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Where are the people? Counting people in millions of street-level images to explore associations between people's urban density and urban characteristics

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ABSTRACT

A thorough understanding of how urban space characteristics, such as urban equipment or network topology, affect people's density in urban spaces is essential to well-informed urban policy making. Hitherto, studies have primarily examined how the characteristics of the urban space impacts the number of people visiting different parts of the urban area (*e.g.*, the city center). However, these studies almost without exception have used relatively small data sets, targeting specific neighborhoods or places. As a result, their findings are confined to specific areas and it is unclear to what extent their findings generalize to other urban areas. This study addresses this gap. We propose a new computer vision-based method to study how the urban space is associated with people's urban density in outdoor urban spaces. Specifically, our method uses a pre-trained object detection model to identify and count people as well as urban-related objects, such as presence of cars, and benches in millions street-level images collected throughout the Netherlands. Importantly, each street-level image is geo-located. Therefore, for each detected person and object its location is known. In turn, we regress urban space characteristics and urban-related objects on the number of people identified as a proxy for density in urban spaces. Our results show that higher numbers of people tend to be observed in places with smaller blocks, suggesting that compact urban development may be an effective way to increase people's density. Moreover, we find that the presence of food places and bicycles is associated with more people, indicating that urban planners could study the location of these amenities to attract more visitors to urban spaces and exploring the causality effects in this relationship. Our methodology offers a complementary way to monitor how the urban space is used over the time and to assess the effectiveness of urban interventions and policies.

1. Introduction

A thorough understanding of the relations between the people's density in urban spaces and urban space characteristics is essential for urban and mobility planning and, consequently, for policy making (Cunha & Moura, 2015). Urban space characteristics concern all city spaces between buildings in the open air (Krier & Rowe, 1979). Attaining a better understanding of these relations enables the assessment of the impact of urban developments, identifying patterns of where people tend to be in cities, deciding where to allocate new services, as well as measure the effects of different urban attributes on people's behaviors. Overall, urban planners and policymakers can use these relations to design better cities to attract more people and create livable and inviting urban spaces.

The number of people in urban spaces is (co) determined by many factors, such as time of day, characteristics of places, and weather conditions. Attributes such as urban layout, appearance, number of benches, or traffic were found to influence the number of people visiting a given space (Lebel, Krittasudthacheewa, Salamanca, & Sriyasak, 2012). It also has been discovered that people tend to visit places with better walking accessibility (Sheng, Wan, & Yu, 2021; Abass & Tucker, 2021), greenery neighborhoods (Abass & Tucker, 2016; Krellenberg, Welz, & Reyes-Päcke, 2014), places with slow-moving traffic or limited parking (Uslu et al., 2010), and neighborhoods with a shorter distance to

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the city center, mixed land-uses, and higher densities (Mouratidis, 2018).

However, these studies have been applied mainly with data from small neighborhoods or specific places, which makes it difficult to generalize methods and results. Most of the data in these studies come from questionnaires (Sugiyama & Thompson, 2006), surveys (Abass & Tucker, 2021), field observations (Lipovská et al., 2013), and paper diary methods (Mossong et al., 2008). These practices do not allow capturing high-resolution data over large areas because they are often time-consuming, error-prone, labor-intensive, or intrusive. Therefore, larger-scale research and new methods of data collection are needed to better understand the relations between urban space and the number of people.

Fortunately, a large number of studies have developed new techniques for counting people in urban places using different technologies. For example, the location of social media posts has been used to infer the number of people in diverse areas (Hamstead et al., 2018; McKenzie, Janowicz, Gao, & Gong, 2015; Steiger, Westerholt, Resch, & Zipf, 2015; Bocconi, Bozzon, Psyllidis, Titos Bolivar, & Houben, 2015). In addition, data from cell phones and Wi-Fi sensors have also been used to measure the movements and number of people in entire cities or regions (Traunmueller, Johnson, Malik, & Kontokosta, 2018; Kontokosta & Johnson, 2017; Danielis, Kouyoumdjieva, & Karlsson, 2017). Recent advances in computer vision also offer promising ways to analyze and collect urban features, human activity data, and people counts from images. Several studies have developed different techniques for estimating the number of people at events and entire cities using images from social media or video recordings (Shami, Maqbool, Sajid, Ayaz, & Cheung, 2018; Jendryke, Balz, McClure, & Liao, 2017; Bansal & Venkatesh, 2015). These methods can capture a massive amount of high-resolution data over large areas for fine-grained studies.

In this study, we combine the idea of using such new approaches to capture more detailed and spatial-extensive data in order to better understand the relations between the people's density in urban spaces and urban space characteristics. It can be described using a variety of variables, including the road network, traffic volumes, street furniture, land uses, etc. Specifically, we use the widespread availability of geo-tagged images (e.g., from Google street-view or Mapillary, 2022) to create high-resolution datasets of different urban characteristics and human behaviors, and thereby facilitate the analysis of their co-relations. Along these lines, several studies have used street-level imagery for urban analysis, see the review of Biljecki and Ito (2021). The increasing use of this data source opens the opportunity to also use it to understand how urban crowds relate to urban characteristics. Therefore, the objective of this study is twofold. First, the substantive aim is to deepen the understanding of the relations between the people's density in any urban space and the characteristics of these places. Second, the methodological objective is to develop a computer-vision-based approach for using images as a potential data source to conduct urban studies. The results will provide insights on how different characteristics of the urban space influence the number of people visiting a particular space, which can be used as a basis for urban and mobility planning for the urban areas analyzed. Also, it provides a general method that could be replicated in many cities.

The remaining part of this document is organized as follows. First, the data and their collection are described and explained. Second, the methodology is presented. Third, we present the case study in the Netherlands. Finally, the results and conclusions are reported.

2. Data

Two types of data are used in this study. First, Geographic Information System (GIS) data from Open Street Map (OSM, 2022), which includes the location of services and amenities, land-use information, and street networks. Second, street-level imagery from Google Street View (GSV) which corresponds to 360-degree images taken and superimposed on the street network. These two data types are retrieved for each analysis area included in our study.

2.1. GIS data collection

This study makes use of five different GIS layers: (1) *city boundaries*, which correspond to the geographic boundaries of the city or municipality within which the rest of the data is collected; (2) *street network edges*, corresponding to the streets of the traffic network within the set boundary; (3) *street network nodes*, corresponding to the structural nodes of the street network and intersections; (4) *amenity locations*, which correspond to the services, places, and facilities within the boundaries, such as restaurants, parking lots, or schools; and (5) *land-uses*, indicating the primary land-use for the different sub-regions within the geographical boundaries, such as residential, commercial, or industrial.

All geographic data are collected from OSM using the Python package OSMnx (Boeing, 2017). This package allows obtaining different GIS layers related to the city, such as street networks, location of various stores or services, water areas, and land uses. Municipal boundaries and street networks can be easily obtained using the internal functions of OSMnx. Amenities and land uses can be obtained with OSM tags using a specific key-value. Table 1 summarizes the different layers used and the tag considered when relevant.

Amenities and land uses both contain different categories. Firstly, an amenity is defined as a useful and important facility for residents and visitors. Facilities range, for example, from public toilets and public telephones to banks, pharmacies, prisons, and schools (OSM Wiki, 2022). In total, over 100 different amenities can be obtained. To simplify the structure of this data, all amenities are aggregated into nine categories: *food place*, *education*, *transportation*, *financial*, *entertainment*, *public service*, *facility*, *waste management* and *other*. Secondly, a land use describes the main function a land is used for (OSM Wiki, 2022). In total, 37 different land uses can be obtained, where the most important and common ones are: *commercial*, *construction*, *education*, *industrial*, *residential*, *retail* and *institutional*. OSMnx provides access to a wide range of GIS data that can be selected based on the nature of the problem or analysis being conducted. In this research, the most widely used and city-agnostic GIS layer were selected to perform cross-sectional analysis across multiple cities.

2.2. Street-level images collection

The images we use in this study come from Google Street View (GSV). Images are queried using specific coordinates. Specifically, within each boundaries of a study area, a grid of points is composed, where each point is separated from the others by d_{grid} meters (e.g., 50 meters). Then, for each point, its longitude and latitude information is specified in Google API to extract the surrounding GSV image id. Each GSV image id corresponds to a unique 360-degree panorama view at the street level. Fig. 1 shows an example of a 360-degree image divided into four individual images based on the rules explained in the next paragraph. In addition, for each image, the date when the picture was taken and its exact coordinates are stored.

Each 360-degree image is divided into four individual images to have more regularity in the angles of view of the images subject to analysis. As shown in Fig. 1, a front, back, and two side views of the street are

Table 1
Summary of GIS layers used collected from Open Street Map (OSM).

Layer	GIS type	OSM tag
Boundary	Polygon	OSMnx function
Edges	Line	OSMnx function
Nodes	Point	OSMnx function
Amenities	Point	{“amenity”: True}
Land uses	Polygon	{“landuse”: True}

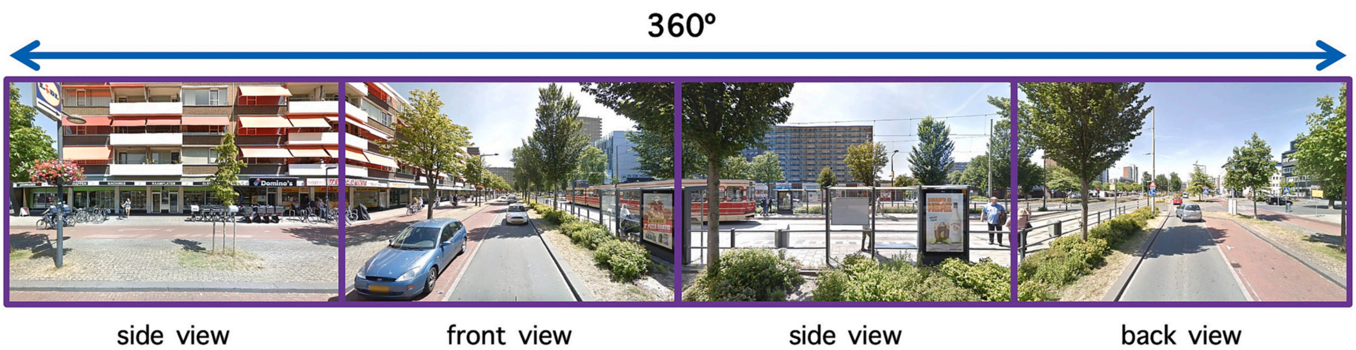

Fig. 1. A 360º panorama view retrieved from Google Street View (GSV). Four individual 90º images are shown: front, back, and two side views (left and right view).

retrieved. To do so, each panorama is associated with the closest street (street network edge) to infer the angle of the street with respect to the horizontal (see angle α in Fig. 2). Fig. 2 shows an example of image coordinates (red dot) associated with the closest edge to identify the angle α. With this angle, four individual URLs are built, corresponding to the four images (Fig. 1).

Following this data collection process, all GIS data and URLs of the images are stored in databases per study area. Next, the methodology described in the following section is applied to the data collected.

3. Methodology

The methodology used in this work is divided into two main steps. First, data processing is performed, which includes processing each collected image with an object detection model (ODM) and then aggregating the detected objects and GIS data into spatial units. Second, data analysis is then carried out, which includes the estimation of linear and spatial models to establish the relation between the number of people counted in the images collected within a given spatial unit (*i.e.*, people's density) with the respective urban characteristics in the same unit. Fig. 3 shows a diagram of the methodology which depicts the analysis flow while referring to the data types retrieved in the data collection process.

In the following subsections, steps one and two of the methodology are detailed.

3.1. *Step 1: Data processing*

This step has two main objectives. First, it aims to process all collected images to extract information contained in them, which is stored in a GIS data format. Second, it aims to aggregate the GIS data retrieved and the image information in spatial units for subsequent analysis.

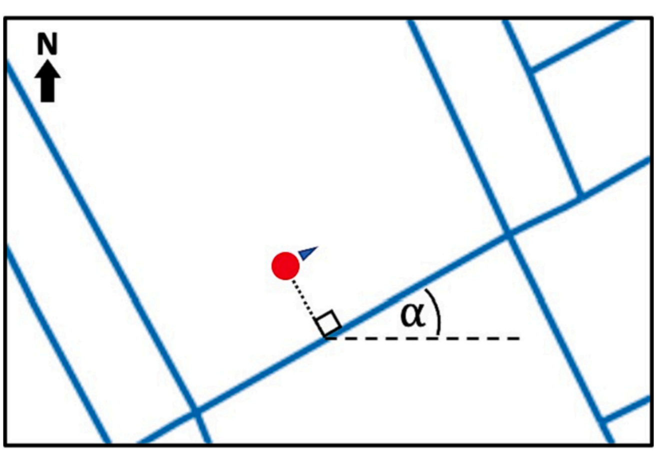

Fig. 2. Angle of the street with the horizontal (α). The street network is inferred for each GSV image to identify the front view.

3.1.1. *Image processing*

GSV images are analyzed to identify people and urban-related objects. For this purpose, images are processed with an Object Detection Model (ODM) - a machine learning method used to recognize objects in images - to identify people and other urban-related things. Specifically, because this work aims at processing a large number of ideas, the pre-trained SSDMobileNetV3 model (Howard et al., 2019) is selected. This model is faster compared to other models available at the time of this study for person identification because it was designed to run on smartphones, which requires less computational power. SSDMobileNetV3 is capable of recognizing a large number of objects, but only 13 urban-related objects are selected for this study, namely *person*, *bicycle*, *car*, *motorcycle*, *bus*, *train*, *truck*, *boat*, *traffic light*, *fire hydrant*, *stop sign*, *parking meter*, and *bench*.

Since each image is geolocated, the number of objects identified in each one can be mapped. This means all detections can be stored as GIS data, similar to the data retrieved from OSM. To complement Table 1, the detections are stored based on the image's coordinates, registering information on the number of detections per category (*e.g.,* person, bicycle, etc.) in each of the images.

3.1.2. *Data aggregation*

In order to analyze the relations between people counts and urban characteristics, a spatial unit of analysis needs to be defined. For this purpose, regular hexagonal cells with d_{side}-meter side (*e.g.*, $d_{side} = 50$ meters) are constructed that tessellate the entire study area. The information collected (see Table 1) and processed (from step 1a) within each hexagon is aggregated using different functions. Fig. 4 shows an example of a hexagon cell and all possible geographic data contained therein.

Edges are aggregated by the sum of the total length of edges within the cell; *nodes* are aggregated by counting the number of nodes per cell; *amenities* are aggregated by counting the total number of places per category per cell (*e.g.*, the total number of educational places, financial places, etc.); *land-uses* are aggregated by the sum of the total area per category per cell (*e.g.*, the total squared-meters of residential area, industrial area, etc.); and *detections* are aggregated by the average number of detections made for the images within the cell per class (*e.g.*, person, cars, etc.). For instance, the aggregated value for the class *person* is obtained by dividing the total number of people detected in all images of a hexagon by the number of processed images within the hexagon.

3.2. *Step 2: Data analysis*

Two types of models have been selected to study the correlation between the people's density (*i.e.,* people's counts) in urban places and their characteristics. Both models are applied at the level of hexagonal

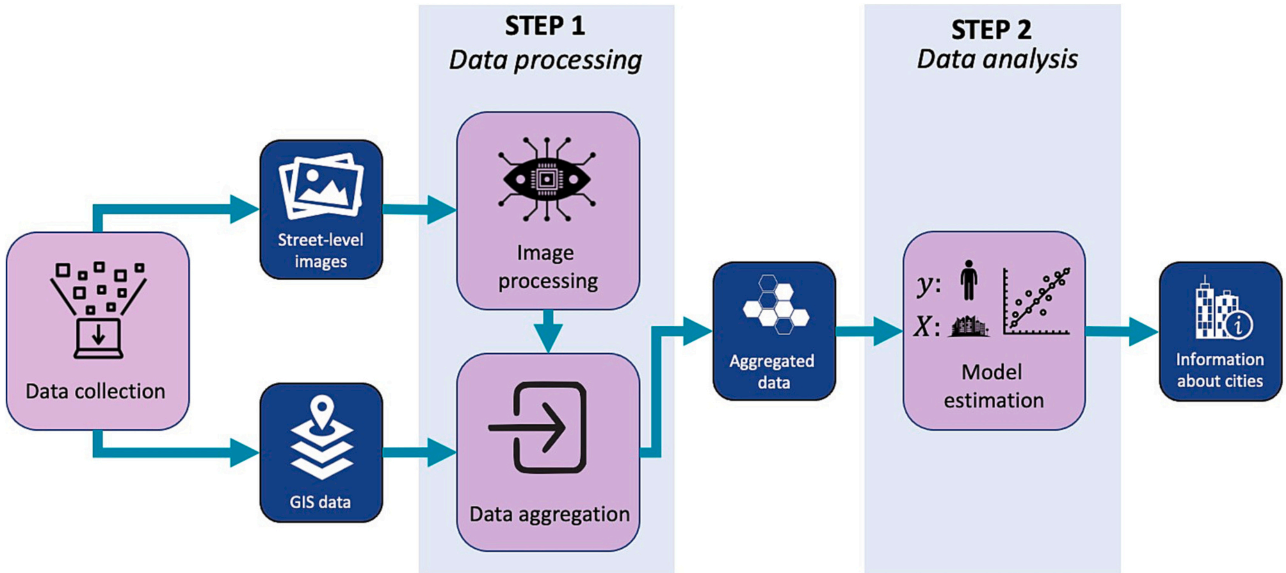

Fig. 3. Summary of the methodology. Purple (large) boxes are sub-steps, and blue (small) boxes are input/output of each sub-step. In data collection, GIS and images are retrieved. Then (STEP 1), images are processed with an object detection model, converted to GIS data, and aggregated in spatial units. Finally (STEP 2), all GIS data is used to estimate various statistical models.

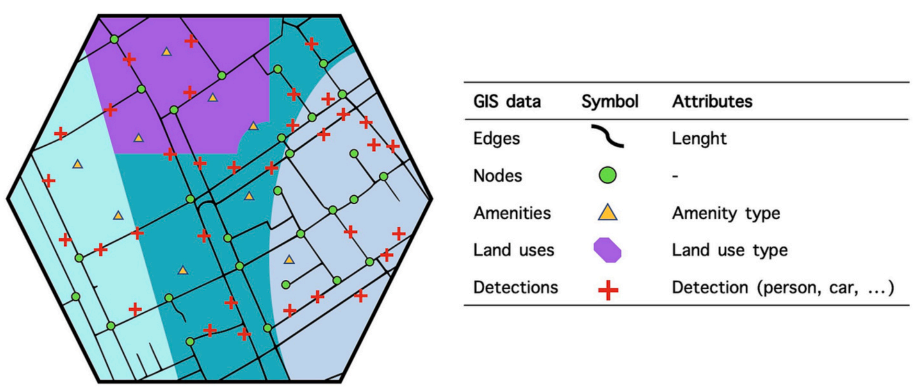

Fig. 4. An illustration of an individual hexagonal cell. For visual purposes, the length of this hexagon's side is set to 340 meters ($d_{side} = 340$ meters).

cells (defined in step 1b). First, a linear regression model is used to infer the impact of each urban characteristic on the number of people present in each cell. Second, a linear model with spatial autocorrelation parameters accounts for the spatial effect of neighboring hexagons on the number of people. In this case, the spatial Durbin model is chosen (Durbin, 1960). In both models, the number of people in the different spatial units (i.e., hexagons) is the dependent variable (Y), and all urban-related variables (e.g., network topology, presence of cars, bicycles, land uses, etc.) are the independent explanatory ones (X). In the subsequent subsections, each model is explained.

3.2.1. *Linear regression model*

A classic linear model is used to study the correlation between the number of people identified and the urban-related variables measured within each cell. In Eq. (1)Y corresponds to the vector of number of people, where each element is the observed number of people within a particular cell, X is the matrix that contains all explanatory variables (with a constant), β represents the vector of parameters for each explanatory variable, and ϵ is the vector of errors associated.

$$Y = X\beta + \epsilon \tag{1}$$

The k explanatory variables ($x_k \in X$) can be divided into four groups: *network* variables which include the number of nodes and total meters of streets, *amenities* and *land-uses* which correspond to the variables previously described, and *detections* which correspond to all variables gathered from image processing. This model aims to identify the associations between all urban variables with the number of people in the urban space, only considering the quantities of each variable. But when spatial variables are studied, near things are more related than distant things (Tobler, 1979). Therefore, another model is used to complement the results.

3.2.2. *Spatial Durbin model*

This model is similar to the linear regression model but takes into account the effect of the neighboring cells' values (spatial correlation) to explain the output (*i.e.*, number of people). Two variables are spatially correlated if they are close to each other and are similar in their attribute values. Specifically, a Durbin model estimation considers the effect of neighbor Y values (number of people in neighboring cells) and the effect of all neighbor X values (*e.g.*, the number of cars in neighboring cells) on the dependent variable (Y). In other words, a Durbin model measure spatial auto-correlation (*i.e.*, effect of Y on Y) and the spatial correlations (spatial effects of Xs). In Eq. (2), the model specification is shown for a spatial Durbin model in matrix notation.

$$Y = \rho WY + X\beta + WX\gamma + \epsilon \tag{2}$$

Y represents the vector of the number of people per cell, X corresponds to the matrix of all explanatory variables per cell, β, and γ are the vectors of parameters for each $x_k \in X$ (with k explanatory variables), linear effect and spatial effect respectively, ρ is the vector of the spatial auto-regressive parameters for Y, ϵ the vector of errors associated, and W is a weighting matrix that measures the effect of neighboring cells. Eq. (3) defines each element of the matrix W where the value w_{ij} corresponds to the effect of cell i on cell j. In this case, w_{ij} is measured as the inverse of the euclidean distance.

$$w_{ij} = d_{ij}^{-1} w_{ij} \in W \tag{3}$$

In particular, to explain the number of people in a specific cell, this model includes (additional from linear regression) the auto-correlation effect of Y with WY (in ρ) and the spatial correlation effect of X with WX (in γ). It means, β parameters take into account the spatial correlations between variables. Therefore, only the β parameters are used in the result section (although the spatial parameters (ρ and γ)) provide information on the spatial correlation, unlike a linear model, β is already accounting for spatial effects of the Xs on Y.

4. Case study

The Netherlands is chosen as a case study. Specifically, we use the proposed method to understand the relation between people's density in Dutch urban spaces and the urban characteristics of those places. Also to demonstrate the potential of using street-level images as a data source for urban analytic and behaviors comprehension. The data used in this case study concerns GIS data and street-level images for all municipalities of the Netherlands. As of March 2022, the Netherlands comprises 344 municipalities and has over 17 million inhabitants (CBS, 2022).

Municipalities in the Netherlands vary in terms of surface area and population size. The average surface area is around $97 km^2$ and ranges between $[7;523] km^2$, and the average population per municipality is around 50 thousand inhabitants with a range of $[943;905k]$ inhabitants.

4.1. Definition and data collection

Within each municipality, 2022 GIS data and images from different years are collected. The grid used to retrieve GSV images is overlaid using $d_{grid} = 50\ meters$. The smaller d_{grid} is, the more images can be collected, but more computation time is needed for analyzing the images in the posterior steps. With d_{grid} equals to 50 meters we found a good trade-off to have a sufficient amount of data and to allow us to collect all the Netherlands. Next, the data are aggregated in $d_{side} = 50\ meters$ hexagon cells. In this case, $d_{side} = d_{grid} = 50\ meters$ was used to have spatial units with the same level of resolution at which the images were collected. Additionally, a spatial unit with a resolution of 50 meters allows us to capture the local variations in the urban data collected (e.g. land uses) within walkable distances, making it a suitable scale for our research aims. However, the methodology is able to manage different values of d_{side} and d_{grid} which allows future exploration in multi-scale analysis.

MAUP effects (Openshaw & Taylor, 1984) can be generated when the data is aggregated into the 50 meters hexagon cells. MAUP can be separated into two main effects: the zoning effect and the scale effect. Zoning effect refers to the changes in results that occur when the boundaries, shape or position of the areal units are changed. We think this effect has no major implications in our results because we have used a random zonification and it is composed by a large number of zones (approximately 19 thousand hexagons per municipality in average). On the other hand, scale effect refers to the changes in results that occur when the size of areal unit of analysis is changed. In this case, scale effects can bias the estimation of spatial relationships and patterns. But we think our scale is small enough. Studies such as Arbia and Petrarca (2011) have shown that greater aggregation zones lead to a decrease in accuracy and precision of the parameters. This means that the lower the level of aggregation (i.e., bigger zones), the greater the loss in efficiency of the parameters. Also, as we mentioned 50 meters can capture local and spatial variations for people which are mostly walking in the urban spaces.

Over 46 million images are collected from 343 municipalities (Baarle-Nassau could not be collected due to issues with border lines between the Netherlands and Belgium). Images are collected from the years between 2008 to 2022. Fig. 5 shows a histogram of the number of images collected per municipality on the left and a map displaying its spatial distribution across the Netherlands on the right. It shows that for most municipalities approximately 100 thousands images are collected. The highest number of images are obtained for Amsterdam and Rotterdam (over 1 million images). Based on the rules to collect images (by the traffic network), the number of images per municipality, depends mainly on the surface and the population.

4.2. Data analysis at different levels of spatial aggregation

Next, we perform three kinds of analysis to explore the associations between people's density in urban places and the attributes of that places at different spatial levels. To do so, the two models presented in the methodology section are used (linear regression and spatial Durbin model) in three different ways. The analyses are (i) a national aggregated model with all data jointly, (ii) a national analysis using independent municipal models, and (iii) individual analyses in Rotterdam and Amsterdam. These three analysis considers the 50 meters-side hexagon as minimal spatial unit, but are performed at different scales. The Table 2 summarizes all analyses and below a detailed description for each is provided.

4.2.1. National aggregated model with all data jointly

Each 50 meters hexagon of each municipality of the Netherlands is used to estimate a unique Linear Regression Model (see step 2a in the methodology section). To this end, an ordinary least square estimation is used to obtain the parameters (βs) of all explanatory variables related to *network*, *amenities*, *land uses* and *detections*.

Since a model is being run at the national level with information collected at the municipal level, it is necessary first to identify which variables can be used to estimate the model. In order to have a robust, cross-sectional result and common variables available across the country, the model is estimated only with the variables present in all municipalities. For example, if there are municipalities that do not have information on military land uses, then this land use will not be included in the national model estimation. Consequently, the following variables have been retained and are included for model estimation: in the *network* variables, the number of nodes and the meters of streets are used; in *amenities*, the number of food places, education places, transportation-related places, financial places, entertainment places, public services, facilities, waste management places, and others are used; in *land uses* only residential, grass area, forest area, and cemetery are used; and for *detections*, bicycle, car, bus, motorcycle, truck, parking meter, and benches are used.

4.2.2. National analysis using independent municipal models

Individual models per municipality are estimated. In this case, to take into account the spatial relationships that are inherent to the data, the Spatial Durbin Model is adopted (see step 2b in the methodology section). By estimating a model per municipality, we can construct a distribution of the different βs across the country. We, therefore, maintain the same subset of variables as those employed at the national level jointly data version. This allows for the direct comparison of municipal-level models.

4.2.3. Individual analysis in Rotterdam and Amsterdam

Finally, the municipalities of Rotterdam and Amsterdam are chosen

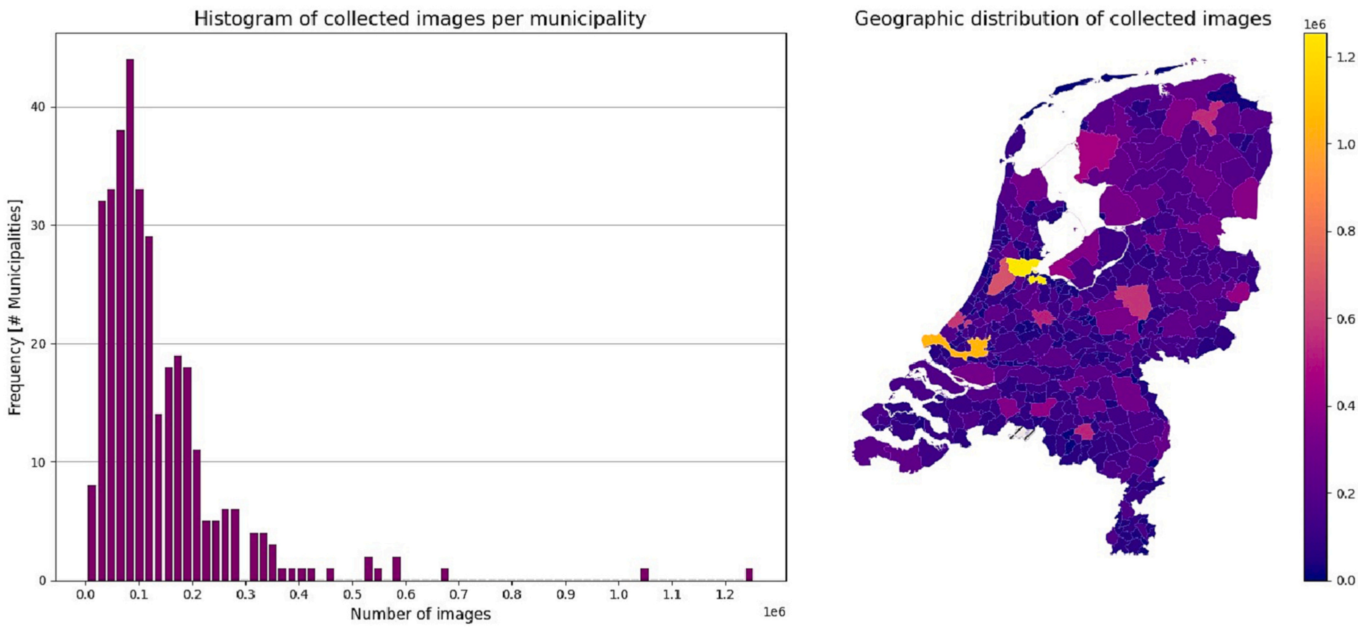

Fig. 5. On the left, a histogram of collected images per municipality in the Netherlands. On the right, a map with the spatial distribution of the number of images per municipality.

Table 2
Summary of the three different analyses conducted in this study.

Analysis	Model	Process
(i) National aggregated model with all data jointly	Linear regression	- Estimation with all hexagons from all municipalities (one model)
(ii) National analysis using independent municipal models	Spatial Durbin model	- One estimation per municipality (343 models)
(iii) Individual analyses in Rotterdam and Amsterdam	Spatial Durbin model	- One estimation per municipality (two models)

for a more detailed analysis. The two cities are the most populated cities in the Netherlands and they are geographically close (forty minutes' distance by train). Amsterdam is the capital and it has an urban landscape similar to most Dutch municipalities (the presence of old city centers). Rotterdam, on the other hand, has a different urban and architectural style, following its destruction in World War II. These two cases are used to demonstrate the results of the data processing section and then to compare the estimated model results. This allows for showing the particularities present in the data.

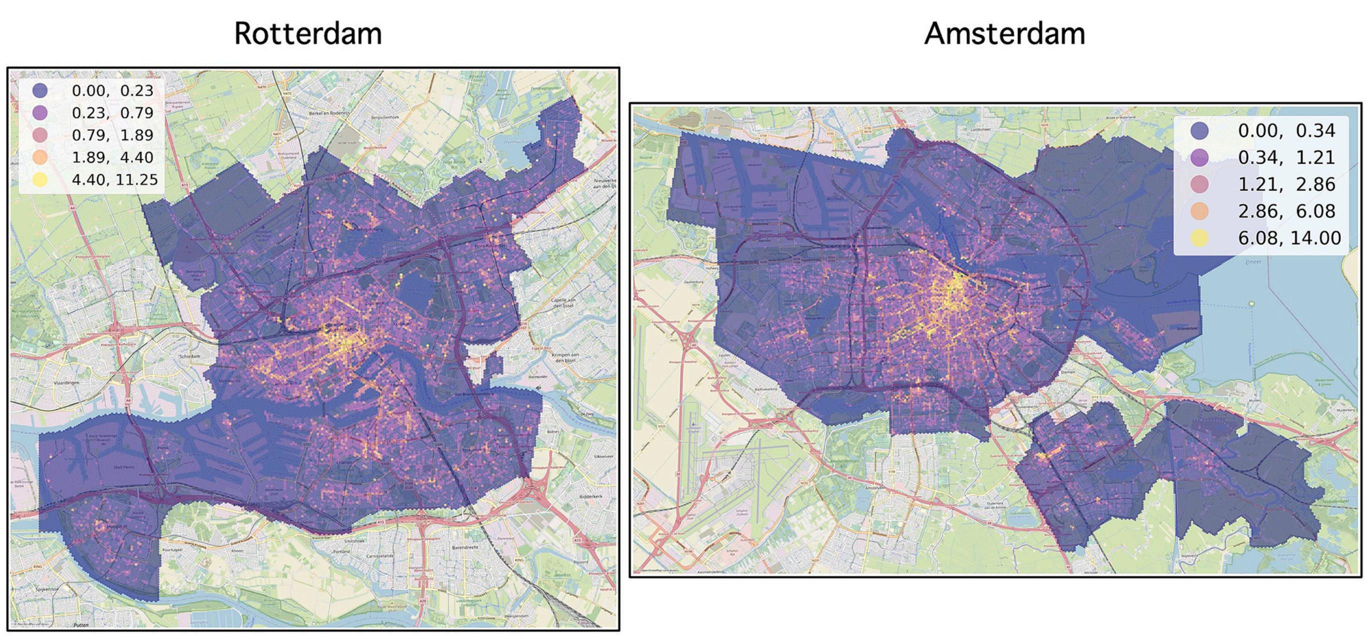

Fig. 6. People detection for the municipality of Rotterdam (left) and Amsterdam (right). Values shown correspond to the average number of people observed in images per hexagon and are presented at the 50-meter-hexagon level using a city-specific *natural breaks* color-scale scheme. The numbers in legend show the interval bounds for each color.

5. Results

We divide our presentation of the results into two parts. First, the results of the data processing (step 1 of the methodology) section are exposed. Second, the results of data analysis with the three different approaches (national aggregated model with all data jointly, national analysis using independent municipal models, and individual analysis in Rotterdam and Amsterdam) are presented and discussed (step 2 of the methodology).

5.1. Results of image processing step

Street-level images are analyzed to identify people and urban-related objects. Then, all the identified information is aggregated into hexagon-shaped cells. To illustrate how the outcome of data processing looks like, results from Rotterdam and Amsterdam are shown for illustration. Fig. 6 shows the spatial variation of the number of people identified within the municipal boundaries of Rotterdam and Amsterdam. As expected, both cities show the highest concentration of people in the respective city center areas. This showcases the possibility of using the information present in images to distinguish between crowded and uncrowded areas.

Fig. 7 shows the spatial distribution of the number of private vehicles (one of the independent variables) detected in the municipalities of Rotterdam and Amsterdam. It can be observed that the spatial distribution of private vehicles is more homogeneous than in the case of people (compare Fig. 7 to Fig. 6). Another pattern that can be observed by visual inspection is that there tend to be fewer cars in places with more people, and vice versa. This applies for both Rotterdam and Amsterdam.

More generally, our results demonstrate that the outputs from the data processing phase enable the analysis of various urban attributes and their spatial distribution in a study area. The data processing results in this study depend on which models are used to identify objects or situations in the images. In this particular case, we used object detection models to identify a limited number of objects of interest in urban environments. However, this method opens up a wide range of possibilities for gaining new insights by exploring other urban features using perhaps other image-processing tools.

5.2. Relation between people's density and urban-related characteristics

One of the objectives of this study is to examine the relations between people's density in urban spaces and the characteristics of those places. This section reports model estimation results for the series of models discussed in the methodology section (Section 3). The results are divided into three parts (as discussed in the case study section): (i) national aggregated model with all data jointly, (ii) national analysis using independent municipal models, and (iii) individual analyses in Rotterdam and Amsterdam.

The analysis of the relation between the number of people (as people's density) and urban-related objects is in each case performed using the 50-meter-sided hexagon as the minimum spatial unit in which the data were aggregated. Municipalities have around 19 thousand hexagons on average, ranging from one thousand to 140 thousand. After removing all hexagons without images, municipalities have about 4 thousand data points (hexagons) on average, ranging between 252 and 18 thousand. An inspection of the deleted hexagons indicates that they mostly correspond to water bodies, agricultural, and natural environment areas.

5.2.1. National aggregated model with all data jointly

We estimate a linear regression model using all hexagons with images from the 343 municipalities included. Almost 2 million data points are used to estimate the linear regression model. The model is estimated based on Ordinary Least Squares (OLS). Fig. 8 shows a bar chart with the values of standardized betas (regression parameters) for each variable. The standardized betas are normalized in standard deviation units, which facilitates the comparison of variables' explanatory power. The goodness of fit index R^2 of this model is 25%, which shows that the model is able to explain a substantial portions of the variance.

The national linear regression model results indicate that the number of bicycles detected, the number of food places, motorcycles detected, and the number of nodes (street intersections) have the strongest correlation with the people's density. The strong correlation between people and bicycles/motorcycles can be explained by the mode of transportation used to reach the most crowded areas. As previously mentioned (6 and 7), where people tend to be, fewer cars are detected. This finding aligns with the results of Uslu et al. (2010), who finds that

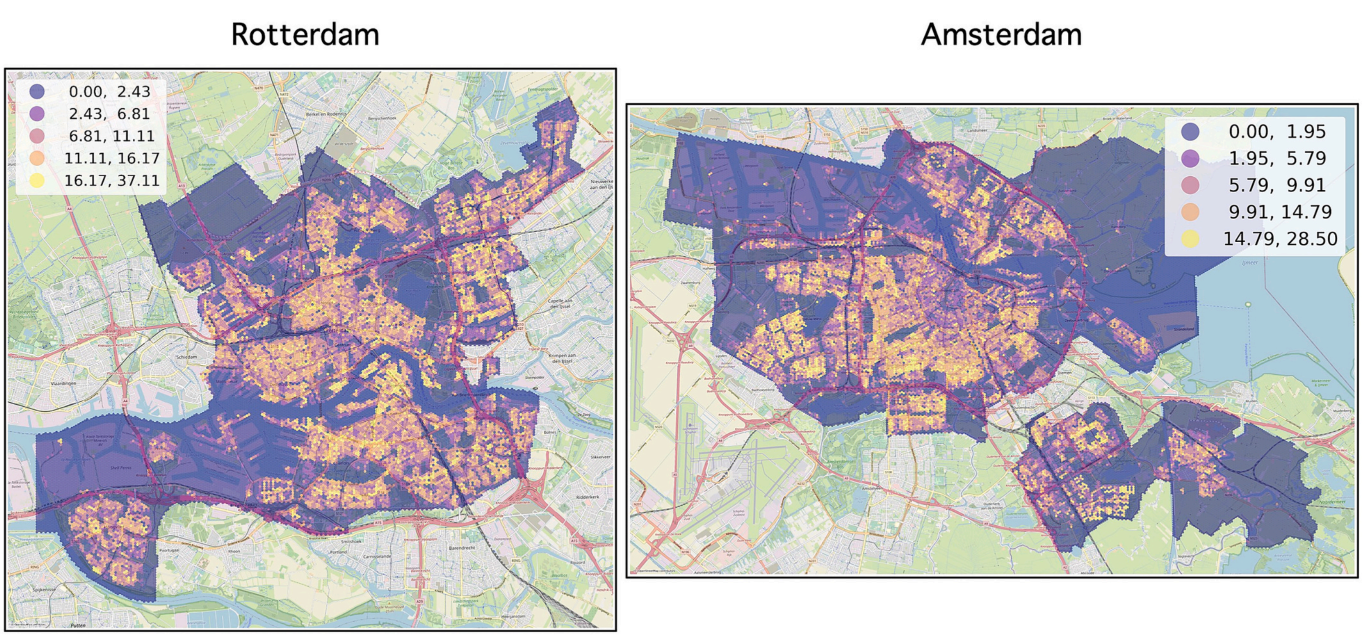

Fig. 7. Private vehicles detection for the municipality of Rotterdam (left) and Amsterdam (right). Values shown correspond to the average number of vehicles observed in images per hexagon and are presented at the 50-meter-hexagon level using a city-specific *natural breaks* color-scale scheme. The numbers in legend show the interval bounds for each color.

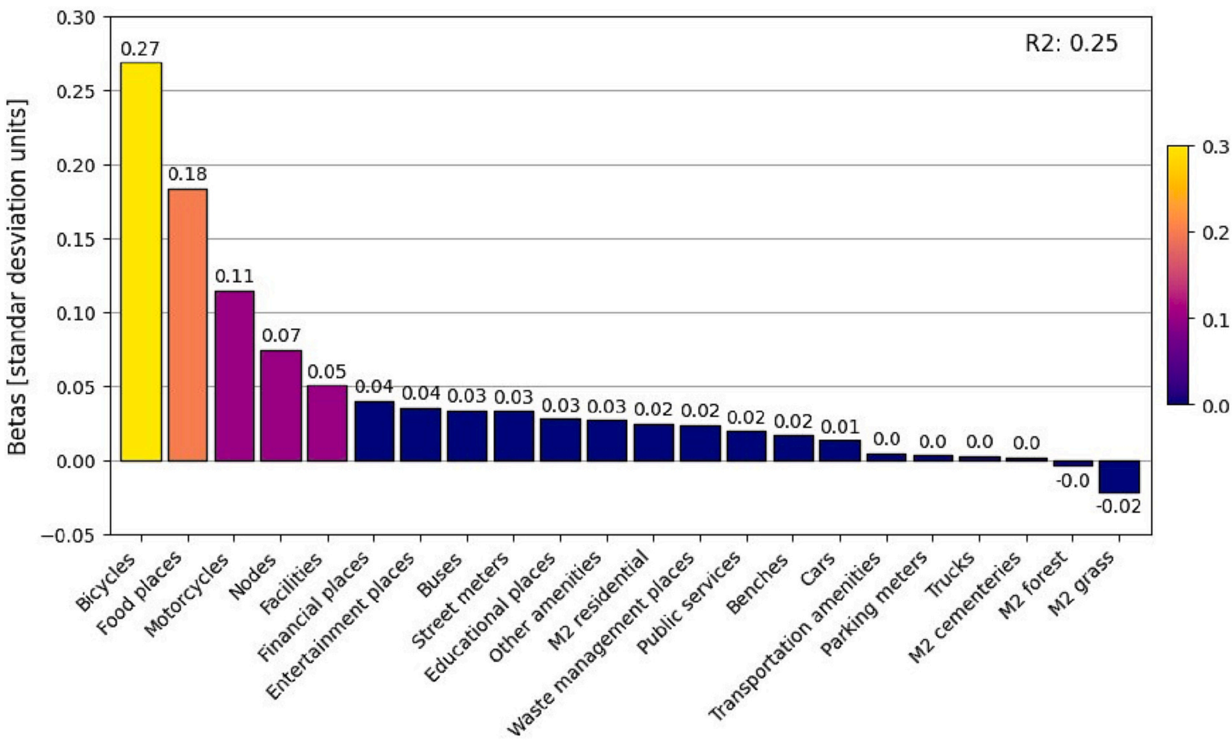

Fig. 8. Standardized betas from OLS estimation using all hexagon data jointly. Standardized betas use standard deviation units to facilitate the comparison of the explanatory power of variables.

less traffic dense areas attract more people. The number of nodes is related to the street network design, indicating that areas of the city with a higher number of intersections positively correlate with the number of people. The number of intersections per hexagon cell could also be related to the block size, indicating that smaller blocks could be associated with more people. This finding is aligned with the work of Jacobs (1961). She suggests that smaller blocks are more walkable, therefore, more attractive to people. Gómez-Varo, Delclòs-Alió, and Miralles-Guasch (2022) provides empirical evidence that local businesses in dense networks may increase urban vitality. This is in line with our finding that food places and small block areas positively correlate with each other. Lastly, the only two negative relations pertain the two land-

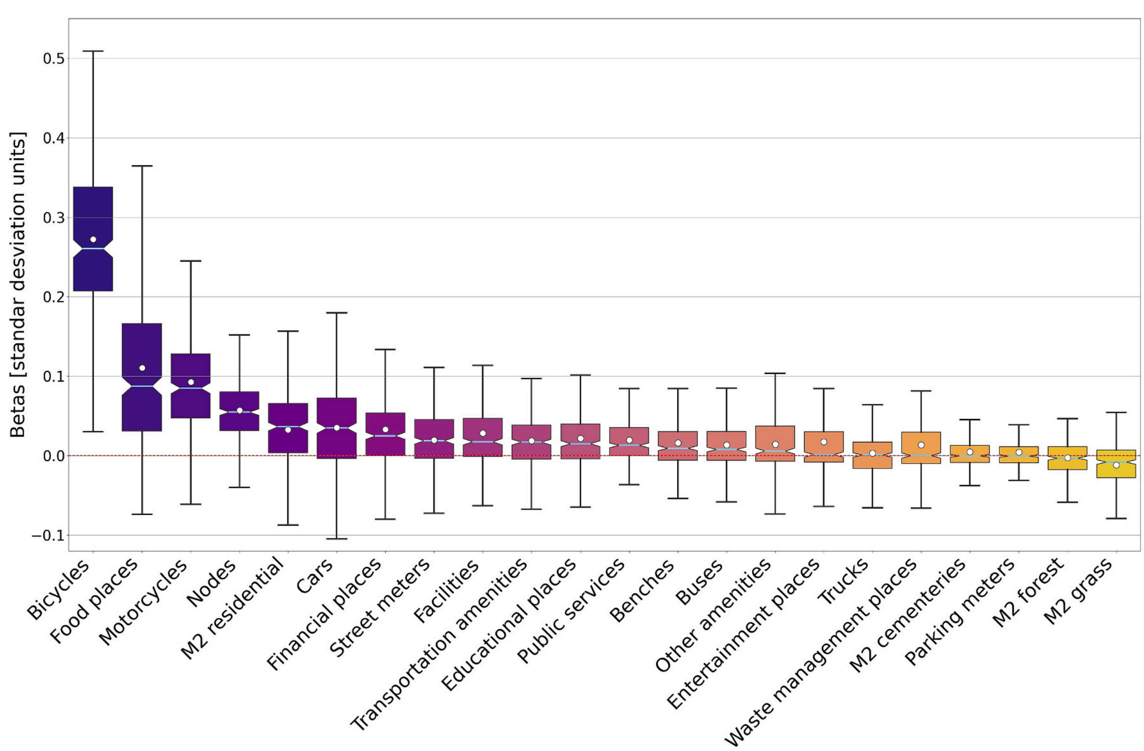

Fig. 9. Standardized betas from SDM estimations per municipality, grouped by explanatory variable. The white dot inside each boxplot shows average values.

use variables, squared meters of forests and grass. These two variables are mostly associated with areas where people do not live, so they are expected to have negative values. Nevertheless, their standardized values have among the lowest predictive power.

5.2.2. National analysis using independent municipal models

The model reported in the previous sub-section provides a general indication of the relation between people's density and different urban characteristics. We expect to find different patterns in different cities, potentially allowing us to unravel local relations from the spatial model (SDM). Therefore, it is important to explore how much difference can be found in the explanatory power of each variable across the country. Thus, 343 individual Spatial Durbin models per municipality are estimated, and thereafter, we construct the distribution of the different standardized βs across all municipalities. These β parameters (from SDM) include the spatial effects of the explanatory variables to disentangle the local impact. In addition, we maintain the same subset of variables as those employed at the national level model and the same number of data points per municipality (only hexagons with images in them). This allows for the direct comparison of all municipal-level models between them and the national linear model. Fig. 9 shows a box plot chart with the values of standardized betas (in standard deviation units) of each municipality for each explanatory variable. The white dot in the middle of each box plot represents the average value of each β across the country. The R^2 values in these models have an average of 24.5% and range widely between [6.7%; 63.8%].

The results of these municipal models point to the same first four variables, which exhibit the most explanatory power as in the national linear model when the box plots are sorted by the median. Fig. 9 shows that the only explanatory variable which is always positive (for all municipalities) is the number of bicycles detected. Bikes and people tend to be highly spatially correlated across the Netherlands. The number of nodes has again the four highest explanatory power (in terms of median and average) and has a positive relation in most municipalities (only fourteen municipalities show a negative correlation). The results generally indicate a significant degree of diversity in the relations studied across municipalities. This support the idea of study the urban phenomena with a local and small perspective (Jacobs, 1961), which underscores the importance of studying local effects in order to identify more informative relationships. Additionally, with this results we can determine which relationships are significant when the spatial distributions of the variables is taken into account.

The results presented in Figs. 8 and 9 reveal an at first sight counter-intuitive finding. Specifically, we find "natural places" such as *grass* and *forest* are weakly (negatively) correlated with people's density. An explanation for this small effect can be found in the rural areas. Rural areas contain comparative many "natural places", but tend to be less populated. As a result, few people are counted in these images. This "counter-intuitive" finding highlights an important notion. The space–time accessibility is not accounted for in this study (e.g., Hägerstrand, 1970). Therefore, the magnitudes of the betas cannot be taken as the isolated effects of the variables (e.g. land-use) on people's density. Rather, the betas represent the strength of the association between the variable and people's density given the spatial and temporal distribution of the variables and images.

The comparison of the national model and the municipal models reveals significant differences in the explanatory power for certain variables, such as cars, square meters of residential land use, and transportation amenities. The national model uses a traditional linear regression and considers data from only one hexagon at a time (one data point), while the municipal models use the Spatial Durbin Model (SDM), which considers spatial effects and data from neighboring hexagons. In addition, by applying one spatial model per municipality, the box plots in Fig. 9 can show for each variable the distribution of the explanatory power across the country. For instance, the low explanatory power of cars in the national model is because cars are distributed evenly throughout the country, whereas people tend to be concentrated in specific areas, mainly in city centers. The national model, being a single model for the entire country, may not accurately capture city-specific effects, leading to a small correlation between cars and people. On the other hand, the individual municipal models indicate that some municipalities have a negative correlation between people and cars, while others have a positive correlation, and the median explanatory power for the municipal models is higher compared to the national model. This is because the SDM model can identify relationships between groups of neighboring cells that have similar values, providing a more comprehensive analysis. This highlights the need for local analysis when making policy decisions, as it allows capturing local effects. The following sub-section delves deeper into the analysis for two specific cities.

5.2.3. Individual analyses in Rotterdam and Amsterdam

Finally, the municipalities of Rotterdam and Amsterdam are selected for further analysis. In this case, SDMs are estimated to find how the spatial effect of the explanatory variables is related to the number of people in urban places. Fig. 10 shows the results for Rotterdam and Amsterdam. These results follow the same format as the one used in Fig. 8, where bars show the standardized beta values. The models for Rotterdam and Amsterdam are estimated with 18,098 and 17,648 hexagons (data points), and the R^2 values are 33% and 28%, respectively.

In terms of differences in explanatory power (standardized betas) of the variables, various differences can be observed between both cities. Rotterdam follows the same pattern observed in the national analyses (previous subsections a and b). Here, the same four variables (food places, bicycles, motorcycles, and number of nodes) appear in the first positions. Compared with Amsterdam, it is a clear difference in the importance of food places. The correlation between the number of people and food places is smaller for Amsterdam. Following this result, Fig. 10 also shows a higher explanatory power (compared to Rotterdam) for entertainment places and other amenities. Due to the high tourist activity in Amsterdam, the lower explanatory power of food places could be explained because it is shared with these other services (entertainment places and other amenities) in Amsterdam. Related to private vehicles, in both models, the number of cars exercises a negative relationship, corroborating the visual inspection made in the heat maps in Figs. 6 and 7. The negative correlation with cars is higher in Amsterdam than in Rotterdam, which makes sense with the restriction on entering vehicles in the city center of Amsterdam (where most people are). For the residential land-use variable, a negative relationship is found in Amsterdam, whereas a positive relationship with the number of people is found in Rotterdam.

6. Conclusions

We have investigated the relations between the people's density in urban spaces and urban characteristics. In addition, we also provide a method for using street-level imagery and GIS data to analyze urban environments.

By processing 46.5 million collected street-level images with an object detection model, we have been able to identify locations where one expects more people's density for selected cases, as well as other objects such as vehicles, bikes, and buses. It seeks to identify in which areas they are frequently observed, giving some indication of urban mobility patterns. Finally, by analyzing the information jointly, *e.g.* location of people and vehicles, it is also possible to perform spatial correlation analysis to identify spatial trends across urban spaces.

Our analysis reveals several interesting substantive results. Firstly, the number of intersections is positively correlated with the people's density. This means that people tend to be in places with a higher number of intersections, which means smaller blocks, suggesting that

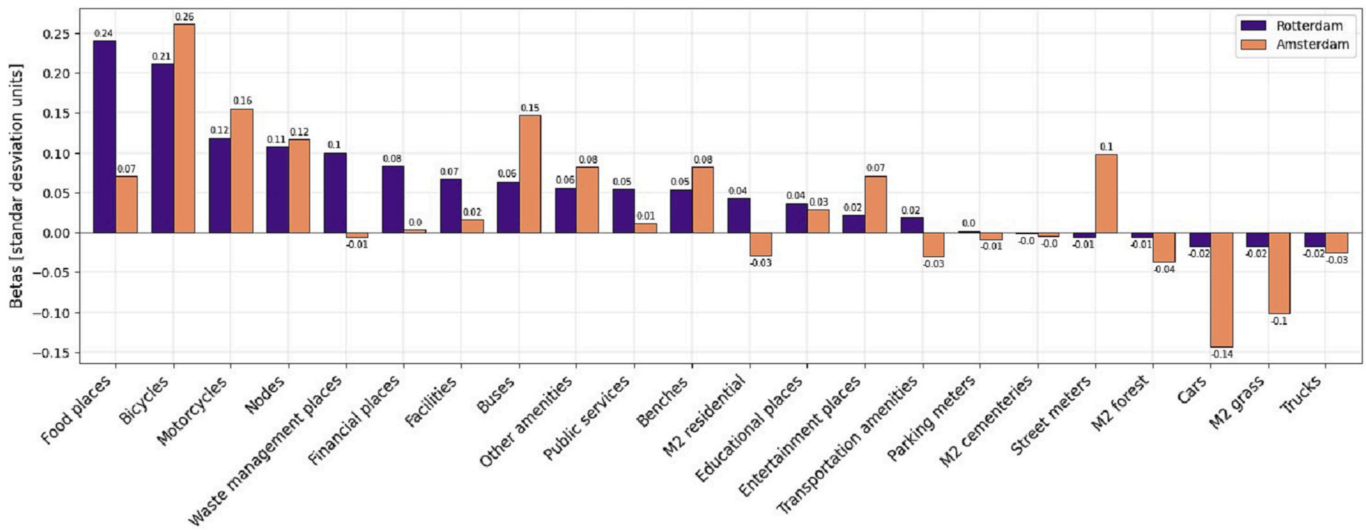

Fig. 10. Standardized betas from SDM estimation in Rotterdam (left darker color) and Amsterdam (right lighter color).

topological parameters of the network, such as block size, are relevant to this relationship. Secondly, people's density is positively correlated with the number of food places, the number of bicycles, and the number of motorcycles. The same results are found in different of our analyses: a linear national model with the data jointly and national analysis with spatial models by the municipality. Finally, the comparative analysis between Rotterdam and Amsterdam shows an example to discover city-specific patterns such as correlation differences between the presence of cars or food places and the number of people. These kind of substantive results can be used to support policies that prioritize the design of smaller blocks, as they may increase foot traffic and contribute to a more vibrant and active community in outside spaces. Also, the promotion of the creation of food places in areas with smaller blocks may attract more people. Another policy implication relates to fostering the use of bicycles and motorcycles as a means of transportation, as their presence seems to be positively related to the number of people observed. This resonates with the findings of Uslu et al. (2010) who concludes that people tend to walk in places where there is less presence of traffic.

This work proposed a new methodology to use images for studying urban phenomena. Through the use of images, we find it is possible to gather information that are difficult to obtain using more conventional sources of information, such as surveys. In addition, using images is inexpensive and easy to keep up to date. Finally, this methodology offers a systematic way of obtaining information in the same format for a country or set of cities, allowing systematic comparisons to be made between different places. The urban environment is constantly changing, many of these changes are made by municipalities on a voluntary basis. Our method offers new avenues for measuring how urban projects change the environment and affect people's behavior. Thereby, it can help municipalities, urban planners, and urban researchers to identify which urban characteristics we should pay attention to when planning urban projects.

The main findings of this study align well with those reported by previous research, which use different methodologies. The associations of people's density with food places (an indicator of local/Business places), the number of intersections (as proxy of network density) and facilities (an indicator of urban equipment) are also reported by Gómez-Varo et al. (2022), Zhang et al. (2021), and Askarizad and Safari (2020).

The findings of this study were validated by comparing them with existing research that explored the same relation using different methodologies. The study found that people's density were associated with food places (as local/business places), the number of intersections (as proxy of network density) and facilities (as urban equipment) in urban areas, which is consistent with the findings of other studies conducted by Gómez-Varo et al. (2022), Zhang et al. (2021), and Askarizad and Safari (2020). The spatial model also reveals the variations of the effects across municipalities, supporting the Jacobs' idea to examine and create policies on a local and small scale for specific regions or cities.

We are aware that this study and the proposed methodology in particular also has several and important limitations.

Firstly, the methodology does not consider the variation of the urban characteristics and the concentration of people caused by temporal, seasonal or occasional events. Such variation could bias the relationships uncovered using our approach. Also, the process behind capturing the images by the Google car such as weather conditions during the captures, route chosen by the car or its speed can bias the results generated by this methodology. To overcome a bit this limitation, we average the detected people in images across years (2008 to 2022) (Note that Google Street View service has a frequency of up to 3 pictures per place per year). As a result, our findings reflect a general trend of people's density in urban spaces and urban elements distribution in cities. We believe that there is potential for future work exploring the effects of seasonality on people's density and using other computer vision techniques, such as assessing weather conditions, to include its effects in the analysis.

Secondly, the analysis considers objects, such as cars or benches that are detected by our employed computer vision model. But, objects not recognized by this model, such as vegetation or water resources, are not considered in our regression analysis. Moreover, our object detection model does not capture comparatively more abstract urban concepts, such as the condition of the urban infrastructure, parks equipment and vegetation type, to name few. Thirdly, the image database that we use lack samples from certain areas. Google Street-view (GSV) has primarily images of locations accessible by car. As a result, parks, forests, or large open public spaces, have been under sampled. Fourthly, the analysis does not include the socio-demographic characteristics of the people in urban spaces, which may be important for understanding the patterns of people's density. Lastly, it is worth noting that our analysis is not able to make claims about causality, only correlation can be established.

These limitations provide opportunities for future research. First, if temporal and spatial dynamics of people in urban spaces aims to be included, this methodology could be modified by using other services such as Mapillary (2022), Apple's Look Around, or local dedicated companies such as CycloMedia (2022) in the Netherlands or Tencent (2022) in China. Some of these platforms offer street-level images with a better time resolution to include temporal dynamism. Also some of these platforms cover areas without accessibility by car which are parks, forest or open public spaces. Second, other computer vision techniques can be applied to the images to uncover more urban characteristics. Other detection models such as YOLO (Redmon, Divvala, Girshick, & Farhadi, 2016), PSPnet (Zhao, Shi, Qi, Wang, & Jia, 2017) or Transformers-based detectors (Carion et al., 2020) or segmentation models (Zhao et al., 2017) can be applied. Even, more sophisticated models to infer perceptions of images (such as beauty or safety) can also be implemented (Rossetti, Lobel, Rocco, & Hurtubia, 2019; Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016). Third, the temporal component of the images can be included in this kind of study in order to establish causal effects between variables.

Our current work utilizes a data-driven approach. For future work, researchers can replicate our methodology and apply it in conjunction with other urban theories like central place theory (Getis & Getis, 1966) and urban size distributions based on Zipf's law (Zipf, 2016). These theories suggest that urban areas are structured hierarchically around central locations. In addition, further research can be done to investigate the effects of aggregating the data at different spatial scales such as neighborhood, district, or city levels - providing a deeper understanding of how urban environments are organized for different transport modes (*e.g.*, walkable, automotive, or transit-friendly areas) and scales. Moreover, the effects of other characteristics of the urban environment on different human behaviors or activities can also be studied. For instance, the proposed methodology can complement works about urban environment and physical activity (Lopez & Hynes, 2006; Sallis et al., 2016), urban mobility (Birenboim, Helbich, & Kwan, 2021), covid-related effects (Lee et al., 2021), characterization of urban spaces based on its functions (Singleton & Longley, 2019) or other behaviors such as walking dogs (Christian et al., 2018). To do so, different behaviors and situations can be identified in the images and perform similar analyses as presented in this research. In addition, this methodology could be used to verify policy measures and quantify its effects in the urban environment, such as car-restrictions zones and new bike-friendly spaces.

CRediT authorship contribution statement

Francisco Garrido-Valenzuela: Conceptualization, Methodology, Software, Formal-analysis, Investigation, Writing-original-draft, Writing-review-editing, Visualization. **Oded Cats:** Supervision, Writing-original-draft, Writing-review-editing. **Sander van Cranenburgh:** Supervision, Writing-original-draft, Writing-review-editing.

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