

# Potential drivers of urban green space availability in Latin American cities

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Urban green spaces play a critical role in regulating air temperature, reducing air pollution and enhancing people's well being. Yet, existing data and research on potential drivers of urban green space availability in Latin America are limited. Here, focusing on 371 large cities in 11 countries in Latin America, we described the total and per capita variability of urban green space, its spatial configuration and green urban parks across the categories of cities' natural, built and socioeconomic environments. We tested the relative importance of geographic (climate) versus city-level built environment (population, population density, street intersection density) and socioeconomic (city gross domestic product per capita, unemployment, education) drivers in explaining urban green space availability. We found a high level of heterogeneity in green space quantity across cities and across categories of cities' environments. Relative to other city factors, climate zone had the largest influence in explaining the quantity of green space, whereas education, street intersection density and population density were the most important drivers of urban park availability. The significance of climate for green space availability, combined with the inequitable quantity of green space, indicates that cities have differing capacities to implement nature-based solutions for heat mitigation and health promotion.

Urban green space (UGS) is generally understood as natural or human-designed vegetated spaces such as urban parks, yards, gardens, forests, woodlands, green belts, some agricultural areas and many other forms<sup>1</sup>. What is labeled as 'green space' can encompass a wide range of vegetation quantity and quality and be configured in a variety of spatial patterns. These variations can impact human well being and ecosystem services provided by UGS<sup>2,3</sup>. UGS benefits range from various ecosystem services (for example, ambient temperature regulation,

air pollution reduction, stormwater drainage) to cultural services and human well being effects such as stress reduction, attention restoration and the promotion of social interactions and physical activity<sup>4,5</sup>. Despite the benefits, if neglected or mismanaged, UGS can become breeding grounds for pests and vectors of disease and engender fears of crime, posing a disservice to public health and safety<sup>6,7</sup>.

By definition, UGS is interwoven with the urban fabric, including its built, natural and socioeconomic elements<sup>8</sup>. Features of the natural

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environment such as topography, soils and climatic conditions shape the conditions for vegetation growth and vegetation types<sup>9–11</sup>. Built environment with its buildings and infrastructure layouts and land-use regulations determine the availability of land for UGS<sup>10</sup>. Rapid urbanization, population growth and urban sprawl can threaten existing UGS and limit opportunities for new UGS creation<sup>12,13</sup>. Urban sprawl has been associated with lower amounts of UGS<sup>14</sup>. However, other urbanization-related indicators such as population density have shown negative<sup>15–17</sup>, positive<sup>11</sup> or no association with the amount of UGS<sup>18</sup>. In addition, cities' socioeconomic characteristics often determine the demand, preferences and resources available for creating, preserving and maintaining UGS<sup>19</sup>, with wealthier cities usually having more abundant UGS<sup>17</sup>.

Understanding relationships between cities' characteristics and UGS can reveal important information about the determinants of UGS availability and distribution. Evaluating the relative importance of environmental factors, such as climate, which are difficult to alter, compared with the effects of policy-modifiable characteristics, such as cities' built environment, can help adjust expectations about the feasibility and potential impacts of changes in UGS and greening initiatives. Finally, knowledge about the role of environmental and socioeconomic characteristics associated with UGS can help identify underserved areas and social inequalities. Such information can facilitate progress towards the United Nations Sustainable Development Goal 11.7—'provide universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities'<sup>20</sup>.

Despite abundant research from the Global North and China, UGS is understudied in Latin America (LA) and other low- and middle-income countries, although this scarcity is changing<sup>21–25</sup>. A recent review identified high research output from Brazil, Argentina and Chile, although UGS research in these countries has predominantly focused on a few large cities such as São Paulo (Brazil), Curitiba (Brazil), Buenos Aires (Argentina) and Santiago (Chile)<sup>26</sup>. Few studies have focused on other LA countries<sup>26,27</sup>, underscoring a knowledge gap within the region.

As one of the most urbanized and biodiverse regions in the world, LA is a unique setting in terms of UGS research needs and opportunities. Over 80% of LA residents are urbanites, making it the second-highest urbanized region in the world after North America<sup>28</sup>. Latin America has urbanized rapidly since the 1960s, and during this period of fast urbanization, there was a lack of effective policies to manage the swift growth of cities (for example, policies to ensure that high-density areas are strategically located and well planned, offering livable, walkable environments with essential urban services and economic opportunities)<sup>26</sup>. Without these measures, urbanization has led to dramatic shifts in land use, including the clearing of urban green spaces to accommodate city growth<sup>26,27</sup>. Still, some LA cities (for example, Curitiba in Brazil) have implemented strategies to increase green areas<sup>26</sup>. However, in most cities in the region, UGS provision is less prioritized compared with the more basic urban infrastructure projects such as housing and sanitation<sup>26,27</sup>. Rapid urbanization has also fueled the rise of informal settlements on the outskirts of cities, characterized by widespread poverty, inadequate housing and limited access to basic services such as water, sewage and sanitation<sup>29</sup>. Residents in these areas often face heightened risks of eviction, disease and violence, and frequently suffer from both a lack of green space and its poor quality<sup>29</sup>. Finally, LA cities are also extremely biodiverse and located in tropical, temperate and arid climate zones. Therefore, compared with more researched cities in colder climates and higher-income contexts, they have different kinds of vegetation. Because the capacity of UGS to cool air and provide other ecosystem services may depend on the prevailing climate<sup>30,31</sup>, the ability of UGS to provide ecosystem and health benefits in LA may not necessarily be aligned with what has been observed in the Global North or Asia, where UGS is far more researched than in LA<sup>32</sup>.

In line with global-scale studies pointing at a socioeconomic gradient in UGS<sup>17</sup>, existing research indicates there is a shortage and unequal

distribution of urban green space in LA cities. Namely, neighborhoods, cities and individuals with high socioeconomic status generally have better access to and make more use of green space<sup>32–34</sup>. However, a recent large-scale study of 371 LA cities revealed a negative relationship between greenness and city socioeconomic status<sup>22</sup>. The full extent of these patterns in LA cities is not known because there has been no research to document them using a large representative sample of LA cities.

The overall goal of this study is to investigate the quantity, spatial distribution and potential factors influencing UGS in Latin America, with a focus on city-level analysis and comparisons across cities. The specific objectives of this study are: (1) to describe UGS quantity and spatial distribution in 371 large LA cities (>100 k residents) in 11 countries, (2) to examine the variability of UGS quantity and spatial distribution across cities' natural, built and socioeconomic characteristics, and (3) to assess the relative importance of the city's climatic zone compared with its built environment and social characteristics on UGS. Through the first objective, this research contributes new insights into the UGS availability and distribution in this unique and less-studied world region. The second and third objectives provide an understanding of potential underlying factors that can explain between-city patterns in UGS in LA.

## Results

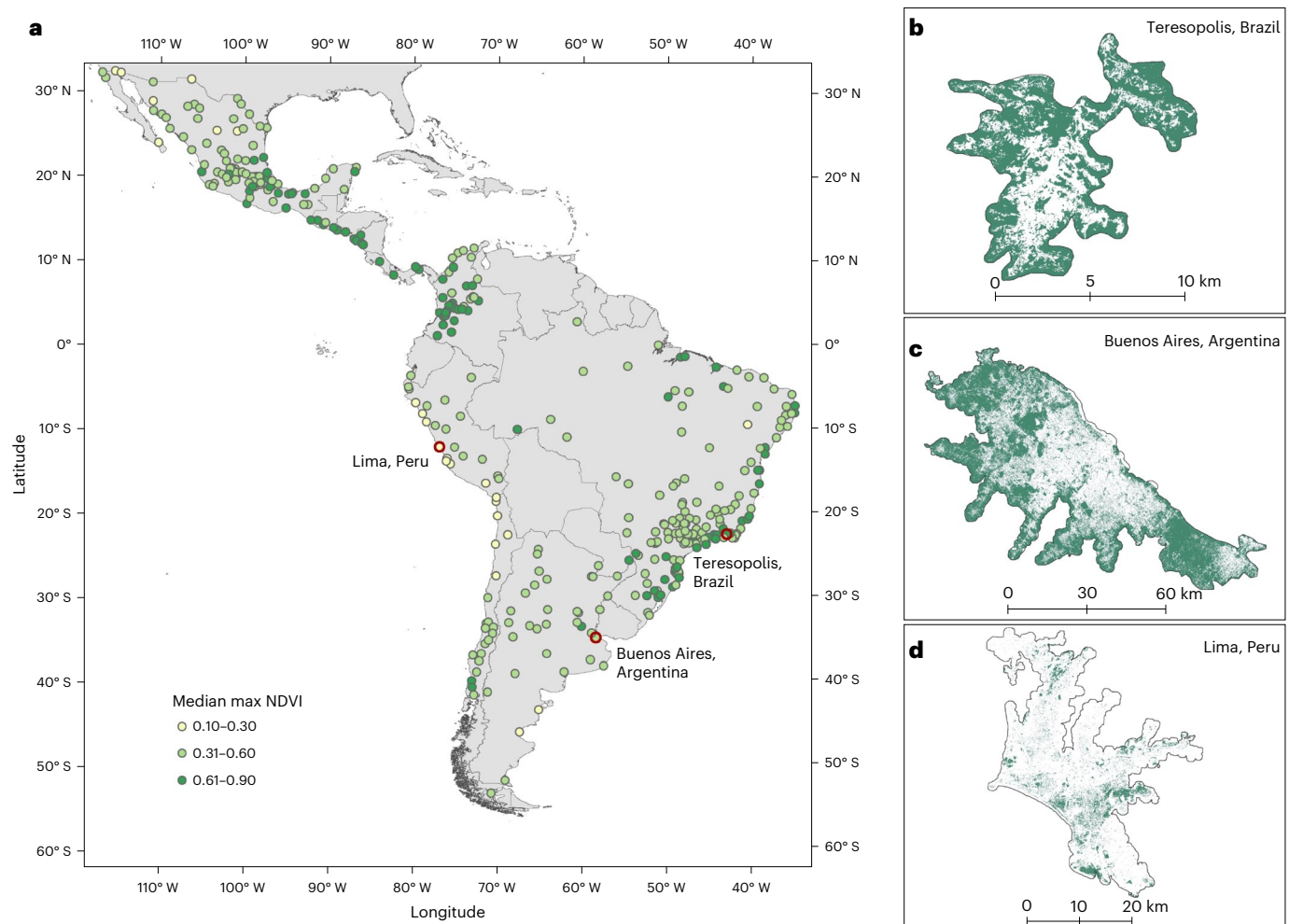
### Quantity and spatial distribution of UGS in 371 LA cities

We observed high variability in UGS characteristics across cities (Supplementary Tables 2 and 3). Greenness, measured by satellite-derived normalized difference vegetation index (NDVI), varied from 0.10 to 0.80, with a mean of 0.53. The range of green space coverage in cities was also large, ranging from 4% to 72%, with a mean of 41%. There was on average 123,220 m<sup>2</sup> of green space area per 1,000 residents. The average park area per 1,000 residents was 2,142 m<sup>2</sup>, which is orders of magnitude lower than green space area per capita. Figure 1 describes UGS in three large cities in the region with different levels of UGS quantity.

### Variability in green space characteristics by city environments

Indicators of UGS varied across cities' natural, built and socioeconomic environment (Table 1). Total and per capita amount of green space varied substantially across climate zones, with arid cities reporting lower NDVI, lower percent green space area and lower total green space area per capita than tropical or temperate cities. On average, the percentage of city area covered by green space in arid LA cities was 12–14% lower than in temperate and tropical cities. Arid cities in our sample were represented by hot ( $n = 55$  cities) and cold ( $n = 24$  cities) arid steppes and deserts, located throughout Mexico, Argentina and along the Pacific coast of Peru and Chile. Arid cities were also characterized by higher park availability compared with other climate zones. The green space landscape in arid cities was more fragmented (higher patch density), more isolated and less aggregated than in non-arid cities (Table 1). Several UGS indicators also varied by topography and coastal location, with higher NDVI, greater percent green space area and less fragmented green space observed in hillier cities, although flatter cities had more parks per capita.

As for the built environment, city area was negatively associated with NDVI whereas other UGS characteristics showed little variability by city area (Table 2). Green space area per capita varied by population and population density. Predictably, green space area per capita decreased in more populous and more densely populated cities. In addition, more densely populated cities had less of their area covered by green space and had less park availability in terms of park count and park area per capita than less dense cities. Finally, cities with high intersection density—a measure of street connectivity, which can reflect the accessibility of green space<sup>35</sup>—had less UGS overall (lower NDVI, lower percent green space area and lower green space area per capita). However, these cities had a higher density of green space patches and greater isolation of these patches but also had more urban parks per capita.



**Fig. 1 | Urban green space in large LA cities. a**, The median of annual maximum NDVI in 2017 for 371 cities in 11 LA countries obtained from the MODIS NDVI satellite imagery. **b–d**, The distribution of green space in Teresopolis (Brazil) (**b**), Buenos Aires (Argentina) (**c**) and Lima (Peru) (**d**)—their locations in Latin America

marked by red circles in **a**—according to the green space land-cover map from Ju et al.<sup>63</sup>. Each 30-m pixel of green space in **b–d** is depicted in green; non-green space areas are in white. An extended explanation of the figure is available in Supplementary Material 1.

We observed substantial variability in UGS across different characteristics of cities' socioeconomic environment (Table 3). For the most part, cities with higher levels of socioeconomic well-being had more abundant green space than their less socioeconomically advantaged counterparts. However, there appeared to be a nonlinear relationship between NDVI and gross domestic product (GDP) per capita and NDVI and unemployment, wherein cities with both high and low levels of these indicators had higher NDVI compared with the cities with moderate levels of those variables. UGS in socioeconomically advantaged cities also tended to be less fragmented and more clustered; the isolation of green space did not reveal a consistent pattern across cities' socioeconomic characteristics.

In summary, Tables 1–3 show that the greatest variability in the amount and configuration of green space and the availability of urban parks was observed by climate zone. Arid cities were characterized by lower amounts of green space, more fragmented and less aggregated green space, but higher availability of urban parks. Regarding the built environment, the highest levels of UGS variability were observed across population density and street intersection density. Cities with high levels of these indicators had less green space (measured by the percentage of green space area and green space area per capita). In cities with high street intersection density, the green space also tended to be more fragmented. Finally, cities with desirable socioeconomic environments tended to be greener, as measured by NDVI or percentage of green space area and had less fragmented and more aggregated green space.

There was also some evidence of a U-shaped relationship between NDVI and several socioeconomic indicators. These conclusions are supported by the adjusted multivariable associations reported in Supplementary Table 6 and by the sensitivity checks in Supplementary Tables 7 and 8 and Supplementary Fig. 3.

### The importance of city characteristics for UGS availability

The random forest regression explained 65% of variance in NDVI (root mean squared error (RMSE) = 0.08), 41% in percent green space area (RMSE = 9%) and 63% in green space area per capita (RMSE = 42,352 m<sup>2</sup> per 1,000 persons). These results (Fig. 2) also showed that climate zone accounted for 54%, 43% and 28% of all variable importance in explaining NDVI, % green space area and green space area per capita, respectively. As explained in Methods, variable importance in a random forest is determined by measuring the decrease in model accuracy after randomly permuting the values of each variable. Variables that cause a larger decrease in accuracy when their values are permuted are deemed more important for the model's predictions<sup>36</sup>. Other important variables for the quantity-related metrics were street intersection density, education and GDP per capita. The relative importance of climate zone was much smaller for the urban park metrics—17% and 8%, respectively, for the number of parks per capita and park area per capita. Education, population density and street intersection density had the highest importance for the park metrics.



**Table 1 | Description of city green space by city natural characteristics<sup>§</sup>**

Indicators of quantity of green space				Indicators of spatial configuration of green space					Urban park metrics							
	Greenness (NDVI)	P <sup>1</sup>	% Green space area	P	Green space area per capita (m <sup>2</sup> per 1,000 residents)	P	Patch density (number of patches per ha)	P	Isolation (m)	P	Aggregation	P	Number of parks per capita (number of parks per 1,000 residents)	P	Park area per capita (m <sup>2</sup> per 1,000 residents)	P
Natural environment																
Climate zone <sup>2</sup>	Arid (N=79 cities)	0.36 (0.13)	30.74 (13.49)		107,522 (68,817)		49.42 (18.31)		3715 (7.64)		0.80 (0.06)		0.43 (0.30)		2,640 (1,494)	
	Temperate (N=125)	0.57 (0.08)	44.87 (8.55)	<0.001	158,613 (77,921)	<0.001	37.69 (14.86)	<0.001	35.61 (4.86)	0.0049	0.83 (0.04)	<0.001	0.33 (0.20)	<0.001	2,308 (1,433)	<0.001
	Tropical (N=166)	0.59 (0.08)	42.93 (8.19)		104,578 (51,046)		46.74 (19.07)		34.69 (4.63)		0.82 (0.04)		0.25 (0.19)		1,782 (1,444)	
Topography/terrain	Flat (N=137)	0.50 (0.13)	38.42 (11.21)	<0.001	121,135 (64,346)	0.70	47.27 (18.23)	0.014	35.87 (6.19)	0.36	0.34 (0.25)	0.18	0.34 (0.25)	0.19	2,341 (1,493)	0.05
	Hilly (N=234)	0.55 (0.13)	42.4 (10.76)		124,440 (72,654)		42.53 (17.94)		35.33 (5.12)		0.31 (0.22)		0.31 (0.22)		2,025 (1,473)	
Coastal	Inland (N=300)	0.54 (0.12)	41.58 (10.43)	0.018	126,348 (67,591)	0.06	44.64 (18.32)	0.44	35.06 (5.27)	<0.001	0.82 (0.05)	0.29	0.32 (0.23)	0.87	2,244 (1,527)	0.006
	Coastal (N=71)	0.51 (0.16)	38.19 (13.22)		110,002 (76,776)		42.76 (17.56)		37.51 (6.2)		0.83 (0.06)		0.32 (0.24)		1,709 (1,222)	

<sup>§</sup>The values shown are means (and standard deviations in parentheses) for each category of city variables (low/small, medium and high/large) are based on sample-wide tertiles for each variable unless noted otherwise. Detailed definitions of the natural, built and socioeconomic indicators can be found in Extended Data Table 1. Definitions of the green space variables are in Extended Data Table 2. <sup>1</sup>P is the P value from the ANOVA test of differences between groups means. A two-sided post-hoc multi-comparison Tukey's honestly significant difference (HSD) test was performed on the ANOVA to identify which subgroup means showed statistically significant differences<sup>45</sup>. The P value from Tukey's HSD accounts for multiple comparisons within the categories of each city indicator and determines whether there is a statistically significant difference in the means of each green space variable across the categories of a city indicator. Grey shading denotes city indicators for whose categories we observe statistically significant differences in the means of green space variables. <sup>2</sup>The sample contained one polar city (Puno), which was excluded from the climate stratification.

## Discussion

### UGS and cities' natural environment

Our study revealed considerable heterogeneity in UGS characteristics across 371 cities in 11 LA countries. Climate zone was responsible for the largest differences in green space characteristics compared with other city factors, with arid cities characterized by lower green space amount, more fragmented and less aggregated green space, but higher urban park availability compared with temperate and tropical cities (Tables 1–3). Climate puts fundamental constraints on plant physiology and choices of the 'locally appropriate' vegetation in landscaping. Even though landscaping in cities may often use global horticultural market options (for example, turf grasses, boxwoods), local vegetation adapted to local climate is still likely to be present especially in urban forests that are remnants of historical forests<sup>8</sup>. Arid vegetation may be naturally sparser due to resource limitations and compact growth habits and less spectrally bright green due to plant investments in protective tissues to reflect excessive solar radiation and deter predators, all of which may impact NDVI<sup>37</sup>.

Green space in arid cities was, on average, more fragmented and less aggregated than in other climate zones. Therefore, the UGS ecosystem services in LA arid cities may differ from those in non-arid cities, even at similar levels of UGS quantity<sup>2</sup>. Evidence from the same cities included in our analysis has shown that (1) higher NDVI in arid cities—but not tropical or temperate—may have a small protective effect against heat-related mortality and (2) evenly distributed (as opposed to highly clustered) green spaces in arid cities have little impact on heat-related mortality<sup>3</sup>. These findings warrant more attention to the regional green space context of LA and suggest considering its climate when evaluating UGS-health associations. Future research may benefit from a more nuanced approach considering ecosystem disservices (allergens from tree pollen<sup>38</sup>, thermal comfort in the tropics<sup>39</sup>, perceptions of crime near large parks<sup>7</sup> and so on), some of which can be unique to LA due to its climates and high urbanization<sup>40</sup>.

Despite having the least amount of vegetated green space, arid cities had the highest number of parks per capita (Table 1). It might be that in the absence of naturally available vegetation, arid cities purposefully invest in green urban parks to create recreational spaces. We speculate this may happen because native vegetation of these arid cities, such as shrubs, succulents and cacti, is not as conducive to typical recreational usages, for example, sports activities that require lawns. In other words, even if natural vegetation is widely available, its properties may not be aligned with recreational uses.

Several UGS indicators also varied by topography: hillier cities had more vegetation-based UGS that was also less fragmented, whereas flatter cities had more parks per capita. This can be attributed to the steep terrain in hillier cities, which is often inaccessible and thus undeveloped<sup>10</sup>. Abundant vegetation in hillier cities, as observed in our study, may provide protection from floods<sup>26</sup>. This is particularly important in LA cities, where informal developments often encroach on the natural vegetation in hilly outskirts, thereby increasing the risk of natural disasters among vulnerable populations<sup>26,40</sup>. Future research may benefit from examining intra-city variations in UGS by topography.

### UGS and cities' built environment and urban form

Larger cities by area had less vegetation-based UGS (Table 2). As cities grow, the demand for space increases, so it is more difficult to protect open space and preserve UGS<sup>41</sup>. Indeed, other work examining how green space quantity scales with city size in Southeast Asia<sup>11,16</sup> has found that UGS scales sublinearly, meaning that UGS increases more slowly than city size. Whereas some studies show negative correlations between city size and UGS<sup>6,11,16</sup>, counter-evidence also exists<sup>15</sup>. Recent global findings suggest that socioeconomic factors modify this relationship: an increase in city size is associated with

**Table 2 | Description of city green space by city built environment<sup>a</sup>**

	Indicators of quantity of green space				Indicators of spatial configuration of green space				Urban park metrics							
	Greenness (NDVI)	P <sup>i</sup>	% Green space area	P	Green space area per capita (m <sup>2</sup> per 1,000 residents)	P	Patch density (number of patches per ha)	P	Isolation (m)	P	Aggregation	P	Number of parks per capita (number of parks per 1,000 residents)	P	Park area per capita (m <sup>2</sup> per 1,000 residents)	P
Built environment and urban form																
City area	Small <sup>2</sup>	0.56 (0.14)		41.21 (11.35)		113,874 (71,630)		41.72 (18.76)		36.45 (6.24)		0.82 (0.05)		0.3 (0.23)		1,739 (1,410)
	Medium	0.52 (0.12)	0.034	39.41 (11.65)	0.14	134,521 (74,771)	0.01	47.19 (18.49)	0.06	35.15 (5.14)	0.07	0.82 (0.05)	0.15	0.32 (0.21)	0.50	2,297 (1,629)
	Large	0.51 (0.12)		42.16 (10.09)		121,356 (60,742)		43.96 (16.94)		34.97 (5.08)		0.83 (0.04)		0.33 (0.25)		2,391 (1,331)
City population	Small	0.56 (0.12)		41.92 (10.19)		146,759 (75,348)		43.79 (18.96)		35.3 (5.66)		0.82 (0.05)		0.34 (0.23)		2,260.92 (1,703)
	Medium	0.53 (0.14)	0.003	39.43 (12.08)	0.21	121,397 (68,113)	<0.001	44.37 (18.1)	0.95	36.14 (5.85)	0.40	0.82 (0.06)	0.08	0.32 (0.23)	0.32	2,204.38 (1,525)
	Large	0.51 (0.13)		41.06 (10.99)		101,488 (57,165)		44.46 (17.79)		35.32 (5.13)		0.83 (0.04)		0.31 (0.23)		2,027.36 (1,182)
Population density	Low	0.51 (0.12)		40.59 (10.87)		176,906 (65,509)		46.44 (18.95)		34.89 (5.24)		0.82 (0.05)		0.40 (0.25)		3,107 (1,627)
	Medium	0.54 (0.11)	0.047	43.38 (9.24)	0.024	125,874 (45,254)	<0.001	44.32 (16.97)	0.10	34.68 (4.93)	0.002	0.82 (0.04)	0.39	0.31 (0.21)	<0.001	2,090 (1,224)
	High	0.54 (0.15)		38.43 (12.56)		66,901 (46,389)		41.87 (18.61)		37.2 (6.1)		0.83 (0.05)		0.26 (0.20)		1,296 (920)
Street intersection density	Low	0.59 (0.09)		46.53 (8.5)		161,190 (75,779)		41.28 (16.6)		34.00 (4.46)		0.82 (0.04)		0.25 (0.18)		1,958 (1,483)
	Medium	0.53 (0.11)	<0.001	40.75 (10.52)	<0.001	124,776 (56,116)	<0.001	48.06 (18.39)	0.011	34.62 (4.86)	<0.001	0.81 (0.05)	0.03	0.32 (0.21)	<0.001	2,288 (1,541)
	High	0.47 (0.15)		35.53 (11.24)		83,705 (51,857)		43.54 (18.92)		37.96 (6.31)		0.83 (0.05)		0.38 (0.27)		2,180 (1,425)

<sup>a</sup>The values shown are means (and standard deviations in parentheses) of green space variables for each category of city indicators. Categories of city variables (low/small, medium and high/large) are based on sample-wide tertiles for each variable unless noted otherwise. Detailed definitions of the natural, built and socioeconomic indicators can be found in Extended Data Table 1. Definitions of the green space variables are in Extended Data Table 2. <sup>i</sup>P is the P value from the ANOVA test of differences between groups means. A two-sided post-hoc multi-comparison Tukey's HSD test was performed on the ANOVA to identify which subgroup means showed statistically significant differences<sup>45</sup>. The P value from Tukey's HSD accounts for multiple comparisons within the categories of each city indicator and determines whether there is a statistically significant difference in the means of each green space variable across the categories of a city indicator. Grey shading denotes city indicators for whose categories we observe statistically significant differences in the means of green space variables. <sup>b</sup>The categories of small/low, medium and high/large were based on tertiles, so sample size for each category is accordingly 1/3 of the total sample size.

more UGS in high-income cities but with less UGS in low-income cities<sup>42</sup>. A similar analysis of our data (not reported) did not reveal such interactions. The negative relationship between city area and UGS quantity in LA cities is most likely a consequence of rapid urbanization, where green spaces on the city peripheries had to give way to urban sprawl<sup>26</sup>. As a result, there might be particularly little UGS in LA's informal settlements, which are located on the cities' outskirts<sup>29</sup>. Whereas we did not have data on UGS availability in the informal settlements, future research should explore this in detail to address the environmental equity needs of the vulnerable population residing there.

LA cities have notably high levels of street intersection density compared with other world regions<sup>43</sup>. Global North studies often link intersection density with desirable health outcomes, such as increased physical activity<sup>44</sup> and healthy weight<sup>45</sup>. However, in LA cities higher intersection density was linked with several environmental and human health risks, such as higher concentrations of particulate matter and increased risk for hypertension<sup>46</sup>, body mass index and obesity<sup>47</sup>. Whereas our study did not include health data, future research can benefit from exploring the combined health effects of intersection density and UGS in LA cities.

Cities with higher population and street intersection densities in our sample had fewer and more isolated vegetation-based UGS (Table 2). Street intersection density reflects a city's connectivity and enhances the accessibility of green spaces<sup>35</sup>. These results thus suggest that green space availability (as assessed here by UGS metrics) does not always coincide with its accessibility (as indicated by urban intersection density). Whereas these findings may seem somewhat circular (higher population density inevitably decreases the amount of resources per person), when considered alongside the findings on intersection density, they highlight the challenge of achieving rapid urbanization without sacrificing green space availability.

**UGS and cities' socioeconomic environment**

Finally, there is substantial variability in UGS by cities' socioeconomic characteristics. Positive associations between socioeconomic well being and greenness have been observed in LA cities at the neighborhood level<sup>48</sup>. This gradient was also observed in a recent global city-level study, but LA cities comprised only 24 of the 159 cities included<sup>17</sup>. However, other studies—both city- and sub-city level—reported opposite associations<sup>22,49–51</sup>. Our findings for NDVI, percent green space area and the per capita metrics (parks and green space area) also suggest a socioeconomic gradient in UGS. However, we also find that cities with both high and low levels of GDP per capita and unemployment are greener (have higher NDVI) compared with cities with moderate levels of those variables, signifying a potential nonlinear relationship. Ju et al.<sup>22</sup> showed that higher GDP per capita in the same 371 LA cities was associated with lower NDVI both at city and sub-city levels, but higher GDP per capita was associated with a faster greening rate during 2000–2015. Our results based on a linear regression agree with those of Ju et al.<sup>22</sup>. These findings and other recent evidence<sup>52,53</sup> challenge a common notion that socioeconomically disadvantaged cities have less green space—the so-called deprivation amplification hypothesis<sup>22,54</sup>.

High amounts of UGS in socioeconomically disadvantaged cities, as found in our study, are not necessarily a positive phenomenon given the ecosystem disservices of poorly maintained green space<sup>6</sup>. High greenness in high-GDP cities could reflect purposeful investment in urban parks, whereas in lower-GDP cities, high levels or greenness can be attributed to underdeveloped urban areas<sup>55</sup>. This explanation is partially supported by our findings linking higher urban parks per capita with higher GDP per capita (Table 3). We also find that green space in socioeconomically advantaged cities tends to be less fragmented and more clustered. To the extent

**Table 3 | Description of city green space by city socioeconomic environment<sup>a</sup>**

	Indicators of quantity of green space				Indicators of spatial configuration of green space				C. Urban park metrics							
	Greenness (NDVI)	P <sup>1</sup>	% Green space area	P	Green space area per capita (m <sup>2</sup> per 1,000 residents)	P	Patch density (number of patches per ha)	P	Isolation (m)	P	Aggregation	P	Number of parks per capita (number of parks per 1,000 residents)	P	Park area per capita (m <sup>2</sup> per 1,000 residents)	P
Socioeconomic environment																
GDP per capita	Low <sup>2</sup>	0.56 (0.10)	39.78 (9.75)		90,683 (52,395)		47.3 (18.61)		35.11 (5.38)		0.82 (0.05)		0.22 (0.15)		1.556 (1.125)	
	Medium	0.50 (0.14)	39.29 (11.39)	0.0021	110,963 (51,256)	<0.001	46.39 (18.58)	0.0005	35.53 (5.75)	0.49	0.82 (0.05)	0.0048	0.36 (0.28)	<0.001	2,247 (1,480)	<0.001
	High	0.54 (0.14)	43.84 (11.54)		169,327 (77,484)		38.99 (16.15)		35.95 (5.49)		0.83 (0.05)		0.38 (0.21)		2,632 (1,601)	
Unemployment	Low	0.52 (0.14)	41.64 (11.99)		133,784 (69,096)		46.88 (17.06)		34.31 (5.19)		0.81 (0.04)		0.30 (0.23)		2,216 (1,507)	
	Medium	0.50 (0.14)	39.9 (11.97)	0.42	141,723 (74,536)	<0.001	42.97 (18.94)	0.15	36.61 (6.74)	0.0041	0.82 (0.06)	0.0039	0.41 (0.25)	<0.001	2,708 (1,506)	<0.001
	High	0.57 (0.10)	41.36 (9.04)		94,540 (55,253)		42.98 (18.4)		35.69 (4.21)		0.83 (0.04)		0.25 (0.18)		1,505 (1,185)	
Education	Low	0.53 (0.14)	41.47 (11.72)		132,676 (67,421)		48.86 (17.75)		33.56 (4.91)		0.8 (0.05)		0.28 (0.25)		2,034 (1,501)	
	Medium	0.54 (0.09)	43.04 (8.62)	0.0038	147,453 (62,328)	<0.001	45.47 (17.6)	0.00002	34.57 (4.43)	<0.001	0.82 (0.05)	<0.001	0.33 (0.18)	0.05	2,565 (1,576)	0.0003
	High	0.52 (0.15)	38.31 (12.11)		89,725 (66,165)		38.51 (17.74)		38.44 (5.95)		0.84 (0.05)		0.35 (0.25)		1,830 (1,279)	

<sup>a</sup>The values shown are means (and standard deviations in parentheses) of green space variables for each category of city indicators. Categories of city variables (low/small, medium and high/large) are based on sample-wide tertiles for each variable unless noted otherwise. Detailed definitions of the natural, built and socioeconomic indicators can be found in Extended Data Table 1. Definitions of the green space variables are in Extended Data Table 2. <sup>1</sup>P is the P value from the ANOVA test of differences between groups means. A two-sided post-hoc multi-comparison Tukey's HSD test was performed on the ANOVA to identify which subgroup means showed statistically significant differences<sup>45</sup>. The P value from Tukey's HSD accounts for multiple comparisons within the categories of each city indicator and determines whether there is a statistically significant difference in the means of each green space variable across the categories of a city indicator. Grey shading denotes city indicators for whose categories we observe statistically significant differences in the means of green space variables. <sup>2</sup>The categories of small/low, medium and large/high were based on tertiles, so sample size for each category is accordingly 1/3 of the total sample size.

that high levels of green space patch density may indicate an equitable green space distribution<sup>56</sup>, this finding points to potential within-city inequities in UGS distribution.

### The importance of city characteristics for UGS availability

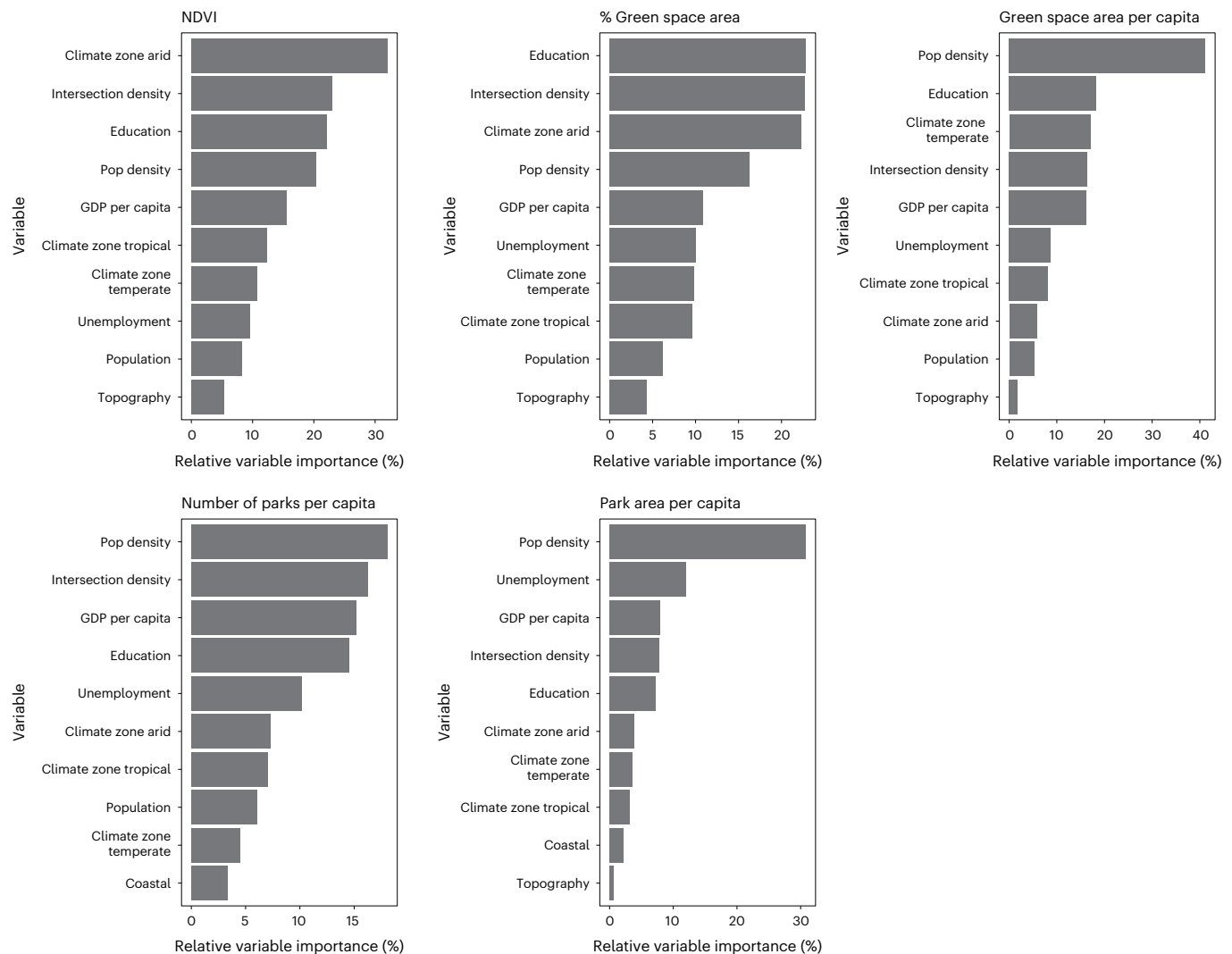
Climate zone—and especially being in an arid climate—had the highest relative importance for explaining variability in the two quantity UGS metrics (NDVI and % green space area), compared with the built and socioeconomic environment variables (Fig. 2). The importance of climate for UGS quantity aligns with findings from a recent global study, which showed that precipitation and temperature were the most determinative features for green space quantity, compared with socioeconomic and built environment features<sup>17</sup>. The paramount importance of climate for UGS quantity (as measured by NDVI, % green space area and green space area per capita), coupled with projected changes in temperature and rainfall variability in LA<sup>57</sup>, suggests that nature-based solutions to provide cooling and shade may be challenged by these climatic changes. This may be particularly true in hot arid cities in Latin America where the cooling effect of UGS is most needed. Whereas the characteristics of the built and socioeconomic environment matter less than climate for UGS quantity in LA, their relative importance nevertheless suggests that changes to UGS are possible if appropriate greening policies are adopted<sup>17</sup>.

In contrast to quantity-based UGS metrics, urban park availability was less constrained by climate and potentially more driven by residents' demand as exemplified by the high relative importance of socioeconomic characteristics (Fig. 2). Therefore, compared with the quantity-based UGS metrics, urban park metrics more directly reflect the outcomes of urban planning and land-use changes. As we mention earlier, we speculate that arid cities may purposefully create parks because their native vegetation, such as shrubs, succulents and cacti, is less suitable for recreational use.

### Limitations and strengths

Several limitations of this study should be mentioned. First, our UGS characteristics did not reflect specific vegetation types, which could provide a deeper understanding of potential social and ecological (dis)services. Second, the temporal alignment between the green space and socioeconomic data was not perfect: UGS data were from 2017 and urban parks from 2020, whereas the years of socioeconomic datasets varied by country, with 2005 the earliest year (for Guatemala). A temporal trend in NDVI from 2005–2017 (Supplementary Fig. 4)—which covers a time period longer than the misalignment period for most countries—shows that changes in NDVI were slow (interquartile range of NDVI change between 2005 and 2017 across all the cities is 0.009–0.062, with the mean increase in NDVI of 0.034). Because NDVI is highly correlated with % green space (Supplementary Fig. 1), we assume that changes in the UGS metrics derived from a land-cover map have also been slow. Therefore, the conclusions for NDVI and land-cover map-based UGS metrics should be minimally affected by the temporal misalignment. The misalignment between the time period of park data and socioeconomic variables is a limitation, and future research could investigate the temporal trends in urban park availability in the region. Third, there was a slight spatial mismatch between the scale of the units used for the analysis and the units used for measuring the socioeconomic variables. The latter were available for cities' official administrative boundaries, whereas the first were assessed for cities' urban extents. Fourth, the park data may be subject to geographical bias, similar to data derived from other geotagging-based platforms. That bias is probably more substantial for units of analysis smaller than city<sup>58</sup> and therefore should not invalidate our results. Finally, the goal of this study was to create a region-wide understanding of green space availability at city level and describe UGS according to cities' characteristics. Therefore, our findings do not easily generalize to smaller, within-city scales,





**Fig. 2 | Relative importance of the natural, built and socioeconomic environment variables for the availability of urban green space and urban parks in LA cities.** Bar graphs show the relative importance of the natural,

built and socioeconomic environment variables for the availability of urban green space and urban parks in LA cities. Measures of variable importance were obtained from the random forest regressions described in Methods.

which would be more appropriate for identifying UGS inequalities and accessibility. Despite these limitations, this study is the first large-scale attempt to describe UGS in LA and how it varies by cities' natural, built and socioeconomic environments. The study combines data from satellite imagery, land-cover map and web-mining data techniques to provide extensive information on UGS and its potential drivers in 371 LA cities, which is representative of the region and its diverse natural and socioeconomic conditions.

### Conclusions and practical implications

Several practical implications can be drawn from this study. Our findings suggest that overall, environmental conditions, such as climate zone, predetermine how much green space may be naturally available in a city. However, other parameters, such as UGS distribution within a city, and particularly urban park availability, are likely to be determined by urban planning policies.

From a planetary health perspective, large discrepancies in green space in the region may imply that cities differ in their capacity to adopt greening as a heat-mitigation and health-promotion strategy. This may be particularly challenging in arid cities where tree planting is especially difficult due to unfavorable climatic conditions. On the other hand, some cities are already very green, and thus further

expanding green space may not be feasible. One of these high-green cities (Teresopolis, Brazil; Fig. 1) was found to also have a high heat-related mortality risk<sup>59</sup>. Such cities will need to develop other heat-mitigation strategies apart from green space expansion, for example, by ensuring equitable access to green space and thereby reducing climate vulnerability of underserved populations. This can be especially beneficial given the already unequal distribution of green space in LA cities<sup>32</sup>.

From a social and public health perspective, the nonlinear associations between some socioeconomic and UGS variables along with the high prevalence of informal settlements in LA cities call to adopt a more nuanced and context-sensitive approach for greening strategies. This is particularly important given some evidence of skewed perception of UGS benefits and UGS disservices. For example, park proximity was linked to higher and lower perceived social disorder in informal and formal areas in LA cities, respectively<sup>23</sup>. Therefore, in addition to the equal allocation of UGS, it is important to maintain its quality, especially in socioeconomically disadvantaged areas. An interesting direction for future research would be describing patterns of UGS within LA cities, while comparing formal and informal neighborhoods.

Finally, from a research methodology perspective, our study emphasizes the different kinds of information that can be provided by combining a wide variety of UGS metrics. Whereas vegetation-based

metrics (for example, greenness, % green space area) offer insight into planetary health benefits (cooling, air quality, noise reduction), urban park metrics may represent opportunities for physical and social activities, which benefit physical and mental health. These metrics are not interchangeable, and future studies should account for these nuances in their choice and definition of green space metrics and ideally use several metrics reflecting multiple aspects of UGS.

## Methods

### Study sample and city characteristics

This study is part of SALURBAL (Urban Health in Latin America), a multi-disciplinary, multi-country collaborative project aimed at studying the determinants of urban health disparities in 371 large (at least 100,000 residents) cities in 11 Latin American countries representing more than 247 million people<sup>60</sup>. We used the entire sample of 371 cities to describe green space in this study. Geographically, the study focused on the urban extent, also known as built-up area<sup>22</sup> or urban cluster<sup>60</sup>, within cities' administrative boundaries (<https://drexel-uhc.github.io/salurbal-city-selection-scroll/>). Cities' urban extent was delimited as follows. First, the SALURBAL team obtained cities' administrative boundaries. Within those boundaries, the urban extent was mapped using systematically identified built-up areas from satellite imagery<sup>60</sup>. Specifically, the urban extent (henceforth referred to as 'cities') was determined by applying a spatial clustering algorithm to the 12-m resolution Global Urban Footprint<sup>61</sup> dataset, which distinguishes between built-up and non-built-up pixels. The urban extent was determined by classifying the Global Urban Footprint pixels into urban, suburban and peri-urban depending on the share of built-up pixels within an area of 1 km<sup>2</sup> (ref. 60). Finally, the urban pixels were merged to represent urban extent—an area of contiguous urban built-up within a city's administrative boundary.

The SALURBAL collaboration also compiled extensive data on cities' natural, built and socioeconomic environment using a combination of satellite images, census and survey data<sup>60</sup>. This study used city characteristics described in Extended Data Table 1. Supplementary Tables 1–3 provide summary statistics and other information on cities' natural, built and socioeconomic characteristics. The unit of data collection for the green space metrics, natural and built environment was cities' urban extent. As explained in Quistberg et al.<sup>60</sup>, population for the urban extent was estimated based on the ratio of built area in the urban extent to the total built area in each sub-city (for example, municipality); populations from each built-up sub-city unit were then added up to the urban extent. The three socioeconomic variables used in the study were available at the level of administrative city boundaries.

**Greenness.** We used three sources of green space data to derive green space measures. The first measure is area-level greenness represented by NDVI, a spectral index describing the amount and vigor of vegetation. NDVI data were obtained from the 250-m, 16-day NDVI product (MOD13Q1.006) of the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument of the Terra satellite<sup>62</sup>. For every pixel in a city, we first computed the annual maximum NDVI value to capture peak greenness. Then, we took a spatial median of that set (across the city). Water bodies were excluded to avoid downward bias in calculated NDVI values. NDVI captures overall UGS conditions and is often used as a proxy for green space, but it does not distinguish among UGS types such as forests, parks and pastures, for example, nor does it directly measure the spatial configurations of UGS.

**Green space quantity and configuration.** Another group of metrics describe green space as a land-cover type and provide information on its spatial arrangement in space. These metrics were obtained from a land-cover map of green space in three consecutive steps. First, a green space land-cover map was created based on the 10-m resolution Sentinel-2 satellite images from 2017. More details on the green space map can be found in Ju et al.<sup>63</sup> Briefly, green vegetated areas

were identified by means of a supervised image classification using a single, median composite of Sentinel-2 Top of Atmosphere (TOA) reflectance images in 2017 as input, with clouds and water removed. The classification was done separately for every city to account for between-city differences in biome and urban form<sup>63</sup>. Using randomly collected validation samples in 11 randomly selected cities, the resulting green space map achieved an overall accuracy between 0.80 and 0.87 in arid cities ( $n = 3$ ), between 0.76 and 0.89 in temperate cities ( $n = 3$ ) and between 0.87 and 0.96 in tropical cities ( $n = 5$ )<sup>63</sup>. The result was a binary map with every 10-m pixel classified as green space or not green space. The urban green space identified by the map included such green land-cover types as green grass, shrubs, forests and farmland<sup>63</sup>. Second, using the map, green space patches or contiguous areas of greenery, were defined using the Moore neighborhood rule: a green space pixel (10 by 10 m grid cell) and the eight green space pixels around it were aggregated into the same green patch. To reduce computational intensity, the green patch map was then resampled to 30 m to compute the landscape metrics depicting green space spatial configuration. Finally, using the map of green patches, a series of landscape characteristics of green space were calculated, including percent green space in a city (based on total green space area), density of green patches, clumpiness of green patches and the mean nearest neighbor distance between green patches, among others (Extended Data Table 2). These measures are widely used in landscape ecology to describe the quantity, fragmentation, aggregation/clustering and isolation of green space, respectively<sup>64</sup>. We also computed a measure of per capita green space availability by dividing the total city green space area by city population.

**Urban parks.** In this study, urban parks were defined as delimited urban open spaces predominantly covered with vegetation. They are accessible and free to the public and are used for recreation, leisure and community gatherings. Urban parks were mapped using a combination of web data mining and remote sensing by Pina, Matos and Skaba (co-authors on this paper), as described in more detail in Supplementary Material 1.

The following criteria had to be met for a location to be identified as an urban park:

1. Be on the list of key terms suggested by local experts (Supplementary Material 1).
2. Among those key terms, a location would have to be categorized as 'park' on Google Cloud collaborators database (Google has a category attached to every geotagged item).

This resulted in Google park-categorized locations representing parks, reserves, sports fields, riverside areas (for example, streams and riverbanks), green trails, community gardens and nature preservation areas. The results were cleaned up to remove, for example, locations that had the word 'park' in them but were not in fact parks (for example, shopping centers with the word park in their name). Zoos, golf courses and green walls were excluded as they did not fit the definition of urban parks (free/accessible to the public). Cemeteries were excluded because they are primarily places for burial and are not used for recreation.

To ensure that these urban parks were indeed green and in cities, the following two steps were applied:

3. The NDVI data were used to find green areas within a 900-m buffer around the locations in step 2.
4. The street network from OpenStreetMap was used to delimit the boundary around the green areas—the boundary of green parks. If there was no street network around a prospective park location, it was not considered an urban park, as the absence of streets indicates it is outside an urban area.



The final classification represented a map of green urban parks in 371 cities in Latin America and was used as input to compute various metrics describing urban parks. The data were validated using official municipality-level data on parks in 77 cities, showing high agreement between the classification results and the official data. We used the number of parks per capita and park area per capita as the metrics for urban parks.

### Statistical analysis

We first present a description of UGS in three example cities with low, moderate and high green space availability (Fig. 1). We then describe UGS quantity, its spatial configuration and urban park measures by categories of cities' natural, built and socioeconomic environment characteristics. The categories for the cities' characteristics were defined based on tertiles except for those describing natural environments, which were based on a climate classification, terrain steepness and coastal vs inland location. For the descriptive analysis, we used the ANOVA test of differences between group means. A post-hoc multi-comparison Tukey's honestly significant difference (HSD) test was performed on the ANOVA to identify which subgroup means showed statistically significant differences<sup>65</sup>. The *P* value from Tukey's HSD accounts for multiple comparisons within the categories of each city indicator and determines whether there is a statistically significant difference in the means of each green space variable across the categories of a city indicator.

To supplement the comparison of the means and assess the relative importance of city variables on UGS, we used random forest (RF) regressions. A random forest regression is a non-parametric method representing an ensemble of regression trees. An advantage of the RF method for analyzing UGS in relation to city-level characteristics is that the RF does not impose a predetermined form (for example, linear) on the relationships of interest. Trees in a RF are constructed by recursively splitting the data at various points based on the values of independent variables, with a random selection of independent variables considered at each split<sup>36</sup>. The splits aim to reduce the variability of the response variable within each leaf, and the model predicts the average value of a dependent variable within each leaf. The final prediction from a random forest regression is the average prediction over all trees. To run a RF regression, a set of hyperparameters, or parameter settings, needs to be specified. We performed a grid search to identify the optimal number of variables randomly sampled as candidates at each split, as this hyperparameter has been shown to exert the highest influence on predictive accuracy. We present results of the RF regression for the quantity metrics and urban parks and not for the spatial configuration metrics as the RF explained at most 26% of the variance for the configuration metrics.

From RF output we first utilized the measures of variable importance, which describe the magnitude of influence of each independent variable on the outcome, while holding the other variables constant. Second, we complemented the comparison of the means with visualizations from the partial dependence plots. These plots depict associations between each city characteristic and the measure of UGS, accounting for all the other covariates. Each point on a plot represents the average prediction made by the model for the value of a particular independent variable when all the other independent variables are controlled for.

Finally, as a sensitivity check, we reported adjusted multivariable associations from linear regressions between each UGS indicator and a set of city-level natural (climate zone, terrain, coastal location), built (population, population density, intersection density) and socioeconomic (GDP per capita, educational, unemployment) characteristics. We included these covariates after inspecting correlations among them (Supplementary Table 4). We did not include city area as it exhibited moderate correlations with the rest of the city-level predictors (the cut-off correlation coefficient was 0.6). For example, city area was strongly correlated with population ( $r = 0.96$ ). The covariates were modeled in

categories based on natural groupings (such as types of climate zone or coastal/inland location) or tertiles, similar to the descriptive analysis above. We also re-estimated the multivariable models with the same set of covariates as described in the previous paragraph and in addition included a random intercept for each country (cities nested within countries). Finally, we estimated linear regressions for each green space variable in relation to the continuous built and socioeconomic environment variables (as opposed to categorical as presented in the main results) and estimated interactions between climate zone, socioeconomic and built environment variables.

### Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

### Data availability

All data except urban parks are publicly available from the SALURBAL data platform at <https://data.lacurbanhealth.org/>. The data for urban parks were derived using Google data and are not publicly available because of Google's terms of use. Please contact SALURBAL.data@drexel.edu to obtain permission for the park data. The park data will be shared and the users will need to sign a data-use agreement.

### Code availability

Code for the statistical analysis is available at <https://github.com/mariabak1/Potential-drivers-of-urban-green-space-availability-in-Latin-American-cities>.

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## Author contributions

Study planning and design: M.B. and M.M.; data curation: M.B., M.d.F.R.P.d.P., Y.J., V.P.d.M. and D.A.S.; statistical analysis: M.B.; original draft: M.B. and M.M. Paper editing: all authors. Funding acquisition: D.A.R.; supervision: D.A.R. and I.D.

## Competing interests

The authors declare no competing interests.

## Additional information

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**Extended Data Table 1 | Characteristics of cities' natural, built and socioeconomic environment and their data sources**

Domain	Variable name	Definition	Data source and year
Natural environment	Climate zone	Categorical variables describing the prevailing climate zone. This analysis includes three climate zones: tropical, temperate, and arid <sup>a</sup>	Köppen-Geiger climate classification <sup>a</sup>
	Topography	A binary indicator for prevailing flat or hilly terrain. Cities whose average slope exceeded 5 degrees were considered steep (flat otherwise).	Shuttle Radar Topography Mission (SRTM)
	Coastal/Inland location	A binary indicator distinguishing between coastal and inland cities. Coastal cities are those whose boundaries are within 1 km from a coastline, whereas inland cities represent the rest.	Global Self-consistent, Hierarchical, High-resolution Geography Database (2017)
Built environment and urban form	City area	Area of the built-up extent in a city in km <sup>2</sup> . Cities were defined by identifying urban extent based on built-up area as of 2017.	Global Urban Footprint (GUF) Dataset (2017)
	City population	The number of residents (persons) in a city in 2017 according to the most recent census data.	Population projections provided by national statistics offices from each country (2017)
	Population density	The number of city residents per km <sup>2</sup> of city area in 2017.	Population projections provided by national statistics offices from each country (2017)
	Intersection density	The number of road/street intersections per km <sup>2</sup> of area. Higher values suggest more connected cities.	Based on the street network data from OpenStreetMap (2017)
Socioeconomic environment	Gross Domestic Product (GDP) per capita	Monetary value of goods and services produced in a city per capita (purchasing power parity) in constant 2011 international US dollars.	2015 subnational GDP estimates based on an econometric analysis by Gennaioli et al. (2013)
	Educational attainment	The percentage (%) of city population aged 25 or older who completed secondary education or above. Higher values indicate higher educational attainment among city population.	National census data <sup>b</sup>
	Unemployment	The unemployment rate among the total population 15 years or above in labor force (%). Higher values indicate larger percentages of the unemployed in city population.	National census data <sup>b</sup>

More details about the data sources for cities can be found in Quistberg et al., 2019. a) The definition of Köppen-Geiger climate zones are as follows (Beck et al., 2018): 1. Tropical: Not arid and air temperature of the coldest month  $\geq 18^{\circ}\text{C}$ . 2. Temperate: Air temperature of the hottest month  $> 10^{\circ}\text{C}$ , and  $0^{\circ}\text{C} < \text{Air temperature of the coldest month} < 18^{\circ}\text{C}$ . 3. Arid:  $\text{MAP} < 10 \times P_{\text{threshold}}$ , where  $\text{MAP}$ =mean annual precipitation (mm/year);  $P_{\text{threshold}} = 2 \times \text{MAT} + 14$ . Summer (winter) is the six-month period that is warmer (colder) between April-September and October-March. b) Years of data for the variables based on census data were as follows: Nicaragua 2005, El Salvador 2007, Argentina 2010, Brazil 2010, Mexico 2010, Panama 2010, Costa Rica 2011, Chile 2017, Peru 2017, Colombia 2018, Guatemala 2018.

**Extended Data Table 2 | Description of the urban green space metrics used in the study**

Domain	Variable	Description	Data source
Green space quantity/availability	Greenness (NDVI)	Area-level median of annual max NDVI in a city. Measures the amount and vigor of UGS. Higher NDVI indicates more vigorous greenery and larger vegetated areas.	MODIS (250x250 meters)
	Green space area (%)	Percent of city area covered by green space. Higher values indicate a greater percentage of city area covered by green space.	A binary map of green space (30x30 meters)
	Green space area per capita (green space availability)	Total green space area (km <sup>2</sup> ) in a city per 1,000 city residents. Higher values indicate higher per capita green space area.	A binary map of green space (30x30 meters)
Green space configuration	Green patch density	The density of green patches in a unit (#/hectare). A green patch represents a contiguous area of green space. At the same level of % green space, higher patch density means more green patches that are smaller in size [green space is subdivided into separate patches]; lower patch density means fewer green patches that are larger per patch size.	A binary map of green space (30x30 meters)
	Isolation (mean nearest neighbor distance of green space patches)	Measures (in meters) the average distance between any given green patch and its closest neighboring patch. Higher values mean that green patches are located further from one another and denote greater isolation.	
	Aggregation (clumpiness of green space patches)	Clumpiness describes the level of clustering of green space in a city. Clumpiness is computed based on a spatial adjacency matrix of green patches, which shows the frequency with which different pairs of patches appear side-by-side in space. The measure varies from -1 to 1, with -1 denoting max disaggregation, 0 – random distribution, and 1 – max aggregation.	
Urban parks	Number of parks per capita	The number of urban parks per 1,000 residents. Higher values mean greater per capita park availability.	Web scraping from Google Cloud
	Park area per capita	Total area of urban parks per 1,000 residents. Higher values mean higher park area per capita.	Collaborator platform + Sentinel-2 satellite images (10x10 meters)

The quantity of green space and green space configuration metrics were computed for the year 2017. Data on urban parks is from 2020.

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Our web collection on [statistics for biologists](#) contains articles on many of the points above.

Software and code

Policy information about [availability of computer code](#)

Data collection	All data collection was done in R version 4.3.3
Data analysis	All data analyses were conducted in R version 4.3.3 and PostgreSQL 9.5.20. No custom algorithms were needed to analyze the data. Code for the statistical analysis is available at <a href="https://github.com/mariabak1/Potential-drivers-of-urban-green-space-availability-in-Latin-American-cities">https://github.com/mariabak1/Potential-drivers-of-urban-green-space-availability-in-Latin-American-cities</a> . R packages

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All data except urban parks are publicly available from the SALURBAL Data Platform: <https://data.lacurbanhealth.org/>. The data for urban parks was derived using



Google data and are not publicly available because of Google's terms of use. Please contact SALURBAL.data@drexel.edu to obtain permission to obtain the park data. The park data will be shared and the users will need to sign a data use agreement.

## Human research participants

Policy information about [studies involving human research participants and Sex and Gender in Research](#).

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Population characteristics	NA
Recruitment	NA
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Note that full information on the approval of the study protocol must also be provided in the manuscript.

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## Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This is a descriptive ecological study of city-level green spaces in Latin American cities, with stratification by city-level natural, built environment, and socioeconomic characteristics.
Research sample	This study is part of SALURBAL (Urban Health in Latin America), a multi-disciplinary, multi-country collaborative project aimed at studying the determinants of urban health disparities in 371 large (at least 100,000 residents as of 2010) cities in 11 Latin American countries. We used the entire sample of 371 cities to describe green space in this study. Geographically, the study focuses on the urban extent, also known as built up area or urban cluster, within cities' administrative boundaries.
Sampling strategy	We included all 371 SALURBAL cities, which are large (>100,000 residents as of 2010) cities in 11 countries in Latin America.
Data collection	Greenspace data were collected from satellite imagery. Data on urban parks were collected using a combination of querying Google Cloud collaborators database and satellite imagery. All other data were collected from countries' censuses and surveys.
Timing and spatial scale	Greenspace data were collected for 2017 with the exception of park data, which was collected in 2020. Years of data obtained from censuses and surveys varied by country from 2005 through 2017.
Data exclusions	No data was excluded from the analysis.
Reproducibility	No experiments were conducted.
Randomization	This was an observational study with no randomization and no experiments.
Blinding	No blinding was necessary as this was a descriptive study.

Did the study involve field work? ☐ Yes ☒ No

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