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Assessing environmental inequalities in the city of Santiago (Chile) with a hierarchical multiscale approach

Ignacio C. Fernández [a, *], Jianguo Wu [a, b]

[a] School of Sustainability, Arizona State University, P.O. Box 874501, Tempe, AZ 85287-4501, USA
[b] School of Life Sciences, Arizona State University, P.O. Box 874501, Tempe, AZ 85287-4501, USA

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ABSTRACT

Environmental inequalities are a common characteristic of urban areas. Environmental inequality is the unequal spatial distribution of environmental risks and goods among social groups. As environmental inequalities are inherently a spatial matter the choice of scale is essential for correctly understanding inequality issues and for designing proper and effective mitigation policies. However, the potential effects of scale of analysis on inequalities results have largely been underestimated in the assessment of environmental inequalities, leading to contradictory results from different studies. In this study we assess the patterns of environmental inequalities and associated scale issues in the city of Santiago (Chile) using a hierarchical multiscale approach. Our approach focuses on the analysis of spatial relationships between three environmental (i.e., surface temperature, air pollution, vegetation cover) and two socio-demographic variables (i.e., household wealth, population density) on multiple grain sizes and extents. We used census data, remote sensing data, and air pollution monitoring stations to generate raster layers at five grain sizes and five nested extents. We tested for inequalities through Pearson correlation analysis resulting in a total of 1530 assessed relationships. Our results show that environmental inequalities are a prevalent phenomenon in the city of Santiago, but the details of these inequalities are highly scale dependent. Changing the grain size and extent of analysis do not only affect the strength of relationships between socio-demographic and environmental variables, but also the spatial distribution of environmental inequalities across the urban landscape. Therefore, due to the scale-dependence of assessment results, researchers and decision-makers should be extremely careful when interpreting their findings and translating them into policy making. If the scale dependency of environmental inequalities is not taken into account, policy interventions may be largely ineffective because the scale at which interventions are designed may not match the scale at which inequalities are generated.

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 (UNDESA, 2014). Urban areas are hubs for human development, but also places of increasing environmental problems and socioeconomic inequalities (Wu, He, Huang, & Yu, 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 homogenous across the landscape, often leading to environmental inequalities (e.g., Bowen, Salling, Haynes, & Cyran, 1995; Daniels and Friedman 1999; Heynen, Perkins, & Roy, 2006; Mitchell and Chakraborty 2014; Pope & Wu, 2014).

Environmental inequality is “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 spatial 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

* Corresponding author.
E-mail address: ignacio.fernandez@asu.edu (I.C. Fernández).

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concept implies that the resource distribution is judged as socially unfair (Kawachi, Subramanian, & Almeida-Filho, 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, Pellow, & Roberts, 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 are often affected by the scale of observation/analysis (e.g., Buyantuyev, Wu, & Gries, 2010; Jelinski & Wu, 1996; Turner, O'Neill, Gardner, & Milne, 1989; Wu, Gao, & Tueller, 1997). In particular, 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 (Baden, Noonan, & Turaga, 2007; Cutter, Holm, & Clark, 1996; Noonan, 2008; Pope & Wu, 2014; Pope, Wu, & Boone, 2016). Nevertheless, potential scale effects have rarely been examined explicitly in assessing environmental inequalities, leading to contradictory results from different studies (Anderton, Anderson, Oakes, & Fraser, 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 (Fotheringham & Wong, 1991; Openshaw, 1989). 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 (Jelinski & Wu, 1996; 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 (Buyantuyev et al., 2010; Jargowsky, 2005; Wu et al., 1997). 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 (Buyantuyev et al., 2010; Wu, 2007; Wu et al., 1997).

The main objective of this study was to assess the patterns of environmental inequalities and associated scale issues in the city of Santiago (Chile) using a hierarchical multiscale approach. Our approach focused on the analysis of spatial relationships between three environmental and two socio-demographic variables on multiple nested scales. The three environmental variables were: vegetation coverage, summer surface temperatures, and winter air pollution. We selected these environmental variables because the scarcity of green infrastructure, summer heat risk and winter air pollution are among the most important factors currently affecting the health and quality of life of Santiago's residents (De La Barrera, Reyes-Paecke, & Banzhaf, 2016; Krellenberg, Müller, Schwarz, Höfer, & Welz, 2013; Toro, Morales, Canales, Gonzalez-Rojas, & Leiva, 2014). The two socio-demographic variables were: household wealth and population density. Household wealth was selected as the main socioeconomic indicator to evaluate environmental inequalities and inequities in Santiago. Population density was used 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.

The following specific questions were addressed: 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. Methods

2.1. The study area

Santiago de Chile (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 km^2 (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).

The 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 decreases in vegetation cover and increases in temperatures and air pollution (Krellenberg et al., 2013; Romero & Vásquez, 2005; Romero, Ihl, Rivera, Zalazar, & Azocar, 1999). 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 (De La Barrera et al., 2016; Escobedo et al., 2006; Reyes-Packe & Figueroa, 2010) and higher environmental risks

(Krellenberg et al., 2013; Romero et al., 2012; Vásquez & Salgado, 2009).

2.2. A hierarchical multiscale approach

Our research design (Fig. 1) 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, we decided to use a raster-based approach because it allowed us to standardize the size and shape of areas of analysis and areal units when performing the multiple-scale analysis. This reduces potential confounding factors in multiple-scale analysis due to aggregating/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 retain the information and spatial accuracy of original vector layer (Congalton, 1997). Therefore, under this approach all spatial layers that are in vector format (e.g., census data) were directly transformed to raster before analysis.

We generated five raster layers as inputs for the assessments (more details in section 2.3): three environmental (i.e., surface temperature, air pollution, vegetation coverage) and two socio-demographic (i.e., household wealth, population density). We resampled each of these five layers into five raster layers with pixel resolutions of 10, 30, 100, 300, 1000 m, which represent the five areal units used for analysis (Fig. 1). We 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 we 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). All data resampling was performed using Quantum-GIS Wien 2.8 (www.qgis.org).

We 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 we then generated a nested subset of layers by cropping the layer to predefined extents. The largest of these sub-extents was 18 × 18 km, which was the largest square fitting into the convoluted shape of Santiago (Fig. 1). This 18 × 18 km square was then subdivided into four 9 × 9 km, nine 6 × 6 km, and thirty-six 3 × 3 km nested extents. Including the city extent, the total number of spatial extents for analysis was 51 (Fig. 1). Table 1 shows main descriptive statics of the five raster layers for the five grain sizes at the two larger extents (city and 18 × 18 km).

2.3. Preparation of data layers

Surface Temperatures (ST) was estimated 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 has a spatial resolution of 30 m/pixel, with no cloud cover for the study area. We decided to work with only one image representing the distribution of surface temperatures of a typical sunny day of Santiago's summer season. We calculated land surface temperatures using the Normalized Difference Vegetation Index (NDVI)-threshold method (Sobrino, Jiménez-Muñoz, & Paolini, 2004). Resulting ST raster layer is shown in Fig. 2a.

The Air Pollution (AP) data layer was generated, via Kriging, from particular matter (PM10) data obtained from 10 public monitoring stations distributed across Santiago (Fig. 2b). We built a single raster layer of 10 m/pixel resolution based in the daily average concentration of PM10 for the April–August period from the years 2012, 2013 and 2014. We decided to use these autumn-winter months because these are times when air pollution often becomes a serious problem in Santiago (Muñoz & Alcafuz, 2012). The values of three consecutive years were used to smooth out potential yearly variability due to climatic variations. We decided to use Kriging as this is a geostatistical interpolation method that provides an effective way of mapping the spatial pattern of air

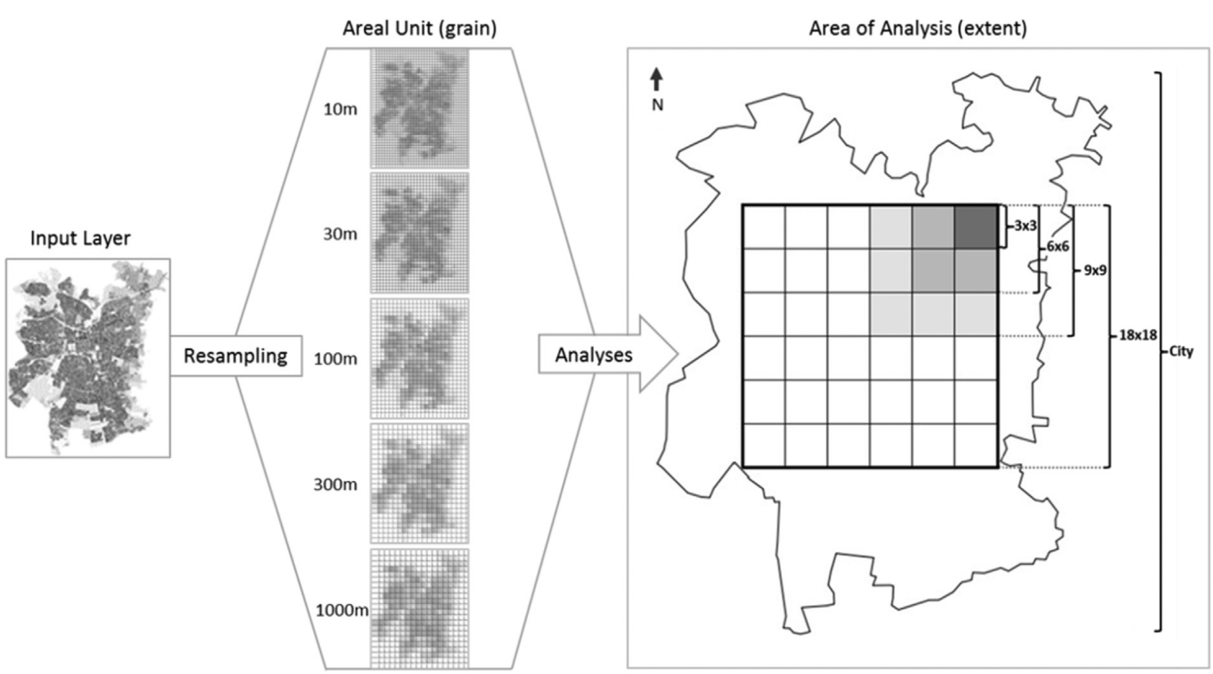

Fig. 1. Illustration of the hierarchical multiple-scale approach used to evaluate environmental inequalities in Santiago, Chile. All original input layers were resampled to raster layers of five different grain sizes (10–1000 m/pixel), representing the areal units of analysis. Correlation analysis was conducted to evaluate the spatial relationship between environmental and socio-demographic variables at five different nested extents (City to 3 × 3 km), totaling 51 areas of analysis.

Table 1
Main descriptive statics of the raster layers used for the analyses. Mean values and standard deviation is shown. Morans'I is an indicator of 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	10 m	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	30 m	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	100 m	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	300 m	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	1000 m	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
18 × 18 km	10 m	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
18 × 18 km	30 m	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
18 × 18 km	100 m	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
18 × 18 km	300 m	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
18 × 18 km	1000 m	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

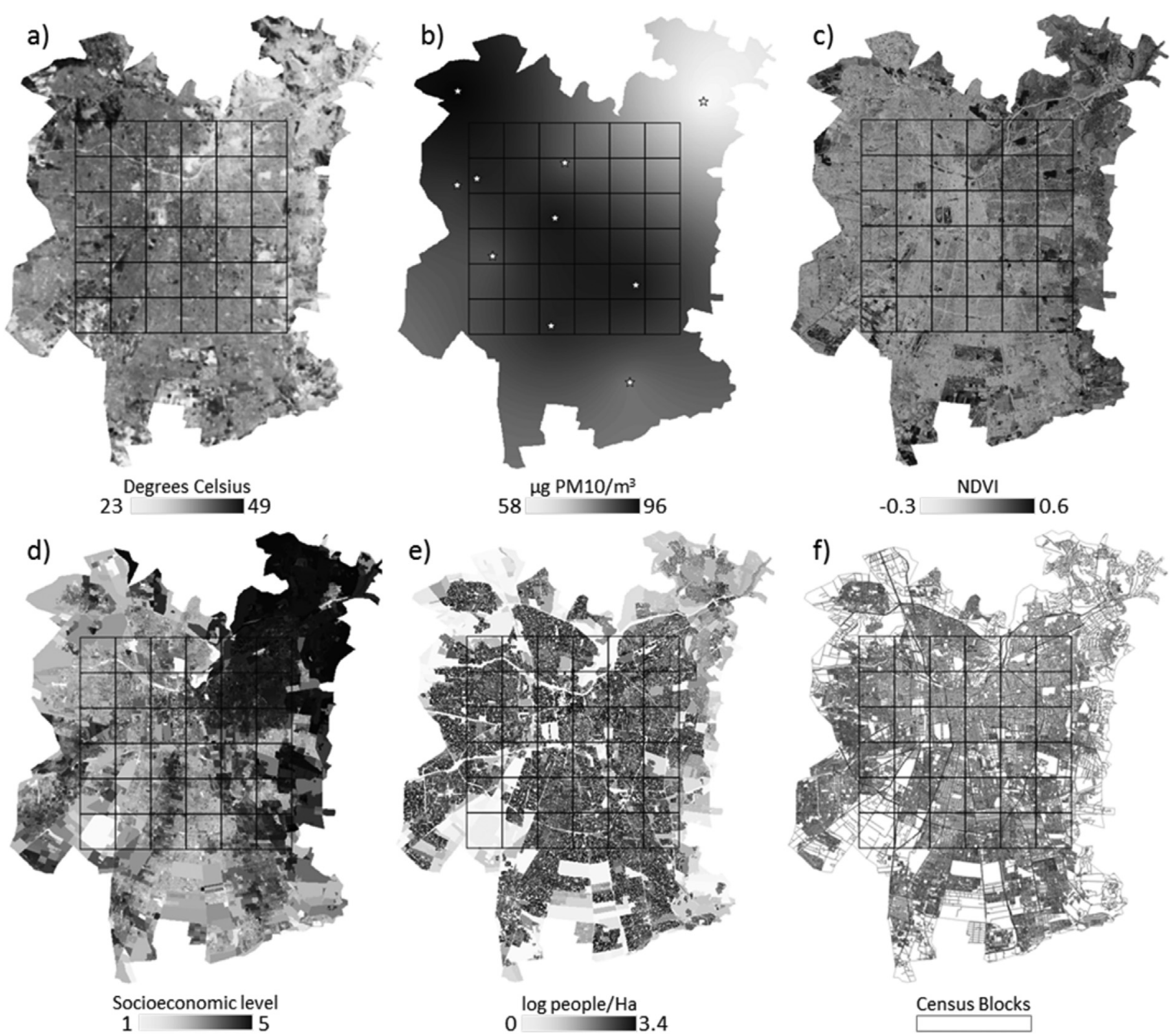

Fig. 2. Generated raster layers (a–e) and original census vector layer showing the block sizes (f). Raster layers are shown in the resolution at which they were generated. Layers and resolution are: a) ST, 30 m/pixel; b) AP, 10 m/pixel (location of PM10 monitoring station are shown as white stars); c) VC, 30 m/pixel; d) HW, 10 m/pixel, e) PD, 10 m/pixel. The grid used to define the different extents of analysis (see Fig. 1) is shown to facilitate visual comparisons between layers.

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, Irarrázaval, Opazo, Salgado, & Smith, 2010). However, as the number of monitor station is relatively small for the area of Santiago, we consider that our pollution data may have low accuracy at finer scales. Therefore, we acknowledge that this raster layer was produced only for this research purpose, and may not be realistic for decision making.

Vegetation Coverage (VC) was estimated using the NDVI, which is a reliable indicator of vegetation cover in semi-arid regions like Santiago (Elmore, Mustard, Manning, & Lobell, 2000). As summer season in Santiago is characterized by an extended hot and dry period (Cruz & Calderón, 2008), not managed vegetation drastically decrease their photosynthetic rates (Gerstmann, Miranda, & Condal, 2010), making NDVI a useful indicator to discriminate vegetation coverage associated to urban green infrastructure. We calculated the NDVI from the same Landsat image from which we obtained surface temperatures. Resulting VC raster layer is shown in Fig. 2c.

Data on Household Wealth (HW) were gathered from the 2012 updated version of the 2002 Chilean Official Census Data developed by Norel, Truffello, Olivares, and Garretón (2013). The HW data layer was in vector format, representing several kinds of socio-economic and demographic information at the city block level. The original lumped variable from which we 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. We 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. Therefore, resulting continuous HW values range between 1 and 5, and are directly related to the proportion of each categorical socio-economic group in each census block. The generated HW vector layer was then converted to a 10 m/pixel resolution raster layer (Fig. 2d).

Population Density (PD) data were also gathered 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. Density at the census block was then computed as the population/hectare ratio. Population data were then log-transformed to remove the huge skewness towards smaller population densities. The resulting PD vector layer was then rasterized to a 10 m/pixel resolution layer (Fig. 2e).

2.4. Data analysis

Relationships between variables were assessed with Pearson correlation analysis. We analyzed the spatial relationships between the three environmental variables (ST, VC, AP) and the two socio-demographic variables (HW, PD) using all the pixels within each sampled extent. These correlation analyses were performed 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 by using the R-raster package (www.r-project.org) in R-Studio v.0.98 (www.rstudio.com).

3. Results

3.1. Environmental inequalities in Santiago: the big picture

Correlation analyses performed at the city extent (at the grain size of 100 m/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. 3). Results show that, in general, people living in wealthy areas tend to be exposed to lower temperatures ($R = -0.389$, $p = <0.001$), lower air pollution ($R = -0.590$, $p = <0.001$), and higher vegetation coverage ($R = 0.300$, $p = <0.001$). People living in the wealthiest areas experienced substantially lower levels of air pollution than the rest of the population, exhibiting a seemingly non-linear decrease (Fig. 3).

Population density was rather weakly correlated with surface temperature ($R = -0.013$, $p = <0.001$), moderately with air pollution ($R = 0.076$, $p = <0.001$), and more strongly 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. 3).

3.2. Scale effects on correlation results

Spatial relationships between the socio-demographic and environmental variables show a strong dependency on the specific extent and grain size used for correlation analysis (Fig. 4).

With regard to changing the extent of analysis, correlation coefficients computed at the two largest extents (i.e., City and 18 × 18 km) 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; Fig. 4b,f). However, when the 18 × 18 km extent was decomposed into smaller areas of analysis, the relationships at the city and 18 × 18 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. 4b) to smoother variations and relatively consistent patterns over all extents (e.g., PD-VC; Fig. 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 (Fig. 4c, f).

The effects of modifying the grain size (i.e., areal unit) were highly dependent on the extent used for the analysis (Fig 4). At the two largest extents (i.e., City, 18 × 18 km), changing grain size from 10 to 1000 m/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. 4b, compared to HW-VC; Fig. 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. 4).

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. 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), and others tended to change more gradually (e.g., VC-PD).

4. Discussion

4.1. Methodological approach

This is probably the first study assessing environmental

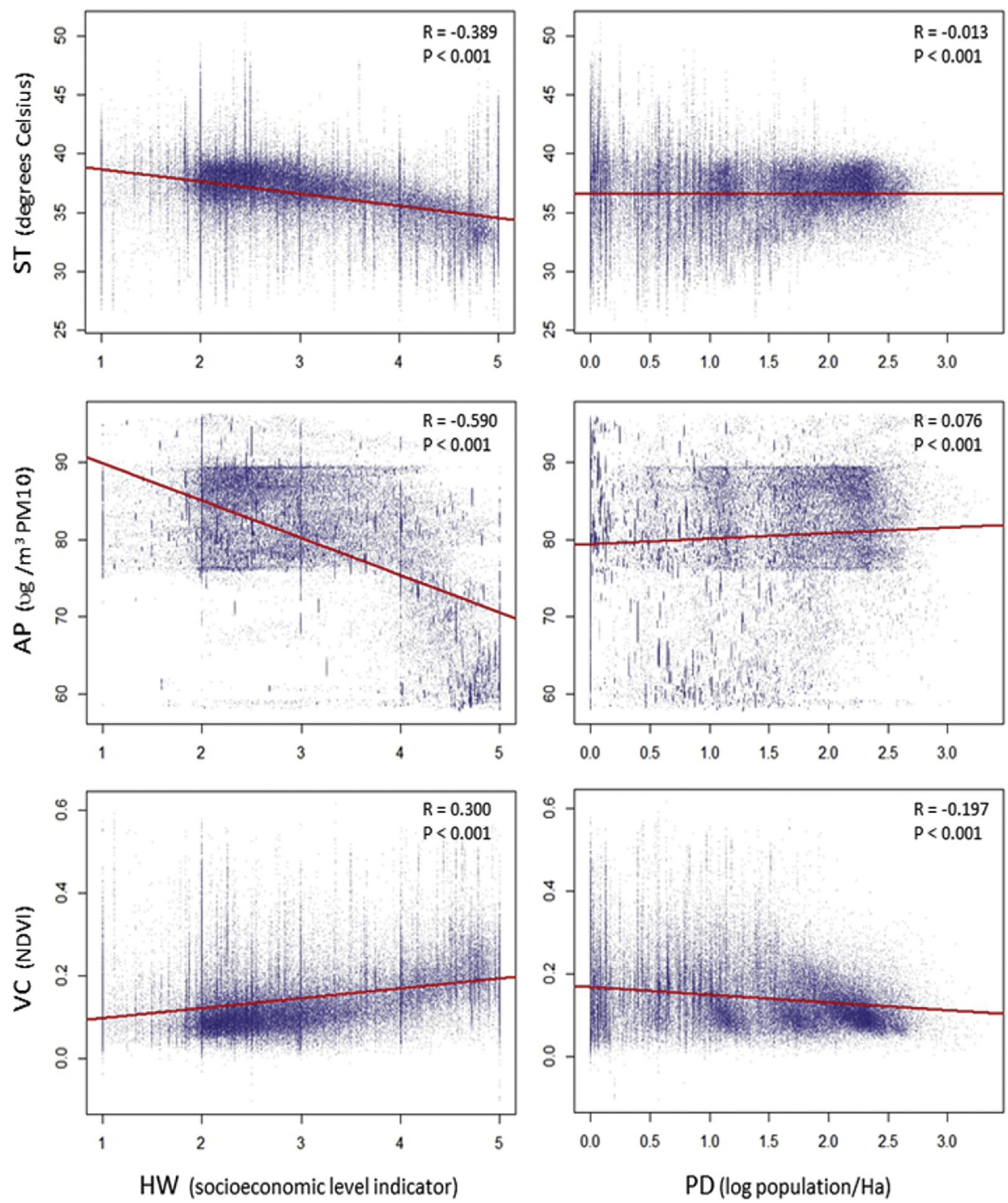

Fig. 3. Scatterplots showing the relationship between three environmental (ST; surface temperature, AP; air pollution, VC; vegetation coverage) and two socio-demographic variables (HW; household wealth, PD; population density) for the city of Santiago. Pearson correlation coefficient (R), p-value, and fitted lines are shown. Analyses were done at the city extent using the 100 m/pixel raster layers.

inequalities in the city of Santiago from a multiple scale approach. Although our main objective with the hierarchical multiscale approach was to evaluate the effects of the scale of analysis on observed environmental inequality patterns, results from our work may also provide insightful knowledge on the level and spatial distribution of environmental inequalities in Santiago. However results from our study have to be carefully used if ought to be compared with other studies, because we based our analysis in raster grids and not in polygons, which has been the most common used method for environmental inequalities studies (Baden et al., 2007; Ringquist, 2005).

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 our 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 increases 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).

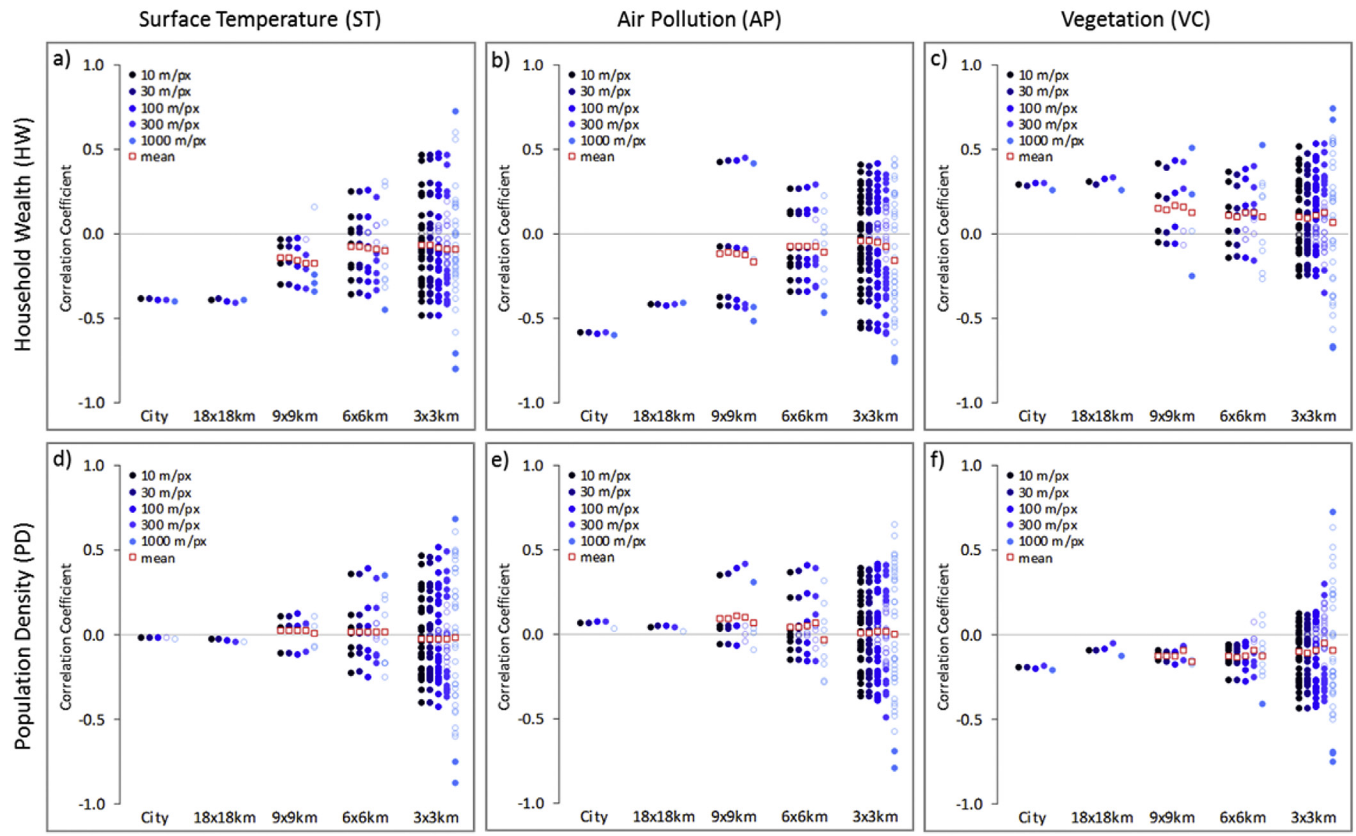

Fig. 4. Pearson correlations between three environmental quality and two socio-demographic variables at five grain sizes (10, 30, 100, 300, 1000 m/pixel) and five nested extents (City, 18 × 18 km, 9 × 9 km, 6 × 6 km, 3 × 3 km). Filled dots represent correlation coefficients statistically different from 0 at p < 0.05, whereas open squares are the means of correlation coefficients at a given extent.

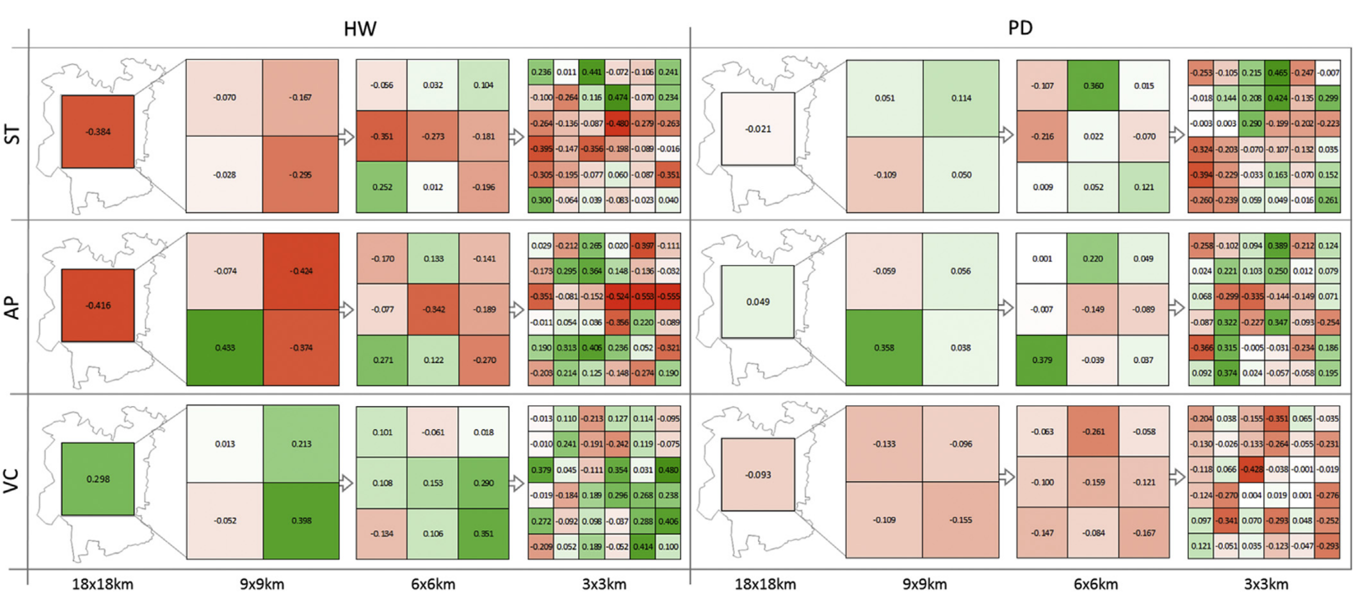

Fig. 5. Spatial distribution of Pearson correlation coefficient for assessed relationships at the four assessed nested extents, with a grain size of 30 m/pixel. Colors represent the strength of the correlation; from green (positive) to red (negative). Correlation coefficients for each extent of analysis are shown. HW: Household Wealth; PD, Population Density; ST, Surface Temperature; AP, Air Pollution; VC, Vegetation Coverage. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 (Aquino & Gainza, 2014; De La Barrera et al., 2016; Romero et al., 2012). We certainly acknowledge that autocorrelation is an important spatial issue that could have affected results from our work. However, if spatial autocorrelation had significantly affected our analysis, we should have observed a trend of larger correlation coefficients at smaller grains because spatial autocorrelation decreases with grain size (Qi & Wu, 1996; see also Table 1). But our 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. 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.

4.2. Patterns and drivers of environmental inequalities in Santiago

Our results 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 & Vásquez, 2005; Romero et al., 1999). 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 huge differences in financial investments between rich and poor municipalities (Escobedo et al., 2006; Reyes-Packe & Figueroa, 2010), and also by relatively larger and highly vegetated residential yards maintained by the richer neighborhoods (De La Barrera et al., 2016; 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 at the city scale of Santiago.

While environmental inequalities of Santiago at the city scale may largely be wealth-driven, our 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 contradicts results from previous studies (e.g., Romero et al., 2010). This contradictory results suggest that drivers dominating environmental inequalities at finer scales are diverse, and not the same throughout the city. In this regard, we thought that population density could provide some insights because it has been reported to be related to air pollution, temperature, and vegetation cover (Aquino & Gainza, 2014; Hoek et al., 2008; Merbitz, Buttstädt, Michael, Dott, & Schneider, 2012). However, our 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 (e.g., autocorrelation). Our 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.

4.3. Scale effects

A great number of studies have shown that the results of spatial analysis are affected by the scale of analysis, including grain size and extent (e.g., Jelinski & Wu, 1996; Turner et al. 1989; Wu et al. 1997; Wu, 2004, 2007). There is increasing evidence that these scale issues may also manifest in environmental inequality studies (e.g., Baden et al. 2007; Cutter et al. 1996; Noonan, 2008).

Our results 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. From our study, this ratio seems 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 our 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 to identifying the characteristic scales of landscape patterns (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 we used the smallest grain size of 10 m, which was only for our purpose to explore 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.

4.4. Implications for policy making

Results from our 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, our 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., Reyes-Packe & Figueroa, 2010; Romero et al. 2010, 2012; Vásquez & Salgado, 2009).

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 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 (Ard, 2015; Padilla et al., 2014), we do not have 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 social distribution of environmental risks and access to environmental amenities, mitigation policies must be developed.

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References

Adimark. (2004). Mapa socioeconómico de Chile. *Nivel socioeconómico de los hogares del país basados en datos del Censo* (Santiago, Chile).

Anderton, D. L., Anderson, A. B., Oakes, J. M., & Fraser, M. R. (1994). Environmental equity: The demographics of dumping. *Demography, 31*, 229–248.

Aquino, F., & Gainza, X. (2014). Understanding Density in an Uneven City, Santiago de Chile: Implications for Social and Environmental Sustainability. *Sustainability, 6*, 5876–5897.

Ard, K. (2015). Trends in exposure to industrial air toxins for different racial and socioeconomic groups: A spatial and temporal examination of environmental inequality in the U.S. From 1995 to 2004. *Social Science Research, 53*, 375–390.

Baden, B. M., Noonan, D. S., & Turaga, R. M. R. (2007). Scales of justice: Is there a geographic bias in environmental equity analysis? *Journal of Environmental Planning and Management, 50*, 163–185.

Borsdorf, A., & Hidalgo, R. (2008). New dimensions of social exclusion in Latin America: From gated communities to gated cities, the case of Santiago de Chile. *Land Use Policy, 25*, 153–160.

Bowen, W. M., Salling, M. J., Haynes, K. E., & Cyran, E. J. (1995). Toward environmental justice: Spatial equity in Ohio and Cleveland. *Annals of the Association of American Geographers, 85*, 641–663.

Buyantuyev, A., Wu, J., & Gries, C. (2010). Multiscale analysis of the urbanization pattern of the Phoenix metropolitan landscape of USA: Time, space and thematic resolution. *Landscape and Urban Planning, 94*, 206–217.

Carruthers, D. V. (2008). *Environmental justice in Latin America. Problems, promise, and practice*. Cambridge, Massachusetts: MIT Press.

Congalton, R. G. (1997). Exploring and evaluating the consequences of vector-to-raster and raster-to-vector conversion. *Photogrammetric Engineering & Remote Sensing, 63*, 425–434.

Cruz, C., & Calderón, J. (2008). *Guía Climatológica Práctica*. Santiago, Chile: Dirección Meteorológica de Chile.

Cutter, S., Holm, D., & Clark, L. (1996). The role of geographic scale in monitoring environmental justice. *Risk Analysis, 16*, 517–526.

Daniels, G., & Friedman, S. (1999). Spatial Inequality and the distribution of industrial toxic release. *Social Science Quarterly, 80*, 244–262.

De La Barrera, F., Reyes-Paecke, S., & Banzhaf, E. (2016). Indicators for green spaces in contrasting urban settings. *Ecological Indicators, 62*, 212–219.

Diez Roux, A. V. (2002). A glossary for multilevel analysis. *Journal of Epidemiology and Community Health, 56*, 588–594.

Dormann, C. F., McPherson, J. M., Araújo, M. B., Bivand, R., Bolliger, J., Carl, G., … Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: A review. *Ecography, 30*, 609–628.

Downey, L. (2006). Using geographic information systems to reconceptualize spatial relationships and ecological context. *American Journal of Sociology, 112*, 567–612.

Elmore, A. J., Mustard, J. F., Manning, S. J., & Lobell, D. B. (2000). Quantifying vegetation change in Semiarid environments. *Remote Sensing of Environment, 73*, 87–102.

Escobedo, F. J., Nowak, D. J., Wagner, J. E., De la Maza, C. L., Rodríguez, M., Crane, D. E., et al. (2006). The socioeconomics and management of Santiago de Chile's public urban forests. *Urban Forestry & Urban Greening, 4*, 105–114.

Fotheringham, A. S., & Wong, D. W. S. (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning A, 23*, 1025–1044.

Freedman, D. A. (2001). Ecological inference. In N. Smelser, & P. Baltes (Eds.), *International encyclopedia of the social and behavioral sciences* (pp. 4027–4030). Elsevier.

Gerstmann, C., Miranda, M., & Condal, A. (2010). Description of space-time variability of the potential productivity of Acacia caven espinales based on MODIS images and the Enhanced Vegetation Index (EVI). *Ciencia E Investigación Agraria, 37*, 63–73.

Heynen, N., Perkins, H. A., & Roy, P. (2006). The political ecology of uneven urban green space: The impact of political economy on race and ethnicity in producing environmental inequality in Milwaukee. *Urban Affairs Review, 42*, 3–25.

Hoek, G., Beelen, R., de Hoogh, K., Vienneau, D., Gulliver, J., Fischer, P., et al. (2008). A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmospheric Environment, 42*, 7561–7578.

Instituto Nacional de Estadísticas. (2015). *Actualización de población 2002-2012 y proyecciones 2013-2020*. http://www.ine.cl/canales/chile_estadistico/familias/demograficas_vitales.php (Accessed 20.07.15).

Jargowsky, P. A. (2005). Ecological fallacy. In K. Kempf-Leonard (Ed.), *Encyclopedia of social measurement* (pp. 715–722). Elsevier.

Jelinski, D. E., & Wu, J. (1996). The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology, 11*, 129–140.

Jerrett, M., Arain, A., Kanaroglou, P., Beckerman, B., Potoglou, D., Sahsuvaroglu, T., … Giovis, C. (2005). A review and evaluation of intraurban air pollution exposure models. *Journal of Exposure Analysis and Environmental Epidemiology, 15*, 185–204.

Kaswan, A. (2003). Distributive justice and the environment. *North Carolina Law Review, 81*, 1031–1148.

Kawachi, I., Subramanian, S. V., & Almeida-Filho, N. (2002). A glossary for health inequalities. *Journal of Epidemiology and Community Health, 56*, 647–652.

Krellenberg, K., Müller, A., Schwarz, A., Höfer, R., & Welz, J. (2013). Flood and heat hazards in the Metropolitan Region of Santiago de Chile and the socio-economics of exposure. *Applied Geography, 38*, 86–95.

Legendre, P. (1993). Spatial Autocorrelation: Trouble or new paradigm? *Ecology, 74*, 1659–1673.

Lennon, J. J. (2000). Red-shifts and red herrings in geographical ecology. *Ecography, 23*, 101–113.

McInerney, D., & Kempeneers, P. (2015). Image (Re-)projections and merging. In D. McInerney, & P. Kempeneers (Eds.), *Open source geospatial tools* (pp. 99–127). Springer International Publishing.

Merbitz, H., Buttstädt, M., Michael, S., Dott, W., & Schneider, C. (2012). GIS-based identification of spatial variables enhancing heat and poor air quality in urban areas. *Applied Geography, 33*, 94–106.

Mitchell, B. C., & Chakraborty, J. (2014). Population and environment urban heat and climate justice: A landscape of thermal inequity in Pinellas County. *Geographical*

Review, 104, 459–480.
Mohai, P., Pellow, D., & Roberts, J. T. (2009). Environmental justice. *Annual Review of Environment and Resources, 34*, 405–430.
Muñoz, R. C., & Alcafuz, R. I. (2012). Variability of urban aerosols over Santiago, Chile: Comparison of surface PM 10 concentrations and remote sensing with ceilometer and lidar. *Aerosol and Air Quality Research, 12*, 8–14.
Noonan, D. S. (2008). Evidence of environmental justice: A critical perspective on the practice of EJ research and lessons for policy design. *Social Science Quarterly, 89*, 1153–1174.
Norel, N., Truffello, R., Olivares, P., & Garretón, M. (2013). *Estimación de número de hogares según GSE en las principales ciudades de Chile y de la población flotante en el Gran Santiago, 2012*. Santiago, Chile: COES-Universidad Adolfo Ibañez.
Openshaw, S. (1989). Modifiable areal unit problem. *Concepts and Techniques in Modern Geography, 38*, 169–174.
Padilla, C. M., Kihal-Talantikite, W., Vieira, V. M., Rossello, P., Nir, G., Le, et al. (2014). Air quality and social deprivation in four French metropolitan areas-A localized spatio-temporal environmental inequality analysis. *Environmental Research, 134*, 315–324.
Pickett, S. T. A., Cadenasso, M. L., Grove, J. M., Boone, C. G., Groffman, P. M., Irwin, E., … Warren, P. (2011). Urban ecological systems: Scientific foundations and a decade of progress. *Journal of Environmental Management, 92*, 331–362.
Pope, R., & Wu, J. (2014). Characterizing air pollution patterns on multiple time scales in urban areas: A landscape ecological approach. *Urban Ecosystems, 17*, 855–874.
Pope, R., Wu, J., & Boone, C. (2016). Spatial patterns of air pollutants and social groups. *A distributive environmental justice study in the Phoenix Metropolitan Region of USA*. Environmental Management. http://dx.doi.org/10.1007/s00267-016-0741-z (in press).
Qi, Y., & Wu, J. G. (1996). Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. *Landscape Ecology, 11*, 39–49.
Reyes-Packe, S., & Figueroa, I. M. (2010). Distribución, superficie y accesibilidad de las áreas verdes en Santiago de Chile. *Eure, 36*, 89–110.
Reyes-Packe, S., & Meza, L. (2011). Jardines residenciales en Santiago de Chile: Extensión, distribución y cobertura vegetal. *Revista Chilena de Historia Natural, 84*, 581–592.
Ringquist, E. J. (2005). Assessing evidence of environmental inequities: A meta-analysis. *Social Experimentation, Program Evaluation, and Public Policy, 24*, 223–247.
Romero, H., Ihl, M., Rivera, A., Zalazar, P., & Azocar, P. (1999). Rapid urban growth, land-use changes and air pollution in Santiago, Chile. *Atmospheric Environment, 33*, 4039–4047.
Romero, H., Irarrázaval, F., Opazo, D., Salgado, M., & Smith, P. (2010). Climas urbanos y contaminación atmosférica en Santiago de Chile. *Eure, 36*, 35–62.
Romero, H., & Vásquez, A. (2005). Evaluación Ambiental del proceso de urbanización de las cuencas del piedemonte andino de Santiago de Chile. *Eure, 31*, 97–118.
Romero, H., Vásquez, A., Fuentes, C., Salgado, M., Schmidt, A., & Banzhaf, E. (2012). Assessing urban environmental segregation (UES). The case of Santiago de Chile. *Ecological Indicators, 23*, 76–87.
Sustainable Development Research Network. (2007). *SDRN briefing two. Environment and Social Justice*. http://www.sd-research.org.uk/research-and-resources/environment-and-social-justice-briefing Accessed 20.07.16.
Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from LANDSAT TM 5. *Remote Sensing of Environment, 90*, 434–440.
Szasz, A., & Meuser, M. (1997). Environmental inequalities: Literature review and proposals for new directions in research and theory. *Current Sociology, 45*, 99–120.
Toro, R., Morales, R. G. E., Canales, M., Gonzalez-Rojas, C., & Leiva, M. A. (2014). Inhaled and inspired particulates in Metropolitan Santiago Chile exceed air quality standards. *Building and Environment, 79*, 115–123.
Turner, M., O'Neill, R., Gardner, R., & Milne, B. (1989). Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology, 3*, 153–162.
UNDESA. (2014). *World urbanization prospects: The 2014 revision (Highlights)*. New York, NY: United Nations Department of Economic and Social Affairs.
Vásquez, A., & Salgado, M. (2009). Desigualdades socioeconómicas y distribución inequitativa de los riesgos ambientales en las comunas de Peñalolén y San Pedro de la Paz. Una perspectiva de justicia ambiental. *Revista de Geografia Norte Grande, 43*, 95–110.
Walker, G. (2009). Globalizing environmental justice: The geography and politics of frame contextualization and evolution. *Global Social Policy, 9*, 355–382.
Wagner, H. H., & Fortin, M.-J. (2005). Spatial analysis of Landscapes: Concepts and Statistics. *Ecology, 86*, 1975–1987.
Wu, J. (2004). Effects of changing scale on landscape pattern analysis: Scaling relations. *Landscape Ecology, 19*, 125–138.
Wu, J. (2007). Scale and scaling: A cross-disciplinary perspective. In J. Wu, & R. Hobbs (Eds.), *Key topics in landscape ecology* (pp. 115–142). Cambridge: Cambridge University Press.
Wu, J., Gao, W., & Tueller, P. T. (1997). Effects of changing spatial scale on the results of statistical analysis with landscape data: A case study. *Geographic Information Sciences, 3*, 30–41.
Wu, J., He, C., Huang, G., & Yu, D. (2013). Urban landscape Ecology: Past, present, and future. In B. Fu, & K. B. Jones (Eds.), *Landscape ecology for sustainable environment and culture* (pp. 37–53). Dordrecht: Springer Netherlands.