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Unequal Appropriation of Urban Vegetation in Argentine Cities

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Abstract

Seventy-five percent of the human population will live in urban areas by 2050, and urban vegetation will be the main source of ecosystem services. Unequal access to urban vegetation might exacerbate existing socioeconomic differences. Studies performed in cities of developed countries show that the population with higher socioeconomic status has more access to ecosystem services provided by vegetation. In urban areas, with small internal climatic variation, plant productivity measured through satellite imagery is a good indicator of vegetation availability that can be mapped. In this study, we characterized the distribution of plant productivity in 40 Argentine urban centers and we identified socio-environmental variables that control its spatial patterns within and among urban centers. We used socioeconomic indicators obtained from the 2010 National Population and Households Census and a 4-year mean plant productivity measured through the integration of NDVI values derived from MODIS satellite images. In most of the analyzed cities, plant productivity increased as socioeconomic status decreased; and only in 25% of the cities, we found a positive relationship between socioeconomic status and plant productivity. In the latter case, most of the cities were placed in arid environments, where both the cost of watering and the effect of subsidized water on plant productivity are proportionally higher. Buenos Aires and Bariloche, which also showed positive associations between socioeconomic status and plant productivity, are located in humid environments, but Buenos Aires is the most densely populated city of Argentina and Bariloche is a touristic city; in these cities, the relative cost of keeping green spaces instead of building housing infrastructure is also high. These results show that vegetation distribution among socioeconomic status is more diverse than suggested by the literature and that the appropriation of vegetation productivity by groups with higher socioeconomic status only occurs when vegetation cost increases to the point of becoming a luxury good.

Key words: vegetation productivity; MODIS; TIMESAT; social inequalities; socio-environmental control; urban vegetation.

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Highlights

- In most Argentine cities lower status socioeconomic groups have increased vegetation productivity.
- Higher status groups appropriate a bigger share of vegetation when vegetation cost is high.
- Aridity and the population density of cities increase the cost of urban vegetation.

Introduction

Socioeconomic status is one of the main factors that determine the spatial patterns of cities (Ossenbrügge 2003). The social, economic and cultural differences of population are reflected in urbanized landscapes and explain access to social infrastructure and vegetation patterns in urban ecosystems (Pedlowski and others 2002; Hope and others 2003; Pickett and others 2008; Luck and others 2009; Clarke and others 2013; Hernández and Villaseñor 2018). Many studies suggest that higher households income is associated with an increase in vegetation cover and access to benefits derived from ecosystem services (Flocks and others 2011; Schwarz and others 2015; Escobedo and others 2015; Fernández and Wu 2016); other studies found that education level is also positively correlated with such variables (Heynen and Lindsey 2003; Dobbs and others 2014).

The human population is undergoing accelerated changes toward a predominantly urban lifestyle (Grimm and others 2008). Current projections estimate that in 2050, 75% of the global population will live in urban areas (Mills 2007). Most of such increase will occur in urban areas of intermediate size (between 1 and 3 million inhabitants) of developing countries (Crossette 2011). In Latin America, economic, sociocultural and spatial variables of urban development indicate an ongoing dynamic structural change, affecting social sectors with different interests and uses of urban resources (Ossenbrügge 2003). In Argentina, 95% of the inhabitants are projected to live in cities by 2030 (CEPAL 2004). Urban vegetation will increasingly constitute the main source of ecosystem services for the human population. Urban vegetation provides different ecosystem services including temperature regulation (Bowler and others 2010) and noise pollution reduction (Janhäll 2015; Ow and Ghosh 2017). Also, urban natural areas provide intangible services that are difficult to measure, such as recreational opportunities, emotional well-being and contributions to mental health (Chiesura 2004). In this context, the ecosystem services provided by urban vegetation and the access to such resources might have social implications due to their contribution to urban inhabitants' well-being.

In general, higher-income groups exhibit increased capacity to appropriate plant productivity in cities, and as a consequence, the distribution of ecosystem services is asymmetric (Iverson and Cook 2000; Pedlowski and others 2002). By appropriation, we refer to the different mechanisms by which people have access to vegetation in cities, such as buying houses close to public green spaces, or with enough space to build their own garden, or the capacity of subsidizing vegetation by irrigation and fertilization. The socioeconomic status of people influences urban environmental management, and as a consequence, plant productivity can be spatially defined according to the needs of the sectors with higher socioeconomic income. Thus, to understand the spatial organization of urban ecosystems, it is necessary to identify the key variables that determine that spatial patterns. Further, understanding the existent composition and structural patterns of urban vegetation is important to inform management and to reach sustainable development (Grimm and others 2008).

The socio-environmental characteristics of urban ecosystems (for example, climate, topography, history) give cities certain uniqueness in terms of their nature–society relationships (Alberti 2008; Wu 2014). Anthropic variables, such as demography and socioeconomic circumstances, determine the spatial arrangement of vegetation within cities (Dobbs and others 2017). Studies carried out in different parts of the world observed the existence of unequal access to urban natural areas and their ecosystem services by different socioeconomic groups (Pedlowski and others 2002; Hope and others 2003; Kinzig and others 2005; Schüle and others 2017). In general, such studies were limited to one or a few cities, for which the factors controlling such unequal distribution of vegetation among cities were not identified. Our study, instead, includes the analysis of several cities. We aim at explaining how socio-environmental variables of cities in Argentina (presenting a wide environmental gradient and cultural homogeneity) affect the spatial relation between socioeconomic status and plant productivity within each urban center. Our hypothesis is that groups with higher socioeconomic status appropriate plant productivity. In this scenario, urban vegetation would become a luxury good and its demand would increase as income increases; thus, vegetation would be an elastic good and would widely respond to income variability (Zhu and Zhang 2008). Also, we hypothesize that in cities with higher socioeconomic inequality, such unequal distribution is more evident and that the climatic characteristics (for example, water availability) and demographic variables, such as population density, control the inequality of vegetation appropriation among cities.

To characterize the distribution pattern of vegetation, we evaluated the spatial relationship between the gross primary productivity (GPP), as a proxy of ecosystem services provision, and the socioeconomic status of urban inhabitants in 40 Argentine cities. We subsequently evaluated the contribution of different socio-environmental indicators at the city scale, to explain the distribution pattern of productivity found in each city.

Materials and Methods

Study Site

Argentina is located at the southern end of South America and has an area of 3,761,274 km^2, of which 2,791,810 km^2 belong to continental America. The country is organized in 23 provinces and the autonomous city of Buenos Aires (CABA) that host the federal government. In 2010 Argentina had 40,117,096 inhabitants unequally distributed through the country, with more than 90% of them living in urban areas (INDEC 2010).

We conducted our research analyzing the main 40 urban centers of Argentina (Table 1) constituted by the most populated cities of the country (that is, population density higher than 2000 inhabitants/km^2). Some adjacent cities coalesce through time and are functionally homogeneous, so they were analyzed as a single case study and their name usually includes ''Gran'' (the Spanish word for ''great''). The analyzed cities cover a total area of approximately 5,200 km^2 and a wide latitudinal range, from 24° (San Salvador de Jujuy) to 46° S (Comodoro Rivadavia). Due to such latitudinal range, cities exhibit wide temperature and rainfall gradients.

In Argentina, Posadas is the most humid city, while Gran San Juan is the most arid urban agglomeration.

The cities included in our analyses also vary in their territorial area and population density. Güemes, Metán and Rawson are the smallest cities (less than 8 km^2 each one); CABA, Gran la Plata, Gran Mendoza, Gran Córdoba and Gran Buenos Aires are the largest cities (more than 200 km^2). Regarding population density, CABA is the most densely populated city, with almost 150,000 inhabitants/km^2. In contrast, Villa María, Luján, Santa Rosa and Clorinda have less than 2500 inhabitants/km^2.

Socioeconomic and Population Data

We performed a socioeconomic characterization of the population based on education level and household infrastructure. We obtained the data from the 2010 national population, households and livelihoods census carried out by the Instituto Nacional de Estadísticas y Censos (INDEC), which analyzes and holds the official statistical information of Argentina. We obtained data at two spatial scales: urban agglomeration and censal radii (CR). Within each urban area, we gathered two socio-environmental variables, that is, population density and Socioeconomic Status Index.

The size of the CR is defined by the number of households. Every CR includes an average of 300 households (INDEC 2010), for which each urban center is composed of a variable number of CR (Table 1). Also, the CRs are georeferenced through a polygon, which allows using Geographic Information Systems (GIS) for their analyses. To extract information of the censal variables, we used the REDATAM + SP software (REcuperación de DATos para Áreas pequeñas por Microcomputador) (De Grande 2016).

Socioeconomic Status Index (SSI)

We developed a Socioeconomic Status Index (SSI) based on census data as a conceptual and quantitative model summarizing different economic and social aspects that characterize the local population. The variables used to create the index were the maximum educational level gained by the heads of households (that is, primary, secondary, tertiary and university) and the levels of household material quality (that is, quality of the household materials and connectivity to public basic services).

The educational level reached by the head of household is an indicator of the occupational hierarchy, monthly income and social status, while the characterization of the household reflects its historic income and assets value. The SSI facilitates a more detailed characterization of households than those provided by other alternatives, such as the UBN (Unsatisfied Basic Needs), which is a binary indicator used by the INDEC to characterize structural poverty (2001 and 2010 censuses (INDEC 2010). To perform our study, households had to be characterized in socioeconomic terms rather

Table 1. Summary of Studied Cities Arranged by Their Population Density

City	Abv	Latitude	Longitude	de Martonne index (mm/°C)	No of CR	Density (hab/ km^2)	SSI	Area (km^2)
CABA	CP	34°36′43″ S	58°26′33″ O	38.8	3555	14,450.80	83.58	203.30
Gran Buenos Aires	BA	34°39′41″ S	58°34′38″ O	39.2	9844	6973.50	62.01	2463.57
Corrientes	CT	27°28′55″ S	58°°48′34″ O	40.6	304	6926.68	66.95	49.97
Viedma	VI	40°47′51″ S	62°58′50″ O	13.6	76	6171.11	70.51	20.44
Gran Salta	GS	24°47′31″ S	65°24′52″ O	25.5	449	6056.46	57.68	91.49
Gran Santa Fe	GF	31°36′58″ S	60°42′11″ O	34.0	390	5868.90	71.14	66.65
Comodoro Rivadavia	CR	45°52′13″ S	67°32′27″ O	10.1	149	5744.13	67.49	30.53
Mar Del Plata	MP	38°0′26″ S	57°34′3″ O	37.5	829	5700.23	73.04	134.21
Güemes	GG	24°40′5″ S	65°2′58″ O	16.1	31	5623.93	43.24	5.62
Gran San Miguel de Tucuman	GT	26°49′2″ S	65°13′19″ O	33.6	760	5023.13	61.65	158.13
Parana	PN	31°44′36″ S	60°30′54″ O	35.8	291	4958.60	68.66	49.84
Concepcion	CN	27°20′50″ S	65°35′43″ O	31.8	46	4880.59	53.12	10.21
Resistencia	RS	27°27′16″ S	58°59′16″ O	42.3	426	4859.19	58.92	79.38
Catamarca	CA	28°27′54″ S	65°46′56″ O	13.1	152	4793.34	67.19	33.18
Gran San Juan	GJ	31°32′12″ S	68°32′13″ O	3.5	427	4690.44	59.06	100.47
Gran Santiago Del Estero	GO	27°47′23″ S	64°16′9″ O	19.1	321	4678.06	62.19	77.15
Bariloche	BR	41°8′37″ S	71°17′34″ O	49.9	111	4554.38	54.08	24.00
Concordia	CO	31°22′43″ S	58°1′10″ O	45.1	150	4547.34	63.27	32.87
Neuquen	NQ	38°56′53″ S	68°5′16″ O	7.0	275	4285.05	72.36	53.95
Trelew	TW	43°15′24″ S	65°18′28″ O	7.9	105	4254.21	65.94	23.02
Gran Jujuy	GU	24°12′29″ S	65°16′22″ O	31.3	299	4214.22	52.77	61.21
San Luis	SL	33°17′52″ S	66°19′53″ O	21.7	185	4211.90	70.43	40.35
Posadas	PS	27°24′23″ S	55°54′58″ O	52.9	324	4156.72	65.43	76.86
Cipolletti	CI	38°55′48″ S	67°59′8″ O	7.4	99	4047.55	71.33	19.20
Gran Cordoba	GC	31°23′12″ S	64°12′56″ O	26.9	1646	3952.13	68.62	371.66
Metan	MN	25°29′49″ S	64°58′26″ O	26.6	26	3929.86	50.45	7.16
Gran La Plata	GL	34°54′58″ S	57°57′48″ O	35.6	940	3854.94	77.24	207.40
Puerto Madryn	PM	42°45′53″ S	65°2′43″ O	6.9	87	3825.08	67.49	21.26
Rawson	RW	43°17′50″ S	65°6′20″ O	7.9	35	3787.08	64.81	7.42
Gran Mendoza	GM	32°55′37″ S	68°49′38″ O	8.5	976	3708.59	68.91	252.70
Gualeguaychu	GY	33°0′35″ S	58°31′35″ O	35.8	110	3453.75	67.72	23.34
La Rioja	LR	29°25′32″ S	66°51′37″ O	10.9	143	2975.17	63.68	60.12
San Rafael	SR	34°37′9″ S	68°20′10″ O	13.2	146	2899.48	68.23	40.71
Rio Cuarto	RC	33°7′16″ S	64°21′4″ O	30.1	189	2759.40	63.91	56.94
San Nicolas	SN	33°20′39″ S	60°12′32″ O	33.8	145	2754.70	64.87	48.48
Villa Mercedes	VM	33°40′26″ S	65°27′59″ O	22.8	133	2555.27	62.55	43.59
Clorinda	CL	25°16′54″ S	57°43′25″ O	41.5	53	2447.32	45.70	21.59
Santa Rosa	ST	36°37′50″ S	64°18′54″ O	25.3	170	2425.09	70.23	51.17
Lujan	LJ	34°33′44″ S	59°7′1″ O	39.3	93	2269.53	68.85	42.88
Villa Maria	VA	32°24′50″ S	63°14′23″ O	28.3	121	2235.24	61.15	35.55

than through extreme poverty parameters. Thus, we consider that, although it has not been used in the previous socioeconomic analyses, the selected combination provides a thorough characterization of the socioeconomic status of urban inhabitants. The SSI is a simple sum additive model, in which the construction quality category and the educational level are ponderated (Table 2); the value of the SSI for a household ranges from 10 to 110. The SSI of each censal radii is the average of all the households that compose it, and the SSI of each city is the average of all its censal radii.

Socioeconomic Inequality

We quantified socioeconomic inequality within each urban center from the SSI range between specific percentiles. To estimate such inequality, we estimated the SSI between the percentiles 5 and 95 of the censal radii of each urban center. Thus, we obtained a dispersion metric, reducing possible biases caused by extreme values. We used this index to evaluate whether socioeconomic inequality of each agglomerate increases the unequal appropriation of vegetation.

Climatic Data

To characterize the climate of urban centers, we used the de Martonne aridity index (Gavilán 2005), which is an indicator of water balance throughout the year (Figure 1). In urban ecosystems, water balance is a major driver of plant functioning, therefore, is a key variable to be considered in vegetation analyses. To estimate water balance, we obtained accumulated annual rainfall and mean annual temperature values for each city based on WorldClim data (Hijmans and others 2005) and estimated the de Martonne index through the following formula: *$Ia = R/(T + 10)$, where R is annual rainfall (in mm) and T is mean annual temperature (in ºC).* The de Martonne aridity index is a measure which associates vegetation hydric requirements to temperature and water availability (through rainfall), for which it summarizes the interaction between temperature and rainfall.

Image Processing

Gross Primary Productivity Estimation

We used 16-day composites (MOD13Q1) Normalized Difference Vegetation Index (NDVI) estimated from Moderate Resolution Imaging Spectroradiometer (MODIS) images from 2009 to 2012 to describe temporal patterns of vegetation phenology and then productivity. For every year, we estimated vegetation phenology from 23 composite images of NDVI with values rescaled from 0 to 1, with a spatial resolution of 250 × 250 m. Although other products may have a better spatial resolution (for example, Landsat), they cannot account for the vegetation productivity of the thorough growing season and are more affected by the time of image acquisition. We analyzed a compound time series of 105 NDVI images using TIMESAT software (Jönsson and Eklundh 2004). TIMESAT quantifies phenological signals from time series of satellite data, adjusts local functions for each point and combines these functions in a model of phenological patterns. Based on the function modeled, TIMESAT provides statistical descriptors of the seasonal pattern of the analyzed variable (NDVI in this case) through the year. For this study, we used the seasonal integral (SI), an indicator of absorbed photosynthetically active energy accumulated in each growing season (Running and others 2004), so it can be used as a proxy of GPP (Paolini and others 2016, 2019; Haedo and others 2017). To obtain a vegetation indicator close to the census year (2010), we used the average of GPP for the years 2009, 2010, 2011 and 2012, which reduces the probability of bias due to extreme values.

Data Analysis

We used two spatial levels of analysis: a finer scale focused on CRs and a larger scale focused on the urban centers. The finer scale included all the CR within each city. For each CR, we obtained population density, average SSI and average GPP. The GPP of each CR was estimated as the average GPP of all the pixels that covered at least some part of the CR. Since some CR can be smaller than the MODIS pixel (6.25 ha), some small CRs may have the same value or may have some common information. The largest analysis scale was used to assess the variation between cities, so we used the 40 polygons corresponding to each city. We also gathered data at the city scale (for example, de Martonne aridity index and territory area).

To analyze how GPP is distributed within each urban center, we performed a correlation matrix between population density, SSI and vegetation GPP at each CR. We used Spearman correlation test. As we observed associations between population density and SSI, we made an analysis to identify the effect of SSI on GPP controlling for population density; it is expected that areas with higher population density have fewer green spaces. The population density was used as a covariate in a multiple regression between vegetation GPP as the

Table 2. Variables Used for the Socioeconomic Characterization and their Respective Scores

Educational level reached	Ponderation	Household and material quality	Ponderation
Initial/primary	5	Quality I	60
Secondary	20	Quality II	25
Tertiary	25	Quality III	10
Universitary/Post	50	Quality IV	5

Table 3. Socioeconomic Inequality and Their Respective Percentiles According to the SSI

Urban centers	Percentile 5% of SSI	Percentile 95% of SSI	Inequality
Rawson	54.22	75.30	21.08
Villa María	47.52	76.54	29.02
Comodoro Rivadavia	52.40	84.44	32.04
CABA	63.87	96.34	32.47
Gualeguaychú	50.18	85.36	35.18
La Rioja	44.10	80.24	36.14
Trelew	47.63	84.25	36.62
Santa Rosa	48.47	88.17	39.70
Lujan	43.32	84.46	41.14
Villa Mercedes	39.11	80.77	41.66
San Rafael	43.21	85.93	42.72
Mar Del Plata	46.48	89.94	43.46
Güemes	25.22	68.71	43.49
Rio Cuarto	42.04	86.99	44.95
Catamarca	43.07	88.05	44.98
Puerto Madryn	42.39	87.70	45.31
Metan	29.13	74.94	45.81
San Luis	45.18	91.37	46.19
Cipolletti	44.47	90.96	46.49
Bariloche	30.18	77.44	47.26
San Nicolas	38.92	87.03	48.11
Viedma	40.88	91.56	50.68
Paraná	41.15	92.05	50.90
Concordia	36.08	87.07	50.99
Gran Mendoza	41.95	93.27	51.32
Gran Buenos Aires	36.63	88.10	51.47
Gran Córdoba	42.90	95.41	52.51
Gran Santiago Del Estero	34.53	87.11	52.58
Clorinda	21.90	74.70	52.80
Neuquén	38.95	92.98	54.03
Gran La Plata	45.13	99.17	54.04
Gran Jujuy	27.11	82.75	55.64
Posadas	33.38	89.69	56.31
Gran San Juan	30.29	87.21	56.92
Concepción	24.33	81.44	57.11
Corrientes	34.24	94.11	59.87
Gran Santa Fe	33.72	94.76	61.04
Resistencia	28.17	89.27	61.10
Gran Salta	26.78	88.00	61.22
Gran San Miguel De Tucumán	28.22	96.82	68.60

response variable and SSI and population density as the predictor variables.

The coefficient of estimation of the SSI calculated from the multiple regression is an indicator of unequal distribution of GPP by socioeconomic status, named as ''index of unequal appropriation of urban vegetation'' (UAUV). Both the sign and magnitude of this index determine its interpretation: a positive value indicates that CR with a higher socioeconomic level has more GPP, whereas a negative value indicates the opposite. When the value is close to zero, the socioeconomic level has no effect on plant productivity vegetation, implying that GPP is equally distributed among SSI groups. The magnitude of the UAUV shows the changes in GPP associated with the changes of each SSI unit.

To identify how socio-environmental differences condition the unequal appropriation of vegetation among cities, we additionally performed simple linear regressions between the UAUV of each urban center and different environmental and social attributes. Among the potential explanatory vari-

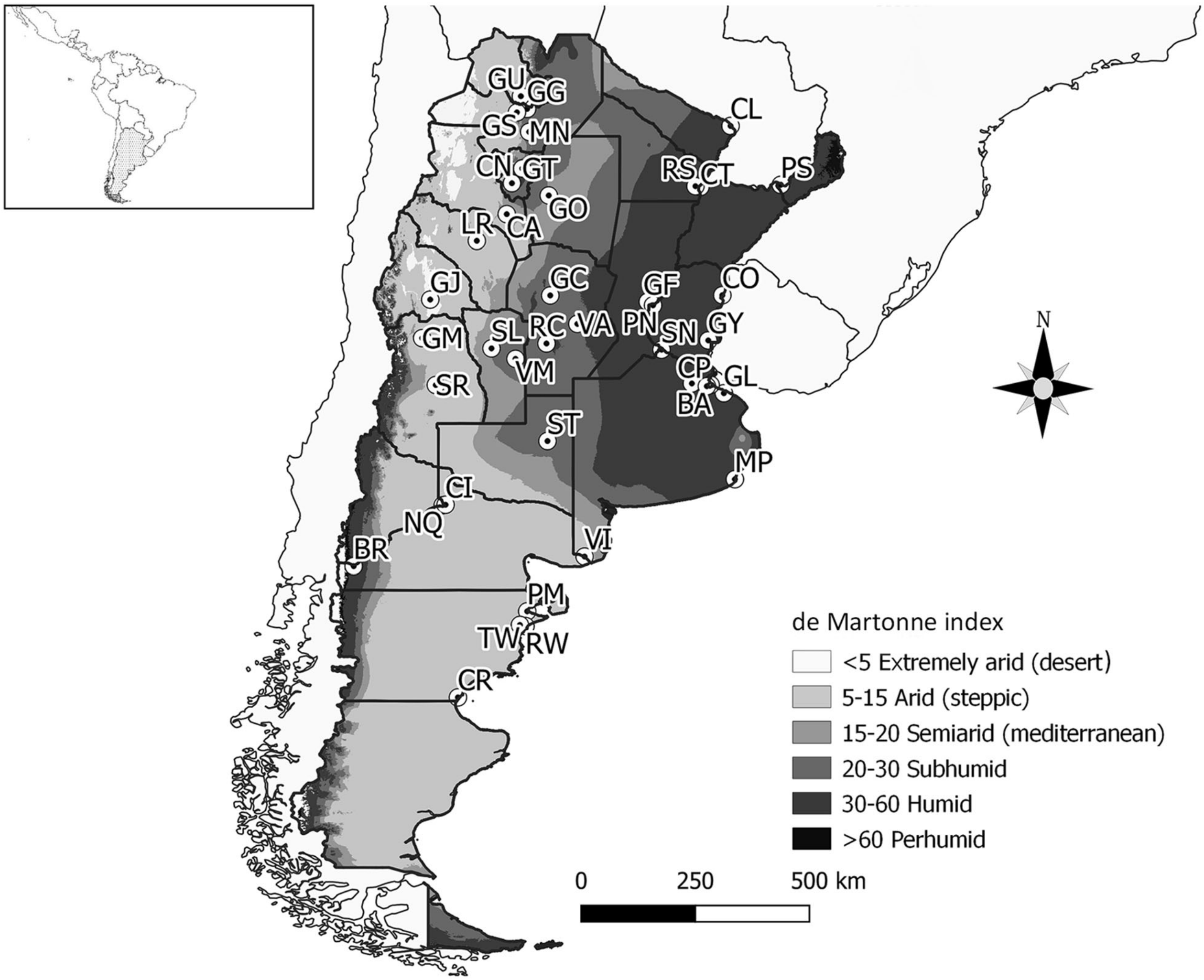

Figure 1. Values for each studied urban agglomeration. Climates according to the de Martonne aridity index through Argentine. The studied cities are indicated by their two-letter code (see Table 1).

ables, we included the area of each urban center, population density, average SSI, socioeconomic inequality and the de Martonne aridity index. Due to that interdependence among explanatory variable is possible, we performed multiple regression analyses to evaluate the contribution of each variable to UAUV and we compared different regressions through the stepwise (backward) method. We started from a saturated model, where all the variables (SSI, population density, area, socioeconomic inequality, aridity) were used. According to the results of these analyses, the variables with the lowest contribution to the model were progressively eliminated, using the adjusted R^2 as the criteria to select the best model. All the analyses of this study were performed using R (R Core Team 2017).

Results

Analyses at the CR Scale

Associations Between Plant Productivity, Socioeconomic Level and Population Density

Only in 25% of the urban centers socioeconomic level and GPP were positively associated, whereas in 75% of the urban centers SSI and GPP were negatively correlated. In five urban centers (12.5%), the correlation between vegetation productivity and SSI was not significant, suggesting that GPP was equally distributed between socioeconomic groups (Table 4). We found a negative association between population density and plant primary productivity in 37 of 40 cities, with only Catamarca, Güemes and Metán showing a positive association between such variables (Table 4).

Unequal Appropriation of Urban Vegetation Relation with Socio-Environmental Variables

The de Martonne index was the variable that best explained UAUV variation among cities ($R^2 = 0.27$, $p < 0.001$). The relation between the de Martonne aridity index and city UAUV was negative (Figure 2A), implying a positive association between UAUV and city aridity. No significant association was found between socioeconomic inequality of the urban centers and UAUV ($R^2 < 0.01$ $p = 0.43$, Figure 2B). A similar result was found for population density and its relation with UAUV ($R^2 < 0.01$, $p = 0.15$, Figure 2C). Neither the area of the urban centers nor the average SSI was associated with the UAUV of the corresponding urban center ($R^2 < 0.001$, p = 0.84; $R^2 < 0.001$, $p = 0.55$, Fig. 2D, E, respectively). The most arid cities of Argentina show a positive UAUV index, as well as Buenos Aires, with a very high population density (Fig. 2).

Stepwise Regressions Results

We identify the best model by performing stepwise regressions using the adjusted R^2 as a measure of goodness of fit. The model including aridity index and population density (M4) was the one that best explained the UAUV index (R^2 adj = 0.35, Table 5). The importance of the population density of each city is evident when model 5 (M5) and model 4 (M4) are compared as the adjusted R2 shifts from 0.27 to 0.35 when the variable is included.

Discussion

Our results suggest that in Argentina, the cost of vegetation seems to determine an unequal appropriation of plant productivity by groups of higher socioeconomic status. High-income groups tend to appropriate a bigger share of vegetation productivity in cities where climate is arid, the land is scarce, or when tourism dominate their economy. However, in most of the cities (75%), the opposite pattern, a negative association between GPP and socioeconomic level, is found. Humid, medium or small size cities show a negative relation between plant productivity and socioeconomic level. That pattern might be due to the fact that, in these areas, existent vegetation does not result from human care and maintenance, but to an optimal hydric balance for vegetation. Besides, the results may be affected by the fact that in these cities the central areas are comparatively less vegetated and tend to be occupied by people with high socioeconomic status.

Our results contrast with most of the literature linking socioeconomic status and vegetation indicators. Using a similar methodology than ours, Szantoi and others (2012) found contrasting results in the state of Florida, USA. Other studies found a positive relationship between socioeconomic level and different indicators of urban vegetation (for example, species diversity and richness, accessibility to green spaces). Such studies, in general, were carried out in large cities of different parts of the world, such as Latin America (Pedlowski and others 2002; Escobedo and others 2015; Fernandez and Wu 2016; Hernández and Villaseñor 2018), the USA (Iverson and Cook 2000; Heynen and Lindsey 2003; Hope and others 2003; Martin and others 2004; Kinzig and others 2005; Pickett and others 2008; Flocks and others 2011; Schwarz and others 2015) and Europe (Tratalos and others 2007; Luck and others 2009; Strohbach and others 2009; Schüle and others 2017). Higher economic income is positively related with access to different ecosystem services (Tratalos and others 2007), and residential vegetation in such cities is largely explained by the ''luxury'' and inherited effects, being richer in areas with higher socioeconomic level (Martin and others 2004).

Our results suggest that in Argentina the cost of vegetation is higher in arid cities (where vegetation must be subsidized), in large cities such as Buenos Aires and in cities where the land price is high due to restrictions to its access, which occurs in both Buenos Aires and Bariloche. In these cities, groups with higher socioeconomic level tend to appropriate vegetation productivity and its associated ecosystem services.

The unequal access to socio-environmental services has been widely described in the literature, where, among others, social segregation is analyzed (expressed by different patterns, such as household, mobility, the distance between work and household, access to educational and sanitary centers, Ossenbrügge 2003). In this study, we aimed at providing information about the current situation regarding vegetation appropriation for different social sectors in Argentina. The analyzed urban centers are located within a wide latitudinal gradient, and they are characterized by certain historic and cultural homogeneity (Itzigsohn and others 2004). Further, they integrate a contrasting region in biophysical (topography, temperature, aridity, and so on) and socioeconomic terms, which allows analyzing and addressing which of such features relate with vegetation patterns in cities.

Table 4. Correlation Results and Climates Based to the de Martonne Aridity Index

Urban centers	Density and GPP	Density and SSI	GPP and SSI	Climate
Gran San Juan	− 0.02	− 0.15**	0.26**	Extremely arid (Desert)
Puerto Madryn	− 0.10	− 0.42*	0.11	Arid (Steppic)
Neuquén	− 0.35**	− 0.27**	0.40**	
Cipolletti	− 0.28*	− 0.48**	0.03	
Rawson	− 0.37*	0.07	− 0.01	
Trelew	− 0.27*	− 0.57**	0.43**	
Gran Mendoza	− 0.16**	− 0.10**	0.12**	
Comodoro Rivadavia	− 0.30**	− 0.25**	0.08	
La Rioja	− 0.22*	− 0.11	− 0.28**	
Catamarca	0.05	− 0.35**	− 0.31**	
San Rafael	− 0.09	− 0.24**	− 0.21*	
Viedma	− 0.17	− 0.27*	0.32**	
Güemes	0.21	− 0.30	− 0.48*	Semiarid (Mediterranean)
Gran Santiago Del Estero	− 0.15*	0.04	− 0.48**	
San Luis	− 0.04	− 0.17*	− 0.58**	Subhumid
Villa Mercedes	− 0.27**	0.32**	− 0.66**	
Santa Rosa	− 0.45**	− 0.12	− 0.24**	
Gran Salta	− 0.30**	− 0.34**	− 0.11*	
Metan	0.19	0.25	− 0.08	
Gran Córdoba	− 0.59**	0.07**	− 0.40**	
Villa María	− 0.56**	0.07	− 0.48**	
Rio Cuarto	− 0.69**	0.39**	− 0.61**	Humid
Concepción	− 0.04	− 0.41**	− 0.41**	
Gran Jujuy	− 0.47**	− 0.24**	− 0.20**	
Gran Sm De Tucumán	− 0.45**	− 0.02	− 0.46**	
San Nicolas	− 0.39**	0.14	− 0.51**	
Gran Santa Fe	− 0.15**	− 0.03	− 0.73**	
Paraná	− 0.22**	− 0.02	− 0.63**	
Gran La Plata	− 0.57**	0.53**	− 0.56**	
Gualeguaychú	− 0.43**	0.04	− 0.64**	
Mar Del Plata	− 0.25**	0.37**	− 0.22**	
CABA	− 0.25**	0.43**	0.06**	
Lujan	− 0.40**	0.03	− 0.62**	
Gran Buenos Aires	− 0.50**	− 0.11**	− 0.24**	
Corrientes	− 0.25**	0.12*	− 0.66**	
Clorinda	− 0.27	0.20	− 0.51**	
Resistencia	− 0.26**	− 0.03	− 0.53**	
Concordia	− 0.30**	0.02	− 0.64**	
Bariloche	− 0.27**	− 0.18	0.30**	
Posadas	− 0.32**	0.13*	− 0.53**	

*$p < 0.05$, ** $p < 0.01$

In contrast with other studies, our analysis does not discriminate between public and private vegetated areas. Several studies focus in public (Chiesura 2004; Boone and others 2009; Dobbs and others 2017) or private green spaces (Loram and others 2008; González-García and Gómez Sal 2008; Peroni and others 2016). The social implications of these approaches might be different. Public green spaces are distinctive due to their surroundings, their positive contribution to the environment and to the experiences with nature they bring, while private domestic areas are also distinctive due to their significance, privacy, freedom and the possibility of gardening (Coolen and Meester 2012). However, it has been proposed that both types of green spaces may be important for human well-being (Shanahan and others 2014). In our case, by analyzing GPP both spaces were combined. The importance of our study thus consists in the analysis of total vegetation primary productivity, without distinguishing between public or private green spaces, or street vegetation such as urban

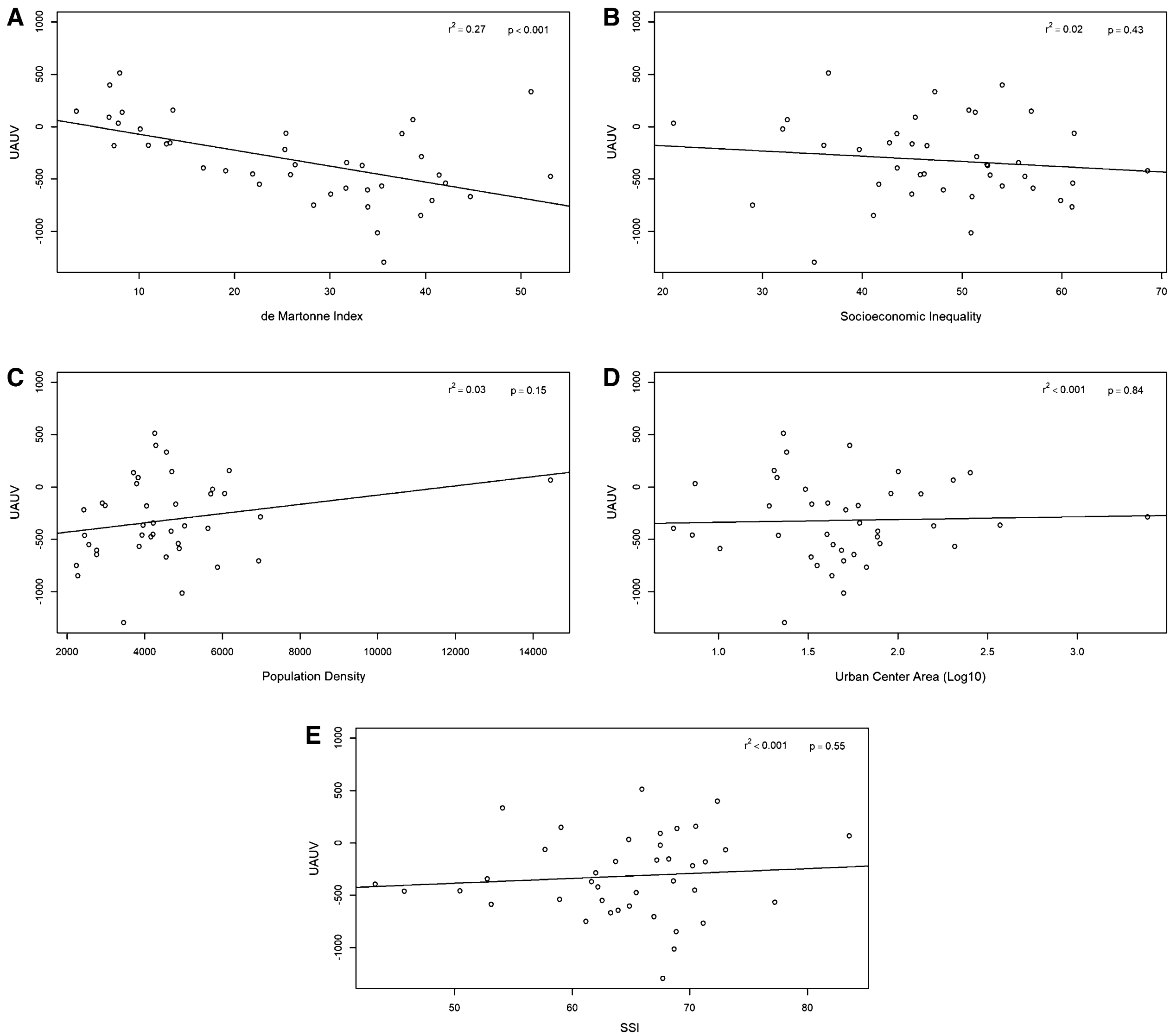

Fig. 2. Simple linear regressions between unequal appropriation index and the different socio-environmental variables of each urban center. **A** de Martonne index, **B** socioeconomic inequality, **C** population density, **D** urban center area (expressed in Log10) and **E** SSI

woodland, which might strongly affect the results. It is necessary to perform further studies to analyze the differential implications of both types of vegetated areas on human well-being and to evaluate the role of public policies in increasing environmental justice (for example, Li and others 2016).

As property cost increases, the possibility of access to private green spaces (gardens) for the population is hindered. Thus, government, regulators and policymakers play an important role, since it must predict the outcomes of such situations before the creation of green spaces becomes infeasible. Our results show that although inhabitants of more arid cities, who can subsidize the lack of hydric resources, have better access to the ecosystem services provided by vegetation it is likely that in less arid cities, the hydric provision is ‘‘masked’’ by naturally occurring vegetation. Thus, the effect of SSI on GPP might not be detectable in less stressed environments. Socioeconomic factors are correlated with vegetation cover, which must be considered by policymakers who have a direct effect on urban vegetation cover and distribution in subtropical areas (Szantoi and others 2012). The quantification of urban vegetation patterns is necessary to define the best local approach to enhance sustainable development in cities (Grimm and others 2008). In further studies, it would be

Table 5. Summary of Backward Stepwise Regression Analyses

Models	Adj. R^2	Estimate (std.)					
		Intercept (UAUV)	de Martonne index	Density	SSI	Inequality	Area
Saturated	0.31	74.6 (549.1)	− 17.2** (4.04)	0.06* (0.03)	− 3.50 (7.02)	− 0.29 (5.56)	0.06 − 0.14
M2	0.32	62.9 (541.8)	− 17.0** (3.96)	0.06* (0.03)	− 3.54 (6.93)	− 0.17 (5.48)	_
M3	0.34	53.3 (435.4)	− 17.0** (3.80)	0.06* (0.03)	− 3.50 (6.71)	_	_
M4	0.35	− 160.6 (145.9)	− 16.7** (3.71)	0.06* (0.02)	_	_	_
M5	0.27	82.2 (115.3)	− 15.2** (3.91)	_	_	_	_

*$p < 0.05$, **$p < 0.001$

important to analyze vegetation behavior in relation to SSI in less arid cities and during the driest periods of the year when GPP is scarcer.

Our study allowed to analyze not only the differential allocation of urban vegetation among different socioeconomic groups within cities, but also to identify the drivers controlling the differences in this allocation between cities. We combined censal data that have proved to be reliable and a vegetation indicator that has proved to correctly characterize urban vegetation (Dobbs and others 2017). We have used particular metrics to characterize socioeconomic groups and their inequality level. We acknowledge that alternative metrics (for example, the use of Unsatisfied Basic Needs (UBN) to characterize SE groups or Gini index to quantify the inequality) might provide different results, the main patterns would probably hold due to the strong association between the variables analyzed. Additionally, we used TIMESAT to integrate MODIS NDVI (Jönsson and Eklundh 2004), which has the advantage of characterizing the GPP through the year and not in a particular moment (Paolini and others 2019). However, this method was chosen at the expense of spatial resolution (MODIS imagery can be obtained only at pixels of 6.25 ha). Some CR may be smaller, so we had to assign an average vegetation productivity value, which could affect the precision of the method and increase spatial autocorrelation. This implies that some patterns and their statistical significance can be overestimated (Fernández and Wu 2016), but in general the main pattern is conserved.

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