental problems (Inostroza, Palme, & de la Barrera, 2016; Martínez, 2009; Norton et al., 2015). 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, Fleischhauer, & Lückenkötter, 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, Saisana, Saltelli, & Tarantola, 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 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 (Gan et al., 2017; Huang, Wu, & Yan, 2015; Nardo et al., 2005; OECD, 2008), 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 a value judgment (Böhringer & Jochem, 2007). For this 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). Both aggregation methods imply some degree of compensability between individual indicators (Gan et al., 2017; 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 (Gan et al., 2017; 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. (1)).

$$X_n = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

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. (2)).

$$EIPI = \sqrt[2]{ESI * SRI} \quad (2)$$

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. 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 (Inostroza et al., 2016; Krellenberg, Müller, Schwarz, Höfer, & Welz, 2013), low levels of green infrastructure in most parts of the city (De La Barrera, Reyes-Paecke, & Banzhaf, 2016; Forray et al., 2012), and high levels of air pollution during the winter season (Toro, Morales, Canales, Gonzalez-Rojas, & Leiva, 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). While other environmental problems such as noise pollution, illegal dumping, and strayed dogs are also relevant environmental issues in Santiago (Ministerio de Medio Ambiente de Chile, 2017), we focus our analysis on urban heat, low vegetation coverage, and air pollution because these three environmental problems can be addressed effectively by implementing vegetation-based urban interventions (Willis & Petrokofsky, 2017). Therefore, identifying areas within Santiago where these three environmental problems are most severe and where social relevance is the highest can provide essential information for policy-makers to design strategies to reduce environmental inequity and promote urban sustainability.

3.1. Scales of analysis

In the following section we apply the EIPI framework to the city of Santiago, focusing on the three environmental problems discussed above (i.e. urban heat, low vegetation coverage, and air pollution). We 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, we perform the assessment with three different scale combinations (Fig. 2), each having a particular objective:

- *City Extent with municipal-level data* (Fig. 2a): At this scale we 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 is more relevant to increase the allocation of resources for enhancing environmental quality.
- *City extent with pixel-based data* (Fig. 2b): This scale of analysis 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. 2c): At this scale the assessment is performed within a particular municipality using the city block as the basic areal unit of analysis. Our objective at this scale of analysis is to show how the EIPI framework could be used within administrative levels to generate actionable knowledge for

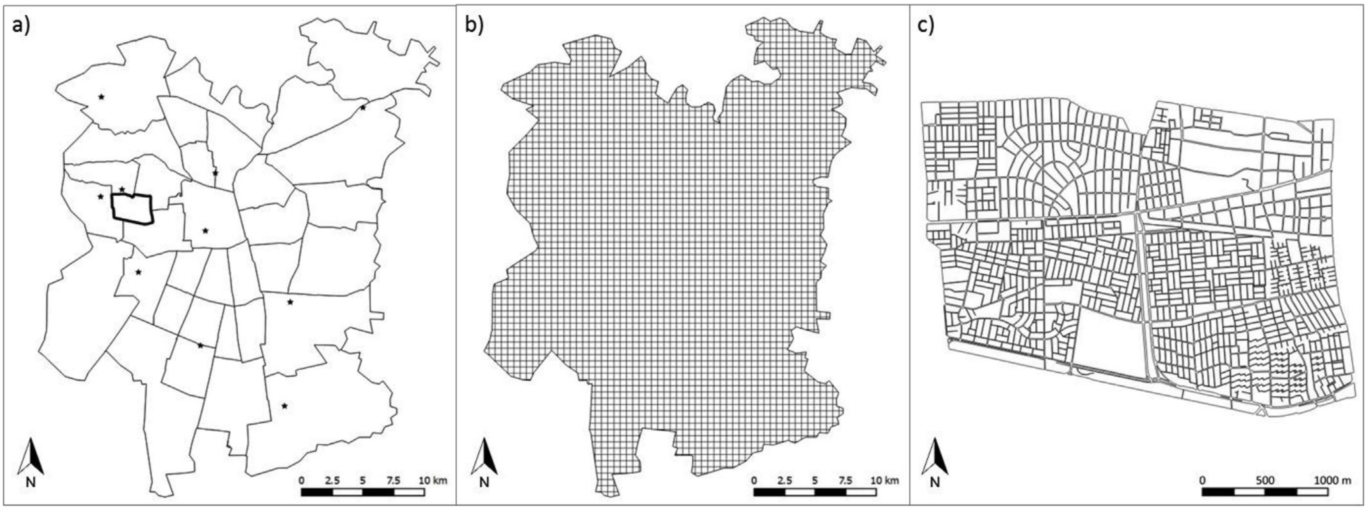

Fig. 2. Three scales used for the assessment. Extent in a) and b) corresponds to the entire city area, in c) to the municipality of Lo Prado, which is highlighted in a). Areal units of analysis correspond to the municipal level in a), 100 m/pixel in b), and census blocks in c). Dots in a) are locations of air pollution monitoring stations. Raster lattice shown in b) is not at scale.

municipal policy-makers to prioritize specific neighborhoods or city blocks for environmental interventions. On this scale, we selected the municipality of *Lo Prado* as an example (see highlighted municipality in Fig. 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.

3.2. Implementing the EIPI framework in Santiago

3.2.1. Step A: Selecting variables and compiling data for calculating ESI, SRI and EIPI

Following the procedures outlined in section 2, we collected and processed the environmental and demographic data at the three different scales. We 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 (http://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 (Fernández & Wu, 2016; Inostroza et al., 2016). We estimated surface temperatures from Landsat TIRS sensor Band 10 following the NDVI-threshold emissivity method (Sobrino, Jiménez-Muñoz, & Paolini, 2004). For vegetation cover we 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, Mustard, Manning, & Lobell, 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, we 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. Air pollution data were obtained from the spatial interpolation (Kriging method) of ten particular matter (PM-2.5) official monitoring stations distributed in Santiago (see Fig. 2a). For the interpolation procedure we 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). We 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 30 m/pixel. For polygon-based analyses the 30 m/pixel values were aggregated (arithmetic averaging) into the respective areal unit of analysis (i.e., municipality, block). For raster-based analyses we resampled the data to a 100 m/pixel (bilinear interpolation method) to reduce the potential presence of outlier values due to local-scale heterogeneity.

Demographic variables were gathered from the 2012 updated version of 2002 Chilean Official Census Database developed by Norel, Truffello, Olivares, and Garretón (2013). From this database we 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, we 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. We transformed this categorical information to ordinal data by assigning numerical values (1–5) to the five SEL categories, with higher values corresponding to higher SEL levels. We further transformed the ordinal data to continuous values using equation (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.

$$\sum_{i}^{n} i * p_i \tag{3}$$

Population density was not directly available in the census dataset, and we 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 we aggregated block-level data using an area-weighted approach. For pixel-based computation we rasterized the original vector layer at a spatial resolution of 100 m/pixel, matching the scale of the raster layer of the environmental variables.

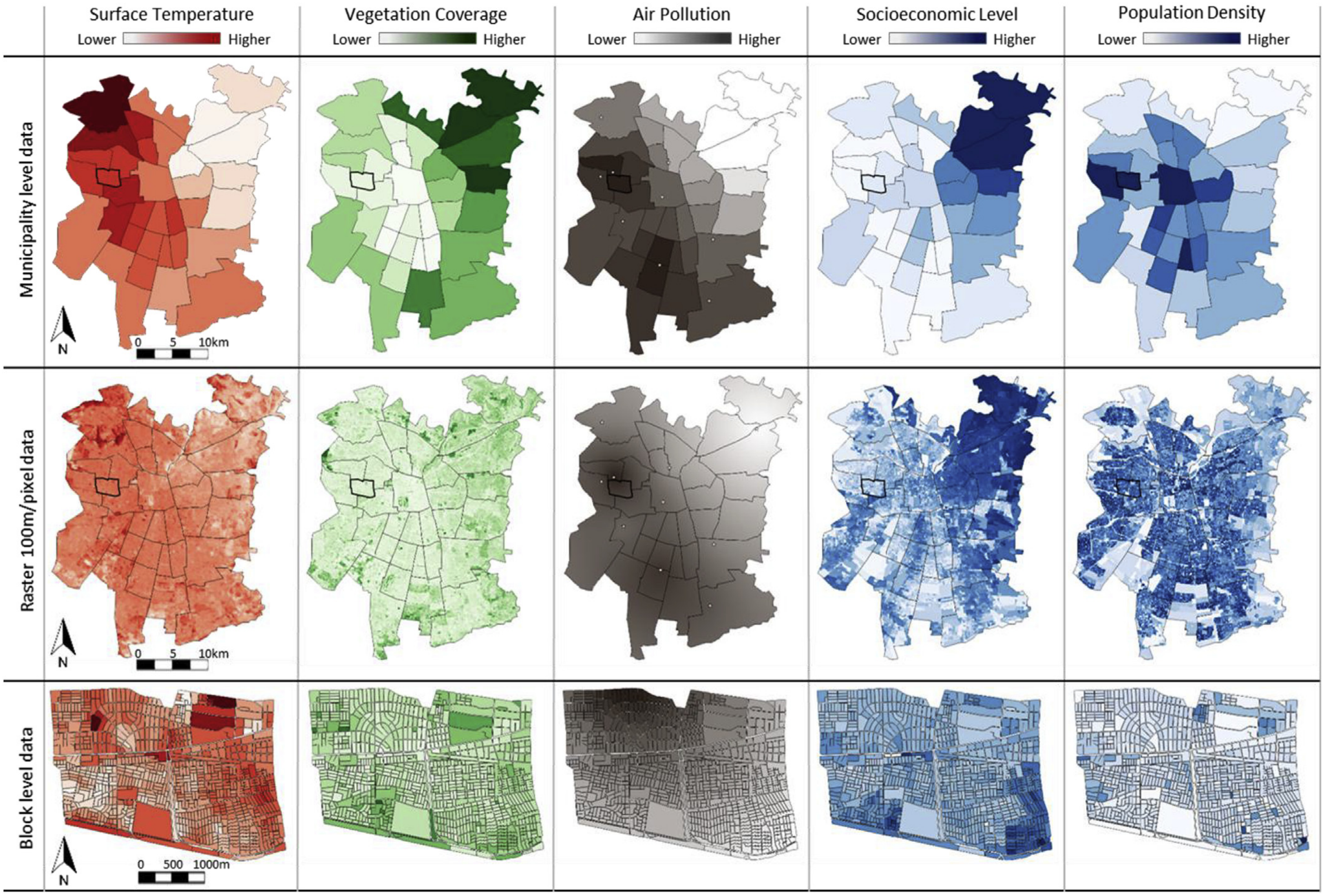

Fig. 3. Maps of the spatial layers of the three environmental and two socio-demographic indicators on three scales of analysis. Maps represent the spatial distribution of each indicator based on relative values. Top row represents Santiago city extent with municipal-level data, middle row Santiago city 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.

3.2.2. Step B: Transform input variables into normalized indicators with compatible units

During this step, we transformed all environmental and demographic variables into indicators ranging between 0 and 1 by using a relative value-based normalization approach. With this we 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 (De La Barrera et al., 2016; Escobedo et al., 2006; Fernández & Wu, 2016; Perez, 2015; Romero et al., 2012).

As for the specific method of normalization, we use the Max-Min method (eq. (1)) for all the variables, except for the demographic variables at the scale combination of *city extent with pixel-based data*, for which we used a ranking-based normalization. We 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, we 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 our 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.

3.2.3. Step C: Weight and aggregate indicators to obtain ESI and SRI

To weight the relative importance of environmental indicators we ran an online survey on August 2015 that we share through two social media applications, Facebook and WhatsApp (See Supplementary Material). We clarify that this survey was not aimed to generate an objective representative sample for Santiago's inhabitants, but rather to reduce our personal bias in selecting potential weights for our case of study. We left the survey open for 4 days, receiving a total of 112 answers from people living in Santiago. Resulting weighting values were: 0.292 for surface temperature, 0.365 for urban vegetation coverage, and 0.343 for air pollution.

In the case of demographic indicators, we 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, we 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. For aggregation of variables into the ESI and SRI we used the geometric

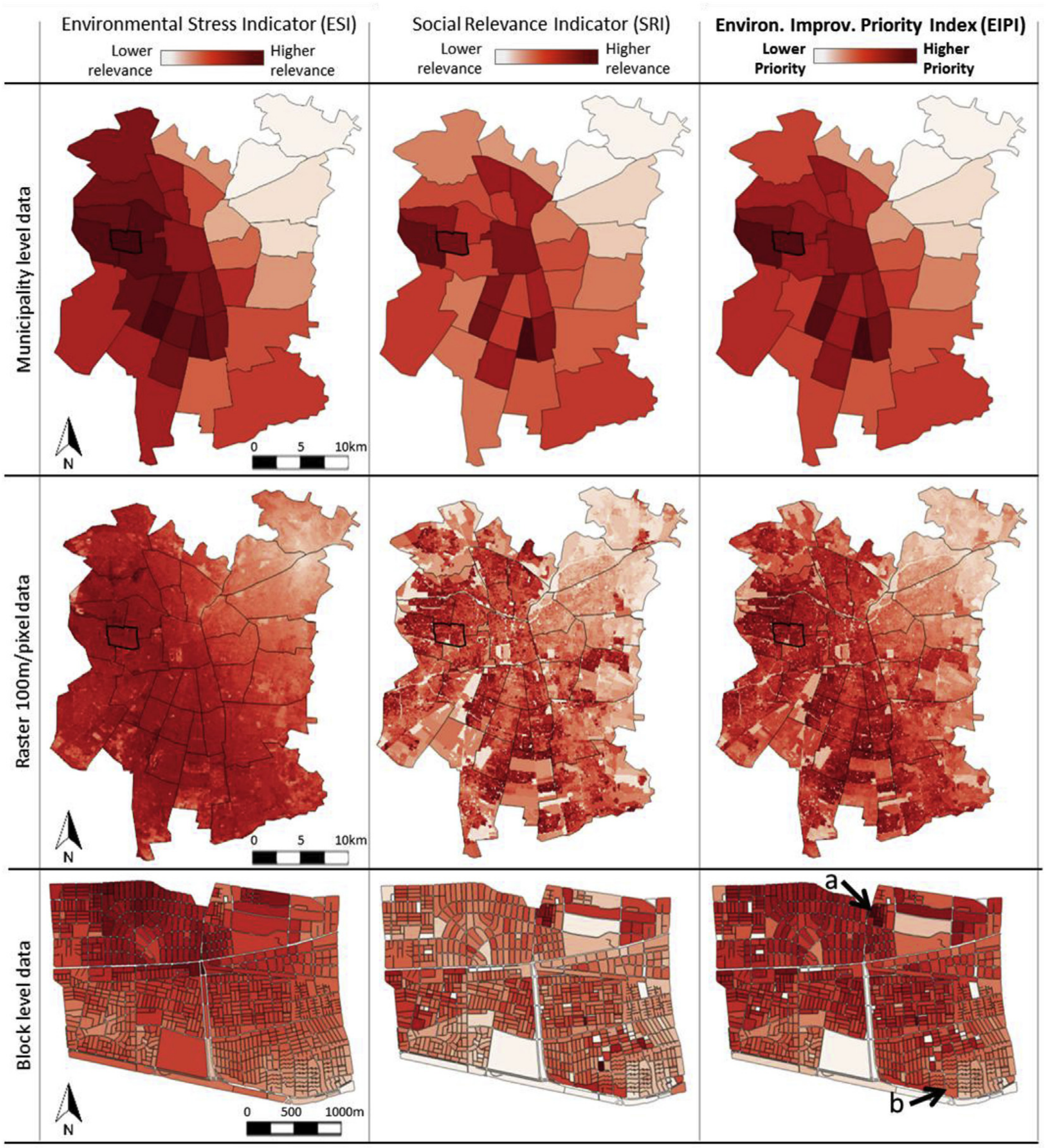

Fig. 4. Spatial patterns of Environmental Stress Indicator (ESI), Social Relevance Indicator (SRI) and Environmental Improvement Priority Index (EIPI) on three assessment scale combinations: City extent with municipal-level data (top row), City extent with pixel-based data (middle row), and Municipal extent with block-level data for Lo Prado (bottom row). 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. Photos from these blocks are shown in Fig. 5.

approach (eq. (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 socio-economic level and high population density.

3.2.4. Step D: Normalizing ESI and SRI and aggregating them into EIPI

In this step, we 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.

3.3. 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. 4. The three scales of analysis used in this study provide different, but complementary information for decision-makers. Analysis at the municipal level (Fig. 4, 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. 4, 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. 4, bottom row) provides specific information on the spatial distribution of these indicators as the analysis takes into account 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.

To show the capability of the framework to identify priority areas, Fig. 5 presents street level photographs from middle and high priority areas identified by the EIPI framework using data at the block level.

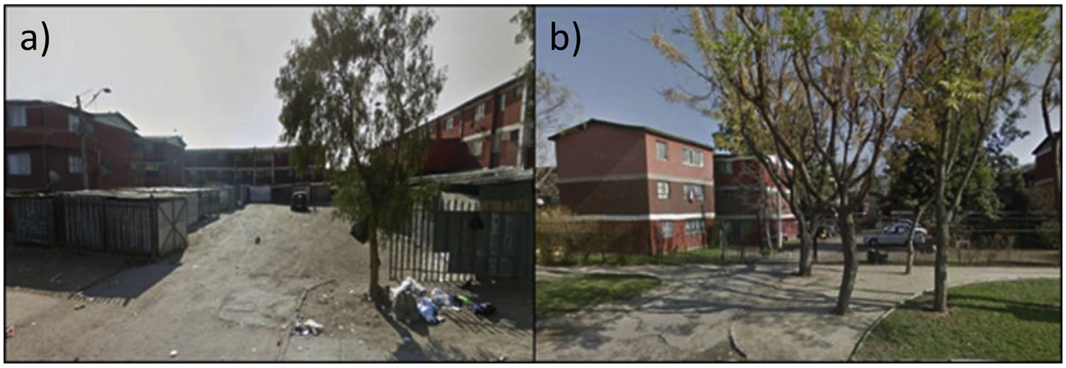

Fig. 5. Photos from blocks identified as highest (a) and middle (b) priority areas after applying the EIPI framework in Lo Prado Municipality (see Fig. 4). Photos were gathered from the Google Street View service. Photos were taken on July, 2015.

4. Discussion

Urban environmental quality is one of the key factors determining the quality of life of urban residents (Matsuoka & Kaplan, 2008; van Kamp et al., 2003). 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 paper 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 (e.g. Fernández & Wu, 2016; Joseph, Wang, & Wang, 2014; Liang & Weng, 2011; Montero, Chasco, & Larraz, 2010; Pope & Wu, 2014), but rather to help identifying the potential areas of the city where environmental improvements could have larger social benefits. A solution framed from an environmental inequity perspective may be particularly relevant for cities having high degrees of socioeconomic segregation, such as Santiago (Fernández et al., 2016). This is 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; Kremer, Hamstead, & McPhearson, 2013; McPhearson, Kremer, & Hamstead, 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., 2016). For these situations, a prioritization approach focused primarily on the potential opportunities 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 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 fundamentally important 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 in order 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, Brady, Ray, Sikora, & Murphy, 2014; Storper, 2014). For example, in our 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 (e.g. 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 (e.g. 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. The multiple-scale approach used in this study also revealed that the specific areas identified as being of higher priority depended on the particular areal unit used for the analysis, which is a well-known problem in spatial analysis – i.e., the modifiable areal unit problem or MAUP (Jelinski & Wu, 1996; Wong, 2009). In this regard, researchers and decision-makers need to be careful about the scales at which the EIPI framework will be applied, because results may differ greatly with changes in the spatial extent and resolution of the analysis, as shown in our study. To overcome the MAUP problem, a multiple-scale approach has been recommended (Jelinski & Wu, 1996; Wu, 2007; Wu, Gao, & Tueller, 1997), which can generate complementary results to better inform decision-makers on where to intervene (Fernández & Wu, 2016).

While the results from our 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 inequities like Santiago. For this purpose, the choices of variables and indicator methods used in this study are justifiable. We have met with metropolitan and municipal decision-makers to obtain feedback on the framework, and incorporated stakeholders opinions into the weighting schemes (Supplementary Material). Nevertheless, the results of our study should be taken with caution if they are to be used for policy making in reality – which would require 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. Furthermore, to include 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).

5. 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. Taking into account 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 study 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.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2018.03.019.

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