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A GIS-based approach to evaluating environmental influences on active and public transport accessibility of university students

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ABSTRACT

Many young adults are susceptible to obesity issues and the increased health risks associated with a lack of physical activity. Those who are prone to gaining weight include university students. An active transport system (walking and cycling), in combination with well-funded public transport, are essential components of a sustainable urban transport network, offering many benefits to the health of the individual, as well as the environment, economy, and society as a whole. The spatial association between active mobility (i.e. the physical activity of a human being for locomotion) of young adults and the environment, however, is poorly understood. This study presents a GIS-based model to determine association of various environmental (natural and built environment) factors with locational accessibility of active and public transport trips taken by university students. A GIS-based ensemble of Frequency Ratio (FR) and the Analytical Hierarchy Process (AHP) model was established. We analysed the characteristics of locations accessed by university students in relation to eight environmental factors including slope, elevation, land use, population density, travel time, building density, intersection density, and public transport service area. The model was applied to the Grenoble metropolitan region of France, an area well-known for policies which promote active transport. The results indicated that intersection density and land use are strongly associated with active and public transport accessibility, with weights of 0.17 and 0.16, respectively. The presence of infrastructure to support active travel, and regulation to limit vehicular speed, also improved accessibility. Approximately 50% of the area of the Grenoble metropolitan region was defined as accessible and suitable ('moderate' to 'very high' degree) for active mobility. The results of this study could allow city planners to monitor the existing status of active and public transport facilities, and identify areas that require additional work to improve accessibility.

1. Introduction

The transition age from adolescence to adulthood (age 18–25), referred to as the "emerging adult" period (Arnett, 2000), is an important phase in a person's life. This period is also closely linked to the educational transition from high school to university

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(Negru, 2012). People in this age group are more susceptible to obesity issues and other health risks due to changes in food intake patterns, lack of physical activity, and other unhealthy lifestyle practices (Kwan, Cairney, Faulkner, & Pullenayegum, 2012; Nelson, Story, Larson, Neumark-Sztainer, & Lytle, 2008). A lack of physical activity during this stage is well documented in the existing literature (Buckworth & Nigg, 2004; Sisson & Tudor-Locke, 2008). It is also universally agreed that instilling healthy habits during this period is crucial in order to sustain these habits into adulthood and through other transitional life stages (Bopp, Kaczynski, & Wittman, 2011).

Active travel (walking and cycling) is one form of physical activity (Bopp, Gayah, & Campbell, 2015; Cohen, Boniface, & Watkins, 2014; Djurhuus, Hansen, Aadahl, & Glümer, 2014; Pucher, Buehler, Bassett, & Dannenberg, 2010), which is regarded as a very environmentally friendly mode of transport (Litman, 2013). Another mode is public transport. Public transport users generally walk or use a bicycle to access public transport networks, thereby participating in physical activity (Bopp et al., 2015). Walking and cycling as a primary means of transport, or in combination with public transport, is referred to as active mobility, and is a way of participating in regular physical activity (Cohen et al., 2014; Gerike et al., 2016; Sahlqvist, Song, & Ogilvie, 2012). Public transport, together with active transport, is considered to be an essential mode of sustainable urban transport, and has been flagged as a solution to current transport-related issues such as increased air pollution, road accidents, and traffic congestion (Zannat & Choudhury, 2019). Active mobility offers the individual commuter potential strategies for incorporating recommended physical activity into their daily routine (Bopp et al., 2011). Increased active mobility and a generally more active lifestyle all have a role to play in minimising health-related risks such as a reduction in obesity rates and coronary heart disease (Bopp et al., 2015; Pucher et al., 2010; Rojas-Rueda, de Nazelle, Teixidó, & Nieuwenhuijsen, 2012). A number of economic benefits are also associated with the promotion of active mobility, since investments in such things as active transport infrastructure provides benefits to a greater percentage of the population (Davis, 2010; Gotschi, 2011; Sælensminde, 2004). Active and public transport are considered essential components of any sustainable urban transport system, due to active mobility benefits related to health, environment, economy, and society in general (Gerike et al., 2016; Gouda & Masoumi, 2017).

Rapid urbanization and economic growth have led to increased motor vehicle use and the environmental and social challenges associated with this. The promotion of 'green transport' to encourage active mobility is one way to address these challenges. A detailed knowledge of the extent of association with various environmental factors (e.g. a variety of destinations, aesthetics, and distance) is essential when developing strategies to promote active mobility (Pan, Shen, & Zhang, 2009). Environmental factors (natural and built environment) at various geographical scales (building, neighbourhood, and city-scale) can affect the individual choice of transport mode, and in turn, affect the active movement pattern (Craig, Brownson, Cragg, & Dunn, 2002; Guerra, Caudillo, Monkkonen, & Montejano, 2018). For instance, the number of transit-related walking trips tends to increase in cities that support regional transit services for commuting purposes (Mahmoudi & Zhang, 2018). Population density, roadway density, and mixed land use also determine mode choice behaviour (Guerra et al., 2018; Panter, Jones, & Van Sluijs, 2008). According to Panter et al. (2008), the different components of urban form, the facilities required to support active travel, and the pattern of social interaction, all influence the travel behaviour of youth. The presence of sidewalks and cycle paths, for example, are among the most important facilities encouraging active travel (Zannat, Raja, & Adnan, 2019).

Several studies have measured the association of environmental factors with active mobility (Guerra et al., 2018; Mahmoudi & Zhang, 2018; Pan et al., 2009; Panter et al., 2008). Most of the existing studies on this topic developed linear regression models based on empirical data obtained from extensive survey work, and the results were explicitly contextual. For instance, population and employment density (components of built environment) can have either a significant (Mahmoudi & Zhang, 2018) or insignificant (Ewing & Cervero, 2010; Ramezani, Pizzo, & Deakin, 2018) influence on active mobility, depending on the context. The relationship of the environment with the active mobility of individuals, however, is non-linear (Rybarczyk, 2018). Due to this factor, linear regression models tend to be less transferable between different situations. The relationship between trip locations (origin and destination), and environmental factors, has also been overlooked in many cases (Pan et al., 2009). A number of studies have developed spatial models to examine the relationship of active mobility with factors influencing this form of travel (Feuillet et al., 2015; Rybarczyk, 2018). Many studies have been undertaken in the USA where active trips are low in number, while only a relatively smaller number of studies have been conducted in Europe (Panter et al., 2008) where the number of active trips can be three to five times greater than those undertaken in the USA (Pucher et al., 2010). This study presents a GIS-based model to objectively measure the association between different environmental factors and the locational accessibility of the active mobility activities (including walking, cycling and active component of active transport journeys) of university students.

2. Materials and methods

2.1. Study area

The study was conducted in Grenoble, the 16th largest city of France (Fig. 1). The urban centre of this region consists of relatively flat land with mountains to the north, west, and south-east (De Wit et al., 2015). The metropolitan region, located about 100 km south of Lyon and 150 km south-west of Geneva, is comprised of 49 municipalities. The region is famous for its tourist attractions and is widely recognized for its contribution to education and research. We selected this region as the study area for several reasons. The region is well-known for its public transport services (Grosbois, 2001) and the city has an integrated land use and transportation plan, an important component in the promotion of active transportation. The presence of various faculties and institutions of Université Grenoble Alpes influences the housing and transportation networks, as well as on the overall planning, of the city. The region is characterized by a population with diverse national, socio-demographic, and cultural backgrounds. A variation in the existing urban

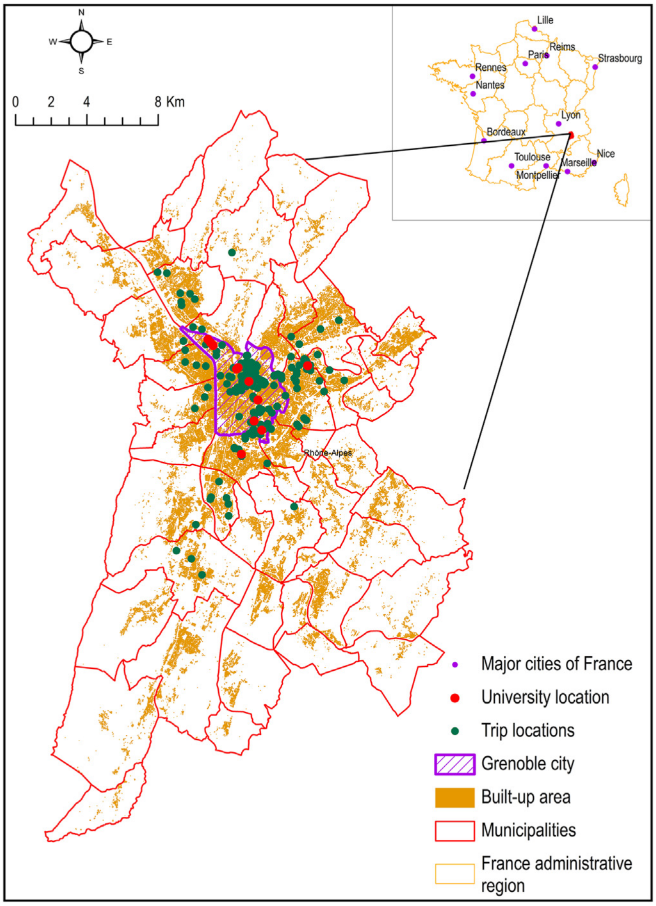

Fig. 1. Grenoble metropolitan area of France

development patterns is also visible. The northern part of the region is characterized by high density and mixed-use developments, with less dense and homogenous land use patterns evident in southern areas. The northern part of the region is known for its long history of settlement and culture, while the south is mostly associated with contemporary development. The total number of students (aged between 18 and 25 years) at the various higher education institutions makes up approximately 8.8% of the total population of this region (INSEE, 2014). The presence of a diverse population, an active transport plan integrated into city development planning and a large percentage of the population consisting of people aged 18 to 25, were the main factors in study area selection.

2.2. Trip location data

Trip location data was obtained by conducting a field survey in April 2017. Face-to-face interviews with university students living in the Grenoble metropolitan area was carried out to gather location data related to of their weekly active transport trips. The interview included a mapping exercise where students were requested to mark the origin and destination point locations of trips (during a typical week) in Google Map (tablets were provided by the interviewers). We requested respondents to provide trip information of the week prior to the survey date. The term "active trips" meant the trips conducted by an active mode of transport (walking and/or cycling). Active travellers typically use a combination of public transport and active modes to travel, as a result, public transport use was also considered as part of active mobility in this work. In Grenoble, the provision of subsidized public transport facilities for students up to 25 years of age by Transports de l'Agglomération Grenoblois (https://www.tag.fr/) encourages the use of public transport by this demographic. We included trips using public transport which involved a certain degree of active travel (Djurhuus et al., 2014). The mode of transport was also recorded against each trip location. The sample size was determined by a simple random sampling procedure (Equation (1)). The city has a total population of 442,772, with the number of university students is approximately 35,422 (INSEE, 2014). We estimated the minimum number of respondents required at the 95% confidence level with a normal distribution response of large population size (Israel, 1992; Zannat, Raja, & Adnan, 2019).

$$n = z^2pq/e^2 \quad (1)$$

where, n is the minimum sample size; z is z-statistic of given confidence level (for 95% confidence level it is 1.96); p is the estimated proportion of an attribute that is present in the population, and q is (1-p) and e is the tolerance level (assumed as 5%). Since a large number of students were living in the metropolitan area and we did not know the proportion of students using active transport (variability), we assume $p = 0.5$ (maximum variability) and thus q was 0.5. The minimum sample size was estimated to 384.

The survey was conducted in the precinct of institutions of Université Grenoble Alpes (UGA). The main campus of UGA is in the Saint-Martin-d'Hères, at the east of Grenoble city. There are also another 15 locations of the university outside the main campus. Of these, 11 are in Grenoble Metropolitan Area, with the others being in Valence, Ardèche (Pradel), Vienne, Villar-d'Arène and Montmaur, France. Within the metropolitan area, 10 are located in Grenoble city and one is in Echirolles. The first author and associated volunteers, who all speak French, formed 11 interview groups. Each group was comprised of 2–3 people. These groups were evenly distributed among the 11 locations of UGA situated within Grenoble metropolitan area. Each group interviewed students at meeting places such as the cafeteria, library, language club, sports centre, etc. Prior to the fieldwork commencing, a training session was organised for all the volunteers involved in the survey. The training sessions were designed to ensure that all the volunteers were fully capable of conducting the survey, as well as to impart useful skills to deal with privacy and anonymity requirements. The training sessions included the following:

- Explanation of the research goal and objective
- Description of the mapping exercise.
- Methods to follow to carry out the mapping exercise.
- Privacy policy and students' voluntary participation in the mapping exercise. This was of utmost importance and given priority.

During the survey it was found that some students were reluctant to participate (either to attend their classes or to catch the bus/tram). Only those students who voluntarily agreed (without any remuneration) for the novel mapping exercise, were included in the actual study.

Students also provided information related to their socioeconomic characteristics (age, gender, housing type, ethnicity, current income status, driving license, and car ownership) by filling in a separate checklist (Table 1). Six modes of travel were reported; walking, bicycle, car, bus, flexo,[1] and tram. The respondents marked 526 unique locations which were accessed by walking, cycling and public transport. The term "unique location", means that if a building was the origin/destination of multiple people, then only a single point was recorded for that building. The geo-codes of origin and destinations were obtained, and then projected into the Lambert Conformal Conical Projection co-ordinate system for further analysis. Trip locations were considered as places accessible by any forms of active transport or in combination with public transport. In general, four types of journeys were observed: a journey to university, work and administrative office, grocery/shop, and recreational centres. The surveyed trip locations are shown in Fig. 1.

2.3. Identifying environmental factors affecting active mobility

Determining the environmental factors affecting travel behaviour is regarded as key to modelling transport accessibility (Saghapour, Moridpour, & Thompson, 2016). Since no exact agreement exists on which variables should be used to explain active mobility, the environmental factors used in this study were selected based on information derived from applicable research found in a literature review (Table 2). Since very few studies concentrated on the activity mobility pattern of university students, major indicators considered in this study were selected from studies which were focused on different age groups and active mobility. Eight variables were selected: slope, elevation, land use, population density, travel time, building density, intersection density, and public transport service area. These are all factors of the natural and built environment.

2.4. Mapping of environmental factors

Thematic raster layers of eight selected environmental factors, at 30m spatial resolution, were created in order to develop an active and public transport accessibility model (Fig. 3). The maps of slope and elevation were created from the Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) data, retrieved from the Earth Explorer website (http://earthexplorer.usgs.gov/). Corin Land Cover (CLC) data, containing 14 types of land use, were collected from Ministere de la Transition Écologique et (2015). Population density data were collected from the WorldPop website (http://www.worldpop.org.uk).

Travel time tends to act as an impediment to active travel so any reduction in travel time would effectively increase active trips (Shannon et al., 2006). A travel-time surface raster to all individual buildings within the Grenoble metropolitan area was developed using a method proposed by Mulrooney, Beratan, McGinn, and Branch (2017). Vector road network data was converted to a 30 m resolution using speed limits as values. Cycling and walking on highways are prohibited in Grenoble, so highways were excluded from the analysis. For secondary and tertiary roads, the speed limits were 50 km/h and 30 km/h respectively. The maximum cycling speed of 20 km/h was considered to be safe, taking into account pedestrian traffic (de Grenoble, , 2015). A walking speed of 6 km/h (Mulrooney et al., 2017) was used for off-road travel. Areas considered unsuitable for active travel, such as mountainous forests, waterbody, and airport, were reclassified as 'no data' regions. The pixel-wise travel time was estimated using equation (2):

[1] Flexo is a special bus line, providing access to the less dense areas of the metropolitan area.

Table 1
Summary statistics of the sample population (n = 384).

Variables	Categories	Value
Age (year)		Mean 22.4 ± 2.1Std. Dev.
Education (%)	Undergraduate	54.8
(Currently enrolled)	Graduate	45.2
Gender (%)	Male	45.2
	Female	54.8
Ethnicity (%)	Non-native	36.9
	Native	63.1
Source of Income (%)	Dependent	45.4
	Employed	54.6
Bicycle ownership (%)		50.0
Car ownership (%)		31.0
Driving license (%)		69.0
Accommodation type (%)	Owner occupied	13.1
	Private rental	67.9
	University dormitory	19.0

$$\text{Travel time (min)} = \frac{\text{pixel resolution (m)} \times 60}{\text{speed limit (km/h)} \times 1000} \tag{2}$$

Each pixel of the output raster represents the time required (by active and public transport) to reach that location from the nearest road, thereby facilitating active transport.

Public transport service area from each transit stop was developed in GIS. The service area indicates public transport accessibility in Grenoble. The location data of existing transit (bus, tram, and flexo) stops was obtained from OpenStreetMap and website of metromobilite (www.metromobilite.fr). The public transport service area was then delineated by using the Network Analyst tool of ArcGIS 10.6.1. When setting up the network model, the maximum walkable distance of 400m from each transit stoppage was considered as accessible (Rattan, Campese, & Eden, 2012, pp. 30–33). Six different combinations of transit coverage were found in the metropolitan region (bus-tram-flexo, bus-tram, bus-flexo, bus, tram, flexo), providing multi-modal accessibility and connectivity.

Building density and intersection density layers were created from building and road network vector data obtained from Pacte, laboratoire des sciences sociales (https://www.pacte-grenoble.fr/). Maps were prepared using the point density analysis tool in the GIS, providing the building and road intersection input location data at 30 m spatial resolution for a neighbourhood size of 400 m radius (the defined maximum walking distance).

2.5. Analysing the inter-relationship between the independent variables

The model developed in this study used trip location as the dependent variable to be tested, with the environmental factors as the independent variables. To overcome the possibility that the independent variables could be subject to multicollinearity issues and hence produce a systematic bias in the model, the correlation coefficients and variance inflation factor (VIF) were calculated in order to assess any multicollinearity among the independent variables. The inter-relationship between the variables as reported from the Pearson Correlation coefficient test is shown in Fig. 4. Gradients of blue and red colour represent positive and negative correlation, respectively. Darker shades represent high and lighter shades represent the low correlation. Elevation and slope yielded negative correlation with travel time, building density, and intersection density. A low correlation exists between most of the variables. The highest correlation coefficients of −0.5 and −0.49 were found between elevation and building density as well as intersection density, respectively. In the case of VIF, a value exceeding 2.5 for a factor creates concern for a model, while VIF greater than 10 indicates the presence of multicollinearity (Midi, Sarkar, & Rana, 2010). Among the selected variables for this study, the highest VIF of 2.03 was found for building density (Table 3). These results indicate the absence of multicollinearity in and within the independent variables.

2.6. The frequency ratio (FR) and the analytical hierarchy process (AHP) models

We applied an ensemble of the bivariate statistical model FR and the multi-criteria decision analysis model AHP to diagnose the association of environmental factors with the active and public transport accessibility (Fig. 2). The bivariate statistical model ‘expresses the probability of the joint occurrence of two variables’ (Denis, 2016). The FR, a popular bivariate statistical model, is widely used in various fields to explain the occurrence of various natural hazards (Adnan, Talchabhadel, Nakagawa, & Hall, 2020; Khosravi, Nohani, Maroufinia, & Pourghasemi, 2016; Tehrany, Kumar, Neamah Jebur, & Shabani, 2019). The simple nature of this model and high prediction accuracy is the main reason its use in a wide range of applications (Khosravi et al., 2016). AHP is a multi-criteria decision analysis technique which determines the priorities of alternative decisions by pairwise comparison of decision criteria. AHP has been widely applied in the field of transportation planning (Piantanakulchai & Saengkhao, 2003; Saaty, 1995; Sivilevičius & Maskeliūnaite, 2010). In the current study, the AHP was applied to determine the relative significance of different environmental factors. Developing an AHP requires expert knowledge, however it can also be subject to bias (Khosravi et al., 2016; Tehrany et al.,

Table 2
Environmental factors to explaining active mobility (walking, cycling and public transport use).

Environmental factors	Definition	Processing	Relationship with active mobility	Sources
Slope Elevation	Slope and elevation explain the topography of an area. Human power (kinetic energy) is associated with active travel.	Generally, various Digital Elevation Models (DEMs) are used to estimate elevation. The DEM is incorporated in a GIS to estimate the slope.	Hilly terrain with a higher slope potentially reduces active travel. A slope greater than or equal to 10% for a distance of 100m or more tends to decrease walking and cycling trips.	(Panter et al., 2008; Troped et al., 2001)
Land use	Land use is one of the built-environmental factors which potentially associated with active mobility. Land use involves the transformation of the natural environment into built environment such as settlements, infrastructure, and arable lands.	To estimate the association of land use with active mobility, both categorical land use types and land use diversity (housing, vegetation, proximity to facilities) are used.	It is widely accepted that diversity in different land use types creates a favourable environment for active travel. Mixed land use is one of the major factors affecting active travel and public transport-based trips.	(Bordoloi, Mote, Sarkar, & Mallikarjuna, 2013; Feuillet et al., 2015; Frank et al., 2006; Hajna, Dasgupta, Halparin, & Ross, 2013; Jun & Hur, 2015; Van Dyck et al., 2010)
Population density	Population density is an indicator of urban spatial structure.	It is measured as the number of people or household per unit area. It is a gross measure of urban density lower than average neighbourhood density.	High population density indicates spatial compactness. The compact spatial structure of cities is strongly associated with mode choice and travel behaviour. It supports transit, walking, and cycling. To ensure efficient public transport service, relatively a high population density is required to support the service.	(Ewing & Cervero, 2010; Guerra et al., 2018)
Travel time	Travel time indicates the time required to reach a destination from an origin.	It is usually estimated either from the self-reported information of travel time or computer derived travel path. Self-reported measures of active travel may be subject to inaccuracies in reporting time taken and distance travelled	Longer travel time to reach destination reduces active mobility. Travel time is associated with available physical facilities to support active travel. Facilities include sidewalks, bicycle lane, bike-sharing facilities, the shared road between motorized and non-motorized traffic, etc. encourage walking and cycling. In addition to ensuring comfort, convenience, and safety, the provision of physical facilities reduces travel time to reach different destinations.	(Feuillet et al., 2015; Lemieux & Godin, 2009; Panter et al., 2008)
Building density	Building density could be either residential or retail density.	It is estimated either by using the building floor area and corresponding land area or by counting the number of building units in each land parcel.	High residential density, land use mix and good connectivity have significant influences on active mobility.	(Frank et al., 2006; Jun & Hur, 2015; Lemieux & Godin, 2009; Leslie et al., 2007; Owen et al., 2007; Van Dyck et al., 2010)
Accessibility to public transport	Availability of public transportation denotes proximity to bus, tram, metro, or train stations. The use of public transport is correlated with active transport, as walking or cycling and public transport usually connect the origin and destination.	Generally, public transport accessibility is evaluated by estimating the distance to the nearest transit stoppage from the individual residential land parcel.	Accessibility to public transport determines active transport movements. Good connectivity to public transport by pedestrian and cycling facilities induces a larger number of active travels.	(Cohen et al., 2014; Djurhuus et al., 2014; Feuillet et al., 2015; Rissel, Curac, Greenaway, & Bauman, 2012; Saghapour et al., 2016)
Intersection density	A measure of walkability that indicates street connectivity.	Estimated as the number of intersections in per unit area.	Street connectivity determines active mobility. High intersection density indicates more alternative paths from origin to destination, which creates a walking-friendly environment.	(Frank et al., 2006; Hajna et al., 2013; Jun & Hur, 2015; Leslie et al., 2007; Owen et al., 2007; Van Dyck et al., 2010)

Table 3
Estimated VIF of selected built-environment factors.

Variables (symbol)	Variance inflation factor (VIF)
Slope (Sl)	1.33
Elevation (El)	2.03
Land use (Lu)	1.20
Population density (Dp)	1.13
Travel time (Tt)	1.09
Building density (Db)	1.47
Public transport service area (Ps)	1.10
Intersection density (Di)	1.51

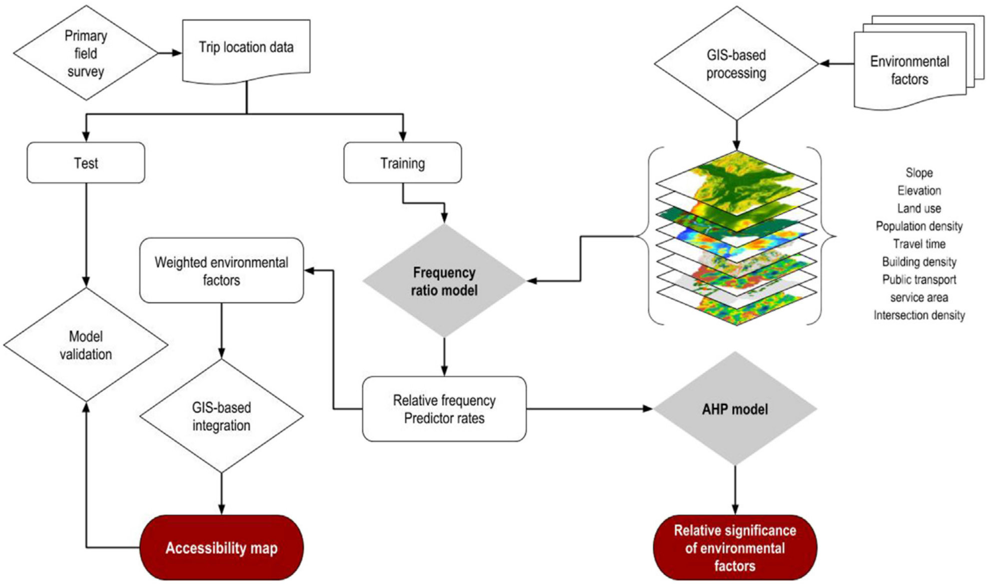

Fig. 2. Methodology flowchart

2019). Integration of the GIS-based model (e.g. FR) with the AHP overcomes some of these short-comings and improves the modelling outcomes (Piantanakulchai & Saengkhao, 2003).

Vector data of trip locations was split into two groups; 70% of the location data was used to train the model and the remaining 30% data was used for validation. Each environmental variable raster was categorized into several factor classes by applying a quantile classification technique. The frequency of trips in different factor classes under the selected variables was estimated using the following equation:

$$FR = \left[N_{pix}(SX_i)/\sum_{i=1}^{n} N_{pix}(SX_i)\right] / \left[N_{pix}(X_i)/\sum_{i=1}^{n} N_{pix}(X_i)\right] \tag{3}$$

where $N_{pix}(SX_i)$ denotes the number of trip locations (pixels) within the ith class of independent variable X, $N_{pix}(X_i)$is the total number of pixels within the ith class of independent variable X, and n is the total number of classes under variable X. The proportion of FR value in a factor class of a variable compare to the total FR of that variable is called the relative frequency (RF) (equation (4)). The weight of each variable is called the predictor rate (PR), which is the ratio of maximum-minimum difference of RF and the minimum difference among all factors (equation (5)). We provided weight to each pixel of the various built-environment factors according to the estimated RF value.

$$\mathrm{RF} = \frac{\text{FR of a factor class}}{\sum \text{FR of all factor classes}} \tag{4}$$

$$\mathrm{PR} = \frac{\mathrm{RF_{max}} - \mathrm{RF_{min}}}{(\mathrm{RF_{max}} - \mathrm{RF_{min}})_{\mathrm{min}}} \tag{5}$$

To start the AHP, variable-wise obtained PR values were organized in a row and a column, and a pairwise comparison matrix created using equation (6).

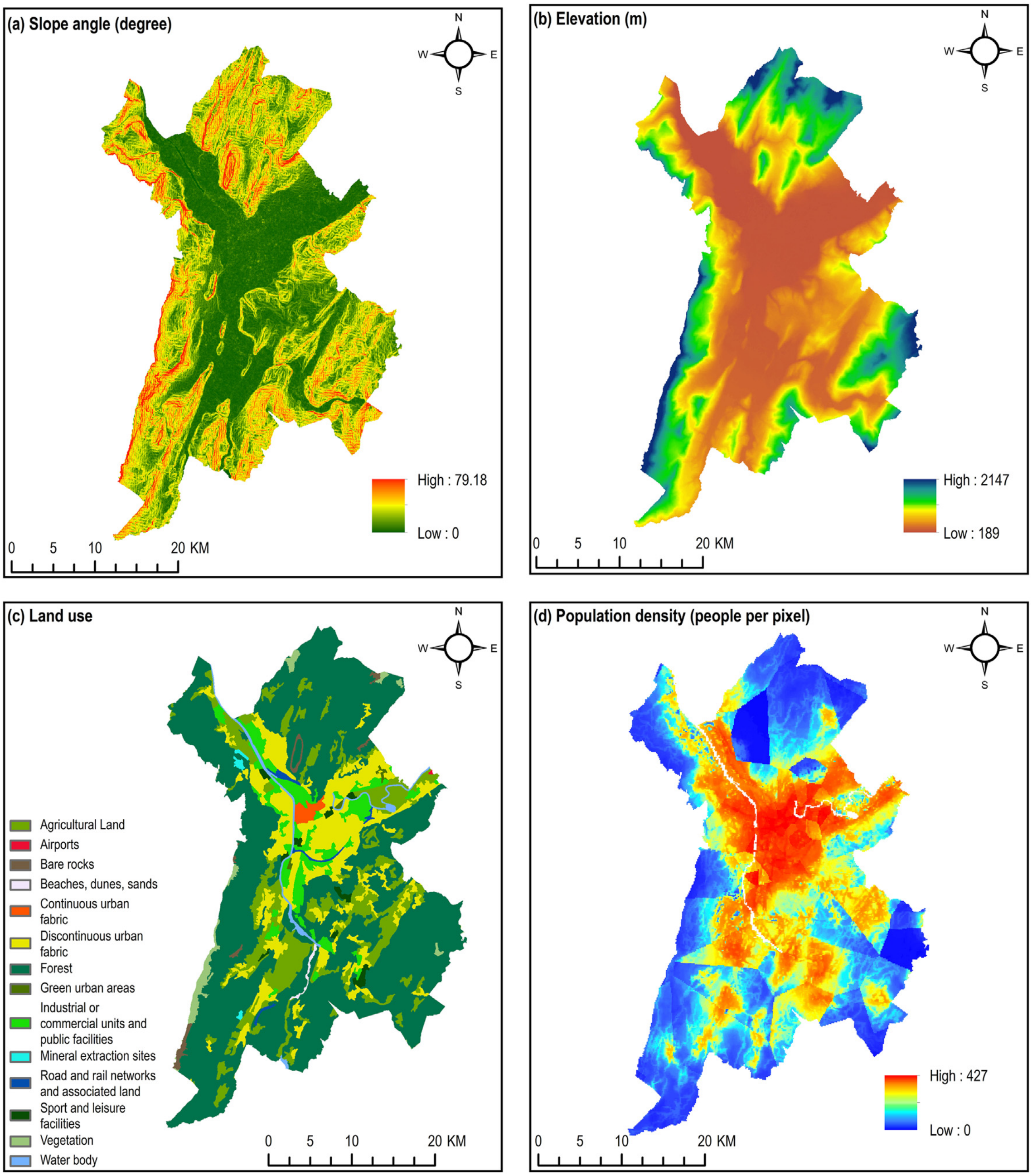

Fig. 3. Built-environment factors affecting trip locations

$$A_{ij} = \begin{bmatrix} PR_1/PR_1 & \cdots & PR_1/PR_j \\ \vdots & \ddots & \vdots \\ PR_i/PR_1 & \cdots & PR_i/PR_j \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{bmatrix} \tag{6}$$

where A_{ij} is a pairwise comparison matrix with *i* number of rows and *j* number of columns, a_{ij} denotes the entry in the ith row and jth column of matrix A. The probability index of ensembled FR and AHP was estimated and normalized (eigenvector matrix) in the range of probability values (0–1), dividing each entry of the matrix A by its respective column total. Then a consistency ratio (CR) was computed (equation (7)), to check the reliability of generated weights (Piantanakulchai & Saengkhao, 2003), using an ArcGIS toolbox written in python.

$$CR = \frac{CI}{RI} \tag{7}$$

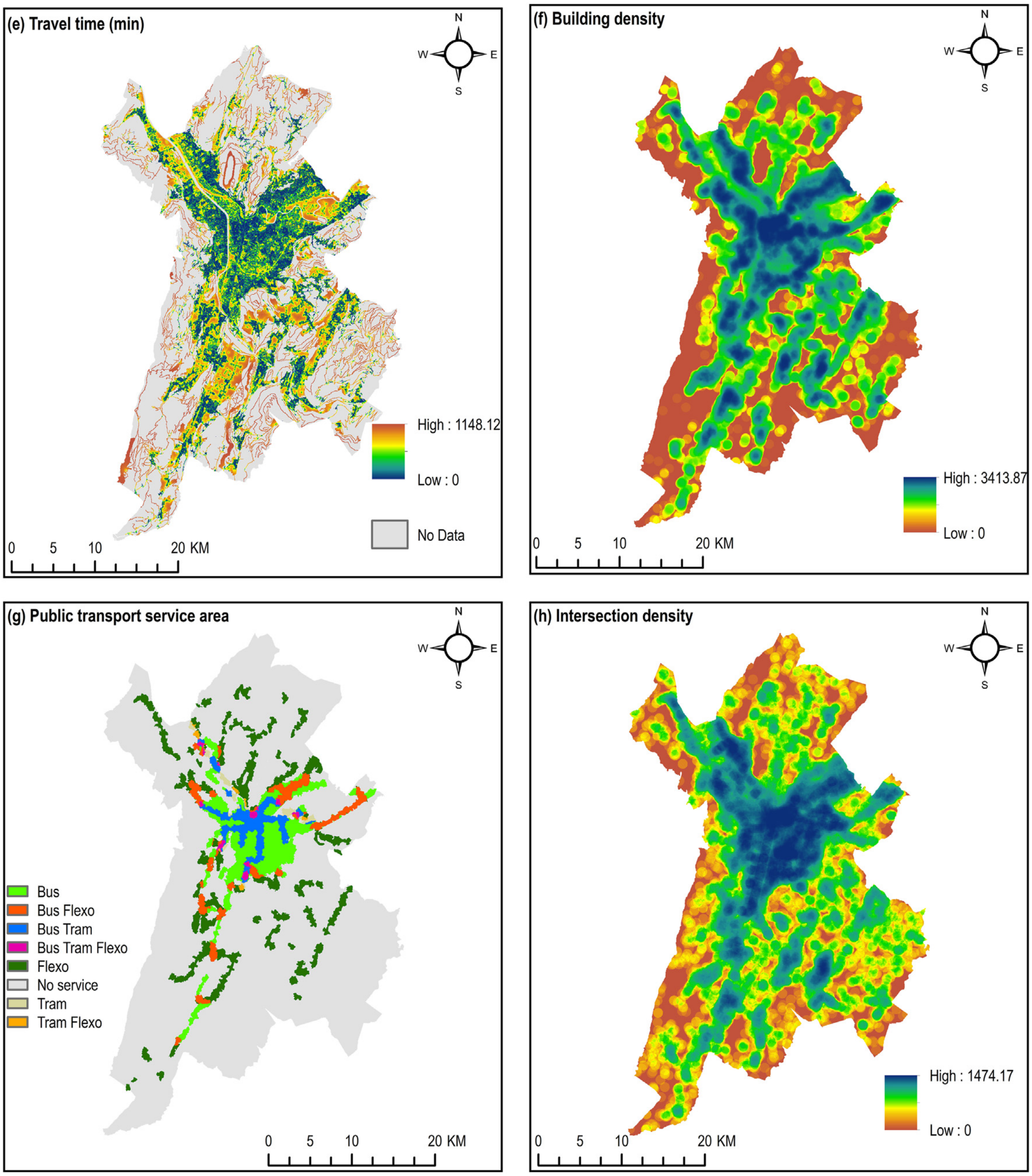

Fig. 3. (*continued*)

$$CI = ((\lambda_{max} - n)/(n-1)) \tag{8}$$

where CI denotes consistency index (equation (8)), RI is the average of the resultant consistency index, λ_{max} is the largest eigenvalue matrix, and n is the rank of the matrix. Finally, an active transport accessibility index (ATAI) map was estimated in GIS using the following composite equation.

$$ATAI = \sum_{i=1}^{n} (PR_i RF_i) \tag{9}$$

where PR_i is the predictor rate of the ith variable, RF_i is the relative frequency of the ith variable, and n is the total number of variables. The obtained accessibility map was categorized into five classes: 'very low', 'low', 'moderate', 'high', and 'very high' level accessibility.

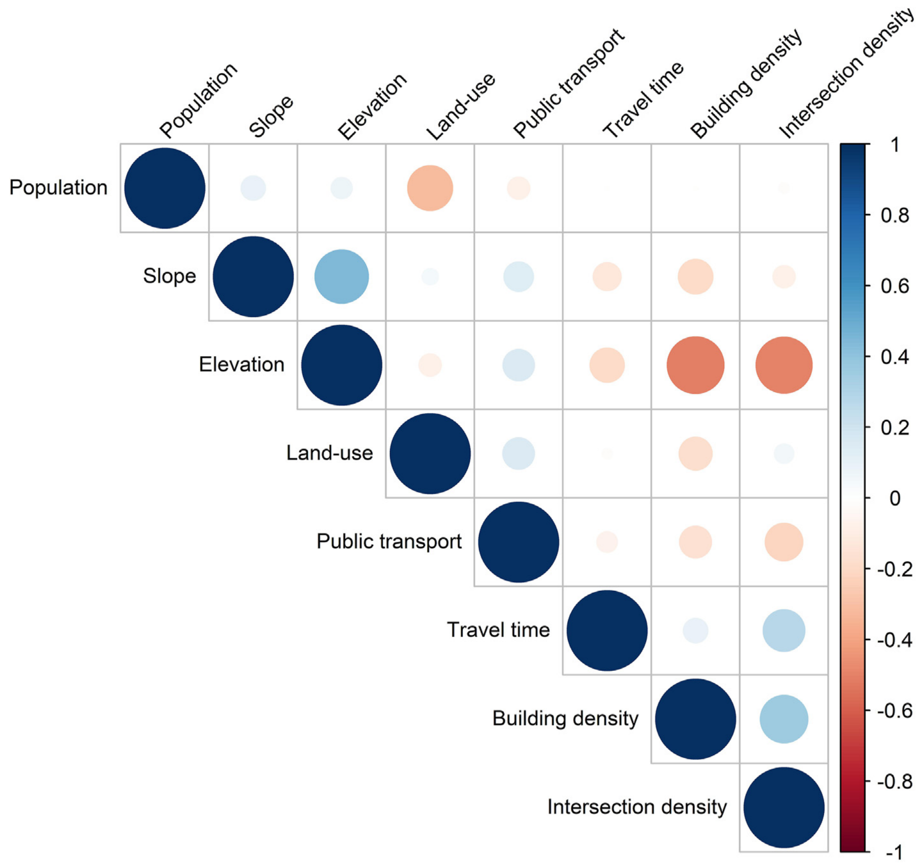

Fig. 4. Correlogram to analyse the inter-relationship between the variables

3. Results

3.1. *Association of environmental factors with active and public transport accessibility*

Table 4 summarises the estimated FR, RF, and PR which explain association between selected environmental factors and active travel of university students. The higher the value of FR, the stronger is the correlation of a class in an environmental factor, with accessibility. Generally, FR values greater than 1 represent a strong relationship, while those less than 1 represent a weak relationship. In Grenoble, most of the active trips of university students took place in areas with a low slope gradient and low elevation. For example, about 93% of the trips taken by the students were in places with a slope less than 7.25°. This subdued topography is found in approximately one-third of the region. Built-up areas such as 'continuous urban fabric', 'discontinuous urban fabric', and 'industrial or commercial units and public facilities' were the origin/destination of most of the trips. In the case of population density, a large number of trips were observed in areas characterised by high population density.

Building density, public transport service area, and intersection density provided an indication of the level of infrastructure development. Most respondents took trips to places that were located a maximum of 18 min from the nearest road. Building density was also positively correlated with the locations of trips. Areas with a higher building density also had a higher concentration of trip locations. The extent of the public transport service network also appears to be an essential element in active and public transport travel in Grenoble. Places served by bus and tram contained the highest proportion of observed trip locations (41.08%). In the case of intersection density, most of the trips were in places with a higher intersection density.

3.2. *The relative importance of environmental factors*

The outcomes of the AHP model indicated the relative importance of one factor in preference to another, while also explaining their impact on active and public transport accessibility. The estimated PR values from FR analysis (Table 4) were incorporated in the AHP model. A pairwise rating greater than 1 demonstrates the degree of importance of one variable (horizontal axis) over another (vertical axis) (Table 5). Slope angle appeared to be the least influential factor since the ratio of PR of the slope to other variables was less than 1. Intersection density had the highest degree of association with the observed trip locations. The pattern of land use also significantly associated with the active transport accessibility of the study participants.

Table 4
Association between different built-environment factors with active and public transport trips.

Variables	Classification	% of trip location	% of class area	FR	RF	PR
Slope angle (S_l)	0–1.86	28.49	11.23	2.54	0.28	1.00
	1.87–3.60	32.26	11.12	2.90	0.32	
	3.61–7.25	32.80	11.11	2.95	0.33	
	7.26–12.66	1.61	11.10	0.15	0.02	
	12.67–17.96	2.15	11.10	0.19	0.02	
	17.97–23.21	1.08	11.09	0.10	0.01	
	23.22–28.85	0	11.10	0	0	
	28.86–36.03	0	11.08	0	0	
	36.04–79.18	1.61	11.08	0.15	0.02	
Elevation (m) (E_l)	189–312	53.76	11.48	4.68	0.53	1.62
	313–454	42.47	11.26	3.77	0.43	
	455–603	0.54	11.06	0.05	0.01	
	604–767	1.08	11.07	0.10	0.01	
	768–941	2.15	11.05	0.19	0.02	
	942–1121	0	11.04	0	0	
	1122–1309	0	11.06	0	0	
	1310–1541	0	11.02	0	0	
	1542–2147	0	10.96	0	0	
Land use (L_u)	Agricultural Land	0.54	13.83	0.04	0	2.47
	Airports	0	0.02	0	0	
	Bare rocks	0	0.69	0	0	
	Beaches, dunes, sands	0	0.17	0	0	
	Continuous urban fabric	32.80	0.55	59.49	0.81	
	Discontinuous urban fabric	32.80	13.83	2.37	0.03	
	Forest	1.61	61.26	0.03	0	
	Green urban areas	0	0.17	0	0	
	Industrial or commercial units and public facilities	27.42	5.42	5.06	0.07	
	Mineral extraction sites	0	0.21	0	0	
	Road and rail networks and associated land	0.54	0.47	1.15	0.02	
	Sport and leisure facilities	3.23	0.78	4.11	0.06	
	Vegetation	0	1.30	0	0	
	Water body	1.08	1.29	0.83	0.01	
Population density (people per pixel) (D_p)	0–2	1.10	61.10	0.02	0	1.82
	3–4	1.10	13.36	0.08	0	
	5–7	1.66	8.30	0.20	0.01	
	8–12	4.42	4.88	0.90	0.03	
	13–20	5.52	3.78	1.46	0.04	
	21–33	12.71	3.09	4.12	0.12	
	34–58	19.34	2.82	6.86	0.20	
	59–427	54.14	2.66	20.33	0.60	
Travel time (min) (T_t)	< 4.5	69.57	36.14	1.92	0.65	1.98
	4.51–18.01	29.35	30.29	0.97	0.33	
	18.02–58.53	1.09	18.79	0.06	0.02	
	58.54–1148.12	0	14.78	0	0	
Building density (D_b)	No building density	0	24.11	0	0	1.72
	0–5.97	0	11.08	0	0	
	5.98–23.87	0	9.75	0	0	
	23.88–67.64	0	9.48	0	0	
	67.65–149.21	2.69	9.30	0.29	0.03	
	149.22–272.55	5.91	9.18	0.64	0.06	
	272.56–487.41	22.04	9.06	2.43	0.22	
	487.42–825.61	12.90	9.05	1.43	0.13	
	825.62–3413.87	56.45	8.99	6.28	0.57	
Public transport service area (P_s)	Bus Tram Flexo	16.22	0.34	47.73	0.62	1.89
	Flexo	2.16	8.01	0.27	0	
	Tram	2.70	0.49	5.49	0.07	
	Bus	20.54	5.92	3.47	0.05	
	Bus Flexo	4.32	2.47	1.75	0.02	
	Tram Flexo	0	0.17	0	0	
	Bus Tram	41.08	2.31	17.77	0.23	
	No service	12.97	80.28	0.16	0	

(*continued on next page*)

Table 4 (*continued*)

Variables	Classification	% of trip location	% of class area	FR	RF	PR
Intersection density (D_i)	0–3.98	0	12.09	0	0	2.63
	3.99–13.93	0	11.21	0	0	
	13.94–27.85	0	11.94	0	0	
	27.86–45.76	0	11.81	0	0	
	45.77–69.63	0.54	10.81	0.05	0.01	
	69.64–109.42	0	10.65	0	0	
	109.43–194.96	3.78	10.65	0.36	0.04	
	194.97–397.89	9.19	10.47	0.88	0.09	
	397.90–1474.17	86.49	10.37	8.34	0.87	

Table 5
Pair-wise rating matrix and weights of explanatory variables.

Explanatory variable	Pair-wise rating								Weight
	Slope	Elevation	Land-use	Population density	Travel time	Building density	Public transport service area	Intersection density	
Slope	1.00	0.62	0.40	0.55	0.50	0.58	0.53	0.38	0.07
Elevation	1.62	1.00	0.65	0.89	0.82	0.94	0.85	0.61	0.11
Land-use	2.47	1.53	1.00	1.36	1.25	1.44	1.31	0.94	0.16
Population density	1.82	1.12	0.74	1.00	0.92	1.06	0.96	0.69	0.12
Travel time	1.98	1.22	0.80	1.09	1.00	1.15	0.70	1.05	0.13
Building density	1.72	1.07	0.70	0.95	0.87	1.00	0.91	0.65	0.12
Public transport service area	1.89	1.17	0.77	1.04	0.96	1.10	1.00	0.72	0.12
Intersection density	2.63	1.63	1.06	1.45	1.33	1.53	1.39	1.00	0.17

Eigenvectors (weight) of the pair-wise rating matrix in Table 3 shows the degree of association that the various environmental factors had on active and public transport accessibility of university students. Intersection density and land use were found to be the most important factors, with weights of 0.17 and 0.16, respectively. Elevation, population density, building density, and public transport service area had similar degrees of association on accessibility, while slope angle was the least influential factor.

3.3. Deriving an accessibility map through ensemble FR-AHP model

The estimated RF and PR were used to create an active transport accessibility index map. This accessibility map was further categorized into five classes using quantile classification, with each class representing the level of active transport accessibility (Fig. 5). We estimated that about 17% of the region had a 'very high' level of active transport accessibility. About 97% of surveyed trips locations were within this zone. Approximately 50% area of Grenoble metropolitan region was accessible ('moderate' to 'very high' degree) for active travel.

Among 49 municipalities of the Grenoble metropolitan region, 22 municipalities with more than 60% of the area were accessible for active travel, where 86% of the total population was living at the time of this study.

3.4. Model validation

Validation of the model was performed using the receiver operating characteristic (ROC) curve and subsequent area under the curve (AUC) method (Fawcett, 2006; Hand & Till, 2001). This plots model sensitivity (cumulative percentage of trips) against false positive rates. To develop this plot, ATAI map was classified into 100 categories, arranged in descending order and plotted against the cumulative percentage of trips. The AUC is a global accuracy statistic used to assess classification accuracy, where the thresholds range from 50% (random prediction) to 100% (perfect prediction). In this study, the AUC was obtained using the test (30%) and training (70%) datasets, which demonstrated the prediction and success rates (Fig. 6). The model has a prediction rate of 93.91% and a success rate of 94.03%. The credibility test of consistency among independent variables was performed by computing the CR value. The estimated CR value was 0.010 for this ensemble FR-AHP model, which is less than the maximum threshold limit 0.1, implying that the model variables are consistent (Mu & Pereyra-Rojas, 2017, pp. 7–22).

4. Discussion

The goal of the study was to develop a GIS-based model to be used to estimate the association between different environmental factors and the active and public transport accessibility of university students. The model was developed in, and applied to, the Grenoble metropolitan region of France, an area well-known for promoting both active and public transport. We categorized the city

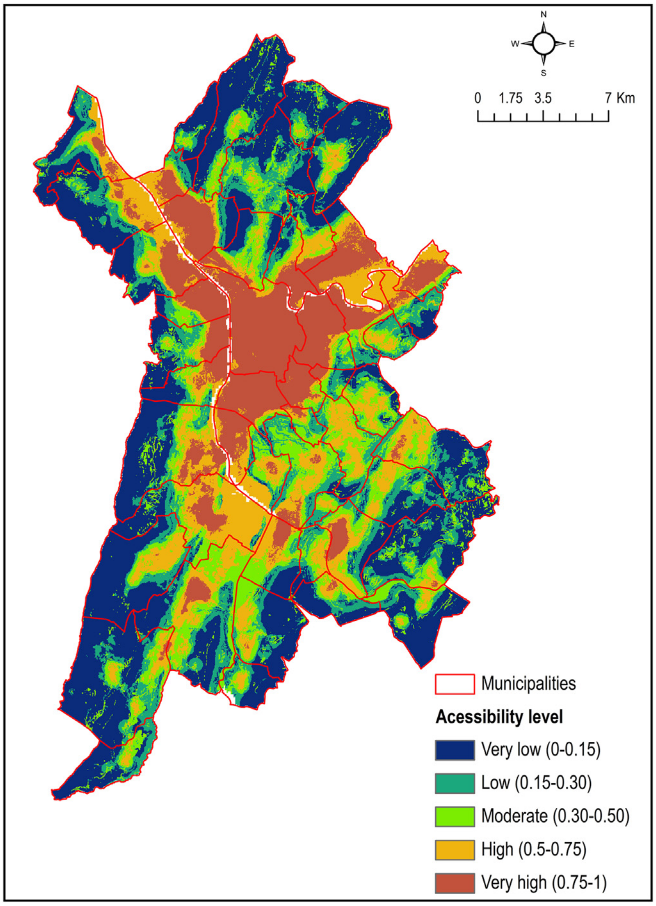

Fig. 5. Active and public transport accessible zone for university students in Grenoble

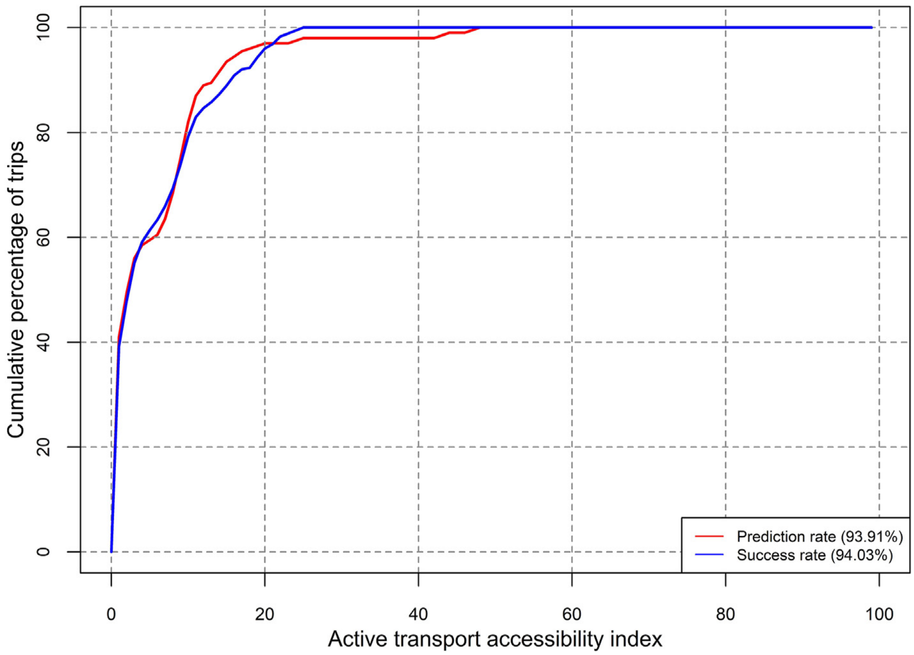

Fig. 6. ROC curve to validate the spatial regression model

according to the various level of active and public transport accessible zones. The developed GIS-based model successfully predicted active and public transport trip locations based on various environmental factors. Influential factors were found to be intersection density, land use, travel time, and public transport network service area.

The factors related to infrastructural development, such as building density, intersection density, and public transport service area, all positively associated with active and public transport travel. Existing studies have reported similar findings and have emphasised the need for the provision of infrastructure which facilitates such trips (Djurhuus et al., 2014; Feuillet et al., 2015; Zannat, Raja, & Adnan, 2019). In Grenoble, infrastructure designed to support active travel (bicycle lanes, walkways, and shared roads by motorized non-motorized vehicles) were observed during the field survey. The majority of the built-up areas were in close proximity to active transport infrastructure, and hence accessible by active transport. The regulated vehicular speed limits on the majority of the roads in Grenoble has made the road network safer for active travellers (Grenoble.fr, 2015).

Land use types also determine the mode choice behaviour of young adults. Many recent studies have reported that improved connectivity of pedestrian facilities with the adjacent land use and other facilities (transit, crosswalk, etc.) would reduce travel time and cost (Bordoloi et al., 2013; Frank et al., 2006; Zannat, Raja, & Adnan, 2019). The central area of Grenoble is characterised by mixed-use development, which encourages young people to make short distance active trips. The spatial planning policy of the city includes mixed land use development to promote non-motorized travel (Grenoble Alpes, 2009). This study underlined the importance of integrating public transport and active transport facilities, as a higher percentage of active trips were in areas served by all three forms of public transport. Several existing studies have noted that a substantial amount of active movement is associated with the use of public transport services, making it an essential component in the promotion of active transport (Cohen et al., 2014; Djurhuus et al., 2014; Frank, Andresen, & Schmid, 2004; Rissel et al., 2012) and reduction in car dependency (Bopp et al., 2015; Pérez et al., 2017). This study has quantified the degree of such association.

This study also found that topographical factors such as slope and elevation were negatively correlated with the observed trips. Previous studies have reported that topographical factors are, such as slope, negatively associated with active travel (Panter et al., 2008; Timperio et al., 2006). The degree of association among factors, however, was minor when compared to factors related to infrastructure development. Due to the fact that the respondents performed trips either by active transport or combining active and public transport, their trips were less influenced by any topographical factors.

Quantifying the spatial association between environmental factors and active and public transport accessibility is a challenging task. The GIS-based model developed for this study categorized the Grenoble metropolitan region according to various levels of active and public transport accessibility for university students. Such modelling can assist city planners in monitoring the existing status of active and public transport facilities, and can also identify areas that may require planning intervention. It will also assist in defining the impact of potential future active and public transport facilities on locational accessibility. For example, a proposed new cycle track can be incorporated into the model to quantify the potential change that it will bring to the existing active mobility. City-level accessibility maps can be used to investigate the characteristics of locations within the city which are currently easily accessible by active and public transport. Such accessibility maps would also characterise the features and attributes of those places, and their relative significance and cultural hegemony in different socio-economic contexts and could assist in increasing the accessibility of other places within the city that are currently less accessible. This approach could be useful in optimising active and public transport infrastructure investment, by monitoring the impacts on potential future infrastructure.

Although this study offers several theoretical and practical benefits, it is not free from limitations. The trip location data may be subject to 'recall bias', as participants may not be able to recall all trip information of the week prior to the survey date. The study is focused on a certain age group forming a small portion of the total city population. Distance can influence active transport on foot or by bicycle, however this study defined travel time as the variable of interest, as it focused on both active and public transport. Public transport stops along the journey were also not considered when estimating the travel time surface. It should be noted that individual, societal, and climatic factors are also associated with active and public transport accessibility.

5. Conclusion

This paper has sought to enhance our understanding of spatial association between various natural and built environment factors and locational accessibility of active and public transport trips taken by the university students. Therefore, an ensemble of frequency ratio (FR) and analytical hierarchy process (AHP) models was established. The model was applied to the Grenoble Metropolitan region of France, to categorise the region according to various levels of active and public transport accessible zones to the university students. The results of this study also quantified the extent of association of various natural and built environment factors with active travel.

This study is an attempt to promote a GIS-based technique in the field of active transport research, a technique which may be transferable to other areas with differing sets of environmental conditions. The proposed model could be a guiding tool for the transport planning authority, urban planner, and urban designer of a city who is looking at designing a sustainable urban transport system. Further research to provide more information on active transport accessibility could involve a large-scale survey incorporating people from different age groups, as well as incorporating various other social factors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

influence the work reported in this paper.

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