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Built Environment Profiles for Latin American Urban Settings: The SALURBAL study

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Cities as Complex Systems

I am pleased to submit our manuscript entitled "Built Environment Profiles for Latin American Urban Settings: The SALURBAL study" Olga L. Sarmiento, Andrés Useche, Daniel A. Rodriguez, Iryna Dronova, Oscar Guaje, Felipe Montes, Ivana Stankov, Maria Alejandra Wilches, Usama Bilal, Xize Wang, Luis A. Guzmán, Fabian Peña, D. Alex Quistberg, John A. Guerra-Gomez, Ana V. Diez Roux to be considered for publication as an original research article in the special issue "Cities as Complex Systems" in PLOS ONE

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The manuscript has not been previously published, is not presently under consideration by any other journal and will not be submitted elsewhere before a final editorial decision from the PLOS ONE is rendered. All authors declare that they have no conflicts of interest or financial interests related to the research. All authors listed have contributed sufficiently to be considered authors of this manuscript.

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Built Environment Profiles for Latin American Urban Settings: The SALURBAL study

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Abstract

The built environment of cities is complex and influences health outcomes. However, information on built environment patterns of Latin American cities is limited. In this study we 1) identified city profiles based on the built landscape and street design characteristics of cities in Latin America and 2) evaluated the associations of city profiles with social determinants of health and air pollution. Landscape and street design profiles of 370 cities were identified using finite mixture modeling. For landscape, we measured fragmentation, isolation and shape. For street design, we measured street connectivity, street length, and directness. We fitted a two-level linear mixed model to assess the association of social and environmental determinants of health with the profiles. We identify four profiles emerging for landscape and four for the street design domain. The most common landscape profile was the “proximate stones” characterized by moderate fragmentation, isolation and patch size and irregular shape. The most common street design profile was the “semi-hyperbolic grid” characterized by moderate connectivity, street length, and directness. The profiles were associated with social determinants of health and air pollution. The “semi-hyperbolic grid”, “spiderweb” and “hyperbolic grid” profiles were positively associated with higher access to piped water and less overcrowding. The “semi-hyperbolic grid” and “spiderweb” profiles were associated with higher air pollution. The “proximate stones” and “proximate inkblots” profiles were associated with higher congestion. In conclusion, there is substantial heterogeneity in the urban landscape and street design profiles of Latin American cities. Type of cities based in urban landscape and street design are associated with social determinants of health and environmental quality.

Introduction

Cities are highly complex systems in which dynamic networks between people and the built environment give rise to patterns in behaviors and health (1,2). Specifically, certain characteristics of the built environment have been associated with social and environmental determinants of health (e.g., poverty, transport, air pollution), mental health (3), non-communicable diseases (NCD) (4), road traffic deaths (5)) and inequities in health (6). Nonetheless, most descriptive information on city built environments and social determinants of health has focused on high-income countries or large cities from low-to-middle income countries; few studies have focused on Latin American cities (7,8).

Certain features of Latin American cities make examination of the built environment of these cities of special interest. Latin America is dense and highly urbanized (9,10). Around 80% of the population lives in urban areas (10). Latin America is infamous for its violence, with 24.7 homicides per 100,000 inhabitants (11,12). The region is also notoriously unequal (13), and 24% of the population lives in dense informal settlements (14). Despite these challenges, Latin America is also known for its innovative and sustainable transportation policies (15), urban development projects (12), and social programs (16).

Existing data suggests that the physical environments of Latin American cities are heterogeneous (17). Some cities are denser (18,19), more complex in shape (17), others have lower street connectivity (17,20), and yet others have higher fragmentation (21). This heterogeneity of built environment features can be exploited to investigate how urban environments influence social determinants of health, health outcomes, and environmental sustainability (22).

One approach to managing the complexity and volume of data for describing widely varying cities is to develop multi-dimensional typologies or profiles. Profiles are intuitive ways of describing units according to an ensemble of characteristics and allow for further studies into the mechanisms that connect the built environment to health.

Several examples of profiles or types based on indicators involving the built environment already exist including: 1) *transit-oriented development* profiles based transit stops (23), 2) *bus rapid transit-oriented development* profiles (24), 3) *environmental profiles* based on indicators of air pollution and biomass burning (25), *global city types* based on visual classification of urban design and land transport (26), and 4) *urban form profiles* of large metropolitan areas in large cities (18). However, to date there have been no systematic attempts to develop a comprehensive typology based on a large set of standardized built environment features for the cities in Latin America.

The SALURBAL project (Salud Urbana en América Latina or Urban Health in Latin America) (22) provides a unique opportunity to assess built environment characteristics across cities in Latin American. A key aim of SALURBAL is to quantify the contributions of city-level built environment factors to differences in health and health inequality among and within cities. We used satellite imagery and OpenStreetMaps data to characterize various features of the built environment of cities and empirically identify profiles of the urban landscape and street morphology of 370 cities of 100,000 residents of more across the region. We then evaluated associations of these urban landscapes and street design profiles with social determinants of health (education, poverty, sewage connection, congestion) and air pollution. Characterizing the built environment profiles of cities is critical to understanding the impact of built environment features on health and environmental outcomes and to the development of urban policies that promote health and environmental sustainability.

Methods

*SALURBAL cities*

The SALURBAL project includes the 11 countries in Latin America: Argentina, Brazil, Chile, Colombia, Costa Rica, El Salvador, Guatemala, Mexico, Nicaragua, Panamá, and Perú. Additional details on the multilevel data structure of the study have been published earlier (27). Briefly, to identify eligible cities (≥100,000 inhabitants as of 2010), SALURBAL cities were selected using two databases (the Atlas of Urban Expansion (AUE) and citypopulation.de (CP)). The lists of these databases were matched, and differences were resolved using satellite imagery and population estimates. For the current analysis, we included all local administrative units associated with the urban extent of each city as determined by satellite imagery. These 370 units are henceforth referred to as "cities" (or Level 1 administrative units). We chose this geographic definition because it matches the area used in mortality and health surveys of SALURBAL while accounting for the urban extent.

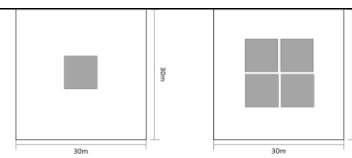
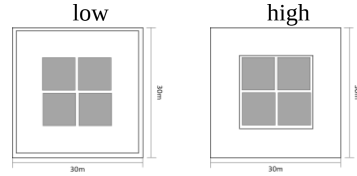
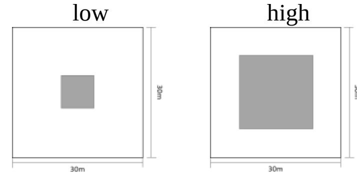
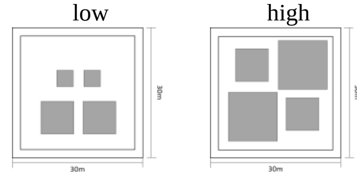
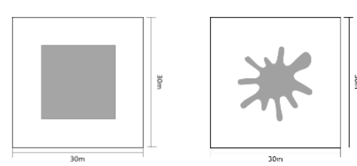
SALURBAL built environment domains and metrics

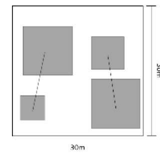
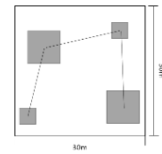
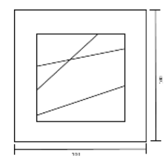
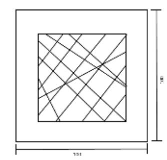
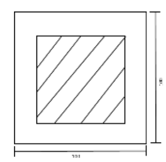
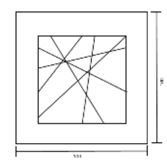
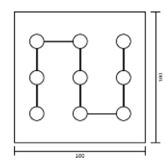
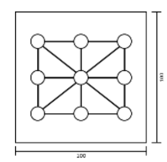
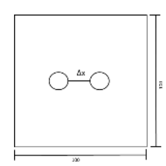
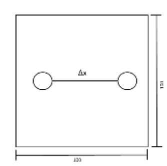
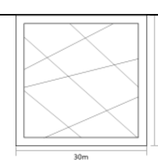
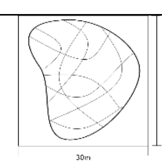
Given their emerging importance (18,20), and the possibility of measuring them reliably across cities and countries, we focused on two built environment domains: the urban landscape and street design. These domains were analyzed separately to account for potential associations between different profiles within each domain and to allow separate investigation of their association with socioeconomic, environmental or health outcomes. Within these domains, experts from transport, landscape architecture and landscape ecology, and urban planning (DR, XW, and ID) selected key metrics to be included in analyses focused on identifying the urban landscape and street design profiles (28).

Urban Landscape Domain

The urban landscape domain measures how urban development is configured within each city. We selected six urban landscape metrics that represent the subdomains of fragmentation, isolation, and shape of developed urban areas. We also included urban area and population size (**Table 1**). To create the metrics, we used the 2012 urban footprint data (in 30m x 30m grid cells) from the Global Urban Footprint project (29). Metrics were calculated based on 30m x 30m grid cells using the FRAGSTATS 4.2 software package (30).

Table 1. Urban development landscape and street design domains, subdomains and population metrics

Subdomains	Metric	Abbreviation	Formula	Description	Icon
Urban Landscape Domain					
Area	Total urban area	TUA	$TUA_i = \sum_{j \in i, j \in urban} A_j$	A_j refers to the area of 30m x 30m gridcell j within the geographic unit i and categorized as urban.	NA
Fragmentation	Number of Urban Patches (N)	NUP	NA	NA	 low high
	Patch Density (N/km2)	PD	$PD_i = \frac{NUP_i}{TUA_i}$	NA	 low high
	Area-weighted Mean Patch Size (km2/N)	AWMPS	$AWMPS_i = \frac{\sum_{j \in i} \frac{UA_j^2}{TUA_i}}{NUP_i}$	Where UA_j refers to the area of urban patch j located in the city i.	 low high
	Effective Mesh Size (km2)	EMS	$EMS_i = \frac{\sum_{k \in i} UA_k^2}{TUA_i}$	Where UA_j refers to the area of urban patch j located in the city i.	 low high
Shape	Area-weighted Mean Shape Index	AWMSI	$AWMSI_i = \frac{\sum_{k \in i} \frac{SHPINDX_k * U}{TUA_i}}{NUP_i}$	Where *SHPINDX*$_k$ refers to the shape index of urban patch *k* inside city *i*, specifically, shape index is the ratio of the actual perimeter of a patch to the minimum perimeter possible for a	 low high

				maximally compact patch with the same size. UA_k refers to the area of urban patch k located in the city i.	
Isolation	Area-weighted Mean Nearest Neighbor Distance (meters)	AWMNND	$AWMNND_i = \frac{\sum_{k \in i} \frac{NNHG_k * UA_k}{TUA_i}}{NUP_i}$	Where $NNGH_k$ is the nearest neighbor distance of urban patch k in city i, UA_k refers to the area of urban patch k located in the city i	 low  high
Street Design Domain					
Street connectivity	Street density (m/km2)	SD	$SD_i = \frac{\sum_{j,k \in E_i} Length_{j,k}}{area_i}$	Where $area_i$ is the area in km^2 of city i and length(j,k) is the length in km of edge (j,k) in the set E_i of all the edges in the street network of city i.	 low  high
	Intersection density (nodes/km2)	ID	$ID_i = \frac{\lvert N_i \rvert}{area_i}$	Where $area_i$ is the area in km^2 of city i and $\lvert N_i \rvert$ is the amount of nodes in the street network.	 low  high
	Streets per node average (streets/nodes)	SNA	$SNA_i = \frac{\sum_{j \in N_i} \delta_j}{\lvert N_i \rvert}$	Where N_i is the set of nodes in the underlying street network of city i, $\lvert N_i \rvert$ is the size of N_i, and δ_j is the amount of edges connecting node j to other nodes in the network.	 low  high
Street length	Street length average (meters)	SLA	$SLA_i = \frac{\sum_{j,k \in E_i} Length_{j,k}}{\lvert E_i \rvert}$	Where E_i is the set of edges in the underlying street network of city i, $\lvert E_i \rvert$ is the size of E_i, and length(j,k) is the length in km of edge (j,k) in the set E_i.	 low  high
Directness	Circuity average	CA	NA	NA	 low  high
Population	Population	Population	NA	NA	NA

Based on prior literature, fragmentation of urban development was defined as the relative discontinuity of the urban landscape (31,32). A fragmented urban landscape has interstitial non-urban spaces, whereas a non-fragmented urban landscape is continuously developed. To characterize fragmentation, we used the following metrics: number of urban patches, patch density, area-weighted mean patch size and effective mesh size. An urban patch was defined as a contiguous area of urban development. Thus, higher numbers of patches reflect higher fragmentation. Patch density was defined as the number of urban patches divided by the total area of the geographic unit, with higher patch density reflecting higher fragmentation. Area-weighted mean patch size was defined as the weighted average of urban patch size, with weights being the area of each patch. Larger values reflect a larger size of urban development and low values reflect higher fragmentation. Effective mesh size was defined as the sum of squares of urban patch size, divided by the total area of the geographic unit with larger values reflecting a larger size of urban development and lower values reflecting higher fragmentation (31,32).

Shape is a measure of development compactness and complexity (31). We used the area-weighted mean shape index to assess shape. The shape index is a ratio of the actual perimeter of a patch to the minimum perimeter possible for a maximally compact patch of the same size. The shape index ranges from 1 to infinity. An index of 1 represents a maximally compact patch, while larger values reflect shapes that are less compact and more complex (31).

Isolation measures the relative spatial isolation of development relative to other development in the area. It is defined as the mean distance to the nearest urban patch within the geographic boundary. To assess isolation, we used the area-weighted mean nearest neighbor distance across patches. This metric was defined as the mean distance (in meters) to the nearest urban patch within the geographic boundary weighted by the area of each patch, with higher values reflecting higher levels of isolation (33).

The total urban area was defined as the total area of all 30m x 30m grid cells classified as urbanized inside the geographic boundary of the city.

Population

Population size measures the total number of residents within the administrative boundary, as reported in Worldpop for the year 2015 adjusting for United Nations' country-level population projections (34).

Street Design Domain

Within the street design domain, we selected five metrics that represent the subdomains of street connectivity, street length, and directness (**Table 1**). To calculate these metrics, we used each geographic unit extracted from the street network of OpenStreetMaps in 2017-2019. These metrics were calculated using the OSMNx software package (35,36).

To assess street connectivity, we used the following metrics: intersection density, street density, and the street per node average (**Table 1**). Intersection density is the number of intersections per km^2. Street density is the length of streets per km^2. Street per node average measures the mean number of streets meeting at each intersection of the street network. The higher the value of these metrics, the greater the degree of connectivity, thus enabling more direct travel between two points using existing streets (35).

Street length is a measure of the total average length of the street network between intersections. Small values represent a shorter average street network and larger values represent a longer average street length network (35).

Directness is a measure of the average ratio of network distances to straight-line distances from every node in the street network to every other node. We used circuity to assess directness (35). This indicator ranges from 1 to infinity, where a value of 1 denotes no circuity (highest directness), and higher values denote higher circuity (lower directness).

<u>Social determinants of health and air pollution outcome variables</u>

Socio-economic characteristics

To assess socioeconomic conditions, we included three variables: the proportion of households with piped water access inside the dwelling (water in dwelling), the proportion of households with more than three people per room (overcrowding per room), and the proportion of the population aged 25 or older who completed primary education or above (completed primary or higher). Socioeconomic indicators were obtained from the national census bureaus (27).

Traffic congestion

To measure the average traffic delay due to congestion, we used the urban travel delay index (UTDI) (37). The UTDI is a proxy measurement for congestion in the street network calculated as the percentage difference between the travel time during peak-hour traffic and the free-flow travel time. For each city, we calculated the travel times for 30 random origin-destination point pairs in the street network during seven-time points in the AM peak of a typical weekday and the midnight hours in June 2019. The Google Maps API was used for these calculations (38).

PM2.5 annual mean concentration (ug/m^3)

To measure air pollution concentration, we used the annual mean concentration of PM2.5 (ug/m^3) estimated from satellite measurements obtained from the Atmospheric Composition Analysis Group of the Dalhousie University Annual means of 2016 gridded format with each grid cell representing 0.01 degrees by 0.01 degrees (~ 1.1km by 1.1km) (27). The mean of all cells in the city was used to characterize air pollution for the city.

Cells that were only partly included in the city were apportioned based on the area of overlap.

<u>*Profile identification*</u>

Model-based Finite-Mixture Modeling

Finite mixture modeling (FMM) was used to identify the profiles of the 370 cities according to the landscape and street design domains. FMM is a statistical framework that enables identification of city profiles (or clusters of cities) to summarize the multidimensional nature of the city-level metrics of urban landscape and street design.(28). We used a formative approach to conduct the FMM under the following theoretical statements: 1) definition of the nature of the latent classes (preexistence of latent classes), 2) causality from metrics to classes (direction of causality between metrics and latent class) and 3) metrics define the class (characteristics of metrics used to define the latent class) (39). First, correlation among urban landscape indicators, street design, social determinants of health and air pollution were evaluated using a correlation matrix and the Pearson correlation coefficient. Second, we fitted a model for each domain (urban landscape and street design) specifying a different number of latent profiles to be extracted. Third, we assessed bivariate correlations between indicators of each domain. To select the number of latent profiles, we examined goodness-of-fit using the Bayesian Information Criteria (BIC) and classification using entropy (40). We used the elbow method with both indicators, using BIC as the stop criteria and assessing whether classes were meaningfully different using entropy, in order to improve the interpretability of the results. Fourth, we assigned cities to profiles based on their most likely profile membership (modal assignment) and used descriptive statistics to assess whether the profiles captured meaningful similarities and differences across cities. Finally, we assigned the labels and icons to each profile based on the percentile distribution of each indicator within the profiles. We used three category labels: 'low' when the 50^{th} percentile of the indicator of interest in profile *i* is lower than the 25^{th} percentile for the overall profiles indicators [$P_{i50}<P_{25}$], 'moderate' when the 50^{th} percentile of the indicator of interest in profile *i* is between the 25^{th} and the 75^{th} percentile for the overall profiles indicators [$P_{25} \leq P_{i50} \leq P_{75}$], and 'high' when the 50^{th} percentile of the indicator in profile *i* is higher than the 75^{th} percentile for the overall profiles indicators [$P_{i50}>P_{75}$]. The FMM models were fitted in R (41), using the FlexMix package (42) and the expectation maximization (EM) algorithm for standard error estimation.

To study associations of profiles with socioeconomic indicators, congestion and air pollution we fitted two-level linear mixed models (cities nested within countries) using the lme4 package (43), with a random intercept for each country. All models were adjusted by area and population (both $\log_{10}$ transformed).

Visualization of profiles

To support the exploration of the profiles, we created a visual analytics tool. The tool links geospatial data visualization units of profiles to descriptive statistics of indicators and profiles. We used open-source visualization libraries such as D3.js (44) and Vega-Lite (45) in JavaScript for running in the browser (https://salurbal.github.io/profiles/).

Results

Urban landscape indicators

Overall, urban landscape indicators varied between countries and cities (**Appendix 1; visualization tool)**. Within the subdomain of fragmentation, the number of urban patches (p50 [p25; p75]) (401.5 [250.5;740.0]) and patch density (0.29 [0.12;0.56]) varied significantly. The most fragmented country characterized by the highest mean number of urban patches and high patch density was Costa Rica (2,888 urban patches; 0.93 urban patches/km^2), and the country with lowest patches and patch density was Perú (173 urban patches; 0.14 urban patches/km^2). The city with the highest number of urban patches (7,549 urban patches) was Buenos Aires (Argentina) and the city with the highest patch density (2.50 urban patches/km^2) was Quetzaltenango (Guatemala). In contrast, the city with the lowest number of urban patches (31 urban patches) was Puno (Perú) and the lowest patch density (0.008 urban patches/km^2) was Antofagasta (Chile). Furthermore, the smallest area-weighted mean patch size showed a large variability (1880.2 [1082.4;3928.5]). The country with the lowest area-weighted mean patch size and effective mesh size, indicating small patches, was Nicaragua (734.7 km^2/urban patches; 17.5 km^2) while Costa Rica had the largest patches (17494.5 km^2/urban patches; 1941.2 km^2). The most fragmented city due to the lowest area-weighted mean patch size and effective mesh size (35.02 km^2/urban patches; 0.65 km^2) was Petropolis (Brazil). The city with the highest area-weighted mean patch size (132006.47 km^2/urban patches) was Buenos Aires (Argentina) and the highest effective mesh size (41125.55 km^2) was Sao Paulo (Brazil).

Within the subdomain of shape, the mean area-weighted mean shape index showed a large variability (4.98 [4.33;6.27]). The country with the highest mean area-weighted mean shape index, indicating a complex shape, was Costa Rica (12.01), and the country with the most compact shape was Nicaragua (3.99). The most complex city (13.26) was Buenos Aires (Argentina) and the most compact city (2.40) was Rio Gallegos (Argentina).

Within the subdomain of isolation, the highest mean area-weighted mean nearest neighbor distance showed a large variability (82.76 [72.28;102.83]). The country with the highest mean area-weighted mean nearest neighbor distance, indicating higher isolation, was Mexico (91.7 meters), and the less isolated country was Costa Rica (65.4 meters).

The city with the highest isolation (370.13 meters) was Quibdó (Colombia) and the city with the lowest isolation (62.48 meters) was Rio de Janeiro (Brazil).

Street design domain

Overall, street design indicators varied between countries and cities (**Appendix 1; visualization tool**). Within the subdomain of street connectivity, the street density (1137.4 [529.3;1956.9]) and intersection density (4.63 [2.02;9.07]) showed a large variability. The country with the highest street and intersection densities was Guatemala (4075.9 m/km^2; 20.42 intersections/km^2), and the country with the lowest street connectivity was Argentina (591.4 meters/km2; 1.73 intersections/km^2). The city with the highest intersection density (42.08 intersections/km^2) was Santiago (Chile) and the city with the highest street density (6742.7 m/km^2) was Sao Paulo (Brazil). The city with the lowest intersection density (0.11 intersections/km^2) and street density (25.3 m/km^2) was Quibdó (Colombia).

The indicator of street length average (134.7 [118.6 163.8]) showed a large variability. The country with the highest street length average was Argentina (164.9 m), and the country with the shortest streets was Guatemala (113.1 m). The city with the highest average street length (510.1 m) was Barreiras (Brazil) and the city with the shortest average street length (82.8 m) was Santiago (Chile).

Within the subdomain of directness, the circuity average (1.0646 [1.0470 1.0891]) showed a large variability. The country with the highest average circuity, indicating less direct streets was Costa Rica (1.12), and the country with the most direct streets was Perú (1.05). The city with the least direct streets (1.37) was Huaraz (Peru) and the city with the most direct streets (1.01) was Santa Rosa (Argentina).

Correlation among urban landscape and street design domains

We found that the highest positive Pearson correlation coefficient among metrics of urban landscape and street design domains was between street density and patch density (0.735, **Table 2**), indicating a positive correlation between high street connectivity and high fragmentation. The highest negative Pearson coefficient was between street density and area-weighted mean nearest neighbor distance (-0.441), indicating a negative correlation between street connectivity and isolation. Furthermore, in the subdomain of fragmentation, the number of urban patches and patch density were positively correlated with area-weighted mean patch size and effective mesh size. These findings indicate the co-existence of high fragmentation due to high patch density and the dominance of one or more large patches that increase mean patch sizes in some cities. One such example is San Jose (Costa Rica), characterized by high fragmentation due to its high patch density, but with large mean patch size due to a large patch of continuous development.

Table 2. Pearson correlation coefficients among urban landscape, street design domains, population metrics, social determinants of health and air pollution

		Fragmentation				Shape	Isolation	Street connectivity			Street length	Directness		Population metrics	Social determinants of health				Air pollution
		NUP	PD	EFS	AWMPS	AWMSI	AWMENND	ID	SD	SPNA	SLA	CA	TUA	POP	PHWPW	PHWM3P	PPA25WCP	UTDI	PM2.5 AMC
Fragmentation	NUP	1.00	0.88	0.27	0.90	0.95	0.64	-0.20	0.55	0.55	-0.02	-0.17	-0.15	0.95	0.10	-0.05	0.19	0.23	0.22
	PD		1.00	0.37	0.64	0.73	0.63	-0.18	0.43	0.47	-0.09	-0.08	-0.14	0.76	0.14	-0.10	0.18	0.15	0.15
	EFS			1.00	0.20	0.19	0.35	-0.38	0.63	0.74	-0.39	-0.24	-0.06	0.25	0.07	-0.09	-0.04	0.18	0.32
	AWMPS				1.00	0.96	0.49	-0.14	0.51	0.50	-0.01	-0.13	-0.08	0.93	0.06	-0.01	0.11	0.21	0.23
Shape	AWMSI					1.00	0.60	-0.18	0.53	0.50	0.03	-0.17	-0.14	0.94	0.08	-0.02	0.17	0.26	0.20
Isolation	AWMENND						1.00	-0.36	0.53	0.55	-0.11	-0.28	-0.13	0.59	0.14	-0.08	0.17	0.27	0.17
Street connectivity	ID							1.00	-0.41	-0.44	0.07	0.43	0.10	-0.18	-0.23	0.16	-0.14	-0.19	-0.20
	SD								1.00	0.97	-0.13	-0.44	-0.17	0.59	0.16	-0.09	0.09	0.36	0.31
	SPNA									1.00	-0.21	-0.36	-0.11	0.56	0.20	-0.14	0.03	0.28	0.33

Street length	SLA	1.00	0.02	-0.50	-0.05	0.07	-0.01	0.05	-0.21	-0.09
Directness	CA		1.00	0.29	-0.18	-0.01	-0.01	-0.12	-0.31	-0.15
Population metrics	TUA			1.00	-0.09	-0.01	0.00	-0.09	0.12	-0.16
	POP				1.00	0.06	-0.01	0.17	0.34	0.22
Social determinants of health	PHWPW					1.00	-0.74	-0.06	-0.12	-0.04
	PHWM3P						1.00	0.11	0.20	0.12
	PPA25WCP							1.00	0.44	0.13
	UTDI								1.00	0.07
Air pollution	PM2.5 AMC									1.00

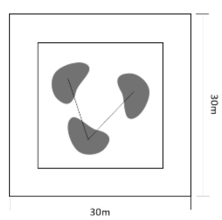
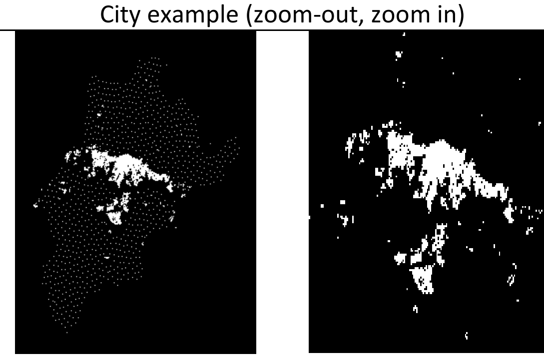
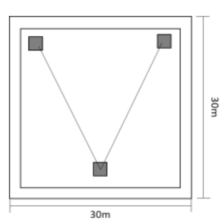
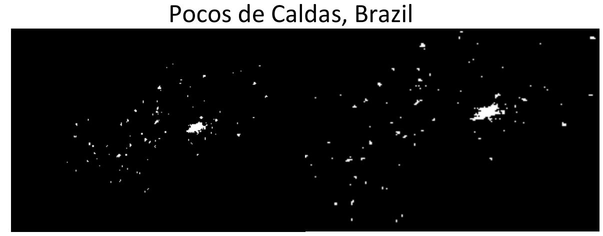
All Pearson correlation coefficients were significant at 5% of confidence level. NUP: Number of urban patches
PD: Patch density
EFS: Effective mesh size
AWMPS: Area weighted mean patch size
AWMSI: Area weighted mean shape index
AWMENND: Area weighted mean euclidean nearest neighbor distance
ID: Intersection density
SD: Street density
SPNA: Streets per node average
SLA: Street length average
CA: Circuity average
TUA: Total urban area
POP: Population
PHWPW: Proportion of households with piped water access
PHWM3P: Proportion of households with more than 3 people per bedroom
PPA25WCP: Proportion of the population aged 25 or older who completed primary of above
UTDI: Urban Travel Delay Index
PM2.5 AMC: PM2.5 annual mean concentration (ug/m3)

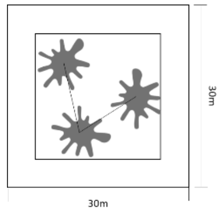
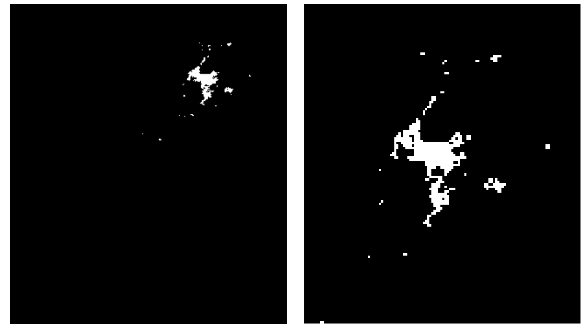
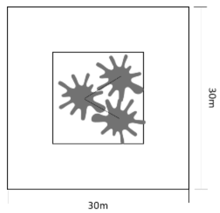
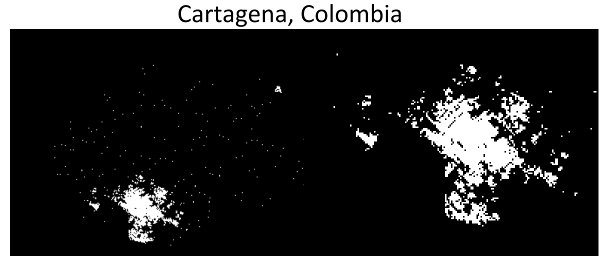
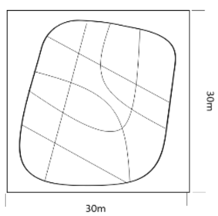
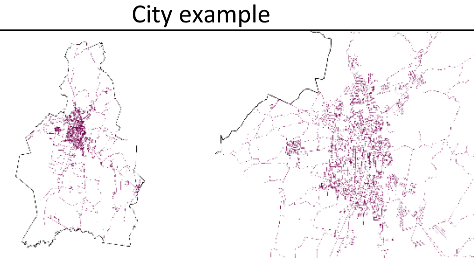
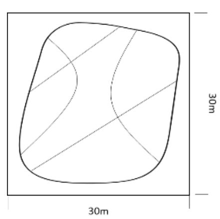
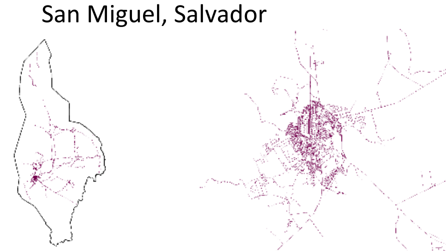
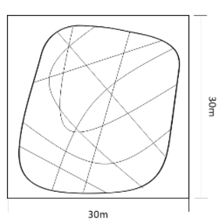
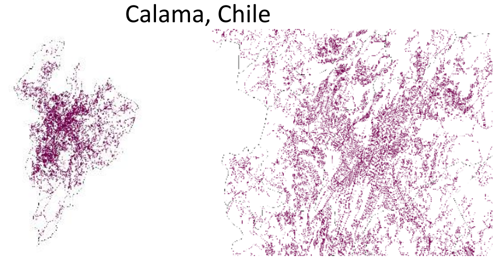
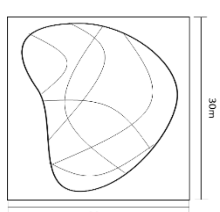
Profiles

Urban landscape profiles

The FMM yielded four profiles according to the BIC criteria (**Table 3**). The entropy criterion for dissolution was 0.92 indicating a high certainty in the classification (**Appendix 3 and 4**). The first profile contained 168 cities (45.4%) and was characterized by cities with moderate patch density ([P_{25}; P_{75}], [0.12; 0.56]), moderate area-weighted mean patch size (1082.4; 3928.5), irregular shape (4.33; 6.27) and moderate isolation (72.2; 102.8). We labeled this profile *proximate stones*. The second profile was characterized by cities with lower patch density ([<P_{25}], [<0.12]), lower area-weighted mean patch size (<1082.4), a compact shape (<4.33) and higher isolation ([>P_{75}], [>102.8]). This profile was labeled *scattered pixels* and included 91 cities (24.6%). The third profile was characterized by cities with a moderate patch density (0.12; 0.56), larger area-weighted mean patch size (>3928.5), complex shape (>6.27) and moderate isolation (72.2;102.8). This profile was labeled as *proximate inkblots* and included 90 cities *(*24.3%). The fourth profile was characterized by cities with a higher patch density (>0.56), higher area-weighted mean patch size (>3928.5), complex shape (>6.27) and lower isolation (<72.2). This profile was labeled as *contiguous large inkblots* and included 21 cities (5.7%). For specific information of profiles by country and cities see visualization tool (Appendix 2).

Table 3. Urban Landscape and Street Design profiles

Urban Landscape			
Label	Description	Caption	City example (zoom-out, zoom in)
Proximate stones	Cities with moderate patch density and moderate area weighted mean patch size, patches with irregular shape and moderate isolation.		 Pocos de Caldas, Brazil
Scattered pixels	Cities with lower patch density and lower area weighted mean patch size, patches with compact shape and higher isolation.		 Fresnillo, Mexico

Proximate inkblots	Cities with moderate patch density and higher area weighted mean patch size, patches with complex shape and moderate isolation.		 Cartagena, Colombia
Contiguous large inkblots	Cities with higher patch density and higher area weighted mean patch size, patches with complex shape and lower isolation.		 Buenos Aires, Argentina
		Street design	
Label	Description	Caption	City example
Semi-hyperbolic grid	Cities with moderate street connectivity, streets with moderate length and moderate directness streets.		 San Miguel, Salvador
Labyrinthine	Cities with low street connectivity, streets with moderate length and moderate directness streets.		 Calama, Chile
Spiderweb	Cities with higher street connectivity, shorter streets, and moderate directness streets.		 Guatemala City, Guatemala
Hyperbolic grid	Cities with moderate street connectivity, larger streets and lower directness.		 Huaraz, Peru

Street design profiles

The FMM yielded four profiles according to the BIC criteria (Table 3). The entropy criterion for dissolution was 0.88 indicating a high certainty in the classification (**Appendix 3 and 4**). The first profile was characterized by cities with moderate street connectivity due to moderate intersection density ([P_{25}; P_{75}], [2.01; 9.07]) and street density (529.3; 1956.9), streets with moderate length (118.6; 163.7) and moderately direct streets (1.0470; 1.0891). This profile was labeled *semi-hyperbolic grid* and included 130 cities (35.1%). The second profile was characterized by cities with low street connectivity due to low intersection density ([<P_{25}], [<2.01]) and street density (<529.3), streets with moderate length (118.6; 163.7) and streets with moderate directness (1.0470; 1.0891). This profile was labeled *labyrinthine* and included 110 cities (29.7%). The third profile was characterized by cities with higher street connectivity due to high intersection density ([>P_{75}], [>9.07]) and street density (>1956.9), shorter streets (<118.6) and streets moderately directed (1.0470; 1.0891). This profile was labeled as *the spiderweb* and included 80 cities (21.6%). The fourth profile was characterized by cities with moderate street connectivity due to moderate intersection (2.01; 9.07) and street density (529.3; 1956.9), long streets (>163.7) and streets with low directness (>1.0891). This profile was labeled *hyperbolic grid* and included 50 cities (13.5%). For specific information of profiles by country and cities see visualization tool (Appendix 2). .

<u>*Overlap among urban landscape and street design profiles*</u>

We found that the most frequent overlap between landscape and street design profiles was among *Labyrinthine* and *Scattered pixels* (53.44% of cities), characterizing cities with isolated patches and a less well-connected street design network. A substantive overlap between *Semi-hyperbolic grid* and the *Proximate stones* (39.26% of cities) profiles was also identified. The cities belonging to these two profiles were characterized by moderate connectivity and moderate fragmentation with irregular shape (**Table 4**).

Table 4. Overlap among urban landscape and street design profiles

	Urban Landscape profiles			
Street Design profiles	Contiguous large inkblots	Proximate stones	Scattered pixels	Proximate inkblots
Labyrinthine	0.00%	12.10%	53.40%	5.30%
Semi-hyperbolic grid	0.70%	39.30%	4.70%	18.90%
Spyderweb	24.70%	8.40%	0.00%	31.80%
Hyperbolic grid	0.00%	19.10%	8.50%	2.90%

Urban landscape and street design profiles by city population and density

Profiles differed by city population and population density (**Table 5**). Smaller and less dense cities were more likely to belong to the proximate stones and the labyrinthine profiles. In contrast, larger cities were more likely to belong to the contiguous large inkblots and the spiderweb profiles and whereas denser cities were more likely to belong to the proximate stones and the semi-hyperbolic grid profiles.

Table 5. Urban landscape and street design profiles classified by city population and density

		Urban Landscape							
	Number of cities	Proximate stones		Scattered pixels		Proximate inkblots		Contiguous large inkblots	
		N	Density	N	Density	N	Density	N	Density
Overall	370	168 (45.4%)	5925 [4833;8068]	91 (24.6%)	6971 [5084;10951]	90 (24.3%)	5873 [5029;7600]	21 (5.7%)	7274 [5963;9626]
[100k:250k)	170	94 (55.3%)	5249 [45378;7109]	71 (41.8%)	6278 [4977;10611]	5 (2.9%)	4636 [2720;6056]	0 (0.0%)	NA
[250k:500k)	95	60 (63.2%)	6664 [5449;8268]	18 (18.9%)	9106 [6632;13159]	17 (17.9%)	5439 [4826;5989]	0 (0.0%)	NA

[500k:1M)	57	13 (22.8%)	8136 [7480;11157]	2 (3.5%)	11095 [10062;12127]	42 (73.7%)	5621 [4872;6880]	0 (0.0%)	NA
[1M:5M)	41	1 (2.4%)	18688	0 (0.0%)	NA	26 (63.4%)	7702 [6460;12840]	14 (34.1%)	6162 [5498;7478]
[5M:20M]	7	0 (0.0%)	NA	0 (0.0%)	NA	0 (0.0%)	NA	7 (100.0%)	10710 [9515;13335]
P-value		<0.001	<0.001	<0.001	0.346	<0.001	0.026	<0.001	0.018

		Street Design							
	Number of cities	Semi-hyperbolic grid		Labyrinthine		Spiderweb		Hyperbolic grid	
		N	Density	N	Density	N	Density	N	Density
Overall	370	130 (35.1%)	5850 [5067;7926]	110 (29.7%)	5937 [4580;7944]	80 (21.6%)	6942 [5391;9774]	50 (13.5%)	7662 [5279;11691]
[100k:250k)	170	60 (35.3%)	5480 [4839;8076]	69 (40.6%)	5710 [4521;7320]	10 (5.9%)	5132 [4422;6915]	31 (18.2%)	7333 [4771;10159]
[250k:500k)	95	37 (38.9%)	6629 [5286;8259]	30 (31.6%)	6730 [5248;9466]	17 (17.9%)	5893 [5222;7901]	11 (11.6%)	7436 [6264;21326]
[500k:1M)	57	25 (43.9%)	5832 [5085;7177]	9 (15.8%)	4810 [4438;8042]	16 (28.1%)	5935 [5432;8255]	7 (12.3%)	8309 [7544;13363]
[1M:5M)	41	8 (19.5%)	6276 [5582;6830]	2 (4.9%)	6302 [5480;7124]	30 (73.2%)	7566 [6015;11593]	1 (2.4%)	18688
[5M:20M]	7	0 (0.0%)	NA	0 (0.0%)	NA	7 (100.0%)	10710 [9515;13335]	0 (0.0%)	NA
P-value		<0.001	0.554	<0.001	0.722	<0.001	0.012	<0.001	0.204

Associations of urban landscape and street design profiles with social determinants of health and air pollution indicators

We found that profiles characterized by moderate to higher street connectivity and moderate to low directness (*semi-hyperbolic grid*, *spiderweb,* and *hyperbolic grid*) were positively associated with more piped water access and negatively associated with overcrowding. Cities with moderate patch density, moderate to larger patch size, irregular to complex shape and moderate isolation (*proximate stones* and *proximate inkblots*) were positively associated with higher congestion. The *semi-hyperbolic grid* and *spiderweb* profiles were positively associated with higher annual mean concentration of PM2.5 (**Table 6**).

Table 6. Multilevel modeling of the associations between social determinants of health and air pollution indicators with urban landscape and street design profiles

Profiles	Urban Landscape (1)	Street Design (2)	(1) + (2)
Proportion of households with piped water access (N = 370)			
Total urban area (log10)*	**17.80 [9.35;26.25]**	**22.12 [14.09;30.15]**	**22.27 [13.59;30.94]**
Population (log10)*	**-14.57 [-22.49;-6.65]**	**-18.06 [-25.81;-10.32]**	**-17.60 [-25.61;-9.59]**
Scattered pixels	referent		referent
Contiguous large inkblots	3.85 [-4.25;11.96]		-1.89 [-10.70;6.91]
Proximate stones	**3.26 [0.56;5.95]**		-0.01 [-3.24;3.20]
Proximate inkblots	**4.27 [0.10;8.44]**		0.01 [-4.83;4.86]
labyrinthine		referent	referent
Semi-hyperbolic grid		**4.79 [2.29;7.28]**	**4.74 [1.72;7.75]**
Spiderweb		**5.12 [1.77;8.47]**	**5.21 [1.31;9.11]**
Hyperbolic grid		**6.21 [2.84;9.57]**	**6.22 [2.53;9.92]**
Proportion of households with more than 3 people per bedroom (N = 365)			
Total urban area (log10)*	**-3.70 [-6.07;-1.43]**	**-5.66 [-7.91;-3.42]**	**-5.08 [-7.50;-2.67]**
Population (log10)*	**3.87 [1.66;6.08]**	**5.07 [2.92;7.23]**	**4.87 [2.64;7.09]**
Scattered pixels	referent		referent
Contiguous large inkblots	**-2.46 [-4.71;-0.21]**		-0.78 [-3.21;1.64]
Proximate stones	**-1.37 [-2.11;-0.62]**		-0.53 [-1.42;0.35]
Proximate inkblots	**-2.04 [-3.19;-0.89]**		-0.90 [-2.23;0.42]
labyrinthine		referent	referent
Semi-hyperbolic grid		**-1.35 [-2.04;-0.67]**	**-1.04 [-1.86;-0.21]**
Spiderweb		**-1.93 [-2.85;-1.01]**	**-1.57 [-2.64;-0.50]**
Hyperbolic grid		**-2.24 [-3.16;-1.31]**	**-1.98 [-2.99;-0.96]**
Proportion of the population aged 25 or older who completed primary of above (N = 370)			
Total urban area (log10)*	**13.29 [9.10;17.47]**	**14.09 [10.00;18.17]**	**-14.03 [9.67;18.40]**
Population (log10)*	**-5.11 [-9.02;-1.20]**	**-6.66 [-10.58;-2.73]**	**-5.65 [-9.66;-1.63]**
Scattered pixels	referent		referent
Contiguous large inkblots	-2.28 [-6.25;1.68]		-3.18 [-7.57;1.19]
Proximate stones	0.74 [-0.56;2.06]		0.28 [-1.31;1.88]
Proximate inkblots	1.17 [-0.85;3.21]		0.55 [-1.85;2.95]
labyrinthine		referent	referent
Semi-hyperbolic grid		0.87 [-0.36;2.12]	0.59 [-0.90;2.08]
Spiderweb		0.88 [-0.79;2.56]	0.84 [-1.09;2.77]
Hyperbolic grid		1.19 [-0.49;2.87	1.06 [-0.76;2.89]
Urban Travel Delay Index (N = 370)			
Total urban area (log10)*	-4.49 [-9.96;0.98]	-2.28 [-7.69;3.13]	-5.25 [-10.97;0.46]
Population (log10)*	**14.69 [9.57;19.81]**	**13.30 [8.09;18.51]**	**15.10 [9.83;20.36]**

Scattered pixels	referent		referent
Contiguous large inkblots	1.66 [-3.54;6.86]		2.14 [-3.59;7.89]
Proximate stones	**2.71 [0.98;4.43]**		**3.23 [1.13;5.32]**
Proximate inkblots	**4.40 [1.73;7.06]**		**4.87 [1.72;8.02]**
labyrinthine		referent	referent
Semi-hyperbolic grid		1.09 [-0.56;2.75]	-0.82 [-2.78;1.13]
Spiderweb		1.69 [-0.53;3.91]	-0.22 [-2.75;2.31]
Hyperbolic grid		0.28 [-1.95;2.51]	-1.27 [-3.67;1.13]
PM2.5 annual mean concentration (ug/m3) (N = 370)			
Total urban area (log10)*	**5.26 [2.21;8.30]**	**6.81 [3.89;9.73]**	**6.38 [3.23;9.52]**
Population (log10)*	**-5.14 [-8.05;-2.23]**	**-5.95 [-8.81;-3.09]**	**-6.07 [-9.03;-3.11]**
Scattered pixels	referent		referent
Contiguous large inkblots	**4.79 [1.60;7.98]**		2.25 [-1.22;5.72]
Proximate stones	**1.80 [0.73;2.87]**		0.72 [-0.55;2.01]
Proximate inkblots	**2.03 [0.38;3.67]**		0.27 [-1.64;2.20]
labyrinthine		referent	referent
Semi-hyperbolic grid		**1.84 [0.84;2.84]**	**1.57 [0.37;2.77]**
Spiderweb		**2.98 [1.65;4.31]**	**2.66 [1.11;4.21]**
Hyperbolic grid		**1.37 [0.03;2.71]**	1.05 [-0.41;2.51]

All results report the estimated value and the 95% confidence interval in squared keys.

Visualization of profiles

The visualization tool (https://salurbal.github.io/profiles/) presents an interactive map illustrating the geographical distribution of the 370 cities. It shows a dashboard where users can select the profiles for urban landscape or street design, and then explore the distribution of cities within them.

Discussion

Our study characterizes the urban landscape and street design of 370 cities in Latin America, highlighting the heterogeneity and complexity of cities in the region. Overall, four profiles emerged in the urban landscape domain. The most common urban landscape profile was the *proximate stones* characterized by moderate fragmentation, moderate patch size, moderate isolation and irregular shape. This profile contains 168 cities and is home to 16.3% of the population that resides in all cities included in this study. The least common profile was the *contiguous large inkblots,* characterized by the largest and highest number of patches, and including all cities with more than 5 million people (47.8% of the population in 7 cities).

Similarly, four profiles emerged for the street design domain. The most common street design profile was the *semi-hyperbolic grid,* and home to 19.4% of the population living in 130 cities, characterizing cities with moderate connectivity, moderate street length, and moderate directness. The least common profile was the *hyperbolic grid* with 5.1% of the population living in 50 cities. This profile is characterized by a less directed street network.

The profiles were associated with social determinants of health and air pollution. Street design profiles were associated with socioeconomic conditions. The *semi-hyperbolic grid*, *spiderweb,* and *hyperbolic grid* profiles were associated with higher access to piped water and less overcrowding. The cities in these profiles exhibit higher socioeconomic conditions compared to the profile with less connectivity and moderate directness (*labyrinthine*). Likewise, the *semi-hyperbolic grid* and *spiderweb* profiles were associated with higher air pollution. Urban landscape profiles were associated with congestion. Specifically, the *proximate stones* and *proximate inkblots* profiles were associated with higher congestion.

The urban landscape profile characterizing the large cities, *contiguous large inkblots* characterized by the largest and highest number of patches is similar to what has been previously described in other multi-country studies that included only cities like Bogotá, Buenos Aires, Brasilia, Córdoba, Lima, and Santiago (18,21). Results of these studies have shown that Latin American cities are denser and less complex in shape than cities in North America and Western Europe (18), but less dense than cities in sub-Saharan Africa and South-East Asia (19). In fact, the density of Latin America is five times higher than the United States and three times higher than in Western Europe (46). In addition, previous studies have shown the heterogeneity of the fragmentation an density of Latin American cities(17,21). Overall, cities in South America, and the Caribbean show a weak trend towards a less-fragmented urban growth between 2000 and 2010 while Central American cities exhibits a small increase (17). In addition, large cities in Latin America exhibit a trend towards increasing fragmentation and decreasing density among cities (46). Our study adds to previous studies by identifying new profiles for medium and small size cities that differ from the *contiguous large inkblots* profiles of large capital cities.

Additionally, when comparing metrics of fragmentation in our study with a study in the US that included 3097 counties, Latin American cities on average are more fragmented. The cities of our study have, on average, 2 times more urban patches and higher variability compared to US counties (32) (660 (SD:834) vs. 324(SD:355)) (32). Compared to prior studies, our study has expanded the profiles of Latin American cities by including multiple cities with populations of one million or fewer inhabitants which are home to more than 100 million people (36.2%) and are mainly characterized by low to moderate patch density coexisting with moderate to high isolation. Future studies will need to longitudinally assess changes in these profiles in order to explain several economic and development dynamics of the region.

A previous study assessing street design metrics in 100 cities across 63 countries in 2017 including nine cities from eight Latin American countries showed that cities in Latin America have less directed streets than in the US and Canada but more directed streets than cities in Europe, Asia, Oceania, Middle East and Africa (47). Furthermore, a study of 919 cities in Latin America shows that cities have high street and intersection density (17). Our study adds to these previous studies by identifying street design profiles for large medium and small size cities.

In addition, previous studies in large and capital cities have shown that fragmentation and complexity are associated with more economic development (21), and higher income (18). Other studies including Latin American cities have shown that compact and well-connected cities exhibit higher levels of productivity measured by density of radiance from the nighttime imagery (17).Our results revealed expanded typologies of fragmentation based on number of patches, patch size and isolation and also showed different patterns in the relationship between fragmentation and economic development. Specifically, we found that the *scattered pixels* profile, which includes fragmentation due to smaller patches plus more isolation, was associated with poorer socioeconomic conditions. These differences could be due to differences in metrics (fragmentation measured with patch density and size), spatial-scales (larger cities vs. medium-smaller size cities), the diversity of the cities analyzed, or urbanization without economic growth which characterizes many cities in Latin America (19). This region has been characterized as having, in part, high levels of urbanization with low economic development and high informality (19). In Latin America, the patterns of urbanization including, high levels of density compared to other regions, are in part a reflection of recent accelerated urbanization since the middle of the 20th century coupled with high incidence of informal settlements that concentrate between 20-30% of the population (48). In terms of economic development, between 1913 to 2008, Latin American has had a significantly lower annual increase in their GDP compared to high income countries with similar levels of urbanization (81% in the USA and 73% in Europe) (19). Future studies will need to investigate the association of urban landscape with measures of housing informality and accessibility (housing, jobs, education, health) to better understand the mechanisms by which urban landscapes are associated with economic development and socioeconomic indicators in Latin American cities.

Previous studies conducted in the US and China assessing the association between air pollution and urban landscape metrics showed an increase in the number of days exceeding the air quality index for PM2.5 with higher fragmentation measured by number of patches and higher population density(32) and edge density (49) . The findings of our study are in part, consistent with these results but expand on the importance of the interaction among the number of patches, patch size and isolation and the street design profiles. The model including only the landscape profiles, showed that the p*roximate stones* profile, *contiguous large inkblots* and *proximate inkblots* profiles were associated with higher air pollution compared to the *scattered pixels* profile. After adjusting for the street design profiles, this pattern, although not significant it is preserved. Furthermore, the *semi-hyperbolic grid* and *spiderweb* profiles were associated with higher air pollution.

The rapid urbanization in Latin America has also likely led to longer travel times and higher levels of congestion (50). In fact, our results of the association between congestion with larger populations is consistent with previous work showing that congestion scales superlinearly with the city population(51). Furthermore, higher levels of fragmentation measured by patch density have been correlated with higher motorization rates that, in turn, could lead to more congestion costs (21,24). Our work further shows the association of congestion with profiles characterized by complex shapes, larger patches, and larger populations as compared to the *scattered pixels* profile.

Although we did not examine the determinants of each domain, each city's history, geography, and political context play an important role (17). It is helpful to consider the reasons why cities appear the way they do and consider what changes can be made to address issues of environment, population health, sustainability, and equity. Historical legacies are related to when the area was settled, how it was settled, and urban form indicators (52). Specifically Latin American cities that were Iberian colonies have more-regular urban layouts and denser street networks (17). Furthermore, for each city, the time when growth spurts occurred also may matter, as growth during the era of the automobile would have given rise to urban landscape and street design patterns that differ from those during earlier periods of growth. The physical geography of the area, including the terrain (e.g., cities built in the Andean mountains are less extensive, denser and with higher risks of natural disasters (17)), proximity to water bodies and arable lands, are also likely to impact the shape and characteristics of cities (53). Finally, policy factors (54), including incentives or disincentives to grow in certain areas (e.g., monocentric [Lima] vs. polycentric [Mexico city]), requirements about the characteristics of that growth (e.g., density, land uses, informal settlements with low integration with formal settlements), road infrastructure and transportation policies (e.g., concentration of public transport in central areas with limited access in the peripheries and suburban areas and road building), and economic development policies (55) are all likely to contribute to shape and reshape urban spaces in the Latin American region.

Our findings should be interpreted considering the following limitations. First, there is currently no “perfect” (i.e., highly accurate) spatial mapping product characterizing built environment at the national level and broad regional scales. However, our metrics are using some of the best available products, such as GUF representing higher-resolution urban footprints circa 2012, and we used a network research toolkit for modeling and analyzing large samples of street networks as nonplanar multigraphs (36). Second, there are differences in the measurement years of the metrics used in our paper and they represent a cross-sectional snapshot of the social determinants of health, the built environment and its configuration, which does not capture the changing nature of cities nor their differing rates of change. However, SALURBAL includes the largest available sample of cities from Latin America with comparable measurements. Third, we did not include variables reflecting mix-land use and informal settlements due to limitations of available data

Despite these limitations, our study represents an important step towards understanding built environment typologies across Latin American cities. Future work could capitalize on this effort to incorporate rates of change and spatio-temporal transformations of cities into such profiling. This approach would require the development of higher-accuracy urban land cover/land use maps at greater temporal frequencies, which remains an important need for many global cities. Finally, our finite mixture modeling approach could be limited by a lack of an absolute measure of fit that made us rely on relative measures such as goodness-of-fit, classification, adherence to hypothesis, and interpretability of profiles(28). However, FMM has several advantages over other clustering methods as it is a parametric modeling approach that could be potentially applied to cities outside of our sample to predict their underlying profiles. Moreover, it allows for the inclusion of control variables as predictors of profiles. This allows for profiles to be used as predictor variables in other studies of health outcomes (56).

To conclude, this study demonstrates the heterogeneity of urban landscape and street design profiles in Latin America. We show that the spatial configuration of the built environment plays an important role in determining urban typologies from the morphologic perspective and is also associated with measures of socio-economic well-being and environmental quality. The profiles identified in our paper can be useful to assess how urban environments influence health outcomes and environmental sustainability and to assess interventions that can alter the trajectory of cities towards more healthy, less unequal and sustainable outcomes. Our inclusion of a data dashboard allows researchers and practitioners to explore their cities in comparison to others in their country and elsewhere in the region.

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