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Comparing access to urban parks across six OECD countries

Talia Kaufmann, Swapnil Vispute, Mansi Kansal, Daniel T. O'Brien, Tomer Shekel, Evgeniy Gabrilovich, Gregory A. Wellenius, Lewis Dijkstra, Paolo Veneri.

This work leverages globally consistent data on parks from Google Maps, in combination with the computational power of Google Maps Directions API to quantify accessibility to parks across nearly 500 metropolitan areas in six countries: Estonia, France, Greece, Mexico, Sweden, and the United States. We combined high resolution population data from Worldpop with parks data and navigation estimates to measure: (1) Fraction of the population with access to parks within a 10-minute walk; and (2) the median walking time to the closest park. We find large differences in access to parks between countries, as well as large variability across cities and their respective commuting zones. To demonstrate how this framework can support cross country comparisons and efforts to track progress towards SDG11, we assessed access to parks by income group in selected countries, finding that the median walking time to a park is shorter for residents of low income neighbourhoods both in French and American metropolitan areas.

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Introduction

The availability of green areas is an important dimension of urban well-being. Access to parks and green spaces in urban areas has been linked to improved mental and physical health as well as improved social capital and community cohesion (Nieuwenhuijsen et al., 2017; De Vries et al., 2013; Jacobs, 1961; Whyte, 1980; Lund, 2003; Hampton et al., 2015). The United Nations included providing "universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities" by 2030 as part of Sustainable Development Goal 11 (UN, 2015). However, tracking global progress towards SDG11 is challenged by the lack of high resolution yet globally consistent tools to measure accessibility to parks across neighborhoods, cities, and countries.

Although hundreds of studies have measured access to parks over the years, most of such studies focused on a handful of cities in a specific country (Giles-Corti et al., 2005; Kaczynski et al., 2014; Shanahan et al., 2015; Schipperijn et al., 2017) and almost none have done so at scale using data that allows for global comparisons. As a result, previous studies differ in data sources, park classification, urban unit of analysis, and definitions of indicators (Zhang et al., 2011; TPL, 2022; Fields in Trust, 2022; Wu, 2021). Two studies performed at the European scale have measured access to green spaces in a large number of cities using the 10 minutes threshold for accessibility. They find large variability in access across Europe with almost no relation to a city's population size and some relation to geographical and topological conditions as reflected by higher access measured in northern vs. southern European cities (Kabisch, 2016; Poelman, 2018). These studies underline the importance of using consistent metrics and data sources for international comparisons, allowing to benchmark access to parks across countries over time.

The newly available large datasets from digital platforms in the past 15 years have enabled researchers to quantify spatial and social patterns at a scale never done before (Lazer et al., 2009). Yet only a handful of studies have used these datasets to capture accessibility to various amenities at scale. Fine grain road network and amenity data from Open Street Map and Google was used to quantify accessibility to cities (Weiss et al., 2018) and to healthcare facilities on a global scale (Weiss et al., 2020), helping to advance policies for improved equity in accessibility. Similarly, high resolution amenities data from Google Maps was used to measure ease of access to banks versus alternative financial institutions, such as check cashers, across racial groups in the US (Small et al., 2021). In addition, high resolution geolocation data was used to assess human mobility patterns and the number of familiar locations (González et al.,2008; Alessandretti et al. 2018), to illuminate large disparities in neighborhood isolation of minority groups (Wang el al., 2018), to establish universal scaling patterns across cities in the quantity and distribution of urban amenities with population size (Kaufmann et al., 2022) and measure income segregation in mixing patterns across cities (Moro et al., 2021; Jarv et al., 2015). Although research done in this golden age of computational social science (Lazer et al., 2009) highlights the importance of measuring social and spatial accessibility at scale over time to illuminate disparities, only a couple of studies were able to overcome the obstacle of using consistent data to support international comparison across countries (Lazer et al., 2020).

Local and global consistency of data for accessibility metrics is essential to support policy decisions for two reasons. First, what is perceived or defined as “accessible” is highly subjective and vary by socio-demographic characteristics (Colabianchi et al., 2007; Coulton et al., 2013). Second, city size can affect the resources and services provided (Nelson et al., 2019). At the same time, it is beneficial to measure accessibility using different time thresholds to accommodate for a variety of users in respect to how mobile they are to travel and accounting for the type of visit, differentiating between short and long visits. Second, measuring accessibility consistently across a large number of cities, paired with other socio-demographic indicators, has the potential to uncover the spatial and social factors contributing to higher quality of life and improved public health. Previous research examining disparity in access to parks across US cities has shown that low-income neighborhoods tend to have higher physical proximity to parks while having less parks to choose from and less total area dedicated to parks in comparison to affluent neighborhoods (Wen et al., 2013; Zhang, 2011). Studies done on a smaller scale using survey data and personal diaries to track park usage for physical exercise and public health have shown that having high physical proximity to parks had a minor effect on park usage (Hillsdon et al., 2006; Kaczynski et al., 2014; Shanahan et al., 2015; Schipperijn et al., 2017) while that the total amount of land dedicated to parks within walking distance, parks safety and richness of facilities offered in those parks have a greater effect on park usage (Scott & Munson, 1994; Giles-Corti et al., 2005; Cutts et al., 2009; Kaczynski et al., 2014; Schipperijn et al., 2017).

Existing administrative databases maintained by cities and governments use a variety of location- or region-specific land use classification schemes, precluding the development of globally consistent metrics of park access. The alternative datasets available to create such metrics include land cover data and data collected and managed by mapping platforms such as Open Street Maps and Google Maps. While land cover data is available for a large set of European and North American countries (Kabisch et al., 2016; Poelman, 2018), such data is based on often too coarse satellite images, with a narrow definition of parks and green spaces and not validated by humans. For example, the Copernicus Urban Atlas dataset excludes small urban parks and gardens as well as areas that are not fully green as seen from the air like community gardens (Kabisch et al., 2016). Mapping platforms data offer publicly available, spatially resolved and validated data on the location of parks and, as such, hold potentially significant value for research and policy. Among such datasets, Google Maps is estimated as the most complete dataset with almost 90% of data spatially validated (Deng and Newsam, 2017; Kaufmann, 2018; Hochmair, 2018).

In this paper, we leverage data from Google Maps - which has a consistent amenity classification across countries and high-resolution park data - to generate fine-grained metrics quantifying access to parks in metropolitan areas, distinguishing cities and their respective commuting zones. These metrics utilize a consistent framework across countries, enabling global comparisons of access to parks in a resolution and scale not possible before. Our framework aims to support global comparisons across cities, inform policy at the city level and enable research to ground the connection between parks accessibility, public health, and quality of life. In addition, we demonstrate how these accessibility metrics can support efforts to track progress towards SDG11 by measuring the relationship between access and socio-economic indicators. For example, we found that the median walking time to a park is shorter for residents of low-income neighborhoods in comparison to middle and high-income neighborhoods in French and American metro areas, showing a greater difference within urban cores. The outcomes of this study are accessibility indicators aggregated at the scale of cities and metropolitan areas to advance data-driven and inclusive policymaking.

Data and Methods

Scope of Study

Before undertaking a larger-scale comparison across many countries, we sought to test whether this approach for measuring accessibility at scale would yield policy-relevant results in a few countries with varying levels of economic development, type of urban development, topography and demography. Accordingly, we selected the following six countries: Estonia, France, Greece, Mexico, Sweden, and the United States. Metropolitan areas and cities are defined consistently across countries by using population grids and applying the UN-recommended method for statistical comparisons at those scales. Cities, also called High Density Clusters (HDCs), are defined as clusters of contiguous high-density grid-cells having a total population of at least 50,000 inhabitants. Metropolitan areas, also called Functional Urban Areas (FUAs) are composed of cities plus their respective surrounding commuting zones, determined using an automated classification process that is independent of country-specific data and local administrative units (Schiavina, M. et al., 2019). Methodological details underlying the boundaries of cities and metropolitan areas are provided by Moreno, Schiavina and Veneri (2021). This process considers population counts of grid cells from the Global Human Settlement Layer (GHSL), travel times to urban centers and their areas to define the HDC (city) and FUA (city + commuting zone) boundaries. Our final dataset includes accessibility indicators for 496 FUAs and 583 HDCs across the six selected countries.

Parks data

The inventory of parks was extracted from the Google Maps and Search datasets in February and March of 2022. We define parks as publicly accessible green areas for predominantly recreational use and suburban natural areas that have become and are managed as urban parks (Poelman, 2018). Specifically, we included locations identified as “parks”, “city parks”, “gardens”, “community gardens”, “public soccer fields”, “dog parks”, “memorial parks”, “ecological parks”, “county parks” and “national parks”. The final dataset included more than 200,000 parks in 496 FUAs. The underlying sources of the parks data from Google Maps included publicly available data, licensed third-party data and data contributed by users. The geographical location (latitude and longitude) and geometric boundary of parks were used for computing park accessibility metrics (see more details in Supplementary Material).

Accessibility metrics

Park accessibility metrics were calculated at a grid level corresponding to spherical geodesics (S2 cells) of roughly 150m x 150m (S2 Geometry, 2022). The S2 library provides a mathematical representation of the Earth’s surface projected onto a 3-dimensional sphere, making it possible to build a worldwide geographic database using a single coordinate system, and with low distortion everywhere compared to the true shape of the Earth. In this study we employ a level of spatial resolution corresponding to the level 16 S2 cells (see the details at this link).

Travel time estimates

We estimated walking time to the nearest park along the shortest feasible route using the Google Maps Directions API (Google Developers, 2022). Note that this is equivalent to network time rather than the commonly used Euclidean distance or friction surface. The Directions API accounts for areas with physical barriers (e.g., bodies of water or private roads) and roads inaccessible to pedestrians. Rather than being based on average walking speed, Google Maps navigation estimates account for the difficulty of crossing freeways on foot. The Directions API is up to date, has high coverage of road networks, topography and elevation data, and uses historical patterns from aggregated location data and advanced machine learning to provide optimal route selection and travel time estimation (Google, 2022).

By using the parks dataset and combining the Google Maps walking navigation estimates with high-resolution population data, we produced a set of indicators of park accessibility (Table 1).

Table 1. Park accessibility indicators

Indicator	Description	Unit of measurement
Median travel time to the closest park	Indicates the time it would take the median person living in this geographic unit to walk to the closest park	Median walking time in *minutes* for each FUA/HDC
Share of population with access to parks within *a given* time interval	Indicates the proportion of population in this geographic unit that can access a park within a walking distance. Also reflects the population without access to parks	Percentage of FUA/HDC population within a 10-minute walk from a park

To estimate accessibility at a city level, for each park we compute the point-to-point navigation metrics from the surrounding populated s2 cells as the source, up to a radius of 10 km, and the park as the destination. We compute the walking time to the edge of the park using walking navigation estimates from Google Maps Directions API (Google Developers, 2022). When the boundary of the park is not available, we use the location (latitude, longitude) of the park centroid. For each S2 cell we recorded the minimum travel time to reach a park in its vicinity. For a populated S2 cell that did not have a single park within 10 km radius, we assigned a default high value of 3 hours of walking time. We then aggregated these travel times per S2 cell to produce a population weighted median travel time to the closest park per FUA and HDC (see more details in Supplementary Materials).

To estimate the share of urban population with access to parks we summed the population of all S2 cells with a park available within 10 minutes of walking time around them and divided it by the city's overall population size, calculating the percent of people that can walk to a park within 10 minutes.

Population data

To capture fine-grained resolution data on population distribution, we use WorldPop data for 2020, a globally consistent and up to date data layer for high resolution population estimates (Worldpop.org, 2022). WorldPop provides population counts of the entire world within a unified grid (Tatem, 2017) with better coverage for some countries in respect to the alternatives (Xu et al., 2021; Hanberry, 2022). The

WorldPop top-down model uses a global database of administrative unit-based census and projection counts for year 2020 and utilizes a set of detailed geospatial datasets like settlement locations, settlement extents, land cover, roads, building maps, health facility locations, satellite nightlights, vegetation, topography and refugee camps to disaggregate the census counts for approximately 100x100m grid cell classified as settled by humans (Stevens et al., 2015; Sorichetta et al., 2015). The top-down model adjusts the population counts to match the United Nations World Population Prospects (population.un.org, 2022) data counts per admin region before disaggregation (top-down constrained UN-adjusted). Population counts will differ from a bottom-up grid produced model using official point data on the number of night-time residents.

Since we computed navigation estimates at the S2 grid cell level, we required estimating the population of each S2 cell. We re-projected WorldPop's high-resolution population model onto the S2 cell grid and performed an area-weighted sum to compute the population within each S2 cell boundary. The population per S2 cell is used as a weighting factor for travel times when aggregated at the HDC, commuting zone and overall FUA levels (median computation).

Income Analysis

We conducted additional exploratory analyses in the US and France due to the availability of cell-level poverty data in these countries. The purpose of the analysis was to gain insights into the socioeconomic correlates of park access in these two countries. To estimate the walking accessibility of different income groups, we first classified each statistical unit as above or below the poverty line using the respective Census data (described below). For the purposes of our work, each statistical unit was considered as under the poverty line if the unit’s share of population under the poverty line was greater than 30% (a threshold tested in the literature, see Small et al., 2021). Poverty attributes were interpolated to S2 cells contained within each statistical unit.

To calculate the share of the population in the metropolitan area with walking access to parks by income level, we sum the population of all statistical units classified as under the poverty line that can walk to the closest park in 10 minutes and divide it by the sum of population in that class, also broken down by city and commuting zone. We did the same with statistical units classified as living above the poverty line that can walk to a park in 10 minutes.

Census data for France and the United States

For France, we use gridded data at a 200m resolution provided by the French National Institute of Statistics and Economic Studies (Insee.fr, 2022) and for the United States, we use census block groups data provided by the US Census Bureau (US Census Bureau, 2022).

These datasets report the estimated number of people per statistical unit living under the poverty line, using the established definition of the poverty line in each country. Such definitions set a yearly income threshold and classify households based on their reported yearly income, family size, and composition. According to the US Census Bureau: “If a family's total income is less than the family's threshold, then that family and every individual in it is considered in poverty. The official poverty thresholds do not vary geographically, but they are updated for inflation using the Consumer Price Index” (US Census Bureau, 2021).

Statistical Analysis

Statistical analyses and visualizations were performed using R software. A two-sided ANOVA test was used to test the significance of difference in means across countries by FUAs and HDCs. A one-sided

ANOVA test was used to test significance within each country between HDCs and FUAs. For both tests, a p-value of < 0.05 was considered statistically significant. A regression model was performed to test the relationship between population density and median walking durations to parks per region (HDC and Commuting zone) within each country.

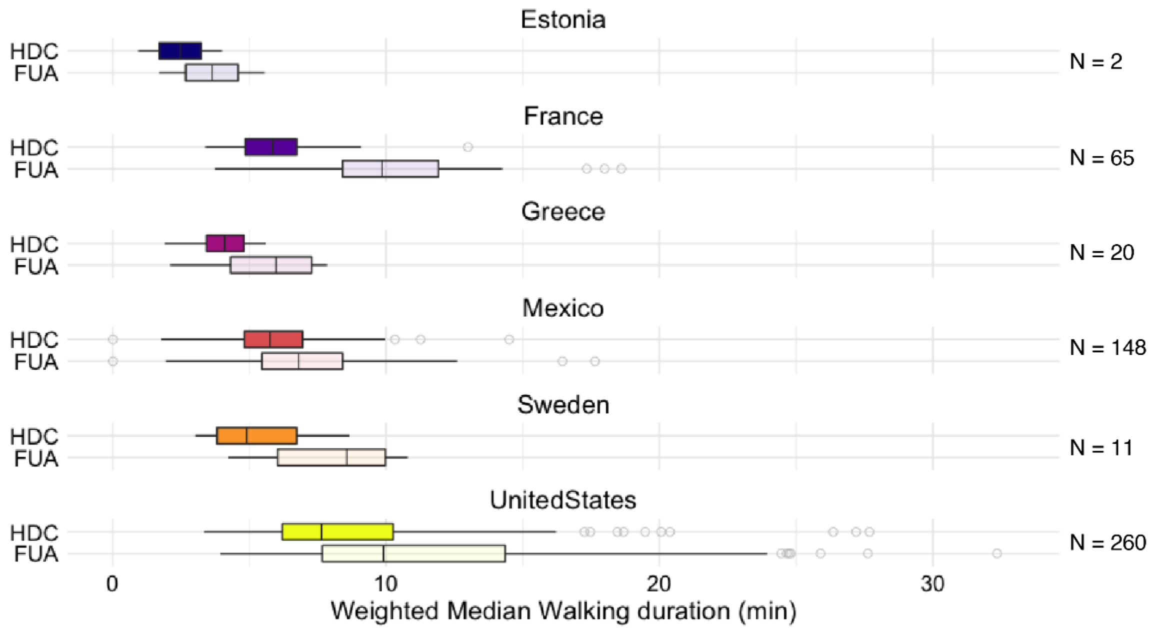
Results

Park Accessibility

We find pronounced variability in park accessibility across the six countries and between cities within countries. Specifically, walking duration to the closest park was statistically significantly different across all HDCs and across all FUAs ($p < 0.001$) (Figure 1). The United States shows the largest variation between FUAs (median walking time to the nearest park ranged from 4 to 33 minutes) with the majority of cities having a median time between 7 and 15 minutes. In some US FUAs we find median walking times exceeded 20 minutes (e.g., 24 minutes for Atlanta, GA and 20 minutes for Nashville, TN), which may be significantly greater than the time a typical person would be willing to spend walking, estimated at 10 to 15 minutes (equivalent of 800m to 1.2km) (Colabianchi et al., 2007; Coulton et al., 2013). The median walking times in France and Mexico tended to be lower than in the US, and more homogenous across metro areas. For example, median walking times ranged from 3 to18 minutes in France and 2 to 18 minutes in Mexico. While the median time to the closest park is 10 minutes in French metropolitan areas, in Mexico the median is about 7 minutes and in the majority of FUAs the walking time is less than 10 minutes. This homogeneity across Mexican FUAs is surprising given the large number of FUAs (148) and the variation in their population size (60K to 21M), suggesting that parks are consistently very accessible in urban areas across Mexico. Sweden and Greece showed even smaller variation between FUAs with a range of 8 and 6 minutes respectively (Sweden: 3-11 minutes, Greece: 2-8 minutes) while the two Estonian FUAs have a median smaller than 6 minutes.

Across most countries, parks are more accessible within cities (HDCs) compared to the broader metro areas (FUAs), with median walking time to a park consistently below 10 minutes. As seen in Figure 1, the distribution of walking duration to parks in HDCs is shifted to the left compared to the distribution in FUAs, with the largest absolute difference between the distributions of FUAs and HDCs observed in France ($p < 0.001$) while the smallest difference observed in Sweden ($p < 0.05$) and Mexico ($p < 0.001$) (See Supplementary Materials for model results).

Figure 1. Distribution of population weighted median walking duration to parks in minutes, by region type and country.

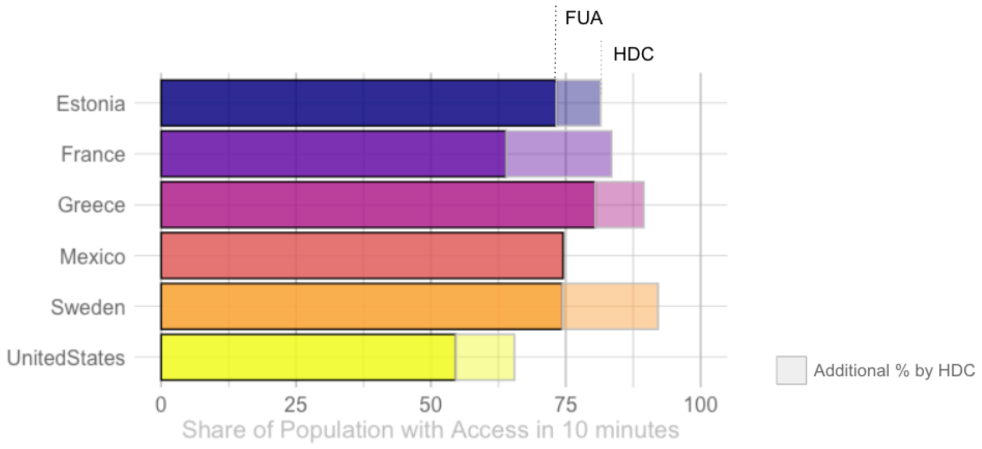


Note: Distribution of population weighted median walking duration to parks in minutes, by region type and country. Each boxplot represents the distribution of the walking durations by and metropolitan area. The upper boxplot shows the distribution across HDCs while the lower the distribution across FUAs. The box edges represent quartiles, and the whiskers represent the range of the data. Outliers (defined as points exceeding 1.5 times the interquartile range) are plotted as circles beyond the box and whiskers.

Share of population with walking access to parks

Summing up the share of urban population in each FUA or HDC with access to parks within a 10-minute walk provides a deeper understanding about differences in access. Conversely, quantifying the proportion of people living in metropolitan areas (FUAs) that cannot access a park in 10 minutes highlights the lack of accessibility at country level (Figure 2). In the United States, more than 100 million people living in FUAs do not have a park that they can walk to within 10 minutes, which is almost one in every two people. In France that number drops to one in three, which makes for 14 million people without walking access. In Mexico, Sweden, and Estonia, only one in four people do not have access to parks, and in Greece one in five. Within city centres (HDCs), substantially more people can access parks in 10 minutes, with increases ranging from 8 pp in Estonia to 20 pp in France. The additional population that can access parks in HDCs is represented by the lightly coloured bars in Figure 2. The overall proportion of people that can access parks in Mexican HDCs is identical to the proportion of FUA population, while in France there is a substantially larger share of population that can access parks in HDCs versus FUA (20pp).

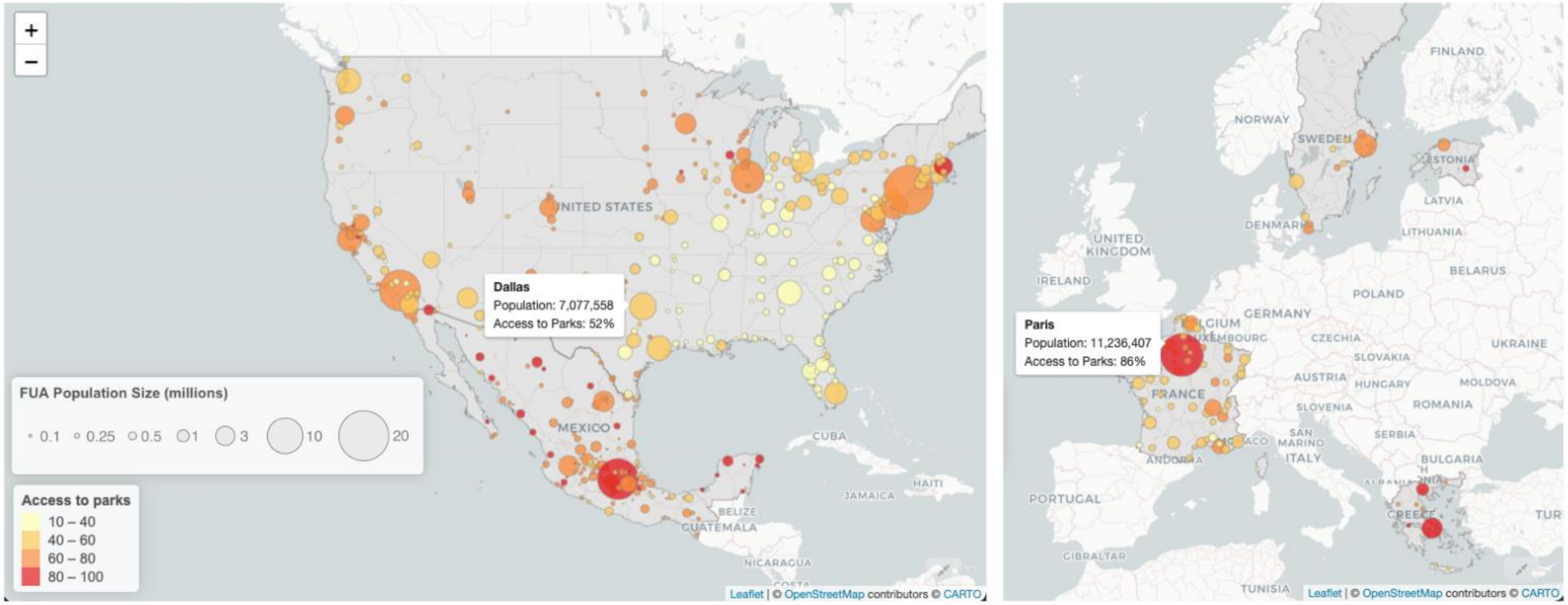
Figure 2. Share (%) of population with access to parks in 10 minutes, by country and FUA/HDC.



Note: Share of population with access to parks in 10 minutes, by country and FUA/HDC. The dark colours represent the share of the FUA population while the lighter colours represent the additional share of the HDC population.

Exploring accessibility to parks within countries on a map (Figure 3) shows that there may be geographical patterns in access to parks. In the United States, southern cities show the largest differences in park accessibility. In more than half of US FUAs, less than 50% of the population can access a park within a 10-minute walk, while in Mexico, only 8% of FUAs have a share lower than 50%. Like the US, France also shows a large variability in share of population with access to parks, where in almost half of FUAs the share of population with accessibility is lower than 50%.

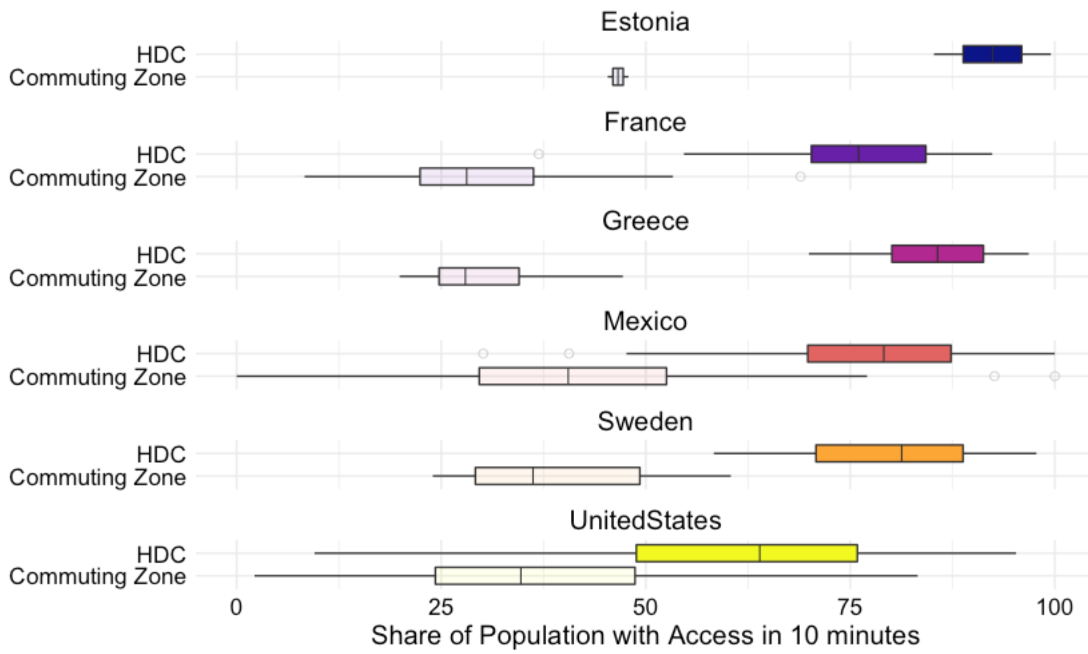
Figure 3. Map of 496 FUAs in six countries



Note: Map of 496 FUAs in 6 countries: Circle size indicates the population size, color coding indicates share of population (%) that can walk to a park within 10 minutes.
Map credits: ©OpenStreetMap contributors and @CARTO

Across cities in all countries, we find that the share of population with access to parks in 10 minutes is significantly larger within cities (HDCs) in comparison to their surrounding commuting areas (Figure 4). In cities across all countries except the United States, more than half of the HDC population can walk to a park in 10 minutes.

Figure 4. Share of population with access to parks in 10 minutes by HDC and commuting Zones by country

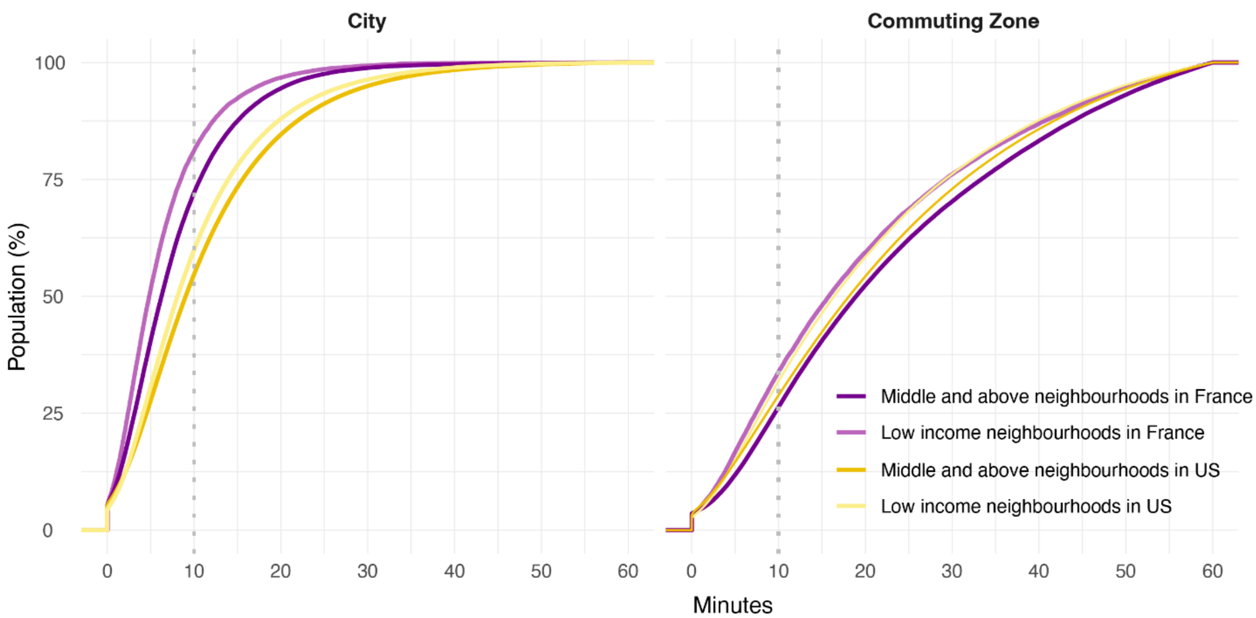


Access to parks by socio-economic group

This section assesses the extent to which access to parks in cities and metropolitan areas varies by socio-economic group. For the analysis, we combine the accessibility indicators with census data for the US and France on poverty, focusing on these countries due to the availability of high-resolution poverty data. For simplicity, we classify statistical units as either low income or not (i.e., low versus middle and high income) (see Data and Methods). We find that the median walking time to a park is shorter for residents of low-income neighbourhoods in comparison to middle- and high-income neighbourhoods in French and American metro areas. Moreover, we show that higher population densities in middle- and high-income neighbourhoods is associated with shorter walking durations in cities and commuting zones in both countries, while they have little to no effect in low-income neighbourhoods. Our results reveal a similar relationship across income groups and walking duration to parks in both countries, with differences between cities and commuting zones (Figure 5). In the United States, 60% of people from low-income neighbourhoods in cities can walk to a park in 10 minutes (median smaller than 10 minutes) while that share is 55% for people living in middle- and high-income neighbourhoods. In France, the share of city population in low- and high-income neighbourhoods able to reach a park within 10 minutes is 81% and 72%, respectively. Commuting zones provide overall lower access to parks. In the US, 32% of people living in commuting zones can reach a park in 10 minutes in low-income neighbourhoods, while that share is 29%

for higher income neighbourhoods. In France, 34% of people living within commuting zones have access to parks within 10 minutes in low-income neighbourhoods, while that share is 26% in more affluent areas within commuting zones. Lower median walking times observed for people living in low-income neighbourhoods may reflect that in both countries these communities tend to be located closer to the city centre, confirming prior research that higher poverty rates in neighbourhoods are associated with an increase in physical proximity to parks (Wen et al., 2013; Zhang, 2011; Cutts et al., 2009).

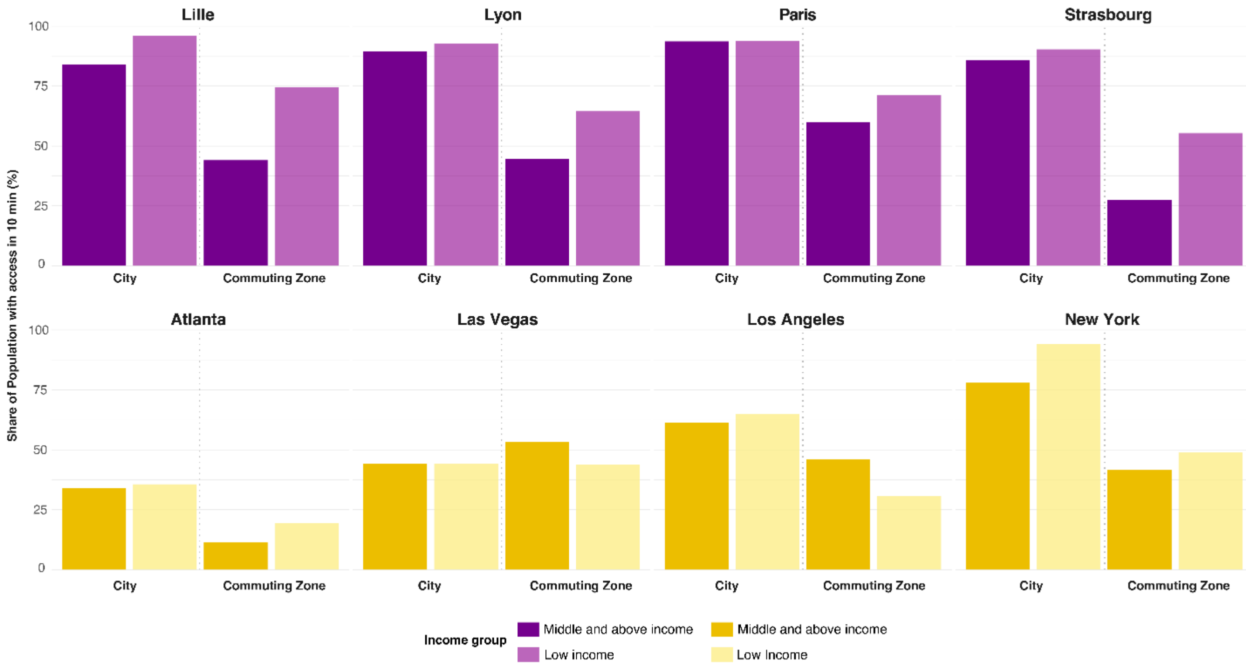
Figure 5. Share of population (%) with access to a park by walking duration (United States and France)



Note: Walking durations to parks in minutes, grouped by income categories in the United States and France within Cities (A) and Commuting Zones (B). Lines show share of populations by each group aggregated in 5-min increments

To further investigate how accessibility to parks differs between population groups within cities, we calculated the share of population living in low versus middle- and above-income neighbourhoods that can walk to a park within 10 minutes for each city and commuting zone. We find that, similarly to the general pattern in both countries, the share of population living in low-income neighbourhoods with access to parks is statistically significantly different from middle- and above-income neighbourhoods across all cities and across all commuting zones ($p < 0.001$) and is mostly higher relative to the more affluent neighbourhoods. However, this general trend differs by cities as we demonstrate in Figure 6. For example, in Paris and Atlanta the share of population with access is almost identical across income groups in cities but is lower for all groups in the broader commuting zone. In the commuting zones of Las Vegas and Los Angeles, low-income neighbourhoods have a lower share of population with access in comparison to the middle- and high-income neighbourhoods.

Figure 6. Share of Population with access to parks within 10 min (%)



Note: Share of Population with access to parks within 10 minutes (%), by City and Community Zone in selected cities

To understand whether the differences across income groups can be explained by features of the built environment across cities, we correlate the median walking durations to parks with the population density (on a double log10 scale) per region and by income group. Such a model teases out the estimated effect of population density on walking durations and how this relationship changes between cities and commuting zones. We find that, in middle- and high-income neighbourhoods located in commuting zones, higher population density is associated to shorter walking durations to parks. This holds more strongly for commuting zones in France (β= -0.65,95% CI=[-0.92,-0.38], R^2=.263) than in the United States (β = -0.14, 95% CI=[-0.21,-0.07], R^2=.049). However, the association between density and walking time to reach a park is still negative, although weaker, for low-income neighbourhoods within commuting zones in France (β = -0.256, 95% CI=[-0.41,-0.10], R^2 = .141) while in the United States an increase in density is associated to longer walking durations to parks (β = 0.1, 95% CI=[-0.05,0.16], R^2=.055), making parks even less accessible for lower income suburban communities.

Interestingly, higher densities within cities in both countries are not associated to the time needed to reach a park for low income communities (p value > 0.05). However, for more affluent city neighbourhoods, a negative association between density and walking duration is observed, more so in French cities (β = -0.495, 95% CI=[-0.66,-0.33], R^2 = .359) compared to American cities (β =-0.278, 95% CI=[-0.37,-0.19], R^2 = .126). These findings suggest, as low-income communities tend to live in higher density neighbourhoods close to city centres, their walking durations to parks is consistently shorter than for other income groups. A change in density at the city level does not really affect accessibility levels (See Table.3 in Supplementary Materials for full regression results).

Discussion

Our study leverages a globally consistent dataset and framework to estimate accessibility to parks and green spaces across ~500 cities in six OECD countries. We combine three globally consistent datasets to measure the population-weighted median walking time to the closest park and the share of population living within a 10-minute walk from a park by metropolitan area, distinguishing cities and their respective commuting zones. The analysis reveals large variability in access between and within countries. Specifically, we found that parks are more accessible within metropolitan areas in Europe and Mexico in comparison to the United States, both in cities and in commuting zones. Subsequently, we assess access to parks by income group in France and in the US, illustrating how our metrics can support policy efforts and enable future research.

The variability in park accessibility observed in this study may reflect differences in several factors, including population size, density, car dependency, and park distribution within cities. Differences in population density across cities within each country account for a large part of the variation in accessibility to parks, however the strength of this effect varies greatly by country. We observe a greater effect in Greece (R^2 = .89), France (.816) and Sweden (.774) and a lower effect in the United States (.341) and Mexico (.275) (See supplementary materials for regression results (Table.4) and Figure 7). In the United States, other factors such as development history may also have a role in explaining differences in parks accessibility. For example, southern cities that developed in the late 50's and 60's, when cars became prevalent in urban living, show the highest share of population without park accessibility. These cities tend to display much larger block sizes creating low population density (Hamidi & Ewing, 2014), making them less walkable and more car dependent. In Mexico, on the other hand, the observed high parks accessibility rates can potentially be explained by the consistently high population density within FUAs (median of over a 1,000 people per km^2), much higher than all other metropolitan areas in our dataset. In France, the large share of suburban and low-density parts of the FUAs, where people live in semi-detached houses with large backyards, may drive the observed low shares of population with parks accessibility.

Different urban environment in terms of density and walkability are potentially linked to the observed differences in parks accessibility between low- and high-income neighbourhoods. Historically, lower income communities were more prevalent within dense urban cores that are walkable (Wilson, 1987; Small, 2013) while the middle- and high-income communities located in the suburban areas, where density is lower and, as a consequence, walking times are greater. Prior research has also shown that low-income neighbourhoods tend to have a higher physical proximity to parks (Wen et al., 2013; Zhang, 2011).

Our results pave the way to deeper and refined cross-sectional analysis of accessibility in cities with respect to various socio-demographic indicators. Still, while this work measures the opportunity space in access to parks, it does not take into account how people actually use these spaces. Hence, having low access to parks in a certain region does not necessarily imply the demand for parks in that region exceeds supply. Possibly an area with perceived low accessibility does not generate demand for public parks, as found by prior research (Scott & Munson, 1994). Studies done on a smaller scale using survey data and personal diaries to track park access and usage have shown that distance to the closest park had a minor effect on park usage (Kaczynski et al., 2014; Schipperijn et al., 2017). Residents living in areas with low walking accessibility may prefer driving to parks, have large private yards in their houses or have access to parks within their community like parks attached to schools, elderly houses, or private clubs. The latter are not open to the public and hence may not be included in our dataset. In addition, the concept of parks accessibility employed in this work does not account for the size, number and quality of parks, all factors that have shown to increase park usage (Giles-Corti et al., 2005; Kaczynski et al., 2014; Schipperijn et al., 2017). To further understand the disparity in unmet park demand to produce specific policy responses, future research should explore important factors such as the size of park accessible to an amount of people to tease out small parks that serve a lot of people in comparison to big parks only accessible to small groups of people.

Our results leverage Google Maps data to enable large-scale cross-sectional analysis with fine-grained resolution. Unlike administrative land-use datasets, which typically include six to ten coarse land-use types (e.g., residential, commercial) and vary substantially in their land and amenity classification, the Google Maps dataset provides a unique opportunity to study land-use patterns at a high resolution using a consistent amenity classification across cities (Weiss et al., 2020). However, the completeness and quality of Google Maps data may vary across countries and are an important limitation of this work. With respect to identification of parks, we observed differences across countries in terms of the proportion of parks with defined boundaries (i.e., parks represented as a polygon rather than a point). Moreover, Google Maps does not provide globally consistent data on park ownership (e.g., private versus public), while there is some information available on amenities offered within parks (e.g., playgrounds, community gardens, trails, or restrooms), the data on amenities is not complete. The data used in this research did not include defined access points, or data on safety, cleanliness, attractiveness, or quality of parks. Despite Google Maps being the best available dataset (Hochmair, 2018) with frequent updates and robust quality controls (Google, 2014; Google, 2021), the validity of the parks data cannot be fully ascertained. Errors due to missing parks and incorrect locations in the lack of ground truth data at international scale may emerge (See Supplementary Materials for more detail).

Moving beyond this study to the global scale, our study can enable cross country benchmarking and support governments in establishing goals for green space provisions (how many people have access to parks in urban areas). Moreover, measuring access to parks over time at scale, opens the possibility to track progress of cities and countries towards the United Nations Sustainable Development Goal, SDG11, of providing "...universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities" by 2030. Specifically, the spatial resolution of our metrics allows policymakers to conduct analyses across scales, understanding which countries have higher disparity in access and most importantly, opens the possibility for more granular analysis in future work to detect which neighbourhoods and communities may be left behind.

In principle, aggregated Google Maps data could be used to enable research on access inequality in various amenities that are linked to higher quality of life and public health like access to healthy food, health services, transportation, education, and recreational facilities. Measuring access to amenities across countries and time on a global scale in fine-grain resolution can indeed pave the way for illuminating the spatial and social inequalities between neighbourhoods through objective data-driven metrics advancing inclusive decision making in policy and planning. Pursuing open and replicable pipelines for these types of study will represent another objective for the future.

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Supplementary Materials

S2 cells data

Our metrics of park accessibility were calculated at the level of S2 cells. The S2 library provides a mathematical representation of the Earth's surface projected onto a 3 dimensional sphere, making it possible to build a worldwide geographic database using a single coordinate system, and with low distortion everywhere compared to the true shape of the Earth (link). The resulting grid of S2 cells can be defined at different levels of spatial resolution, varying from level 0 (6 cells of 7842 km^2 covering the entire sphere in) to level 30 (the finest resolution of cells with average size of 0.74 cm^2). S2 cells at a level of resolution are of similar but unequal sizes, such that L16 S2 cells, which are the predominant level of spatial resolution used in this work, are roughly 150m x 150m in size with an area of about 0.02 km^2 (link).

Accessibility computation

For each park we compute the point-to-point navigation metrics from the surrounding populated s2 cells as the source, upto a radius of 10 km, and the park as the destination. We compute the navigation to the boundary of the park. When the boundary of the park is missing we use the location (latitude, longitude) of the park.

A point-to-point navigation API call is relatively time and computationally intensive. The change in the navigation estimates is high (sensitive to small distance changes) in the vicinity of the park and decreases as we are farther away from it. For optimized computation and to keep the relative error in estimates negligible, we compute the navigation estimates using high resolution S2 cells of level 16 (roughly 150m x 150m) in the region within 3 km from the park and gradually increase the size of the S2 cells as we move further away. We stop increasing the size of the S2 cell when it reaches the level 14 (roughly 600m x 600m). We convert the level 15 and level 14 S2 cells into level 16 child S2 cells contained within them and assign them the same metrics as that of their parent. In this way, every populated S2 cell within a 10 km radius of a park will be assigned a walking time. If a populated S2 cell has multiple parks in their vicinity, we retain the data associated with the park requiring the least walking time.

For a populated S2 cell that did not have a single park within 10 km radius, we assigned a default high value of 3 hours of network walking time.

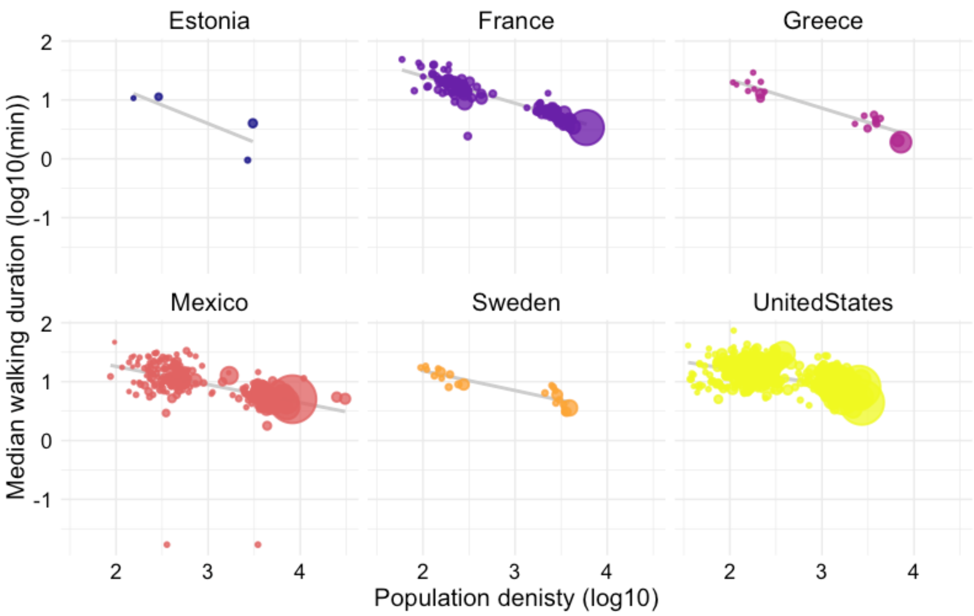
Parks data

To assess the coverage and quality of our inventory of parks, we performed a manual comparison for France against Copernicus Urban Atlas land cover data. The lack of globally consistent dataset for parks makes such a global comparison challenging. Our initial comparison found few overlaps in both datasets, mostly large parks. The parks identified in the Copernicus dataset were limited to very large national parks and forests or roadside greenery, potentially because the data captures green spaces from satellite imagery. Within urban areas, we found Google maps to be complete and accurate for small urban parks for the French cities we manually validated.

Effect of density and walking durations

To validate our results, we tested what percentage of the variation in walking durations can be explained by the variation in population density. For that, we correlated the density (population by area in km²) with our indicator of median walking duration across all regions by country, on a double log10 scale. We find a strong correlation in all countries except Estonia (which has only 2 cities) in the same direction - higher density is associated with lower walking durations as seen in Figure 7. Higher density has a stronger effect on walking durations in Greece (adj.$R^2 = .89$, $p < 0.001$), France (adj.$R^2 = .82$, $p < 0.001$) and Sweden (adj.$R^2 = .77$, $p < 0.001$) and weaker effect in the US (adj.$R^2 = .34$, $p < 0.001$) and Mexico (adj.$R^2 = .28$, $p < 0.001$). See full regression results in Table.4.

Figure 7. Linear regression models by country between walking durations to parks (in minutes) to population density (in km²) on a double log10 scale



Model's results

Table 2. Anova by country

Cntry_name	term	df	sumsq	meansq	statistic	p.value
Estonia	sub_region_1_code	1	1.34174	1.34174	0.22153	0.68421732655
Estonia	Residuals	2	12.11347	6.05674	NA	NA
France	sub_region_1_code	1	581.64733	581.64733	104.15416	0.00000000000
France	Residuals	127	709.22958	5.58448	NA	NA
Greece	sub_region_1_code	1	12.98734	12.98734	4.31811	0.05229148470
Greece	Residuals	18	54.13768	3.00765	NA	NA
Mexico	sub_region_1_code	1	88.67128	88.67128	20.24286	0.00000983446
Mexico	Residuals	294	1,287.82979	4.38037	NA	NA
Sweden	sub_region_1_code	1	34.62545	34.62545	7.34386	0.01348089691
Sweden	Residuals	20	94.29767	4.71488	NA	NA
UnitedStates	sub_region_1_code	1	1,008.09840	1,008.09840	46.81269	0.00000000002
UnitedStates	Residuals	517	11,133.45260	21.53472	NA	NA

Note : Anova test by country and region code. Testing the difference between cities and commuting zones per country.

Table.3. Regression results for population density and walking duration, for France and the United States, by region and income

Country	Region	Income	term	estimate	std.error	statistic	p.value	conf.low	conf.high	Adj. R^2
France	City	nonpoor	(Intercept)	2.1007	0.2250	9.3369	0.00000	1.6510	2.5504	0.3590
France	City	nonpoor	log10(density)	-0.4950	0.0822	-6.0231	0.00000	-0.6593	-0.3307	0.3590
United States	City	nonpoor	(Intercept)	1.7723	0.1340	13.2300	0.00000	1.5085	2.0361	0.1261
United States	City	nonpoor	log10(density)	-0.2783	0.0451	-6.1707	0.00000	-0.3671	-0.1895	0.1261
France	City	poor	(Intercept)	0.9334	0.1554	6.0081	0.00000	0.6229	1.2440	0.0360
France	City	poor	log10(density)	-0.1249	0.0682	-1.8301	0.07204	-0.2613	0.0115	0.0360
United States	City	poor	(Intercept)	0.9245	0.1034	8.9425	0.00000	0.7209	1.1281	-0.0020
United States	City	poor	log10(density)	-0.0264	0.0380	-0.6940	0.48830	-0.1011	0.0484	-0.0020
France	Commuting Zone	nonpoor	(Intercept)	2.2745	0.2183	10.4209	0.00000	1.8383	2.7106	0.2630
France	Commuting Zone	nonpoor	log10(density)	-0.6535	0.1339	-4.8820	0.00001	-0.9210	-0.3860	0.2630
United States	Commuting Zone	nonpoor	(Intercept)	1.4961	0.0794	18.8347	0.00000	1.3397	1.6525	0.0496
United States	Commuting Zone	nonpoor	log10(density)	-0.1422	0.0373	-3.8085	0.00017	-0.2157	-0.0687	0.0496
France	Commuting Zone	poor	(Intercept)	1.2418	0.0513	24.2181	0.00000	1.1393	1.3442	0.1409
France	Commuting Zone	poor	log10(density)	-0.2566	0.0757	-3.3906	0.00121	-0.4078	-0.1054	0.1409
United States	Commuting Zone	poor	(Intercept)	0.9174	0.0369	24.8584	0.00000	0.8447	0.9901	0.0559
United States	Commuting Zone	poor	log10(density)	0.1091	0.0272	4.0184	0.00008	0.0557	0.1626	0.0559

Table.4. Regression Results for population density and walking duration for each country

Country	term	estimate	std.error	statistic	p.value	conf.low	conf.high	Adj. R^2	df
Estonia	(Intercept)	2.48499	0.88868	2.79626	0.10763535144	-1.33871	6.30868	0.52766	2
Estonia	log10(density)	-0.62888	0.30148	-2.08601	0.17228644869	-1.92603	0.66827	0.52766	2
France	(Intercept)	2.32576	0.05605	41.49146	0.00000000000	2.21484	2.43668	0.81682	127
France	log10(density)	-0.46044	0.01926	-23.91156	0.00000000000	-0.49855	-0.42234	0.81682	127
Greece	(Intercept)	2.31084	0.11594	19.93060	0.00000000000	2.06725	2.55443	0.89087	18
Greece	log10(density)	-0.48335	0.03869	-12.49398	0.00000000026	-0.56463	-0.40207	0.89087	18
Mexico	(Intercept)	1.87574	0.09159	20.47980	0.00000000000	1.69548	2.05600	0.27540	293
Mexico	log10(density)	-0.30840	0.02905	-10.61783	0.00000000000	-0.36556	-0.25124	0.27540	293
Sweden	(Intercept)	1.85497	0.11395	16.27950	0.00000000000	1.61728	2.09265	0.77429	20
Sweden	log10(density)	-0.33520	0.03922	-8.54640	0.00000004139	-0.41701	-0.25338	0.77429	20
United States	(Intercept)	1.71910	0.04198	40.94793	0.00000000000	1.63663	1.80158	0.34195	517
United States	log10(density)	-0.25441	0.01548	-16.43699	0.00000000000	-0.28482	-0.22401	0.34195	517