Transportation Research Part D 86 (2020) 102423

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Understanding cycling travel distance: The case of Medellin city (Colombia)

Juan P. Ospina[a,*], Verónica Botero-Fernández[b], Juan C. Duque[c], Mark Brussel[d], Anna Grigolon[d]

[a] Department of Civil Engineering, Universidad Nacional de Colombia, Sede Medellín, Colombia
[b] Department of Geosciences and Environment, Universidad Nacional de Colombia, Sede Medellín, Colombia
[c] Research in Spatial Economics (RiSE-group), Department of Mathematical Sciences, Universidad EAFIT, Colombia
[d] Department of Urban and Regional Planning and Geo-information Management, University of Twente, the Netherlands

ARTICLE INFO

Keywords:
Cycling
Travel distance
Travel behavior
Cycling routes

ABSTRACT

The relevance of cycling as a mode of transportation is increasingly being recognized in many cities around the world, and the city of Medellin (Colombia) is no exception. To better understand cycling travel behavior in Medellin, we perform a multiple regression to analyze the importance of route characteristics in explaining cycling travel distance. We control for socio-economic and built environment variables at the origin and destination. Our results reveal that the effects of the socio-economic and built environment characteristics at the origin and destination are modest or statistically insignificant in explaining travel distance. However, the variables that characterize the built and natural environment along the route are significant and appreciably improve the explanatory power of the baseline econometric model. An analysis of interacting effects shows that the interaction between the dedicated infrastructure along the route and the degree of deviation from direct routes has a relevant effect on explaining travel distance. The findings of this work are useful for designing cycling policy and developing more usable cycling infrastructure.

1. Introduction

The current global urbanization trends imply major challenges for urban planning. Energy consumption and greenhouse gas emissions, in addition to equitable access to cities, represent some of the challenges that current urban sustainability agendas are seeking to address (UN-Habitat, 2013). These challenges are particularly important in developing countries that are facing rapid urbanization processes, which go from 50% in 2005 to a projected 68% in 2050 (United Nations, 2019).

In an attempt to mitigate these adverse trends, urban transport agendas are including the promotion of cycling due to its widely recognized societal and environmental benefits (Broach et al., 2012). Thus, an increasing number of cities are seeking to improve cycling conditions to make this mode of transportation more attractive (Buehler and Dill, 2016; Handy et al., 2014; Rosas-Satizábal and Rodriguez-Valencia, 2019). Research on this area aims to support pro-bicycle policies by attaining a better understanding of the travel behavior of cyclists (Heinen et al., 2010; Pucher et al., 2010).

Travel distance is a key factor in the understanding of cyclists' travel behaviors. According to Heinen et al. (2010) and Pucher and

* Corresponding author.
E-mail addresses: jpospinaz@unal.edu.co (J.P. Ospina), vbotero@unal.edu.co (V. Botero-Fernández), jduquec1@eafit.edu.co (J.C. Duque), m.j.g.brussel@utwente.nl (M. Brussel), a.b.grigolon@utwente.nl (A. Grigolon).

https://doi.org/10.1016/j.trd.2020.102423

Available online 23 June 2020
1361-9209/

Buehler (2008), travel behavior is affected by individual characteristics and by built and natural environmental conditions. However, most of the studies on this topic consider built and natural environment conditions solely at the origin and destination and very few studies analyze how these characteristics along the route affect cycling travel behavior (Appleyard, 2016). A recent study on urban form and urban growth in Latin American cities by Duque et al. (2019) shows that these highly organic and, in many cases, poorly planned cities show great heterogeneity within their urban extents in terms of land use patterns, street network characteristics, topography, population distribution, among others. These changing urban textures and structures can imply that the built and natural environment conditions along a route are considerably different from those of the origin and destination and, therefore, have a significant impact on the behavior of pedestrians and cyclists (Cervero et al., 2009; Larrañaga et al., 2016; Oliva et al., 2018).

In this paper, we use cycling routes in Medellin (Colombia), a highly heterogeneous city in terms of both topography and urban structure, to study how natural and environmental factors of origin, destination, and along the route itself, affect bicycle travel distance when used for commuting. We use multiple regression models that include interaction effects between selected pairs of explanatory variables.

In many cities, decision-makers are seeking to improve cycling infrastructure to render cycling a more attractive mode of transportation. These actions become very challenging in contexts such as those from the global south, where the resources are limited, and the urban planners need to prioritize the provision of cycling infrastructure to get the maximum impact. A more accurate estimation of travel distances in developing cities will help policy and planning in at least in three aspects: (1) better allocation of resources to develop new cycling infrastructure, (2) improve the design and layout of new bike paths within the city, and (3) increase the usability of such infrastructure.

The rest of the paper is organized as follows. Section 2 presents a review of the literature. Section 3 explains the model structure, variables, and data used for our analysis. Section 4 shows the results, and finally, Section 5 summarizes and concludes this work.

2. Literature review

Travel distance is a key element in understanding and predicting cyclists' travel behavior. In the field of accessibility, a better prediction of travel distance is critical for a more accurate estimation of the number of urban activities that a person can reach from a given location (Iacono et al., 2008). Previous works within the fields of travel mode choice and the route choice identify the individual, trip, and environmental characteristics as determining factors of cycling travel distance (Appleyard, 2016; Broach et al., 2012; Heinen et al., 2010). This section will summarize the main findings on these three factors.

The individual characteristics include variables such as age, income, gender, trip purpose, and types of bicycles (private and public) used as a mode of transport. Larsen et al. (2010) found that cyclists between 25 and 44 years of age travel longer distances than younger and older people. Garrard et al. (2008) and Larsen et al. (2010) concluded that men travel longer distances than women. Iacono et al. (2008) reported that cyclists commuting to work are willing to ride longer distances than those cycling for other purposes. Moreover, empirical studies revealed that private bike users travel longer distances than those using bike-sharing systems (Campbell et al., 2016). Regarding frequency levels, Heinen et al. (2011) showed that regular bicycle use has a positive effect on travel distance. Larsen et al. (2010) did not find significant differences in the travel distances of cyclists with and without access to a motorized mode of transport. Using data from Santiago, Chile, Oliva et al. (2018) found that high-income groups and women are less likely to commute by bicycle. Additional works by La Paix Puello and Geurs (2015), Fernández-Heredia et al. (2016), Motoaki and Daziano (2015), and Oliva et al. (2018), explored the impact of latent variables such as emotions, feelings, and perceptions on cycling travel distance.

Regarding the built environment at the origin and destination, the literature frequently includes groups of variables related to density, land use, and infrastructure (Cervero et al., 2018; Oliva et al., 2018; Pucher and Buehler, 2006; Saelens et al., 2003). Previous studies reported that higher densities, mixed land use, and the presence of dedicated infrastructure are positively associated with the number of trips taken and the distances traveled by cyclists (Ewing and Cervero, 2010; Handy et al., 2002). Studies focusing on the effect of density have found that dense street patterns, frequently associated with city centers, favor connectivity and reduce travel distances (Handy et al., 2002; Moritz, 1998; Pucher and Buehler, 2006). However, Larsen et al. (2010) found that cyclists starting their trips from locations close to city centers, where environments are dense, travel longer distances than those starting their trips from less dense environments. Keijer and Rietveld (2000) found that cycling mode share in the Netherlands is higher when traveling shorter distances in high densities and mixed land uses. There is also some evidence that more mixed land uses favor proximity and accessibility to jobs and services, increasing cycling rates (Cervero and Duncan, 2003; Litman, 2018; Saelens et al., 2003). However, Oliva et al. (2018) found that land use mixtures discourage cycling. Kockelman (1997) and Handy et al. (2002) reported that cycling trips are shorter when they originate from mixed urban environments. Besides, other studies have analyzed the effect of the infrastructure at the origin and destination on cyclists' travel behavior (Cervero and Duncan, 2003; Faghih-Imani et al., 2014; Oliva et al., 2018). Their findings suggest a positive association between the presence of dedicated infrastructure and the number of cycling trips.

Additional studies extend the previous findings with some evidence about how the built and natural environment characteristics of the route, such as density, land use, and infrastructure, impact bicycle travel distances (Broach et al., 2012; Cervero et al., 2018; Larrañaga et al., 2016; Menghini et al., 2010). Broach et al. (2012) found that more intersections along cyclists' routes reduce their willingness to travel long distances due to the degree of effort involved. Cervero et al. (2018) similarly reported that long-distance cycling commuters are more sensitive to detours than those traveling shorter distances. Cervero et al. (2018) and Saelens et al. (2003) reported that bicycle commuting levels are higher in mixed land uses in which cyclists travel short distances to reach their destinations. Moreover, the type of infrastructure that cyclists use along the route determines their level of exposure to vehicle traffic, consequently their perceptions and attitudes towards cycling (Cervero et al., 2018; Fitch et al., 2019; Heinen et al., 2010). Broach et al. (2011) found that satisfaction resulting from the use of dedicated infrastructure is equivalent to reducing the cycling travel distance for various trips purposes. Furthermore, studies not necessarily focusing on travel distance complement these findings. For instance, Fitch et al. (2019) found that students would travel more frequently to schools if they had better road environments for bicycling. Broach et al. (2012) and Cervero et al. (2018) suggest that cyclists prefer routes that limit their exposure to motor vehicle traffic. Finally, Cervero et al. (2009) on their study in Bogotá, Colombia, found that while road facility designs, like street density, connectivity, and proximity to bike paths lanes, are associated with physical activity, other attributes of the built environment, such as density and land use mixtures, are not.

Following the literature, the natural environment refers to climate and weather patterns, as well as topographic features (Heinen et al., 2010). Despite very little is known about the impact of climate on cycling travel distance, the weather has been found to negatively affect cyclists travel behavior (Fernández-Heredia et al., 2016; Heinen et al., 2010; Motoaki and Daziano, 2015). Fernández-Heredia et al. (2016) studied the intended use of a new bike system by introducing four latent variables, and they found that external restrictions, such as climate, affect negatively the intent of using the bike system. Motoaki and Daziano (2015) found that rain and snow deter cyclists' decisions with lower skills more than those with better cycling skills. However, Cervero and Duncan (2003) found that the weather has an insignificant effect on cycling. Regarding topographic features, Broach et al. (2012), Menghini et al. (2010), and Cervero et al. (2018) found that cyclists avoid steep terrain when engaged in long-distance commuting. Fernández-Heredia et al. (2016) and Motoaki and Daziano (2015) concluded that physical determinants, such as distance and topography, also negatively affect the decisions to cycle. Particularly, Motoaki and Daziano (2015) evaluated the interaction effect between the cyclists' physical condition and the topography, finding that the more fit the cyclist the less bothersome a steeper route.

The analysis of how the built and natural environment affects cycling travel distance has mostly focused on the conditions at the origin and destination. Only a few studies have emphasized on how the environmental characteristics along the route affect cycling travel distance. Also, despite the numerous studies in the global south, neither the cycling commuting distance nor the relationship between the built environment variables along the route and the travel distance have been explored. Moreover, with few exceptions, interaction effects between variables have been rarely evaluated in previous studies. The heterogeneity of urban forms and topographies encountered on cyclists' routes, as well as how cyclists perceive these routes, may affect the cyclists' decisions to travel a certain distance. Additionally, those effects may vary in contexts beyond those of the global north, where most studies on this issue have been conducted. This suggests that the distance traveled by cyclists may be determined by these factors differently, especially by those along the route, in contexts such as Medellin, Colombia. Moreover, some of the factors explaining the cycling travel distance may have quadratic forms or interaction between them, which consequently should be accounted for.

This paper aims to contribute to the existing literature in three different directions. First, regarding explanatory variables, this study examines how natural and built environment factors related to origins and destinations, and especially along the routes may affect cycling travel distances when used for commuting. Second, context contribution. Our case study uses cyclist routes traveled within Medellin (Colombia) to give new insights on the relationship between the built environment and cyclists' travel distance in the global south. Third, the methodological contribution. We use multiple linear regression models, taking advantage of this method to explore several interactions as well as the non-linear effects of certain variables.

3. Methods

3.1. The model

Following the literature review and the previous findings, we propose the multiple regression model illustrated by Eq. (1) to estimate the impact of the individual, trip, and built and natural environment characteristics on cycling travel distances:

$$d_{ij} = \beta_0 + \beta_1 \boldsymbol{SE} + \beta_2 \boldsymbol{BE_i} + \beta_3 \boldsymbol{BE_j} + \beta_4 \boldsymbol{BE_{ij}} + \beta 5 \boldsymbol{NE_{ij}} + \varepsilon, \tag{1}$$

where $\boldsymbol{d_{ij}}$ is the travel distance between origin i and destination j; $\boldsymbol{SE}$ is a vector of individual and trip characteristics; $\boldsymbol{BE_i}$ and $\boldsymbol{BE_j}$ are vectors of built environment characteristics related to origin i and destination j; $\boldsymbol{BE_{ij}}$ is a vector of built environment characteristics related to the route taken by a cyclist from origin $\boldsymbol{i}$ and destination $\boldsymbol{j}$; $\boldsymbol{NE_{ij}}$ is a vector of natural environment characteristics related to a given route; $\boldsymbol{\beta_0}$ is the intercept parameter; $\boldsymbol{\beta_1, \beta_2, \beta_3, \beta_4}$ are the slope parameters in the relationship between d_{ij} and every variable included in the vectors (SE, BE_i, BE_j, BE_{ij}, NE_{ij}), which are estimated by ordinary least squares (OLS) method; and ε is the error term which is assumed to be normally distributed with zero mean and variance σ^2.

In addition to the variables included in the vectors, which are expressed in linear form, we take advantage of the regression analysis method to analyze some quadratic forms and the interaction effects between certain variables. Quadratic forms are used in applied economics to capture decreasing or increasing marginal effects. Interaction effects include the simultaneous effects of two or more independent variables on the dependent variable. When significant, the interaction between two independent variables implies that the effect of one variable, changes depending on the level of change of the other variable (Wooldridge, 2013). When added to a regression model quadratic forms and interaction effects can considerably expand the understanding of the relationships among the variables in the model and allow more hypotheses to be tested (Wooldridge, 2013). These quadratic forms and interaction effects will be described in Section 3.4. Metrics.

There are also some concerns about the potential endogeneity in the relationship between residential self-selection on travel behavior (Cao et al., 2009, 2006; Guan et al., 2019). On the one hand, residential location, from which the measurements of the built environment variables at the origin are obtained, affect travel distance. On the other hand, people inclined to cycling tend to live in certain locations. However, this issue is uncertain in spatially and socio-economically segregated contexts in which the residential self-selection is highly determined by other factors. For instance, the urban extent of each Colombian city is stratified, from one (low) to six (high), according to the housing characteristics and quality of the neighborhood. Even though this stratification is based on principles of solidarity, it has a direct impact on the location of activities and the population in cities (Duque et al., 2015; Samper Escobar, 2010). Consequently, rather than depending on the residential built environment characteristics or the closeness to the center(s) of activities, people's decisions on where to live are highly influenced by the socioeconomic stratum. Therefore, unlike cities in more developed countries, the potential endogeneity tends to be less problematic in developing countries.

3.2. The study area

Medellin is used as a case study in this paper. It is the second largest Colombian city with close to 2.5 million inhabitants. The city is located in the western region of Colombia (see Fig. 1) where the Andean mountains reach altitudes of 1,500 m to 2,500 m above sea level. The average relative humidity level is 67%, which is less than the average of other cities located within humid subtropical zones, and temperatures fluctuate from 17 to 28 °C with an annual average of 22 °C.

Three aspects render Medellin a case for which determinants of travel distance for cycling may differ from previous studies. The first relates to the presence of diverse urban environments, ranging from planned neighborhoods to informal settlements. While previous studies examine more uniform urban street networks, the streets of Medellin negotiate with the steep topography, giving rise to organically shaped street patterns (Samper Escobar, 2010). The second relates to levels of socioeconomic inequality confirmed by a Gini index of 0.46 (DANE, 2018) and by a spatially segregated pattern that divides the city into two halves. The southern side, where high-income populations reside, hosts a broad combination of urban activities. The northern side, mostly occupied by the lowest income strata, is positioned on the outskirts of the city far from the main city services and activities (Duque et al., 2015). Third, the city is characterized by variable topography, with gradients of 0% to 6% found in the flattest areas and with those of more than 20% found in hilly areas. Fig. 2 shows the urban perimeter of Medellin city within the Valle de Aburra Metropolitan Area in addtition to the topography surrounding it.

Over the last decade, cycling has become a priority in tackling the challenges of air quality in Medellin (Área Metropolitana Valle de Aburrá, 2017). Currently, bicycle trips represent 1% of the modal share, and the city hopes to increase this level to 10% of all trips by 2030 (Área Metropolitana del Valle de Aburrá, 2015). Moreover, even though the city includes close to 120 km of cycling paths and supports a bike-sharing system, the scarcity of dedicated infrastructure is a key factor preventing people from commuting by bicycle in Medellin (Arbelaez, 2015). Therefore, the construction of new dedicated infrastructure and the expansion of the Encicla bike-sharing system have been accelerated over the past few years.

3.3. The data

We used cyclists' trip data taken from a survey conducted in Medellin in 2017 ([dataset] Ospina et al., 2018). The survey, distributed online, by telephone and in person, was designed to record cyclists' routes from public and private bicycle commuters. The questionnaires included three sections: The first section discriminated bicycle users from those using other modes of transportation. The second section, which targeted current cyclists, focused on their basic individual sociodemographic characteristics. The third section recorded the origins, destinations, and routes of the participants' most recent cycling trips.

The survey involved 810 cyclists of different socioeconomic backgrounds and living in different areas of the city. Of the survey respondents, 70% are men and 30% are women, and the average age is 29 (all cyclists included). Cyclists commute by bicycle 4.15 times per week on average. In terms of income groups, 17% of the cyclists are low-income residents, 61% are middle-income residents, and 22% are high-income residents. Fig. 3 presents the spatial distribution of the 810 routes taken through the city.

Regarding the routes taken by cyclists, the average one-way commuting distance traveled by bicycle is 4.17 km, which is similar to the distance of 4.20 km estimated by the Medellin Origin and Destination Survey (2012). On average, the routes taken by cyclists are characterized by 45% on dedicated infrastructure, 49% on major streets, and 5.7% on minor streets. Besides, on average, 13 intersections are passed per kilometer (4.12 of them with traffic signals). Finally, the average positive slope is 2.28% (elevation gained/distance). Annex 1 presents the descriptive statistics for the variables as well as the respondent's age, income, and gender distribution.

3.4. Metrics

Each route derived from [dataset] Ospina et al. (2018) was geocoded using street network information taken from Open Street Maps (OSM). Due to the metrics associated with each route, the geocoding process involved a careful revision of geometric properties and attributes associated with each link of a route, e.g., directionality and connectivity and attributes such as speed, the number of lanes, and the presence of bike paths. As some of the metrics are calculated within a buffer along a given route, the revision of the street network also involved accounting for street segments positioned within buffers. It is important to note that in a few cases we had to deviate from the common practices in the literature when producing the metrics for our paper. The contribution of empirical evidence from cities in developing countries comes with many challenges including data availability. Therefore, for each case, we seek to make the best use of the official information and each variable was approved for inclusion if and only if the resulting spatial patterns make sense to the eyes of a team with a deep knowledge of the city of Medellin.

The first metric calculated from each geocoded route is the geometric distance along the road network (our endogenous variable)

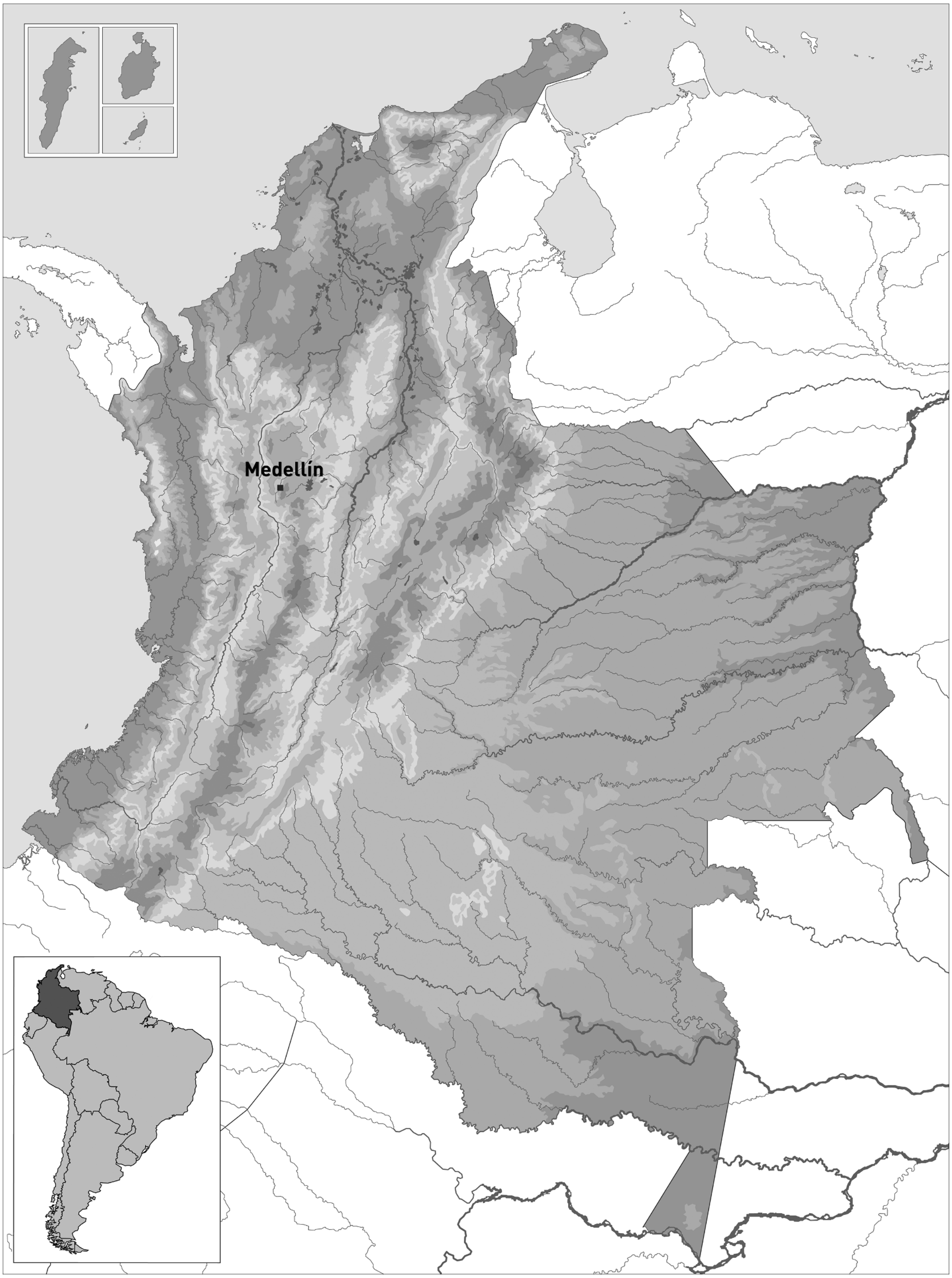

Fig. 1. (Left) Medellin metropolitan area location in Colombia.

in kilometers. Fig. 4 presents the distance decay curve resulting from [dataset] Ospina et al. (2018), which indicates that 50% of cyclists are willing to travel up to 4 km, and only 5% would ride farther than 8 km. Fig. 5 presents the spatial distributions of trip origins, whose values are proportional to travel distances. We also found that the southwestern side of the central business district (CBD) generates the most trips.

Moreover, we verified the possible spatial autocorrelation problems by using the *Local Moran's I (Ii),* which is a local indicator revealing the significance of the spatial clustering of similar (or dissimilar) values around one observation. Using the local indicator rather than the global indicator is advantageous in that this approach allows identifying the concentrations of similar values: high

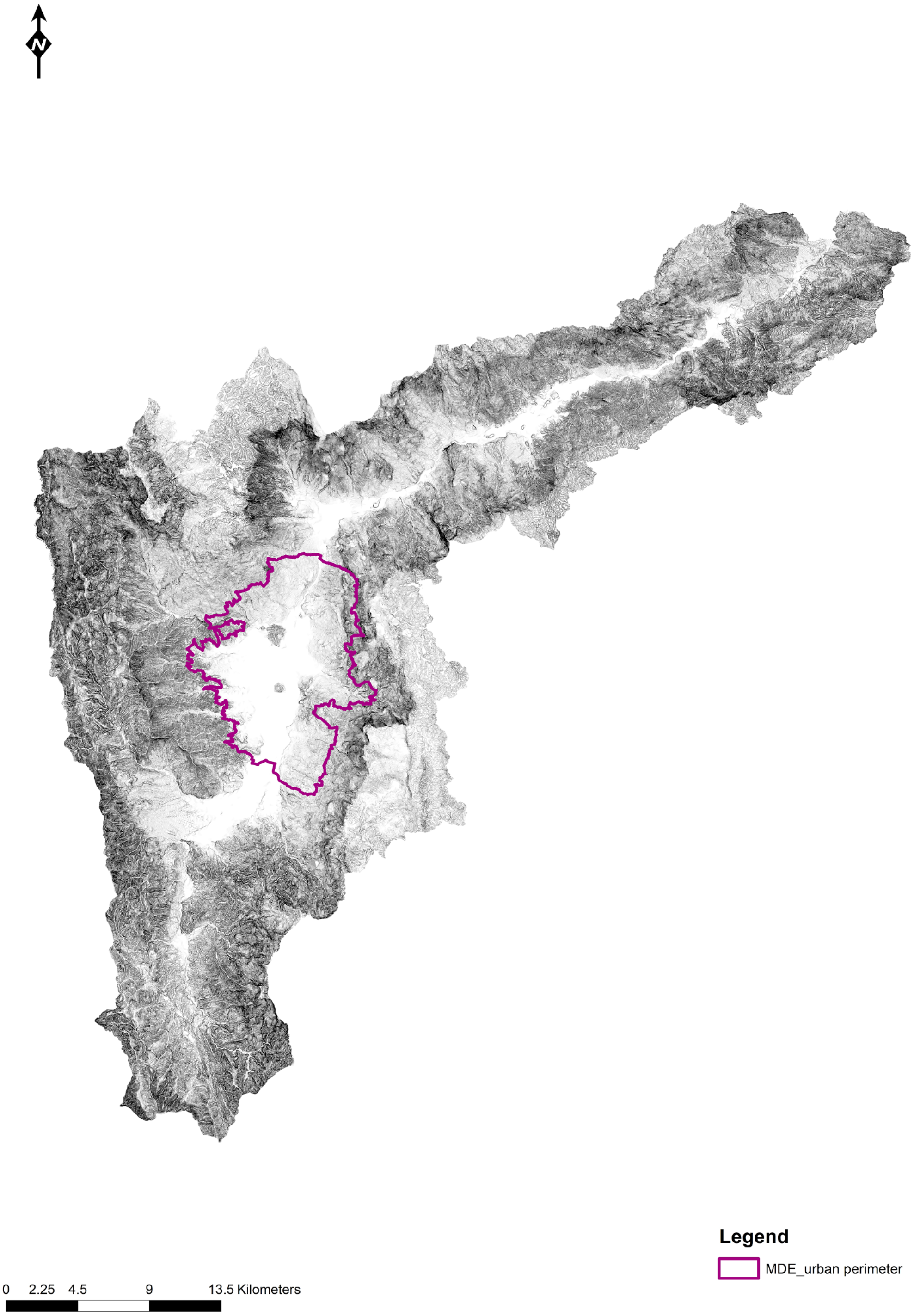

Fig. 2. Medellin location in the Aburra Valley Metropolitan Area. Medellin's urban perimeter in purple.

values close to high values (*high-high*) and low values close to low values (*low-low*). The approach allows identifying dissimilar locations as well: high values close to low values (*high-low*) and low values close to high values (*low–high*) (Anselin, 1995; Moreno and Vayá, 2000). Fig. 6 presents the four cluster categories obtained according to the *Local Moran's I* statistic. The *high-high* cluster is the most representative in our case which indicates that origin locations related to longer trips are concentrated in the northern, western, and southwestern areas of the city. While this clustering may imply an autocorrelation problem, we assume that the distance traveled by a cyclist is not influenced by the distance traveled by his or her neighbors, as could be the case for the number of cycling trips.

We then calculated variables belonging to each explanatory dimension of the model (individual, trip, and built and natural

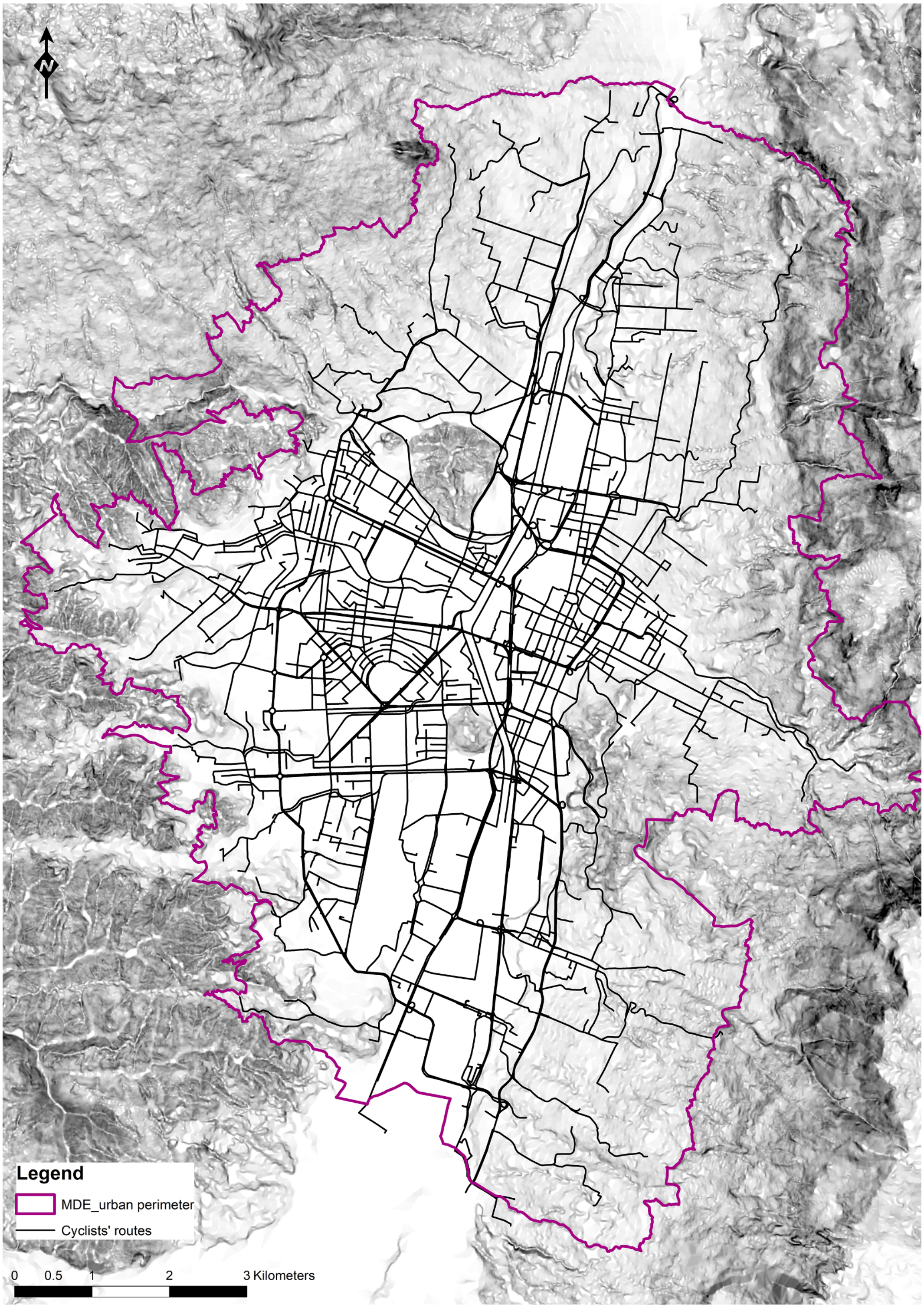

Fig. 3. Spatial distribution of the 810 routes taken through the city. Medellin's urban perimeter in purple.

environment characteristics). For individual and trip characteristics dimension (*SE*), we considered variables identified from the literature on transportation (Ortúzar and Willumsen, 2011), especially those affecting cycling travel distances such as age, income, gender, trip purpose, the availability of other modes, and the type of bicycles (private and public) used as a mode of transport. In addition to these variables, we also included the use of other modes in combination with cycling and the use of cycling to return

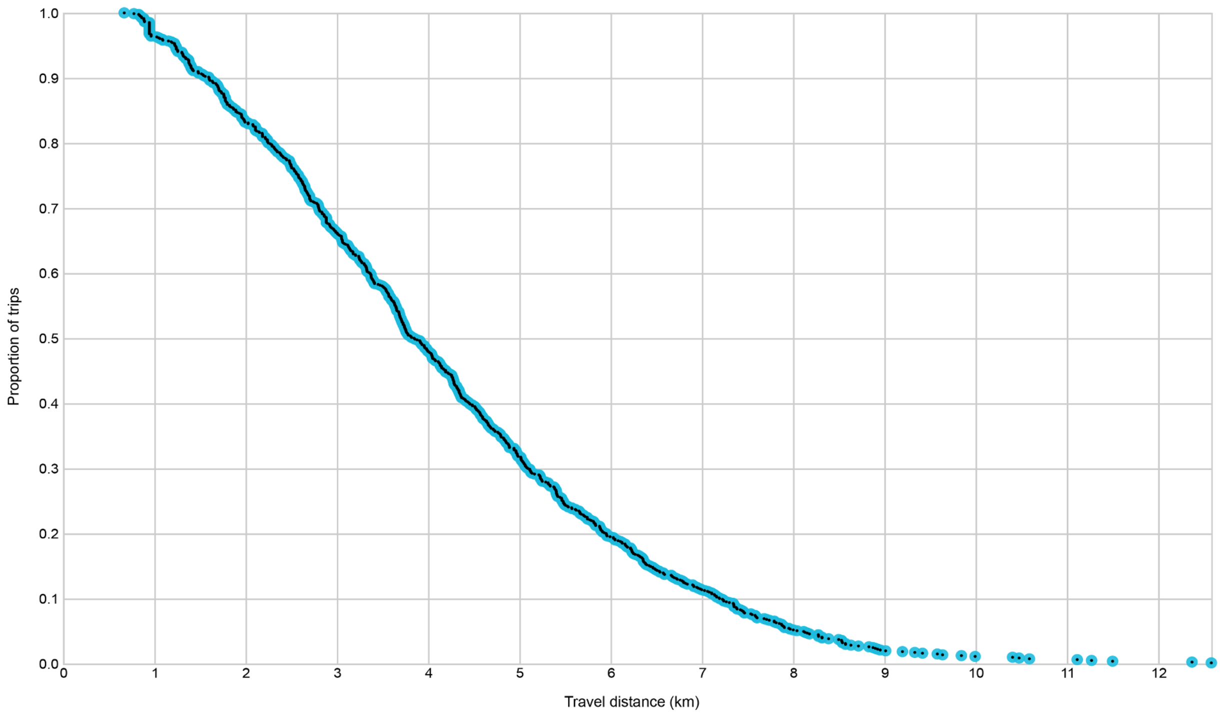

Fig. 4. Distance decay curve relating travel distance to the cumulative proportion of cyclists.

home, factors typically associated with cycling transportation analysis. According to Ortúzar and Willumsen (2011), the variables of qualitative nature such as age, income, gender, among others, usually show non-linear behavior when included in linear regression models. In this context, there exist two alternatives to incorporate non-linear variables into a model: first, transforming the variables (for instance raising to a power or taking logarithm), second, using dummy or categorical variables. Although distinguishing between age classes could have been an option, we chose the first alternative, which is aligned with Cervero et al. (2018). Supported by previous findings, we expect to have a positive effect of age until a certain stage of the lifecycle, which, following Cervero et al. (2018), is susceptible to decline as people get older. Consequently, to capture such an effect, the age variable is expressed in both linear and quadratic forms. In this direction, we expect to have a positive effect of age in its linear form and a negative correlation of age squared. Moreover, based upon Oliva et al. (2018) previous findings, we expect that women and high-income populations ride shorter distances than men and low-income populations respectively. Following Iacono et al. (2008), we expect that those going to study, cycle shorter distances that those going to work or to both purposes. Additionally, based on Campbell et al. (2016), we expect that private bike users cycle longer distances than those using public bikes. Finally, as previous findings are uncertain about the effect of those having access to other modes as well as those using their bikes as a complementary mode, we expect them to ride shorter distances. Table 1 describes the variables of this subdimension and their anticipated associations with travel distance.

The literature on built environment characteristics of trip origins (*BEi*) and destinations (*BEj*) have focused on three subdimensions: density, land use, and bicycle infrastructure (Ewing and Cervero, 2010; Handy et al., 2002; Saelens et al., 2003). With respect to *density*, this one can be expressed in terms of population and employment density, street density, or intersection density (Cervero et al., 2018; Rodríguez and Joo, 2004). In this work, we measured street and intersection density levels within a buffer of 600 m from the trip destinations[1]. We also measured Euclidian distances from origin locations (*i*) to the CBD. Following Pucher and Buehler (2006), Moritz (1998), and Handy et al. (2002) we expect density to have a negative correlation with travel distance. Table 2 describes the variables of this subdimension and their anticipated associations with travel distance.

Regarding *land use*, the second subdimension of the built environment, usually relates to the mixture of land use, which can be analyzed in terms of the number of restaurants, retail stores, offices, and other commercial amenities present at trip origins and destinations (Faghih-Imani et al., 2014; Krizek and Johnson, 2006). Different indexes such as the land use diversity index and entropy index are also used to analyze the levels of land use mixture (Cervero et al., 2018; Cervero and Kockelman, 1997). Although the literature uses such variables to study the land use, in our case, the official information is very limited considering the high rates of informality in labor and business activities. Bernal (2009) found that the informal labor market in Colombia, defined as not reported and not covered by the official regulation, is between 60% and 75%. According to Cárdenas and Rozo (2009) and Hamann-Salcedo and Mejía (2012) the informality of the business market is between 45% and 60%, which makes it difficult to count with accurate

[1] Prior studies have used buffers of 100 m to 1600 m from the start point of a trip (Cervero, 1996; Cervero and Duncan, 2003; Rodríguez and Joo, 2004). We apply a buffer of 600 m, as 95% of cyclists travel more than 1.2 km.

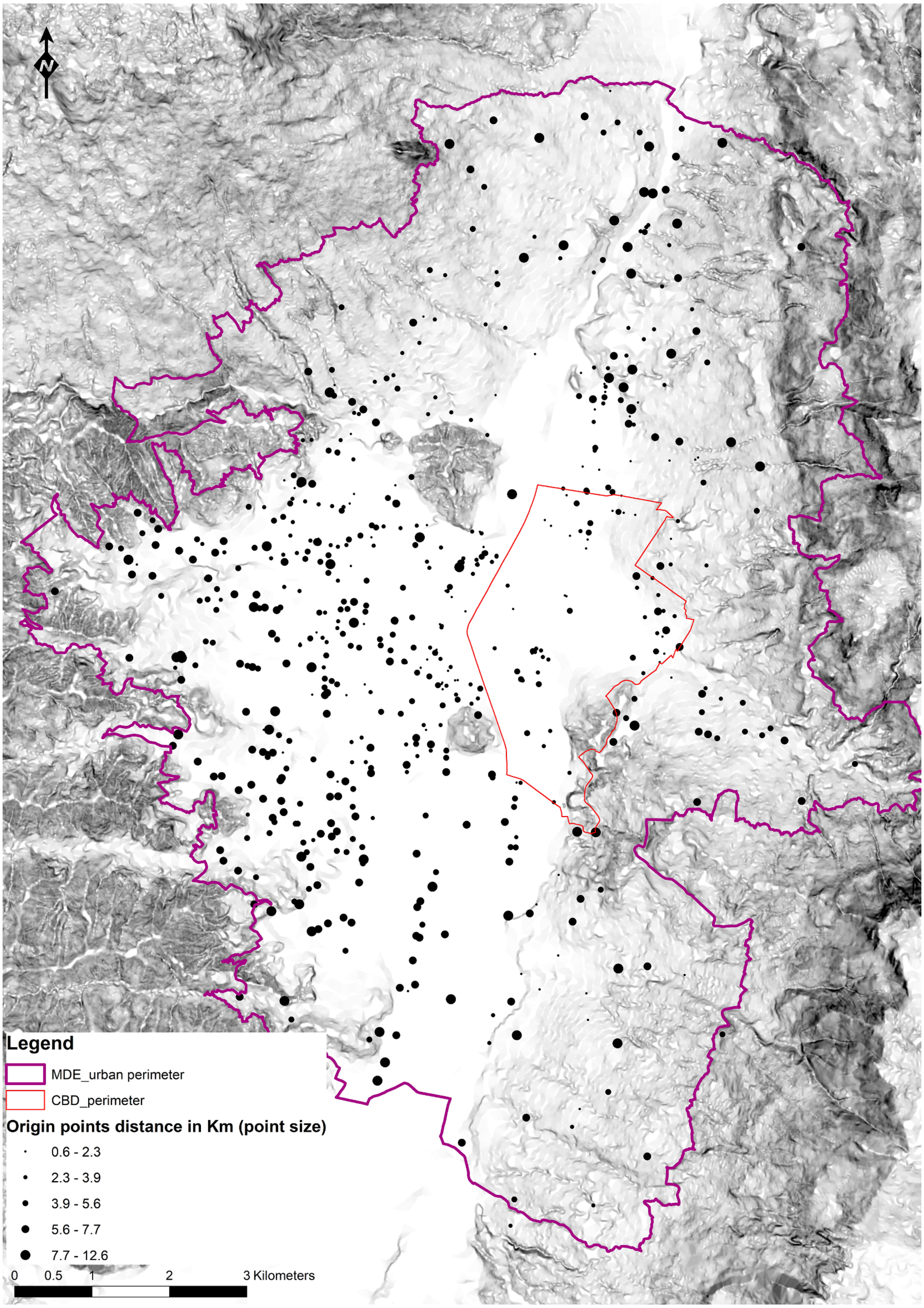

Fig. 5. Spatial distribution of trip origins. Point sizes are proportional to travel distances. Medellin's urban perimeter in black.

information from official sources. Consequently, in the present study, we use the urban development plan (POT) to calculate the levels of the land use mixture within a 600 m radius around origins and destinations. The POT in Medellin reports land uses at the block level. Despite land use categories include commercial, industrial, institutional, residential, green areas, etc., the official available information consists of a map, at the block level, with the following categories of land uses: high, medium and low mixture.

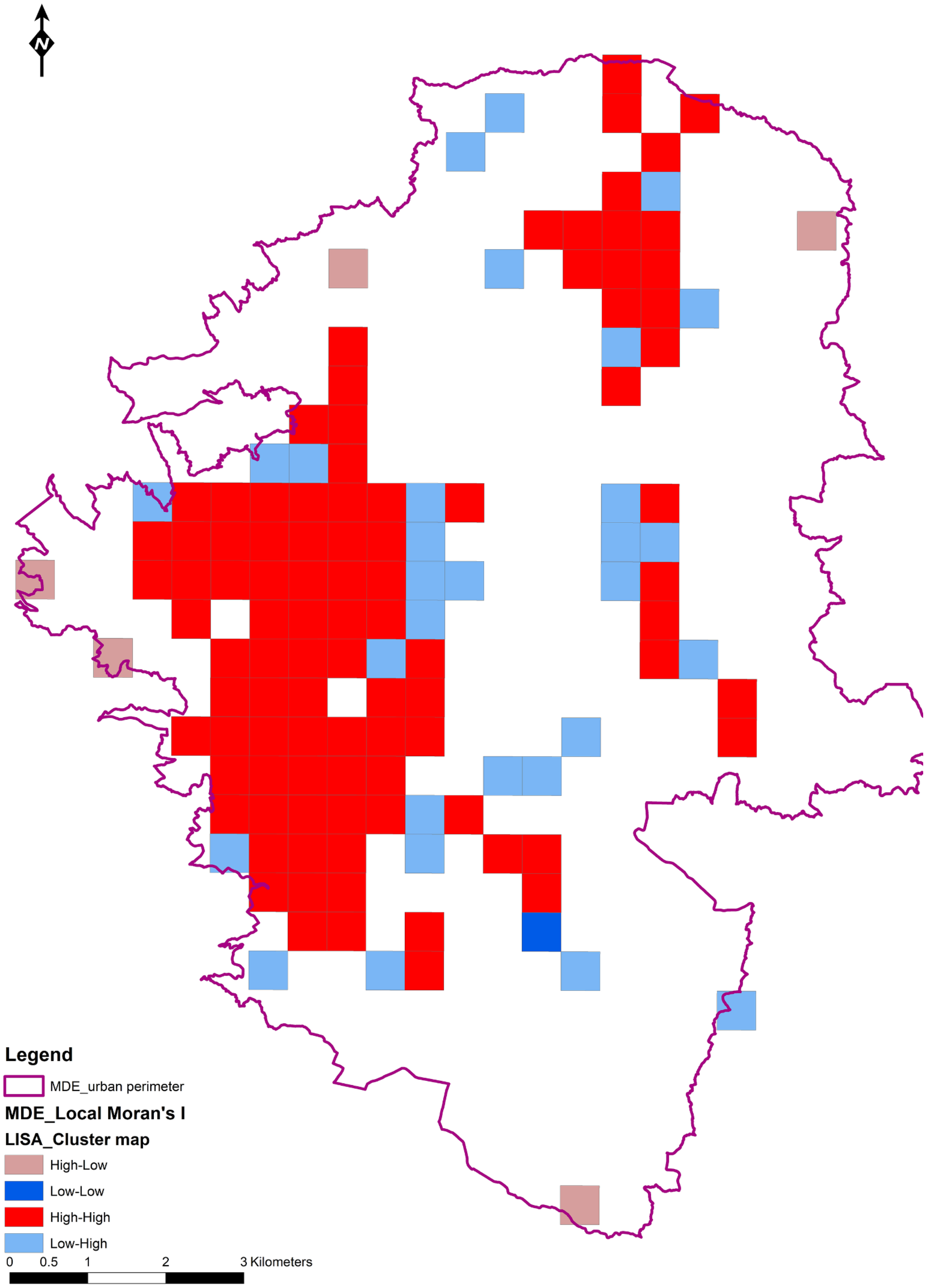

Fig. 6. Map of average trip length cluster categories obtained according to Local Moran's I statistic. Medellin's urban perimeter in black.

Since this was the only official available information, we opted to calculate the percentage of land use belonging to the high mixture category as the closest measure to the habitually used diversity of land use. Based on previous findings by Handy et al. (2002), Oliva et al. (2018), and Kockelman (1997), we expect that high land use mixture affects negatively the cycling travel distance. Table 2 describes the variables of this subdimension and their anticipated associations with travel distance.

The third built environment subdimension relates to the type of *infrastructure* present in the vicinity of origins and destinations. Studies usually refer to the length of bicycle paths, the density of bike-sharing stations, the lengths of major (arterials and highways) and minor (local streets and collectors) roads as determinants of cycling trips (Cervero and Duncan, 2003; Faghih-Imani et al., 2014; Oliva et al., 2018; Pucher et al., 2010). Although the evidence on how these variables affect travel distance remains unclear, we expect the presence of dedicated infrastructure, a higher density of bike stations, and lower levels of stress to encourage cyclists to

Table 1
Descriptions of individual and travel variables and of their anticipated relationships to travel distance. Data source: [dataset] Ospina et al. (2018).

Subdimension	Variable	Description	Expected correlation
Individual	age	Age (number of years)	Positive. Cycling travel distance increases with age.
	age2	Age squared.	Negative. From a certain age onwards the cycling travel distance begins to decrease.
	gender	Gender. Two categories: Women, Men. (Binary, Women = 1)	Negative. Women ride shorter distances than men.
	Hinc, Minc, Linc	Income. Three categories: High, middle, low. Low income is used as the basis of the regression model. (Binary. Yes = 1; No = 0).	Negative. High and middle-income populations ride shorter distances than low-income populations.
Trip	study, work, bothpurp	The trip purpose when using a bike as a mode of transport. Three categories: study, work, both. Work is used as the basis of the regression model. (Binary. Yes = 1; No = 0).	Negative. Cyclists commuting to school ride shorter distances than those commuting to work. Positive for both purposes. Those cycling for both purposes travel longer distances than those who only cycle to work.
	pubbike, pribike, bothbike	Cycling is regularly used as a mode of transport. Three categories: public, private, both. Private bikes are used as the basis for the regression model. (Binary. Yes = 1; No = 0).	Negative. Public bike users ride shorter distances than those using private bikes alone. Negative for both types of bikes. Those using both types of bikes travel shorter distances than those using private bikes.
	frecweek	The number of times per week the same cycling trip is traveled.	Positive. Higher frequency cycling improves the physical condition and allows for traveling longer distances.
	dispo_tp, dispo_pv, dispo_none	Availability of other modes. Three categories: public transport, private vehicle (including cars and motorcycles), and none. The adoption of none of these is the basis used for the regression model. (Binary. Yes = 1; No = 0).	Negative. People with other modes of transport available (public transport or auto) travel shorter distances by bike.
	intermodal	Use of a complementary mode of transport besides cycling (Binary. Yes = 1, No = 0).	Negative. Cycling as a complementary mode of transport involves riding shorter distances.
	retour	Returning by bike to the point of origin (Binary. Yes = 1; No = 0).	Positive. People who ride both ways are in better physical condition to travel longer distances.

Table 2
Built environments related to origin and destination variables by subdimension (density, land use, and infrastructure) and expected relationships with travel distance. Data source: [dataset] Ospina et al. (2018).

Subdimension	Variable	Description	Expected correlation
Origin and destination density	o_i_dens d_i_dens	Origin and destination intersection density (intersections per square kilometer within a buffer of 600 m from the trip destination).	Negative. High-density levels shorten distances traveled.
	o_km_dens d_km_dens	Origin and destination street density (street length per square kilometer within a buffer of 600 m from the trip destination).	Negative. High-density levels shorten distances traveled.
	o_cbd	Distance from origins to the CBD.	Positive. The closer a trip starts to a CBD, the shorter the distance.
Origin and destination land use	o_pLU_Hmix d_pLU_Hmix	The proportion of land use dedicated to mixed-use within a 600 m buffer from the trip destination.	Negative in both cases (origin and destination). Mixed land use shorten distances traveled.
Origin and destination infrastructure	o_LCycle d_LCycle	Length of cycling paths (in kilometers) within a 600 m buffer from the trip origin and destination.	Positive. More dedicated infrastructure favor distances traveled.
	o_bikest_index d_bikest_index	The number of stations divided by a 600 m buffer area.	Positive. A high density of bike stations favors the distance traveled.
	o_Hls, d_Hls	High levels of stress. Length of major roads (in kilometers) within a 600 m buffer from the trip destination.	Negative. Higher levels of stress discourage cyclists from traveling long distances.
	o_Lls, d_Lls	Low levels of stress. Length of minor roads (in kilometers) within a 600 m buffer from the trip destination.	Positive. Lower levels of stress encourage cyclists to travel long distances.

travel longer distances. We measured all of the variables within a 600 m buffer around origins and destinations. The lengths of bicycle paths were estimated from the number of kilometers of dedicated cycling infrastructure separated from or running alongside the vehicle network. We calculated the density of bike-sharing stations as the number of stations divided by the 600 m buffer area. Finally, following Cervero et al. (2018) and Faghih-Imani et al. (2014), we defined the lengths of major and minor roads as proxies for the levels of stress that vehicles place on cyclists. The variables of this subdimension and their anticipated associations with travel distance are presented in Table 2.

The built environment along a given route (*BEij*) is the third explanatory dimension included in our model. As is the case for built environments at origins and destinations, *BEij* also includes the subdimensions of density, land use, and infrastructure (Broach et al., 2012; Cervero et al., 2018). In the literature, the *density* along the route is also expressed in terms of population and employment density, street density, or intersection density (Broach et al., 2012; Cervero et al., 2018; Menghini et al., 2010). Despite intersections

Table 3
Built and natural environment relations to route variables by subdimension (density, land use, infrastructure, and slope) and their expected relationships with travel distance. Data source: [dataset] Ospina et al. (2018).

Subdimension	Variable	Description	Expected correlation
Route density	r_i_tflights	The ratio between the number of traffic signals and the total number of intersections along a route.	Negative. More traffic signals imply more stops and thus more effort required to travel long distances.
	r_detour	The ratio between real and Euclidean distances from origins (*i*) to destinations (*j*).	Negative. More detours imply more effort required to travel long distances.
	r_detour2	Quadratic form of r_detour	Negative. The increasing marginal effect has a maximum and at some point, the function curve starts to decrease
Route land use	r_pLU_Hmix	The proportion of land use dedicated to mixed-use land within a 100 m buffer from trip destinations.	Negative. Mixed land use shorten the distance traveled.
Route infrastructure	r_LCycle	Lengths of cycle paths (in kilometers) along routes.	Positive. More dedicated infrastructure favors the distance traveled.
	r_Hls	High levels of stress. Lengths of major roads (in kilometers) along routes.	Negative. Higher levels of stress discourage cyclists from traveling long distances.
	r_Lls	Low levels of stress. Lengths of minor roads (in kilometers) along routes.	Positive. Lower levels of stress encourage cyclists to travel long distances.
Route slopes	g_elevat	The sum of every gain in elevation made throughout a cycling trip.	Negative. Considerable elevation gained implies more effort required to ride long distances.
	g_elevat2	Quadratic form of g_elevat	Negative. The increasing marginal effect has a maximum and at some point, the function curve starts to decrease
Interaction effects	r_LCycle_det	The interaction term between the detour and the length of cycling infrastructure	Uncertain

require cyclists to stop, this is not always the case and heavily depends on whether or not there is a traffic light on the intersection. Consequently, we calculated the intersection density as the ratio between the number of traffic lights and the total number of intersections along a route. To avoid endogeneity problems, we did not standardize these values to the length of the route (Wooldridge, 2011). Following Broach et al. (2012) we expect that the variables associated with density have a negative impact on travel distance. We also calculated detours as the ratio between the real distance and the Euclidean distance from the origin to the destination which, following Cervero et al. (2018), we expect to negatively affect travel distance. Table 3 describes the variables of this subdimension and their expected associations with travel distance.

Regarding *land use* encountered along routes, as in Cervero et al. (2018), we applied buffers along routes to calculate the proportion of land dedicated to mixed uses. However, in our case we applied 100 m buffers (rather than 50 m buffers) to better suit the average block size in Medellin. In the same direction as the mixture of this variable at the origin and destination, we expect it to be negatively correlated with cycling travel distance. Table 3 describes this subdimension variable and its expected association with travel distance.

The type of *infrastructure* that cyclists use along the route, the third *BEij* subdimension, includes variables such as the length of bicycle paths, the density of bike-sharing stations, the lengths of major (arterials and highways) and minor (local streets and collectors) roads (Broach et al., 2012; Cervero et al., 2018; Menghini et al., 2010). The types of roads are also measured in several studies as the level of stress, which is related to the level of vehicle traffic to which the cyclists are exposed (Caviedes and Figliozzi, 2018; Cervero et al., 2018). As we did with the origins and destinations, we measured the lengths of bicycle paths to evaluate the availability of dedicated cycling infrastructure. We also estimated the level of stress as the length of different types of roads positioned alongside cycling routes. Both variables are treated in absolute terms to avoid having our endogenous variable, distance, present in the right-hand side of the equation (Wooldridge, 2011). Aligned with previous findings from Broach et al. (2012), Fitch et al. (2019), and Cervero et al. (2018), we expect to have a positive association between the presence of dedicated cycling infrastructure, as well as the low-stress roads, and the distance traveled by cyclists. Table 3 describes the variables of this subdimension and their expected associations with travel distance.

The natural environment (NE_{ij}) encountered along a route is the last explanatory dimension included in our model. According to the literature review, it includes the weather and climate patterns, as well as the topography. Nevertheless, in this study we only consider the topography, as in our area of study (Medellin-Colombia), seasonal temperatures vary minimally throughout the year (the annual average temperature is 22.5 °C with temperatures fluctuating from 17 °C to 28 °C) and rainy seasons are more characterized by intense rain in a short period. Regarding the topography, studies such as Broach et al. (2012), Menghini et al. (2010), and Cervero et al. (2018), calculated the slope as the average ratio of the height difference between the start and endpoints of every link of a route divided by the distance between them. However, in this study, we use the cumulative elevation gain instead of the normalized elevation gain. The reason why we used the cumulative elevation gain is that we want to avoid the endogeneity that the normalized version of this variable would generate by having the travel distance on both sides of the Eq. (1) (Wooldridge, 2011). This cumulative elevation gain is commonly used in the sports literature and considers the sum of every gain in elevation (in meters) made throughout a cycling trip (Hayes and Norman, 1994; Scarf, 2007). Table 3 describes the variables of this subdimension and their expected association with travel distance.

Ortúzar and Willumsen (2011) consider that it might not be realistic nor necessary to assess all possible interaction effects in a model, therefore, our selection is based on the literature review, as well as on the particularities related to our context. For instance, Motoaki and Daziano (2015) analyzed the interaction between the slope and the cyclists' physical condition. Moreover, although Broach et al. (2012), Menghini et al. (2010), and Cervero et al. (2018) did not explore interactive effects, they found that the deviation from direct routes, the presence of cycling infrastructure along the route, and steep terrains affect the cyclists' travel distance. In addition to the literature review, we were interested in evaluating some new hypothesis closely related to our urban contexts in Latin America. In this direction, particularities of our context include the spatial and socioeconomic segregation, the irregular and diverse shapes of the street network, as well as the topographical variations within the city. Consequently, we believe that all these factors could affect travel distance individually or by interacting with other variables. After testing several interaction effects, we only kept those that resulted statistically significant. In this direction, in our case, it might seem evident that travel distance gets longer as the detour and the elevation increase. However, we expect that at some point, the distance function curve starts to decrease as the detour increases and the elevation gets higher. Therefore, to capture such effect, as suggested by Wooldridge (2013), we included the detour squared (*r_detour2*) and the elevation squared (*g_elevat2*) in addition to their linear forms, for which we expect to have a negative effect on travel distance. Additionally, we were interested in analyzing whether the detour taken by cyclists was a consequence of cyclists' desire of reaching paths with dedicated cycling infrastructure. Consequently, we included the interaction effect between the detour and the length of cycling infrastructure (*r_LCycle_det*) in Eq. (1). Table 3 describes the variables of quadratic and interaction variables and their expected association with travel distance.

4. Results

Travel distance, our dependent variable, enters the regression model in log form to compress the long tail usually present in this variable (Páez et al., 2012). This leads to the formation of a log-linear model where each explanatory variable presents marginal rates with respect to the natural log of distance (Cameron and Trivedi, 2005). In a log-linear model, $100^*\beta$ is interpreted as the expected percentage change in distance for a unit increase in X (Benoit, 2011). For instance, for $\beta_i = 0.06$ associated with attribute X_i, a 1-unit change in X_i (approximately) corresponds to an expected increase of 6% in travel distance.

To obtain robust OLS estimators, we verified the potential presence of multicollinearity and heteroskedasticity. On one hand, a strong linear relationship between independent variables (*multicollinearity*) can lead to considerable variances in OLS slope estimators, biasing test statistics and confidence intervals (Wooldridge, 2013). Therefore, we verified the variation inflation factor (VIF) for every alternative of the model. The mean VIF value is < 10 for the full model, indicating that multicollinearity is not a concern (Belsley et al., 1980). In this process, we find that variables such as *street density* and *intersection density* along the route are highly correlated and cannot be included together in the same specification. In the same way, *street density* and *levels of stress at the origin and destination* are highly correlated. This multicollinearity can be attributed to the fact that these variables capture the same type of information: density in the first case and the length of infrastructure for the second. We estimated a regression model for each variable and found the results to be very similar. We therefore only present model results for the *intersection density* of a route and *levels of stress* experienced at origins and destinations. Alternative results can be obtained from the first author upon request.

We also tested for the potential presence of *heteroskedasticity*. When an OLS model exhibits heteroskedasticity, the usual standard errors and test statistics for estimators are no longer applicable (Wooldridge, 2013). The presence of heteroskedasticity was confirmed after running a Breusch-Pagan test (Cameron and Trivedi, 2005). In our case, this heteroskedasticity may be attributed to the overlapping of origin locations (or destination locations), producing subsets of observations of an equal attribute value. For instance, two trips starting from the same origin (i.e., a bike-sharing station) presented the same built environment attributes at the starting point. To overcome this, we estimated the robust standard error clustered at the commune level, which is an administrative unit for the city (Medellin is divided into 16 communes). As a result, we obtained heteroskedastic, consistent, and valid standard errors for the OLS estimators even though the functional form of this heteroskedasticity is unknown (Cameron and Trivedi, 2005). In other words, formal modeling of heteroskedastic structures was not required (Cameron and Trivedi, 2005; White, 1980). In this section, we present robust standard errors clustered at the commune level for every alternative model.

We performed a hierarchical regression analysis to determine whether the variables related to the route, beyond socio-economic and the origin and destination dimensions, improved the explanatory power of cycling travel distance predictions. Hierarchical regressions are useful for evaluating the contributions of predictors above and beyond previously entered ones as a means of statistical control and of measuring incremental validity (Lewis, 2007). In addition, the present analysis allows for the use of predictors over multiple steps by adding single variables or by adding combinations of variables to the model. Our model includes three collections of variables corresponding to each of the dimensions examined: (1) the socioeconomic dimension (*SE*), (2) the built environment at the origin and destination (BE_i and BE_j), and (3) the built and natural environment along the route (BE_{ij} and NE_{ij}) The order in which such dimensions are entered is determined by the research problem (Lewis, 2007). As we used 3 blocks of variables, 6 potential order combinations were explored. As it is common in this type of econometric exercises, we only considered for discussion those variables exhibiting constant statistical significance across all model combinations. The variables included in our model are based upon a literature review. Consequently, the estimations include those variables that resulted statistically significant as well as those that did not. The significance, or not, of a variable is a result per se, which might be aligned with or opposed to previous findings. Consequently, non-significant variables cannot be removed from the final results.

Table 4 presents one of the order combinations, which includes the built and natural environment along the route (BE_{ij} and NE_{ij}) across all three alternative models. Annex 2 shows an alternative combination where BE_{ij} and NE_{ij} are also present across all three alternative models[2]. The first alternative model shown in Table 4 relates to the built and natural environment along the route (BE_{ij} and NE_{ij}) and is presented in the left column of Table 4. The second alternative, shown in the middle column of Table 4, adds the built environment of the origin and destination (BE_i and BE_j). Finally, the third alternative model presented in the right column includes

Table 4
Regression model estimation results. Dependent variable: natural logarithm of the distance.

VARIABLE	*Model including BE_{ij} + NE_{ij}*		*Model including BE_i + BE_j + BE_{ij} + NE_{ij}*		*Model including SE + BE_i + BE_j + BE_{ij} + NE_{ij}*	
	Est.Coeff	*t-Stat*	*Est.Coeff*	*t-Stat*	*Est.Coeff*	*t-Stat*
age					0.00588	0.67
age2					−8.89e-05	−0.83
gender					−0.0441*	−1.83
Hinc					0.0561	1.26
Minc					0.0677*	2.05
study					0.0642	1.27
bothpurp					0.111*	2.11
pubbike					−0.124***	−5.05
bothbike					−0.00717	−0.38
frecweek					−0.0126**	−2.75
dispo_tp					0.0410	0.84
dispo_pv					−0.0271	−1.27
intermodal					−0.0287	−0.88
retour					0.0233	0.39
o_i_dens			0.000198	0.45	−1.75e-05	−0.05
o_cbd			0.0923***	3.21	0.0945***	3.5
o_pLU_Hmix			−0.107	−0.89	−0.100	−0.92
o_LCycle			−0.101**	−2.93	−0.0764**	−2.78
o_bikest_index			−0.00208	−0.1	−0.00314	−0.15
o_Lls			0.0106*	1.86	0.0118*	1.95
d_i_dens			0.000982	0.97	0.000532	0.58
d_pLU_Hmix			0.363***	2.98	0.371***	3.35
d_LCycle			−0.0279	−0.9	−0.0178	−0.75
d_bikest_index			−0.0102	−0.92	−0.00700	−0.57
d_Lls			−0.000320	−0.03	0.00448	0.43
ratio_itf_ri	−0.00817**	−2.87	−0.000189	−0.08	−0.000191	−0.1
r_detour	1.729***	3.12	1.925***	3.95	1.765***	3.94
r_detour2	−0.463**	−2.76	−0.468***	−3.22	−0.422***	−3.1
r_pLU_Hmix	0.230	1.01	0.220*	2.11	0.207*	2.03
r_LCycle	0.313***	7.66	0.361***	6.91	0.371***	7.03
r_Lcycle_det	−0.102***	−3.65	−0.133***	−3.85	−0.138***	−3.89
r_Lls	0.161***	5.08	0.132***	3.41	0.127***	3.97
g_elevat	10.76***	9.72	8.971***	8.97	8.702***	10.27
g_elevat2	−16.10***	−6.29	−12.73***	−5.65	−12.52***	−6.54
Constant	−0.6390432	−1.13	−1.680***	−3.28	−1.663***	−3.47
Observations	810		810		810	
R-squared	0.523		0.676		0.697	
Adj. R-squared	0.518		0.668		0.684	
Log-Likelihood:	−399		−242		−215	
AIC	818		526		499	
VIF	19.6		10.0		9.2	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the socioeconomic dimension (*SE*).

When comparing the results of the three alternative specifications provided in Table 4, the better fit corresponds to the full model, which presents the highest log-likelihood and lowest Akaike information criterium AIC values (Anselin, 1988; Korner-Nievergelt et al., 2015). Besides, the full model provides an Adjusted R-square value of 0.697 versus values of 0.523 and 0.676 generated by the first and second alternative models, respectively. The results of the three alternative models show evidence for the importance of considering built environment attributes along a route to improve the explanatory power of cycling travel distance predictions.

5. Discussion

This section discusses the outputs of the three alternative models. The effects of the socioeconomic *(SE)* dimension on cyclist travel distances are first discussed, which is followed by effects of the built environment at the origin and destination (BE_i and BE_j) and then by effects of the built and natural environment along a route (BE_{ij} and NE_{ij}). Each dimension is discussed in terms of its predictive significance, its relation to prior expectations and findings, and interpretations of predictors β in terms of percentage changes in distance. Recall that we consider in the analysis only those variables that exhibit consistent significance behavior across the permutations of alternative models included in Table 4 and Annex 2.

[2] We recall that alternative results can be obtained from the author upon request.

The full model shows that three variables are significant within the socioeconomic (*SE*) dimension: ***bothpurp***, ***pubbike***, and ***frecweek***. First, as expected, the results suggest that people using their bicycles for both purposes (***bothpurp)*** travel 11.1% longer distances than those only cycling to work (the basis of this categorical variable). This result is consistent with Heinen et al. (2011) who found that cycling for several purposes has a positive effect on the distance traveled to work. In our context, this may be understood in two ways: (1) cyclists commuting for both purposes (work, study) are in better physical condition, and (2) work and study locations are not necessarily positioned close to one another. Second, aligned with prior expectations and consistent with previous findings from Campbell et al. (2016), public bike users (***pubbike***) travel 12.4% shorter distances than those using private bikes, which is the base category. This may be due to the concentration of most bike share stations in certain areas of the city, especially in the center, which shortens distances between stations. Finally, contrary to prior hypotheses and previous findings from Heinen et al. (2011), our model shows that regular commuters prefer to ride shorter distances. In this case, a one-unit increase in the frequency of cycling per week (*frecweek*) is associated with a 12.6 m (i.e., 1.26% of 1 km) reduction in travel distance.

Regarding the built environment at the origin and destination (BE_i, BE_j), our estimations suggest that cyclists are sensitive to the distance from the origin to the CBD (*o_cbd*), the length of cycling paths (*o_LCycle*) and the length of minor roads (*o_Lls*) around the origin, as well as to the proportion of mixed land use at the destination (*d_pLU_Hmix*). Even though previous studies have reported on the effects of these variables on the generation (or attraction) of trips (Cervero and Duncan, 2003; Faghih-Imani et al., 2014), the effect on distance has been less studied. First, our results suggest that starting a trip one kilometer further from the CBD implies a 9.45% (94.5 m) increase in cyclist travel distances. This is in line with previous findings from Cervero and Kockelman (1997), Pucher et al. (2010), and Saelens et al. (2003) showing that travel distance declines when a trip starts close to a CBD. This may be attributable to the fact that cyclists living close to a CBD are also located close to city services and activities and consequently have no need to commute farther away. Second, the proportion of mixed land use at the destination (*d_pLU_Hmix*) is also positively associated with travel distance. Contrary to our hypothesis, the results suggest that an increase of one unit in the proportion of mixed-use produces a 37.1% increase (371 m) in travel distance. Mixed land use destinations supply job opportunities, services, and urban activities, consequently, it may be attractive even to those needing to travel long distances to access them. From a cycling public policy perspective, both results suggest that mixed land use is attractive at the origin and destination, though it is preferable to promote mixed land use in areas closer to the city center to limit the need for cyclists to travel long distances. Third, the length of cycling paths around the origin (*o_LCycle*) is negatively associated to travel distance. Our results indicate that an increase of 1 km in the length of cycle paths close to the origin would reduce the cyclist travel distance in 7.64% (76.4 m), which is opposed to prior expectations. According to Fig. 6, most of the longer trips started from the northern, western, and southwestern, where the dedicated cycling infrastructure is still very scarce, which is consequent with our *o_LCycle* result. Finally, the result of the length of minor roads (*o_Lls*) is coherent with our prior expectations meaning that an increase of one unit in the length of slow streets around the origin would produce a 1.18% (11.8 m) increase in cyclist travel distance. Aligned with the *o_LCycle* result, this suggests that origin locations associated with longer trips are mostly surrounded by low-stress roads while those related to shorter trips are mostly surrounded by dedicated cycling infrastructure. From a public policy perspective, dedicated cycling infrastructure close to origin locations is as important as low-stress roads to limit cyclists' exposure to traffic and motivate people to cycle even for long-distance trips.

Regarding the natural environment encountered along a route (NE_{ij}), our results confirm our hypothesis on the existence of a quadratic relationship between the cumulative elevation gained (*g_elevat*) and travel distance. Since β_{g_elevat} is positive and $\beta_{g\_elevat2}$ is negative, there is an increasing marginal effect until a certain value of *g_elevat* (turning point) is reached, at which the partial effect on travel distance becomes zero (Wooldridge, 2013). After that turning point, the effect of *g_elevat* on travel distance becomes negative. The partial effect of *g_elevat* can be determined by deriving the entire estimated function from the regression model:

$$\frac{dy}{dx} = \frac{d(Ln(d))}{d(g_{elevat})} = \beta_{gelevat} + 2 * \beta_{gelevat2} * g_{elevat} \tag{2}$$

The turning point, from positive to negative partial effects, is calculated by equalizing the previous expression to zero and by clearing *g_elevat* as shown in the following expression:

$$g^*_{elevat} = -\frac{\beta_{gelevat}}{2 * \beta_{gelevat2}} = -\frac{8.702}{2 * (-12.52)} = 0.348km = 348m$$

The result denotes that with 348 m of gained elevation, the effect of *g_elevat* is null and becomes negative after this point. For the first part of the parabolic shape, contrary to the findings of Broach et al. (2012) and Menghini et al. (2010), our estimations suggest that cyclists do not necessarily avoid steep terrain. For the second part, the results suggest that the effect of *g_elevat* may become negative at some point, but it is difficult to believe that this occurs after 348 m of climbing. Consequently, as < 1% of our cyclists reach elevations of greater than 348 m, the right side of the quadratic function can be ignored for practical purposes (Wooldridge, 2013). Medellin's topography is hilly, and consequently, cyclists traveling long distances are more likely to negotiate with the slopes. However, their willingness to cycle on steep terrains may have a limit.

With regard to the built environment of the route dimension (BE_{ij}), all of the variables are statistically significant except for the intersection ratio (*ratio_itf_ri*) and the proportion of mixed land use along the route (*r_pLU_Hmix*). Concerning the type of infrastructure that cyclists use along a route, the length of minor roads (*r_Lls*) is positively associated with travel distance consistent with our prior hypothesis. Aligned with previous findings from Broach et al. (2012) and Cervero et al. (2018), our results show that cyclists are sensitive to high traffic volumes and prefer to limit their exposure to traffic by using low-speed roads. An increase in one unit in the length of low-speed roads would produce a 12.7% increase (127 m) in travel distance. One may assume that cyclists seek out this

Table 5
Partial effect of r_detour on log travel distance d(Ln(d))/d(r_detour).

r_LCycle	*r_detour* = 1.0	*r_detour* = 1.330	*r_detour* = 1.774	*r_detour* = 2.094	*r_detour* = 2.69	*r_detour* = 3.113
0.00	0.92	0.64	0.27	0.00	−0.51	−0.86
1.53	0.71	0.43	0.06	−0.21	−0.72	−1.07
3.00	0.51	0.23	−0.15	−0.41	−0.92	−1.28
4.00	0.37	0.09	−0.28	−0.55	−1.06	−1.41
5.61	0.15	−0.13	−0.51	−0.77	−1.28	−1.64

type of road despite increasing travel distances. However, we tested for possible interaction effects between the detour ratio (*r_detour*) and the lengths of minor roads (*r_Lls*), they were not significant.

Moreover, our results reveal a quadratic effect of the detour ratio (*r_detour)* and simultaneously an interaction effect between *r_detour* and the length of cycling paths (*r_LCycle*). Consequently, as suggested by Wooldridge (2013), the results for both variables are analyzed as a whole. The interaction between *r_detour* and *r_LCycle* for cyclist travel distances is analyzed in two directions, each of which is related to their partial effects on travel distance. On the one hand, the partial effect of *r_detour* on the log travel distance (ln *(d)*) is determined by Eq. (3) below when deriving the model estimation from *r_detour*:

$$\frac{dy}{dx} = \frac{d(ln(d))}{d(r_{detour})} = \beta_{rdetour} + \beta_{rLCycle*rdetour2} * r_{LCycle} + 2 * (\beta_{rdetour2}) * r_{detour} \tag{3}$$

$$\frac{dy}{dx} = \frac{d(ln(d))}{d(r_{detour})} = 1.765 - 0.138 * r_{LCycle} - 2 * (0.422) * r_{detour}$$

According to this expression, the partial effect of *r_detour* on the log travel distance (*d*(ln*(d))/d(r_detour)*) depends on *r_LCycle* and *r_detour* variables. Since $\beta_{rdetour}$ and $\beta_{rdetour2}$ predictors are both significant with opposing signs, this result denotes a parabolic shape of this effect. To provide an adequate interpretation of this simultaneous effect, we fixed the value of one variable while assigning different values to the other and vice versa. Table 5 shows the partial effects of *r_detour* on travel distance while assigning different reasonable *r_LCycle* and *r_detour* values (between the minimum value and 75-quartile including the mean).

As indicated in Table 5, for a given value of *r_detour*, its partial effect on travel distance (*d(Ln(d))/d(r_detour)*) declines while the length of cycle paths is increased. Besides, for a given cycle path length (*r_LCycle*), the partial effect of *r_detour* declines while its value increases. In other words, each parabolic shape depends on both values simultaneously, as shown in Fig. 7. These curves indicate that the turning point value of the parabolic shape decreases while increasing the lengths of route cycle paths (*r_LCycle*). These curves are built by using the exponential of the model estimation $Y = e^{\ln(d)}$, varying *r_LCycle* and *r_detour*, and fixing all the remaining variables

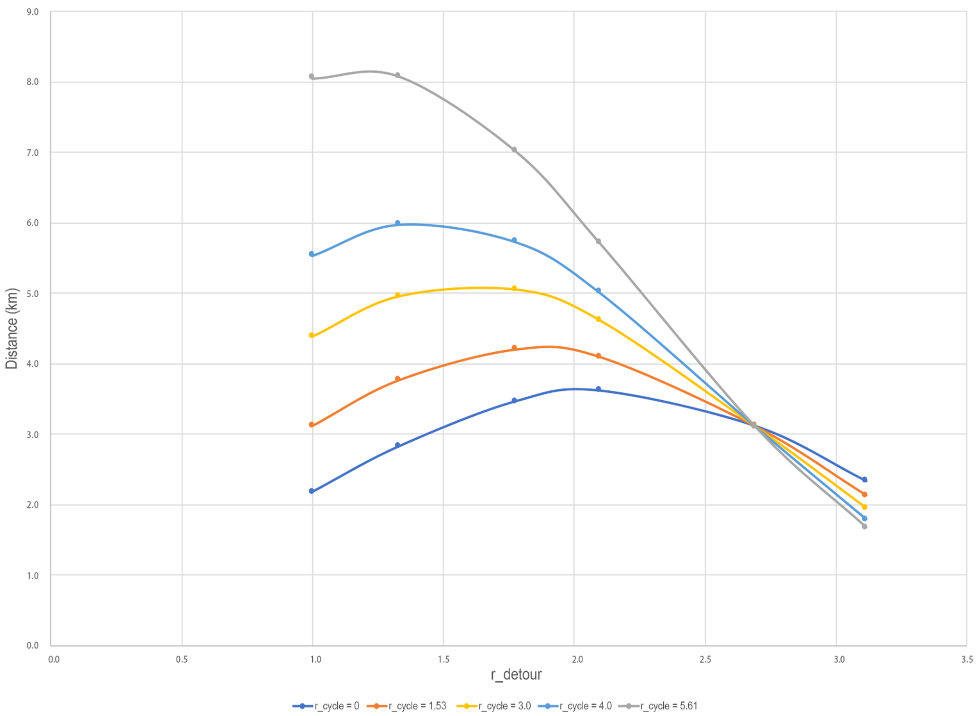

Fig. 7. (Left) Travel Distance (d) estimation based on r_LCycle variations.

Table 6
Partial effect of r_LCycle on log travel distance d(ln(d))/d(r_ LCycle).

	r_detour					
	1.0	**1.330**	**1.774**	**2.094**	**2.69**	**3.113**
$\frac{d(ln(d))}{d(r_{LCycle})}$	0.23	0.19	0.13	0.08	0.00	−0.06

on the mean values.

On the other hand, when analyzing the partial effect of *r_LCycle* on the log travel distance (*d(*ln*(d))/d(r_LCycle)*), we found that the effect depends on the value of *r_detour*, as shown in the following Eq. (4):

$$\frac{dy}{dx} = \frac{d(ln(d))}{d(r_{LCycle})} = \beta_{rLCycle} + \beta_{rdetour} * r_{detour} \tag{4}$$

$$\frac{dy}{dx} = \frac{d(ln(d))}{d(r_{LCycle})} = 0.371 - 0.138 * r_{detour}$$

By assigning different values to *r_detour*, we obtain the (*d(*ln*(d))/d(r_LCycle)*) values shown in Table 6, which correspond to the slopes of each straight line shown on Fig. 8.

As is shown in the Table 6 and as confirmed by Fig. 8, while *r_detour* increases, the slope of the straight line (*d(*ln*(d))/d(r_LCycle)*) decreases until it reaches a value of zero for *r_detour* = 2.69. This point coincides with the point at which all parabolic curves converge, after which point the partial effect of *r_LCycle* on travel distance becomes negative.

When combining both directions of analysis to determine the combined effect of *r_detour* and *r_LCycle* on cyclist travel distances, one main conclusion arises: even though it may imply traveling longer distances, cyclists are willing to deviate from direct routes to minimize their exposure to traffic by searching for dedicated infrastructure. However, when the detour becomes too long (greater

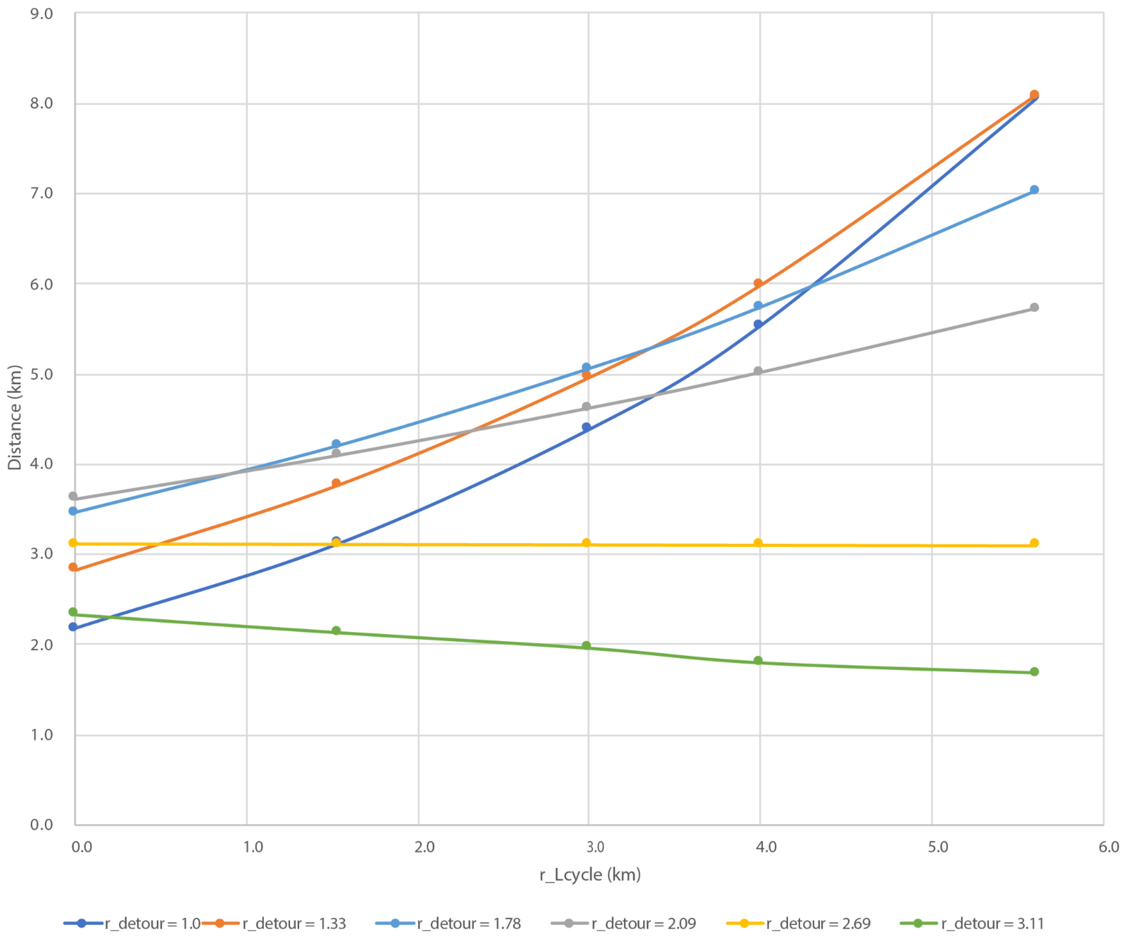

Fig. 8. (Right) Travel Distance (d) estimation based on r_detour variations.

than 2.69 according to our results), cyclists do not want to deviate any further. This is consistent with Cervero et al. (2018) who found that taking more detours implies increased traveling distances, which demotivates people from traveling by bicycle. This is also coherent with Cabral et al. (2019) findings that suggested that cyclists prefer a network of dedicated and direct cycling facilities.

From a public policy perspective, our results suggest that dedicated cycling infrastructure has an impact depending on the detour value: it is stronger for shorter detours (more direct routes) and becomes less strong as the length of the detour increases. In other words, decision-makers should invest in more direct routes and provide cycling dedicated infrastructure to maximize their impact and increase the levels of cycling.

6. Conclusion

This paper contributed to the existing literature in three directions. First, regarding the explanatory variables, this paper reveals the importance of built and natural characteristics along the road in explaining cycling travel distances while controlling for socioeconomic and built environments measures at origins and destinations. Second, the context contribution, our results for Medellin show no significant effects of cyclists' demographics on travel distance, which contradicts the existing literature, but our findings on the relationships between the built and natural environment and travel behavior are in line with existing literature. Third, the methodological contribution, beyond supporting previous findings and highlighting the importance of route characteristics, this paper shows the relevance of including the interaction and quadratic effects of some variables to achieve a more robust model.

Moreover, natural and built environment features along the routes play significant roles in explaining cycling travel distances in Medellin. First, cyclists do not necessarily avoid steep terrain when traveling a certain distance, which is probably because they are already used to cycling on hilly areas or perhaps because they have no other alternative. However, even when cyclists are exposed to hilly urban topography, their willingness to cycle on slopes has a limit. Second, cyclists make use of low-stress roads, probably to reduce their exposure to high traffic volumes. Third, the interaction effect between the dedicated infrastructure along a route and the degree of deviation from direct routes plays a particularly relevant role in explaining travel distance. Even though they have to deviate from direct routes, cyclists find routes with dedicated cycling infrastructure very valuable. However, the impact of dedicated infrastructure is stronger for shorter detours (more direct routes) and decreases as a detour increases the travel distance. Consequently, policy directions to promote bicycle commuting should include the design of direct routes with a dedicated infrastructure as well as routes drawn along low-speed roads.

Moreover, regarding the built environment features associated with origins and destinations, mixed land use does not always contribute to reducing travel distances. On the one hand, living closer to a CBD reduces the need for long cycling trips due to proximity to city services and activities. On the other hand, mixed land use destinations are attractive even for those having to travel long distances to access them. From a public policy perspective, as cyclists value destinations with land use diversity, it would be better to promote such amenities in areas closer to city centers to limit the need to travel longer distances. Besides, concerning the type of infrastructure surrounding the origin locations, dedicated cycling infrastructure is as important as low-stress roads to limit cyclists' exposure to traffic and motivate people to cycle even for long-distance trips.

Furthermore, our results for Medellin show no significant effects of cyclists' demographics on travel distance. These results indicate that once individuals decide to commute by bicycle (a decision for which, according to the extensive literature on travel behavior, demographic characteristics do matter), their demographic characteristics make no difference concerning travel distance. This finding implies that any intervention intended to improve dedicated cycling infrastructure should have a similar effect on all current users.

Our research contributes to the planning and design of dedicated cycling facilities based on travel distance, which we found to be very sensitive to dedicated infrastructure, detours, and the combination of land use. These recommendations will be essential for route design that maximizes the use of cycling infrastructure. Moreover, our research findings can be used in further studies seeking to understand cyclists' accessibility to urban opportunities based upon the variations on distance thresholds, which depend on the dimensions studied in this paper. Additionally, the results of this study can support the design of cycling networks while considering the impact of dedicated cycling infrastructure, low-stress roads, detour limitations and the mixture of urban land uses.

Credit authorship contribution statement

Juan P. Ospina: Investigation, Conceptualization, Methodology, Formal analysis, Writing - original draft. **Verónica Botero-Fernández:** Conceptualization, Writing - review & editing, Funding acquisition. **Juan C. Duque:** Investigation, Conceptualization, Methodology, Writing - review & editing. **Mark Brussel:** Supervision, Writing - review & editing. **Anna Grigolon:** Validation.

Acknowledgments

The survey project which served as the basis of the current paper, was possible thanks to the financing from Universidad Nacional de Colombia-Medellin (project code QUIPU 202010017827) and the PEAK Urban Programme, supported by UKIR's Global Challenge Research Fund, Grant Ref.: ES/P011055/1. Additionally, greetings are dedicated to Gustavo A. García Cruz, associate professor at the Department of Economics, Universidad EAFIT.

Annex 1. Descriptive statistics

Dimension	Variable	*Descriptive statistics*			
		Mean	*Std.Dev.*	*Min*	*Max*
SE	**age**	29.23	10.64	16.00	72.00
	age2	967.8	818.2	256.00	5184.00
	gender	0.31	0.46	0.00	1.00
	Hinc	0.21	0.41	0.00	1.00
	Minc	0.61	0.49	0.00	1.00
	study	0.36	0.48	0.00	1.00
	bothpurp	0.32	0.47	0.00	1.00
	pubbike	0.26	0.44	0.00	1.00
	bothbike	0.29	0.45	0.00	1.00
	frecweek	4.16	1.73	0.50	6.00
	dispo_tp	0.87	0.33	0.00	1.00
	dispo_pv	0.32	0.47	0.00	1.00
	intermodal	0.22	0.41	0.00	1.00
	retour	0.93	0.25	0.00	1.00
$BE_i + BE_j$	**o_i_dens**	182.68	49.71	8.84	445.63
	o_cbd	3.21	1.42	0.26	7.67
	o_pLU_Hmix	0.28	0.20	0.00	0.84
	o_LCycle	1.03	1.07	0.00	4.66
	o_bikest_index	0.98	1.14	0.00	6.19
	o_Lls	10.41	3.70	1.00	22.00
	d_i_dens	177.38	36.55	61.01	275.87
	d_pLU_Hmix	0.42	0.22	0.00	0.88
	d_LCycle	1.30	0.91	0.00	4.98
	d_bikest_index	0.98	1.14	0.00	6.19
	d_Lls	6.99	2.75	2.00	17.00
$BE_{ij} + NE_{ij}$	**ratio_itf_ri**	16.11	9.26	0.00	49.00
	r_detour	1.35	0.22	1.00	3.11
	r_detour2	1.86	0.67	1.00	9.69
	r_pLU_Hmix	0.40	0.16	0.00	0.82
	r_LCycle	1.67	1.39	0.00	7.72
	r_Lcycle_det	2.27	1.97	0.00	10.38
	r_Lls	0.22	0.30	0.00	2.19
	g_elevat	0.03	0.04	0.00	0.55
	g_elevat2	0.00	0.01	0.00	0.30

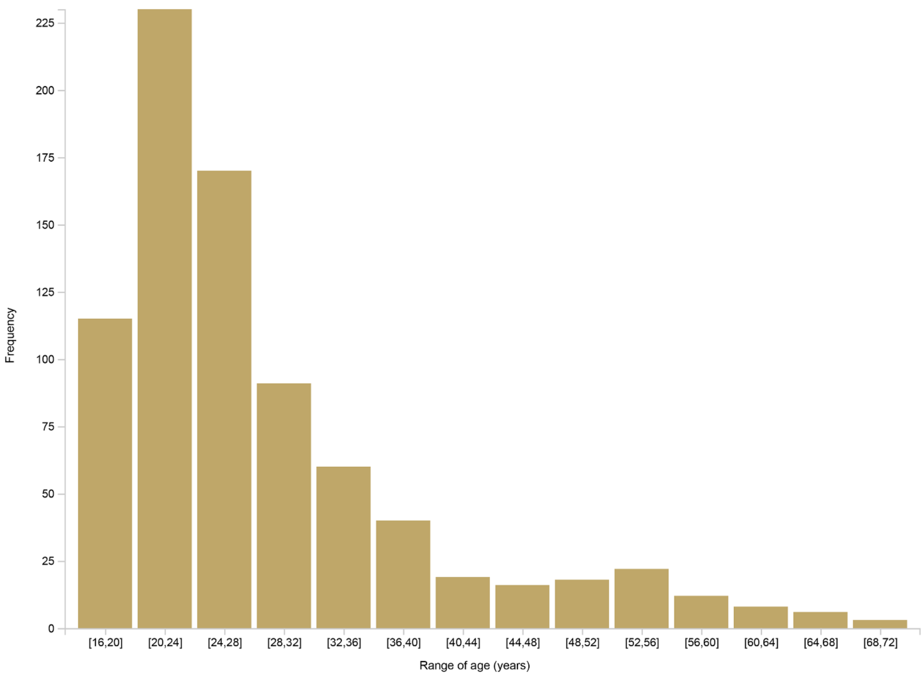

Fig. 9. Distribution of respondents' age.

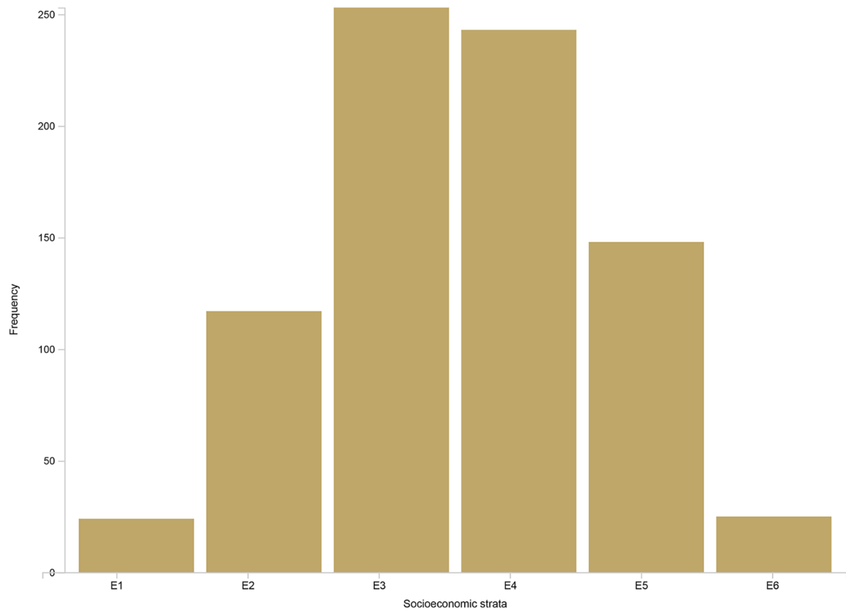

Fig. 10. Distribution of respondents' income strata.

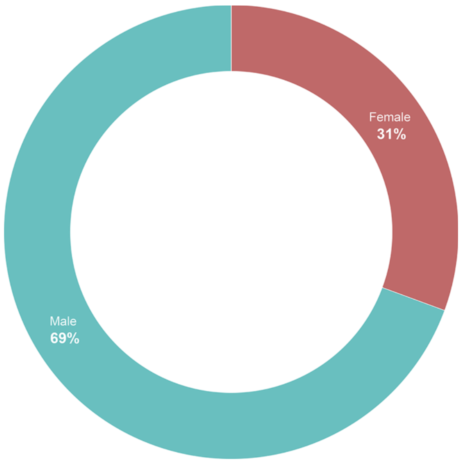

Fig. 11. Distribution of respondents' gender.

Fig. 9 shows the distribution of respondent's age. According to this distribution, 87% of respondents are younger than 40 years, while the remaining respondents are included in the range of age between 40 and 72 years. Fig. 10 presents the distribution of respondent's income strata, where the lowest (1st) and highest (6th) strata were the least represented (3% in each case), while the 3rd and the 4th strata were the most represented in our sampling framework (31% and 30% respectively). Also, the 2nd and 3rd income strata had a representation of 14% and 18%. Finally, according to Fig. 11, our sample was composed of 69% men and 31% women.

Annex 2. Regression - Alternative combination

VARIABLE	*Model including BE_{ij} + NE_{ij}*		*Model including BE_i + BE_j + BE_{ij} + NE_{ij}*		*Model including SE + BE_i + BE_j + BE_{ij} + NE_{ij}*	
	Est.Coeff	*t-Stat*	*Est.Coeff*	*t-Stat*	*Est.Coeff*	*t-Stat*
age			0.0043	0.55	0.00588	0.67
age2			−7.18E-05	−0.82	−8.89e-05	−0.83
gender			−0.0471	−1.25	−0.0441*	−1.83
Hinc			0.0152	0.18	0.0561	1.26
Minc			0.0335	0.56	0.0677*	2.05
study			0.0636	1.09	0.0642	1.27

bothpurp			0.122**	2.15	0.111*	2.11
pubbike			−0.298***	−9.8	−0.124***	−5.05
bothbike			−0.0857**	−2.22	−0.00717	−0.38
frecweek			−0.00875*	−1.82	−0.0126**	−2.75
dispo_tp			0.0537	1.21	0.0410	0.84
dispo_pv			−0.0167	−0.62	−0.0271	−1.27
intermodal			−0.0702**	−2.54	−0.0287	−0.88
retour			0.0266	0.45	0.0233	0.39
o_i_dens					−1.75e-05	−0.05
o_cbd					0.0945***	3.5
o_pLU_Hmix					−0.100	−0.92
o_LCycle					−0.0764**	−2.78
o_bikest_index					−0.00314	−0.15
o_Lls					0.0118*	1.95
d_i_dens					0.000532	0.58
d_pLU_Hmix					0.371***	3.35
d_LCycle					−0.0178	−0.75
d_bikest_index					−0.00700	−0.57
d_Lls					0.00448	0.43
ratio_itf_ri	−0.00817**	−2.87	−0.00622**	−2.67	−0.000191	−0.1
r_detour	1.729***	3.12	1.490***	3.17	1.765***	3.94
r_detour2	−0.463**	−2.76	−0.401**	−2.93	−0.422***	−3.1
r_pLU_Hmix	0.230	1.01	0.168	0.74	0.207*	2.03
r_LCycle	0.313***	7.66	0.322***	6.68	0.371***	7.03
r_Lcycle_det	−0.102***	−3.65	−0.0968**	−2.69	−0.138***	−3.89
r_Lls	0.161***	5.08	0.132***	3.65	0.127***	3.97
g_elevat	10.76***	9.72	9.767***	10.23	8.702***	10.27
g_elevat2	−16.10***	−6.29	−14.60***	−6.77	−12.52***	−6.54
Constant	−0.6390432	−1.13	−0.504	−1	−1.663***	−3.47
Observations	810		810		810	
R-squared	0.523		0.582		0.697	
Adj. R-squared	0.518		0.570		0.684	
Log-Likelihood:	−399		−346		−215	
AIC	818		739		499	
VIF	19.6		12.24		9.2	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Anselin, L., 1995. Local indicators of spatial analysis–LISA. Geogr. Anal. 27, 93–115.

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Appleyard, B., 2016. New methods to measure the built environment for human-scale travel research: Individual access corridor (IAC) analytics to better understand sustainable active travel choices. J. Transp. Land Use 9, 121–145. https://doi.org/10.5198/jtlu.2015.786.

Arbelaez, O., 2015. Modelación de la elección de la bicicleta pública y privada en ciudades. Universidad Nacional de Colombia, Medellín.

Área Metropolitana del Valle de Aburrá, 2015. Plan Maestro Metropolitano de la Bicicleta del Valle de Aburrá. Medellín.

Área Metropolitana Valle de Aburrá, 2017. Estrategias Ambientales Integradas - Plan Integral de Gestión de la Calidad del Aire PIGECA. https://doi.org/10.1016/j.virusres.2015.07.006.

Belsley, D.A., Kuh, E., Welsch, R.E., 1980. Regression Diagnosis. Indentifying Influential Data and Sources of Collinearity. John Wiley & Sons Inc, Hoboken, New Jersey, USA.

Benoit, K., 2011. Linear Regression Models with Logarithmic Transformations. ASEE Annu. Conf, Proc.

Bernal, R., 2009. The Informal Labor Market in Colombia: Identification and Characterization. Desarro. Soc. 145–208.

Broach, J., Dill, J., Gliebe, J., 2012. Where do cyclists ride? A route choice model developed with revealed preference GPS data. Transp. Res. Part A Policy Pract. 46, 1730–1740. https://doi.org/10.1016/j.tra.2012.07.005.

Broach, J., Gliebe, J., Dill, J., 2011. Bicycle route choice model developed using revealed preference GPS data. TRB 2011 Annu. Meet. 5464.

Buehler, R., Dill, J., 2016. Bikeway networks: a review of effects on cycling. Transp. Rev. 36, 9–27. https://doi.org/10.1080/01441647.2015.1069908.

Cabral, L., Kim, A.M., Shirgaokar, M., 2019. Low-stress bicycling connectivity: Assessment of the network build-out in Edmonton. Canada. Case Stud. Transp. Policy 7, 230–238. https://doi.org/10.1016/j.cstp.2019.04.002.

Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics. Methods and Applications. Cambridge University Press, New York, New York, USA.

Campbell, A.A., Cherry, C.R., Ryerson, M.S., Yang, X., 2016. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. Transp. Res. Part C Emerg. Technol. 67, 399–414. https://doi.org/10.1016/j.trc.2016.03.004.

Cao, X., Handy, S.L., Mokhtarian, P.L., 2006. The influences of the built environment and residential self-selection on pedestrian behavior: Evidence from Austin. TX. Transportation (Amst) 33, 1–20. https://doi.org/10.1007/s11116-005-7027-2.

Cao, X., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: A focus on empirical findings. Transp. Rev. 29, 359–395. https://doi.org/10.1080/01441640802539195.

Cárdenas, M., Rozo, S., 2009. Firm informality in Colombia: Problems and solutions. Desarro. Soc. 211–243.

Caviedes, A., Figliozzi, M., 2018. Modeling the impact of traffic conditions and bicycle facilities on cyclists' on-road stress levels. Transp. Res. Part F Traffic Psychol. Behav. 58, 488–499. https://doi.org/10.1016/j.trf.2018.06.032.

Cervero, R., 1996. Mixed land-uses and commuting: Evidence from the American housing survey. Transp. Res. Part A Policy Pract. 30, 361–377. https://doi.org/10.1016/0965-8564(95)00033-X.

Cervero, R., Denman, S., Jin, Y., 2018. Network design, built and natural environments, and bicycle commuting: Evidence from British cities and towns. Transp. Policy. https://doi.org/10.1016/j.tranpol.2018.09.007.

Cervero, R., Duncan, M., 2003. Walking, Bicycling, and Urban Landscapes: Evidence from the San Francisco Bay Area. Am. J. Public Health 93, 1478–1483. https://doi.org/10.2105/AJPH.93.9.1478.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds : Density, design and diversity. Transp. Res. Part D Transp. Environ. 2, 199–219.

Cervero, R., Sarmiento, O.L., Jacoby, E., Gomez, L.F., Neiman, A., 2009. Influences of built environments on walking and cycling: Lessons from Bogotá. Int. J. Sustain. Transp. 3, 203–226. https://doi.org/10.1080/15568310802178314.
[dataset] Ospina, J.P., López, V.I., Botero, V., Duque, J.C., 2018. A database to analyze cycling routes in Medellin, Colombia . https://github.com/Rise-group/databe_cyclists_medellin.git.
DANE, 2018. Pobreza Monetaria y Multidimensional en Colombia. Año 2017. Bogota.
Duque, J.C., Lozano-Gracia, N., Patino, J.E., Restrepo, P., Velasquez, W.A., 2019. Spatiotemporal dynamics of urban growth in Latin American cities: An analysis using nighttime light imagery. Landsc. Urban Plan. 191, 103640. https://doi.org/10.1016/j.landurbplan.2019.103640.
Duque, J.C., Patino, J.E., Ruiz, L.A., Pardo-Pascual, J.E., 2015. Measuring intra-urban poverty using land cover and texture metrics derived from remote sensing data. Landsc. Urban Plan. 135, 11–21. https://doi.org/10.1016/j.landurbplan.2014.11.009.
Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plan. Assoc. 76, 265–294. https://doi.org/10.1080/01944361003766766.
Faghih-Imani, A., Eluru, N., El-geneidy, A.M., Rabbat, M., Haq, U., 2014. How land-use and urban form impact bicycle flows: Evidence from the bicycle-sharing system (BIXI) in Montreal. J. Transp. Geogr. 41, 306–314. https://doi.org/10.1016/j.jtrangeo.2014.01.013.
Fernández-Heredia, Á., Jara-Díaz, S., Monzón, A., 2016. Modelling bicycle use intention: the role of perceptions. Transportation (Amst). 43, 1–23. https://doi.org/10.1007/s11116-014-9559-9.
Fitch, D.T., Rhemtulla, M., Handy, S., 2019. The relation of the road environment and bicycling attitudes to usual travel mode to school in teenagers. Transp. Res. Part A Policy Pract. 123, 35–53. https://doi.org/10.1016/j.tra.2018.06.013.
Garrard, J., Rose, G., Lo, S.K., 2008. Promoting transportation cycling for women: the role of bicycle infrastructure. Prev. Med. (Baltim) 46, 55–59. https://doi.org/10.1016/j.ypmed.2007.07.010.
Guan, X., Wang, D., Cao, X.J., 2019. The role of residential self-selection in land use- travel research : a review of recent findings. Transp. Rev. 1647, 1–21. https://doi.org/10.1080/01441647.2019.1692965.
Hamann-Salcedo, F.A., Mejía, L.F., 2012. Formalizando la informalidad empresarial en Colombia. El Merc. Trab. en Colomb. hechos, tendencias e Inst. Capítulo 10. Formaliz. la informalidad Empres. en Colomb. Pág.399-427.
Handy, S., Boarnet, M.G., Ewing, R., Killingsworth, R.E., 2002. How the built environment affects physical activity. Am. J. Prev. Med. 23, 64–73. https://doi.org/10.1016/S0749-3797(02)00475-0.
Handy, S., van Wee, B., Kroesen, M., 2014. Promoting cycling for transport: research needs and challenges. Transp. Rev. 34, 4–24. https://doi.org/10.1080/01441647.2013.860204.
Hayes, M., Norman, J.M., 1994. Running uphill : an experimental result and its applications. J. Oper. Res. Soc. 45, 25–29.
Heinen, E., Maat, K., Van Wee, B., 2011. The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transp. Res. Part D Transp. Environ. 16, 102–109. https://doi.org/10.1016/j.trd.2010.08.010.
Heinen, E., Van Wee, B., Maat, K., 2010. Commuting by bicycle: an overview of the literature. Transp. Rev. 30, 59–96. https://doi.org/10.1080/01441640903187001.
Iacono, M., Krizek, K., El-Geneidy, A., 2008. Access to Destinations: How Close is Close Enough? Estimating Accurate Distance Decay Functions for Multiple Modes and Different Purposes.
Keijer, M.J.N., Rietveld, P., 2000. How do people get to the railway station? The dutch experience. Transp. Plan. Technol. 23, 215–235. https://doi.org/10.1080/03081060008717650.
Kockelman, K., 1997. Travel behavior as function of accessibility, land use mixing, and land use balance: evidence from San Francisco bay area. Transp. Res. Rec. J. Transp. Res. Board 1607, 116–125. https://doi.org/10.3141/1607-16.
Korner-Nievergelt, F., Roth, T., von Felten, S., Guélat, J., Almasi, B., Korner-Nievergelt, P., 2015. Model Selection and Multimodel Inference, in: Bayesian Data Analysis in Ecology Using Linear Models with R, BUGS, and Stan. https://doi.org/10.1016/B978-0-12-801370-0.00011-3.
Krizek, K.J., Johnson, P.J., 2006. Proximity to trails and retail: effects on urban cycling and walking. J. Am. Plan. Assoc. 72, 33–42. https://doi.org/10.1080/01944360608976722.
La Paix Puello, L., Geurs, K., 2015. Modelling observed and unobserved factors in cycling to railway stations: application to transit-oriented-developments in the Netherlands. Eur. J. Transp. Infrastruct. Res. 15, 27–50.
Larrañaga, A.M., Rizzi, L.I., Arellana, J., Strambi, O., Cybis, H.B.B., 2016. The influence of built environment and travel attitudes on walking: A case study of Porto Alegre. Brazil. Int. J. Sustain. Transp. 10, 332–342. https://doi.org/10.1080/15568318.2014.933986.
Larsen, J., El-Geneidy, A., Yasmin, F., 2010. Beyond the quarter mile : examining travel distances by walking and cycling, Montréal, Canada. Can. J. Urban Res. Can. Plan. Policy 19, 70–88.
Lewis, M., 2007. Stepwise versus Hierarchical Regression: Pros and Cons. Southwest Educ. Res. Assoc.
Litman, T., 2018. Land Use Impacts on Transport. https://doi.org/10.1007/978-3-642-54876-5.
Menghini, G., Carrasco, N., Schüssler, N., Axhausen, K.W., 2010. Route choice of cyclists in Zurich. Transp. Res. Part A Policy Pract. 44, 754–765. https://doi.org/10.1016/j.tra.2010.07.008.
Moreno, R., Vayá, E., 2000. Técnicas econométricas para el tratamiento de datos espaciales: La econometría espacial. Universitat de Barcelona, Barcelona.
Moritz, W.E., 1998. Adult bicyclists in the United States: Characteristics and riding experience in 1996. Transp. Res. Rec. 1636, 1–7. https://doi.org/10.3141/1636-01.
Motoaki, Y., Daziano, R.A., 2015. A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. Transp. Res. Part A Policy Pract. 75, 217–230. https://doi.org/10.1016/j.tra.2015.03.017.
Oliva, I., Galilea, P., Hurtubia, R., 2018. Identifying cycling-inducing neighborhoods: A latent class approach. Int. J. Sustain. Transp. 12, 701–713. https://doi.org/10.1080/15568318.2018.1431822.
Ortúzar, J.D.D., Willumsen, L.G., 2011. Modelling Transport, 4th ed. Wiley, London. https://doi.org/10.1002/9781119993308.
Páez, A., Scott, D., Morency, C., 2012. Measuring accessibility: positive and normative implementation of various accessibility indicators. J. Transp. Geogr. 25, 141–153.
Pucher, J., Buehler, R., 2008. Making cycling irresistible: lessons from The Netherlands, Denmark and Germany. Transp. Rev. 28, 495–528. https://doi.org/10.1080/01441640701806612.
Pucher, J., Buehler, R., 2006. Why Canadians cycle more than Americans: A comparative analysis of bicycling trends and policies. Transp. Policy 13, 265–279. https://doi.org/10.1016/j.tranpol.2005.11.001.
Pucher, J., Dill, J., Handy, S., 2010. Infrastructure, programs, and policies to increase bicycling: an international review. Prev. Med. (Baltim) 50 (Suppl 1), S106–S125. https://doi.org/10.1016/j.ypmed.2009.07.028.
Rodríguez, D.a., Joo, J., 2004. The relationship between non-motorized mode choice and the local physical environment. Transp. Res. Part D Transp. Environ. 9, 151–173. https://doi.org/10.1016/j.trd.2003.11.001.
Rosas-Satizábal, D., Rodriguez-Valencia, A., 2019. Factors and policies explaining the emergence of the bicycle commuter in Bogotá. Case Stud. Transp. Policy 7, 138–149. https://doi.org/10.1016/j.cstp.2018.12.007.
Saelens, B.E., Sallis, J.F., Frank, L.D., 2003. Environmental correlates of walking and cycling : findings from the transportation, urban design, and planning literatures. Behav. Med. 25, 80–91.
Samper Escobar, J.J., 2010. The politics of peace process in cities in conflict: the Medellin case as a best practice. Dep. Urban Stud. Plan.
Scarf, P., 2007. Route choice in mountain navigation. Naismith ' s rule, and the equivalence of distance and climb 0414. https://doi.org/10.1080/02640410600874906.
UN-Habitat, 2013. Planning and design for sustainable urban mobility. New York.
United Nations, 2019. World Urbanization Prospects. The 2018 Revision, Demographic Research. New York. https://doi.org/10.4054/demres.2005.12.9.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–838.
Wooldridge, J., 2013. Introductory Econometrics. A modern approach, fifth ed. Cengage Learning, Mason, OH, USA.
Wooldridge, J., 2011. Econometric analysis of cross section and panel data. The MIT Press, London. https://doi.org/10.1515/humr.2003.021.