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Analyzing the activity space parameters of human daily intra-city movements: the home and workplace relative to the city center

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ABSTRACT

The study of intra-city movement patterns has been a continuing research topic in GIScience, urban planning, traffic forecasting, and location-based services. Previous studies have mainly considered the effect of demographic parameters such as age, gender, etc., on the intra-city human movement and less on the places where the person moves between them. Therefore, in this study, a method has been proposed to investigate the impact of home and workplace of people relative to the city center on movement on weekdays and weekends. In this method, the concept of activity space and quantification of its parameters have been used. Therefore, two new indices were introduced, including the Activity Range Index (ARI) and Activity Linearity Index (ALI), to compute the range of movement and their linearity, respectively. The concept of entropy has also been used to examine the predictability of people's movements. The proposed method results on the MDC dataset of Switzerland showed that the users whose homes and workplaces are both in the city center have the lowest ARI on weekdays and weekends (on average, 24.19% and 34.84% above the avg. of avg. of the movement range parameters, respectively). Also, the users whose homes are in the city center and their workplaces are outside the city center or vice versa have the lowest ALI (highest linear movement) on weekdays and the highest ALI (lowest linear movement) on weekends (on average, 14.9% below and 29.71% above the avg. of avg. of each movement linearity parameter, respectively). Eventually, the users whose homes and workplaces are both located inside the city center have the most irregular pattern on weekdays or weekends (on average, 11.23% and 1.45% above the avg. of avg. of movement entropy on weekdays and weekends, respectively.

KEYWORDS

Intra-city mobility
Activity Space
Movement parameters
City center
Home and workplace

1. Introduction

The importance of studying human movement and also the increase of spatial data makes the study of human movement patterns a continuing research topic in GIScience (Gudmundsson, Laube, & Wolle, 2008). Discovering human movement patterns and behaviors makes better urban planning (Xia et al., 2018), traffic forecasting (Liu, Li, Wu, & Li, 2018), and location-based services (Xu, Belyi, Bojic, & Ratti, 2018). These studies have examined the relationship between socio-demographic parameters such as age, gender, income, educational level, and car ownership on human movement (Feng, Dijst, Wissink, & Prillwitz, 2015; Giuliano & Narayan, 2003; Olivieri & Fageda, 2021; Shao, Sui, Yu, & Sun, 2019; Yuan, 2013). And also the impact of built environment such as land use patterns and transportation systems on human movement behaviors was assessed (Eldeeb, Mohamed, & Páez, 2021; Yuan & Raubal, 2016). A critical aspect of human movement considered in GIS studies is the activity space (Hirsch, Winters, Clarke, & McKay, 2014; Li & Tong, 2016). Activity space is a concept that shows the spatial extent, frequently visited places, and traveling between them (Schönfelder & Axhausen, 2002). Studying activity space makes it easier to understand better human behavior and its relationship with the socioeconomic phenomena and built environment (Xu et al., 2016).

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Activity space is considered in human movement studies from both aspects of the morphology, e.g., shape and size, and the internal structure, e.g., randomness of movement. Also, the impact of different parameters has been assessed on it (Yuan & Wang, 2018). For example, (Yuan & Raubal, 2016) investigated the impact of demographic variables such as age and gender on range, linearity, and entropy of activity space. Moreover, the impact of city size was assessed on range and Entropy of individual activity space (Yuan & Raubal, 2013). However, the physical aspect of one's living environment or built environment impact on movement behavior is one of the most studied topics. This is due to the rapid urbanization that results in the urban population's growth and expanding the built areas in cities that define the spatial opportunities/constraints of an individual's daily activities (Wang & Cao, 2017). Built environment parameters such as transportation availability may affect the shape and size of activity space. Hence, while some people only depend on local areas, others move to more remote areas to go to shops and churches (York Cornwell & Cagney, 2017). People move between frequent places, such as home and work, which are called anchor points that influence human activity space (Ahas, Silm, Järv, Saluveer, & Tiru, 2010; Schönfelder & Axhausen, 2002; Xu et al., 2015). Hence, considering home and the workplace is essential in human movement studies and better urban planning.

City centers and suburbs have been considered in urban studies as well. As the central built area is usually the area with the best urban amenities, including public transport, schools, shopping malls, hospitals, etc., it attracts many people (P. Zhao, Lu, & de Roo, 2011). Therefore, how people move relative to the city center has been previously considered in some studies (Ahas, Aasa, Silm, & Tiru, 2010; Gan, Yang, Feng, & Timmermans, 2018). To analyze individuals' daily movement rhythm in Tallinn, Ahas et al. (2010) measured how far away they travel from the city center during a day or week. They discovered that Saturday afternoons are a typical time for shopping or leisure, and therefore, people move near the city center. However, in North America and recently in European countries, there was a shift from city center shopping locations to out-of-town shopping malls (Gorter, Nijkamp, & Klamer, 2003; Hubbard, 2017). This change in the location of shopping centers and the other facilities may cause a change in human movement patterns. In addition to the city centers, people go to the suburbs for shopping and leisure too. Living near or far from the city center affects the size of human activity space as well. (Feng, Dijst, Prillwitz, & Wissink, 2013) reported that the people in Nanjing who lived far from the city center had shorter travel times and distances than the people living close to the city center. (Isaacman et al., 2011) got similar results by studying human mobility in Los Angeles and New York.

Consequently, human activity space in an urban area is affected by the home and work locations, as well as the city center as the dimensions of built environment. The previous research studies have considered only the distance of home and workplace from each other (Wang & Zhou, 2017; P. Zhao, Lü, & de Roo, 2010) or the distance of travels from the city center (Ahas, Aasa, et al., 2010). However, this paper proposed a method to investigate the impact of both home and workplace locations relative to the city center on human activity space parameters. To this end, the users' spatial extent and movement are characterized by ellipse-based activity space attributes. Hence, the range parameters, i.e., area, radius, and radius of gyration (ROG), and the linearity parameters, i.e., compactness, ratio, and Shape Index, were calculated. The entropy as a parameter that shows the degree of predictability of users' movement is also considered. Furthermore, the human movement within the city is influenced by time and is different in diverse seasons, days of week, or even hours of the day (Gariazzo, Pelliccioni, & Bogliolo, 2019; Isaacman et al., 2011) However, as most of the movement difference is between working days and weekends (Ahas, Aasa, et al., 2010), two time sections of weekends and weekdays were considered in the proposed method. To implement the proposed method, the Mobile Data Challenge (MDC) dataset was used.

The paper's remaining parts are organized as follows: The study area and dataset are explained in section 2. Section 3 discusses the proposed method: home and workplace detection, defining city center, modeling activity space of users' trajectory (as the concept employed to characterize the movements), presenting Activity Range Index (ARI) and Activity Linearity Index (ALI) (as two new movement parameters), comparing the means of groups, and interpreting the parameters. Section 4 presents the experimental results. Section 5 discusses the results and provides the concluding remarks of the paper.

2. Study Area and Dataset

This paper used the MDC dataset related to the Lausanne data collection campaign that was collected in Switzerland around the Geneva lake from October 2009 to late 2011 (Kiukkonen, Blom, Dousse, Gatica Perez, & Laurila, 2010; Laurila et al., 2012). Each volunteer was asked to carry a Nokia N95 cell phone on whose background the software of the campaign was running. The phones collected and uploaded the GPS data daily during the week. The GPS data were preprocessed for outlier detection by a statistical technique called the three sigma rule. According to (Pukelsheim, 1994), outliers can be efficiently identified using the mean and the standard deviation. This rule was applied to the speeds to detect points that have unusually high speeds and accelerated improbably compared to their average behavior.

The dataset mentioned above included different types of information related to locations (GPS, WLAN), demographic information of users (age, gender, occupation, etc.) and etc. (Laurila et al., 2012). Additionally, each user's stop areas and their categories were defined in this dataset. In this study, these tables were used: 'gps' (spatial locations), 'visit20min' (stop regions), 'places' (stop categories), 'records' (interface table).

As this research aims to investigate the impact of users' work and home locations from the city center on their range of movement, thus the employed users should be selected for this study. Moreover, the size and shape of a canton can affect a user's movement (Kang, Ma, Tong, & Liu, 2012), and aggregating the dataset of several cantons may cause the 'scale effect' as a sub-problem of Modifiable Areal Unit Problem (MAUP) [(Wong, 2004) for more information about MAUP]. Thus, only the users whose homes and workplaces were within the same canton were used to have integral results. Hence, canton Vaud was chosen because it has the most users that both their homes and workplaces were in. Accordingly, the GPS points of 73 users whose both homes and workplaces were in the canton Vaud were used in the study. The number of GPS points of the selected users during the project are about three million that contains for about fifty-five thousand travels (displacements between two consecutive stops). the GPS points of the selected users are shown in Figure 1.

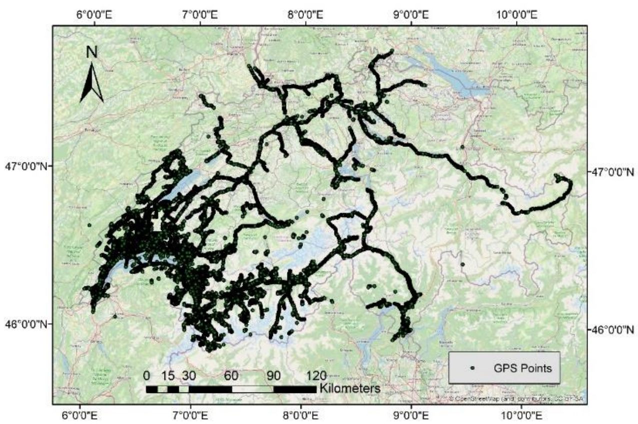

Figure 1. GPS Points of employed users whose homes and workplaces are in the canton of Vaud.

In addition, the extracted data from OpenStreetMap was used to determine the transportation network of the study area. To this end, the shapefile data of Switzerland roads was exported from Geofabric[1] website, which is related to OSM. This dataset includes minor and major roads, freeways and roads of residential areas in Switzerland (Figure 2).

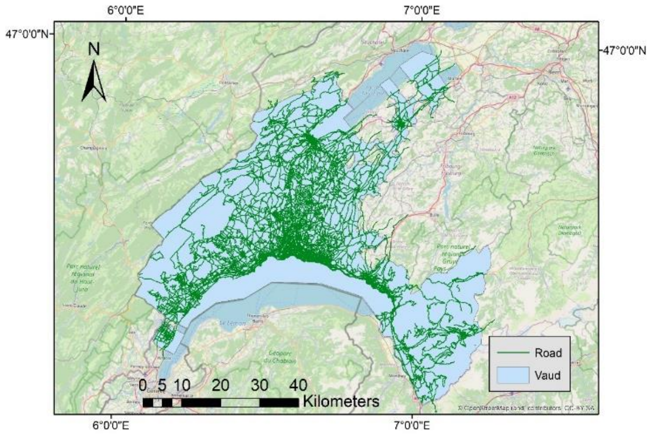

Figure 2. The Canton of Vaud's road system extracted from OSM.

3. The Proposed Method

The proposed method for investigating the relationship among users' movement and the location of their homes and workplaces relative to the city center is shown in Figure 3. As shown in this figure, since the users' movement behaviors are different on weekdays and weekends, the GPS data are separated temporally based on two main groups: weekdays and weekends.

Moreover, by having the location of users' home and workplace (section 3.1) and defining the city center using the Kernel Density Estimator (section 3.2), users are spatially grouped into four sets based on their home and workplace relative to the city center:

- Both home and workplace within the city center (InIn)
- Home within the city center and workplace outside the city center (InOut)
- Home outside the city center and workplace inside the city center (OutIn)
- Both home and workplace outside the city center (OutOut)

Accordingly, eight groups of users' GPS data have been distinguished, including: *InInWeekday*, *InInWeekend*, *InOutWeekday*, *InOutWeekend*, *OutInWeekday*, *OutInWeekend*, *OutOutWeekday*, *OutOutWeekend*. Activity space and movement parameters including area, radius of gyration, compactness, ratio, shape index, and entropy are calculated for each user in each group (section 3.3).

[1]https://download.geofabrik.de/europe/switzerland.html

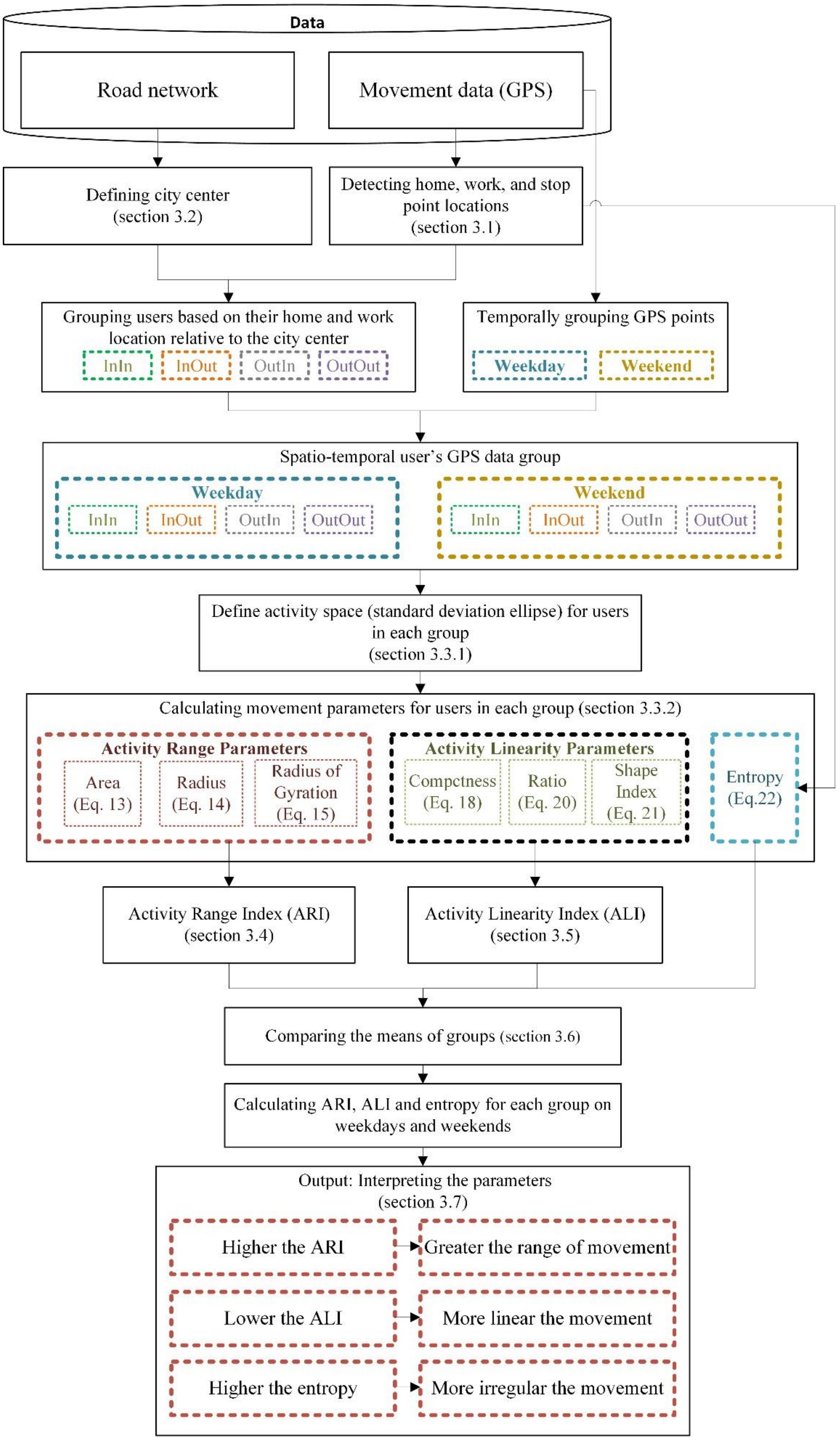

Figure 3. The proposed method.

The final value for each movement parameter in each group is calculated by averaging the values of that parameter for the users in the group. Then, the means of groups were compared by the t-test (section 3.6). Moreover, the proposed Activity Range Index (ARI) (section **Error! Reference source not found.**) and Activity Linearity Index (ALI) (section 0) are calculated for each group. Finally, by interpreting the calculated parameters, the eight groups can be compared in terms of movement extent, linearity, and Entropy (section 0).

3.1. Home, work, and stop points detection

In this research, in order to spatially group users, their homes and workplaces are needed. Also, for each user, the stopping points and the number of times they have been visited are needed to define the user's degree of predictability and entropy (as described in section 3.3.2).

The MDC dataset has the stop regions, as well as their categories for each user. In order to identify these stop regions, the MDC technical team has identified a user's stop regions longer than 20 min duration with a maximum radius of 200 m by the method proposed by (Montoliu & Gatica-Perez, 2010). The volunteers were then asked to label the obtained stop regions with ten predefined labels, including home, workplace and so on.

As shown in Figure 4, the information related to stopping regions is stored in two separate tables: 1. 'Visit20min': stop duration, start and end time of stop regions, and 2. 'Places': information related to the category of stop regions. By joining these two tables, the time and category of stop regions are achieved as a new table called 'StopRegionCat'. Spatial information of stops is not implicit in MDC data. But instead, almost every five-second location of users is stored in the 'gps' table. Joining these two tables, i.e. 'gps' and 'records', results in a 'UserGPS' table that contains the GPS location points for each user. Eventually, using 'UserGPS' and 'StopRegionCat' tables, a set of GPS points in the interval of each stop region for each user is obtained ('StopRegionCatPoints').

In order to detect a user's home and workplace, the centroid of points in the 'StopRegionCatPoints' table that contains the home category for each user was considered as the user's home location. Also, the centroid of points with the workplace category for each user was considered as the user's work location.

In order to determine the stop points and their number of visiting times, firstly for each stop region, the centroid of points related to that stop region was calculated from the table 'StopRegionCatPoints'. As some stop points are related to the same location, the stop points with the same category were clustered. The number of clusters shows the number of separated stop points, and the number of points in each cluster shows the number of visits to that location. The points that do not belong to any cluster are the stop points that were visited just once.

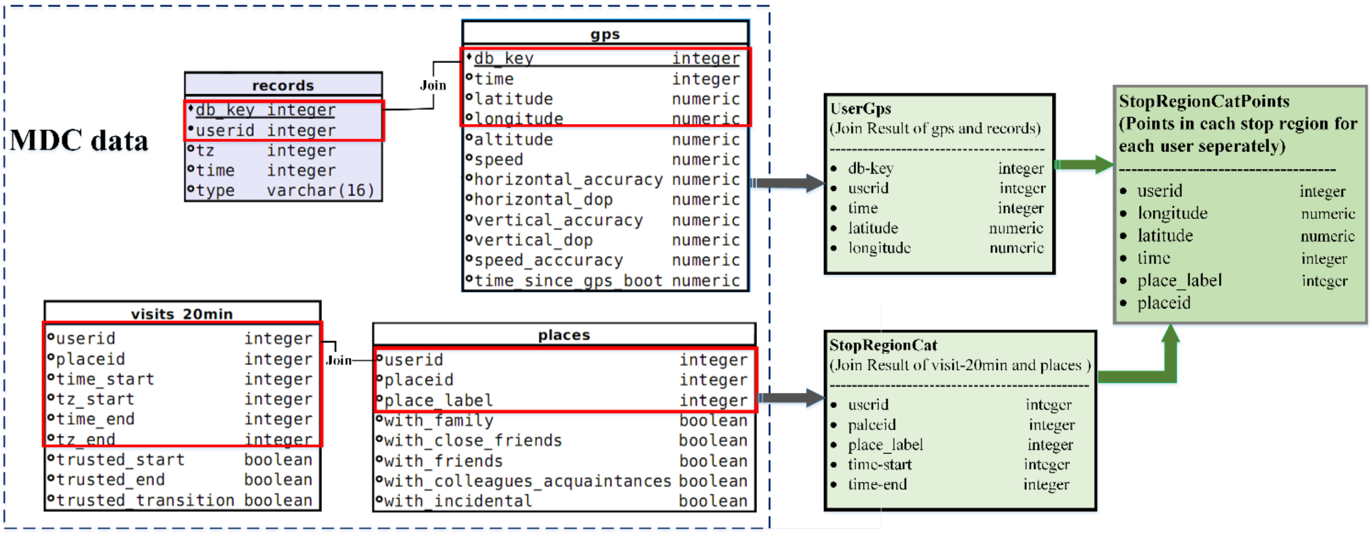

Figure 4. Process of detecting GPS points in every stop region for each user.

3.2. Defining City Center

To determine homes and workplaces' location relative to the city center, the city center should be defined first. There are various approaches to define the city center. For example, it could be determined either as a 'cognitive region' defined by individuals' understanding (Montello, Friedman, & Phillips, 2014) or using User Generated Content (UGC) data such as TripAdvisor, OpenStreetMap (OSM), Gowalla, and Foursquare (Hobel, Fogliaroni, & Frank, 2016; Sun, Fan, Li, & Zipf, 2016). Moreover, the road network density is another important indicator of distance from the city center in a way the road network density describes the structure of a city, and it has high-density in the city center and low-density in the suburbs (Cai, Wu, & Cheng, 2013; G. Zhao, Zheng, Yuan, & Zhang, 2017). Accordingly, in the proposed method, the road network density approach was used as it shows the level of accessibility in a given city (Yuan, Raubal, & Liu, 2012).

Among density estimation methods, kernel density is proposed for different problem solving as it provides better results (Deshpande, Chanda, & Arkatkar, 2011). So this research deployed the kernel density function to determine the density of roads network. The kernel density estimation function, based on Rosenblatt – Parzen, is defined by Eq. (1) (Cai et al., 2013):

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x-x_i}{h}\right), \qquad (1)$$

where k() is called the kernel function that here is a commonly used function as quartic function (Loo, Yao, & Wu, 2011); n is the number of observations, x_i is the observation, h is the bandwidth that is always greater than 0 and obtained by equation presented in (Silverman, 2018); $(x-x_i)$ is the distance between the specific point and the sample point x_i

To determine the high density area of the road network, first, the density map of the road network was created using the kernel density estimation Then the mean (μ) and standard deviation (σ) of the total density of the study area was calculated. In order to divide the area into two parts of low and high density, the cluster break line $\mu+3\sigma$ was specified. Since based on Chebyshev's inequality for non normally distributed variables at least 89% values fall within three standard deviation of the mean (Kvanli, Pavur, & Keeling, 2005) and based on three-sigma rule for normally distributed variables at least 95% of variables fall within three standard deviation of the mean (Pukelsheim, 1994). Therefore, regardless of the type of road density distribution at least 89% of the density values are less than $\mu+3\sigma$. Hence, as our aim is to define high road density areas, the cells whose density values were more than $\mu+3\sigma$ were labeled as high density.

3.3. Modeling Activity space and calculating movement parameter

3.3.1. Modeling Activity Space

The activity space of each person refers to the part of the space in which the person moves and somehow reflects the distribution of the places where the individual has been present (Sherman, Spencer, Preisser, Gesler, & Arcury, 2005). Various methods model the activity space, such as the ellipse-based approach, network-based approach, density-based approach, and minimum convex-hull polygons (MCP) (Patterson & Farber, 2015; Yuan & Raubal, 2016). Since this study aims to investigate the geometrical characteristics, shape, size, and dispersion of the activity space, the ellipse-based approach was used. The standard deviation ellipse is the Euclidean and bivariate criterion representing the dispersion of the points from their mean (Albert, Gesler, & Levergood, 2003). Hence, it is generally used to illustrate the activity space of an individual's movement (Sherman et al., 2005).

The standard deviation ellipse, representing the user's activity space, can be calculated by having the center's coordinates $(\bar{x}, \bar{y})$ and the length of major and minor axes of an ellipse $(2a, 2b)$. The center coordinate of each user's activity space is calculated using the arithmetic mean of the points in their trajectory. Besides, the lengths of major and minor axes of the ellipse are obtained using the eigenvalues (λ_1, λ_2) by solving the characteristic equation (Eq. (6)) from Eqs. (2)—(12) (Schönfelder & Axhausen, 2003):

$$a = \sqrt{l_1}, \qquad (2)$$

$$b = \sqrt{l_2}, \qquad (3)$$

$$l^2 - (s_x^2 + s_y^2)\,l + (s_x^2 s_y^2 - s_{xy}^2) = 0, \qquad (4)$$

$$(-l)^2 + tr(S)(-l) + |S| = 0, \qquad (5)$$

$$S - lI = 0, \qquad (6)$$

$$tr(S) = s_x^2 + s_y^2, \qquad (7)$$

$$|S| = s_x^2 s_y^2 - s_{xy}^2, \qquad (8)$$

$$S = \begin{bmatrix} s_x^2 & s_{xy} \\ s_{xy} & s_y^2 \end{bmatrix}, \qquad (9)$$

$$s_{xy} = \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{y})}{n}, \qquad (10)$$

$$s_x^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2, \qquad (11)$$

$$s_y^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2 .a \qquad (12)$$

3.3.2. Movement Parameters

In this approach, the parameters of activity space used to derive the users' movement behaviors are as follow:

- **Area**: it represents the spatial extent of the area of activity space. Besides, it shows the degree of concentration of points (Eq. (13)) (Schubert & Kirchner, 2014).

$$\text{Area} = \pi\, ab, \tag{13}$$

where $2a$ and $2b$ are the length of major and minor axes of an ellipse.

- **Radius:** the radius of activity space estimates the area of physical movement of individuals based on the trajectories (Eq. (14)) (Gonzalez, Hidalgo, & Barabasi, 2008).

$$\text{Radius} = \frac{a+b}{2}. \tag{14}$$

- **Radius of gyration:** radius of gyration is used to measure the territory of a person's activity space. The radius of gyration of the user α up to time t is calculated by Eq. (15) (Kang et al., 2012):

$$r_g^a(t) = \sqrt{1/n_c^a(t)\sum_{i=1}^{n_c^a(t)}((x_i - x_c)^2 + (y_i - y_c)^2)}, \tag{15}$$

where (x_i, y_i) is the *ith* coordinate of user α ($i = 1, 2, ..., n_c^a(t)$) and (x_c, y_c) is the coordinate of user's trajectory mass center (Eqs. ((16— (17)):

$$x_c = \frac{1}{n_c^a(t)}\sum_{i=1}^{n_c^a(t)} x_i, \tag{16}$$

$$y_c = \frac{1}{n_c^a(t)}\sum_{i=1}^{n_c^a(t)} y_i. \tag{17}$$

- **Compactness:** The compactness of activity space is always between 0 and 1, indicating the degree of linearity or circularity of the activity space (Eq. (18)). The closer this number is to 1, the more similar the activity space's shape is to the circle. In planning the urban areas, the shape or the compactness of space indicates the capacity of the neighborhood to hold the opportunities for living and working (Harding, Patterson, & Miranda-Moreno, 2013).

$$\text{Compactness}_i = \frac{\text{Perimeter}_{\text{circle}_i}}{\text{Perimeter}_{\text{MCP}_i}}, \tag{18}$$

where $\text{Perimeter}_{\text{MCP}_i}$ is the perimeter of the *MCP* of individual *i* and $\text{Perimeter}_{\text{circle}_i}$ is the perimeter formed by a circle having the same area as the *MCP* of individual *i*:

$$\text{Perimeter}_{\text{circle}_i} = 2 * \pi * \sqrt{\frac{\text{Area}_{\text{MCP}_i}}{p}}, \tag{19}$$

where $\text{Area}_{\text{MCP}_i}$ is area of the MCP of individual *i*.

- **Ratio:** the ratio of the length of the two axes of ellipse is a measure for the degree of ellipse fullness and the deviation from the main path (the large axis of the ellipse) (Eq.(20)) (Hasanzadeh et al., 2019; Newsome, Walcott, & Smith, 1998).

$$\text{Ratio} = \frac{b}{a}. \tag{20}$$

- **Shape Index**: eccentricity or simply *e* indicates how much the user's activity space deviates from the circular shape (Lima, Stanojevic, Papagiannaki, Rodriguez, & González, 2016). For example, $e \approx 1$ indicates that the person is nearly commuting between two fixed locations, e.g., home and work. In the study of movement, linear motions are more critical, so $1 - e$ is being used (Eq.(21) (Yuan, 2013):

$$\text{ShapeIndex} = 1 - \sqrt{1 - (\frac{b}{a})^2}. \tag{21}$$

- **Entropy:** Entropy is used to measure the degree of uncertainty, irregularity, and predictability of one's visiting POI[2]s and activity patterns (Eq.(22). The higher the entropy, the greater the irregularity and the less predictability of the activity pattern is (Song, Qu, Blumm, & Barabási, 2010).

$$\text{Entropy} = -\sum_{j=1}^{N_i} p_i(j)\log_2 p_i(j), \tag{22}$$

where $p_i(j)$ is the probability of visiting location j and N_i is the number of locations visited by user i.

3.4. Activity Range Index (ARI)

The three indices of Area, Radius, and ROG represent the dispersion and the range of movement of an individual; hence we call them the *Movement Range Parameters*. The higher these parameters are for a user, the more extensive the individual's range of movement is. Therefore, since the theory and concept of these three indices are the same, an integrated index can be introduced to represent the extent of

[2] Point of Interest (POI) is a specific point location that someone may find useful or attractive such as restaurants, sightseeing sites, etc (Yuan, Cong et al. 2013).

individuals' movements by normalizing them. In this paper, the sum of min-max normalized movement range parameters, as an index for the range of movement, is expressed as the Activity Range Index (ARI):

$$\mathrm{ARI} = \mathrm{A}^{\mathrm{N}} + \mathrm{R}^{\mathrm{N}} + \mathrm{ROG}^{\mathrm{N}}, \tag{23}$$

where A^{N} is the min-max normalized area, R^{N} is the min-max normalized radius and $\mathrm{ROG}^{\mathrm{N}}$ is the min-max normalized Radius of Gyration. The higher the ARI, the greater and more dispersed the range of movement. On the contrary, the lower the ARI, the smaller and more compact the range of movement.

3.5. Activity Linearity Index (ALI)

The Compactness, Ratio, and Shape Index parameters express the degree of closeness of a user's movement to a line by a number between 0 and 1. Therefore, we call them the *Movement Linearity Parameters*. The closer the value of these parameters to 0, the more linear the movement and the closer to 1 the more circular the movement. Therefore, since the concept of these three indices is the same, an integrated index can be introduced to represent the linearity of movement of individuals by normalizing them. In this paper, the sum of min-max normalized movement linearity parameters, as an index of linearity of movement, is expressed as the Activity Linearity Index (ALI):

$$\mathrm{ALI} = \mathrm{C}^{\mathrm{N}} + \mathrm{Rt}^{\mathrm{N}} + \mathrm{ShI}^{\mathrm{N}}, \tag{24}$$

where C^{N} is the min-max normalized compactness, Rt^{N} is the min-max normalized ratio and $\mathrm{ShI}^{\mathrm{N}}$ is the min-max normalized Shape Index.

The lower the ALI, the more linear the movement. Also, the higher the ALI, the less linear and more circular the movement.

3.6. Comparing the means of groups

To test how significant the difference between the means of two groups is, the t-test is used (Kim, 2015). This paper used two kinds of t-test, including 'Paired t-test' and 'Independent t-test'. The paired t-test was adopted to assess whether there was a significant difference between the means of a specific parameter of a user group on weekdays and weekends. For example, to test the significance of the difference between the mean radius of InInWeekday and the mean radius of InInWeekend the paired t-test was used as the users are the same in those groups and just the period of time is different. Moreover, to determine if there is a significant difference between the means of a specific parameter on weekends or weekdays between two groups, the Independent t-test was used. For instance, to test the significance of the difference of the mean Ratio of OutOutWeekend and the mean Ratio of OutInWeekend, the Independent t-test was used as the users are different in those groups.

The Significance value (Sig.) as the output of t-test shows the degree of meaningfulness between means values. The Sig. value less than 0.05 shows that there is a significant difference between the means values. However, the Independent t-test gives us two Sig. values that based on whether the variances are equal or not, one is selected. The Sig. value of Levene's test shows whether the variances are equal or not. Hence, the Levene's Sig. value more than 0.05 shows that the condition of equal variance is met (Kim, 2015).

3.7. Interpreting the parameters

Finally, after going through the mentioned steps and calculating the ARI, ALI, and entropy for each group, the results must be interpreted in order to compare the groups in terms of extent, linearity, and entropy of their movement as follows:

- The range of ARI is from 0 to 3. The higher the ARI (or movement range parameters), the greater and more dispersed the range of movement. On the contrary, the lower the ARI, the smaller and more compact the range of movement.
- The range of ALI is from 0 to 3. The lower the ALI (or movement linearity parameters), the more linear the movement. Also, the higher the ALI, the less linear and more circular the movement.
- Entropy value is greater than zero. The higher the entropy, the greater the irregularity and the less predictability of the movement is.

4. Experimental results

Firstly, for modeling the activity space and grouping users the GPS data were preprocessed for outlier detection. Then the cleared GPS points for each selected user of canton Vaud were separated based on weekdays and weekends. Next, each user's activity space and movement parameters were calculated separately on weekdays and weekends. Figure 5 shows three random users' activity spaces in the canton Vaud both on weekdays and weekends. Afterward, the users were grouped based on their homes and workplaces relative to the city center. Then, by using a kernel density estimator, the road density map was determined (Figure 6a), and by using $\mu + 3\sigma$ the city center was defined (Figure 6b). The number of users and the number of their travels in all four groups that their homes and workplaces are known and their movement data was gathered from 2009 to 2011 is shown in Table 1.

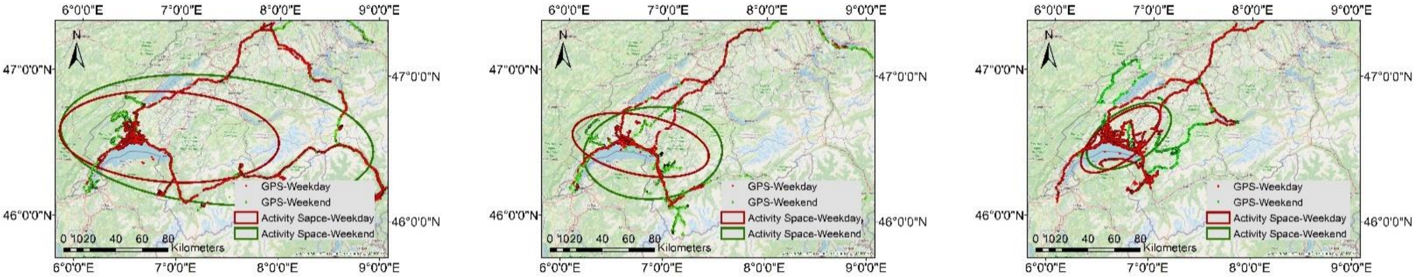

Figure 5. Activity Space of three random users in the canton Vaud both on weekdays and weekends. a) User 5945, b) User 5979 c) User 6004.

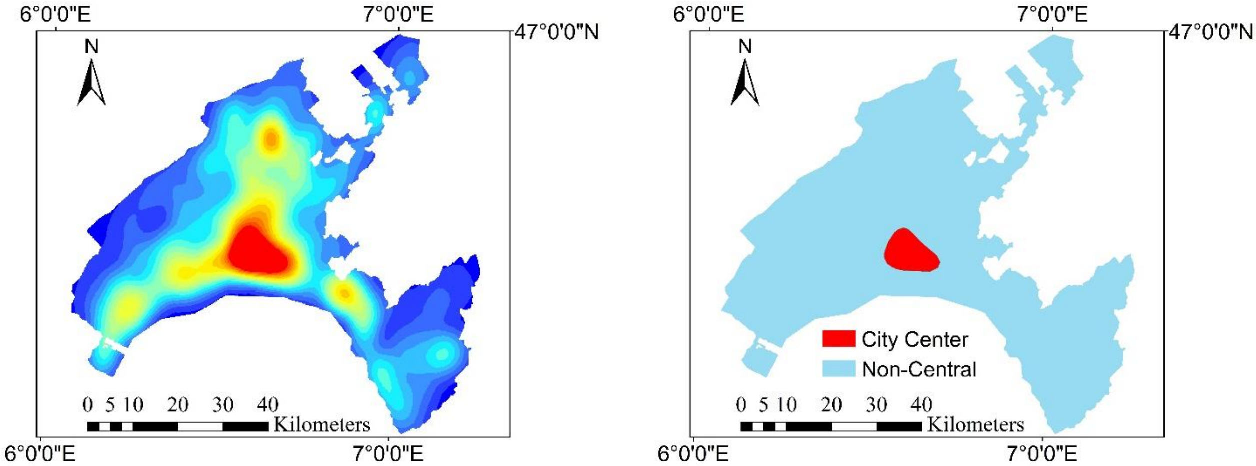

Figure 6. a) road density map; b) central and non-central urban area.

Table 1. Number of users and number of their travels in each group with movement data from 2009-2011.

No. user	No. of Travels	Group
19	15297	Both home and workplace within the city center (InIn)
15	10515	Home within the city center and workplace outside the city center (InOut)
22	11412	Home Outside the city center and workplace inside the city center (OutIn)
17	14624	Both home and workplace outside the city center (OutOut)

After grouping users and determining their ellipse activity spaces, the range parameters (area, radius, and radius of gyration), linearity parameters (compactness, ratio, and shape index), and entropy for each user were calculated separately on weekdays and weekends. Accordingly, the averages of each calculated parameter for the users in each group (InIn, InOut, OutIn, OutOut) were determined separately on weekdays and weekends. To determine the degree of meaningfulness of differences between the means of each two groups, the t-test was used. The Sig. values resulting from the t-tests were less than 0.05, showing significant differences between their means values. Table 2 and Table 3 show some examples of the paired and independent t-test results, respectively. Then, the ARI and ALI were defined for each group. The results are presented below in sections 4.1, 4.2, and 4.3.

4.1. Range of Activity Space

The average of each movement range parameter for the individuals in each group is presented in Figure 7 and Table 6. Also, the normalized movement range parameters and the difference of values from average are shown respectively in Table 7 and Table 8 to compare the results better.

The avg. value of each range parameter in each group on weekends is higher than that of the weekdays (Figure 7). Also, the avg. of avg. of each parameter in the four groups is higher on weekends than on weekdays (Figure 7). Group InOut, both on weekends and weekdays, has the highest avg. of range parameters, followed by OutOut, OutIn, and InIn, respectively (Table 6). The InIn group has the most significant difference from the avg. of avg. in all movement

Table 2.Examples of the Paired T-test results.

Groups and Variables		Sig. (2-tailed)
InIn	WeekendRadius – WeekdayRadius	0.040
InIn	WeekendROG – WeekdayROG	0.033
InIn	WeekendEntropy – WeekdayEntropy	0.001
OutOut	WeekendRatio – WeekdayRatio	0.041
OutOut	WeekendShapeIndex– WeekdayShapeIndex	0.047
OutOut	WeekendEntropy – WeekdayEntropy	0.002

Table 3.Examples of the Levene's test and Independent T-test results.

Groups and Variables	Equal variance or not	Levene's Test for Equality of Variances		t-test for Equality of Means
		F	Sig.	Sig. (2-tailed)
Ratio (WeekendOutIn, WeekendOutOut)	Equal variances assumed	0.216	**0.648**	**0.013**
	Equal variances not assumed	-	-	0.029
ShapeIndex (WeekendOutIn, WeekendOutOut)	Equal variances assumed	3.039	**0.099**	**0.018**
	Equal variances not assumed	-	-	0.087

range parameters, both on weekdays and weekends (Table 8). On average, their movement range parameters are 27.51% below the avg. of avg. of each movement range parameter on weekdays and on average, 39.78% below the avg. of avg. on weekends.

After determining the range of movement parameters, ARI was calculated for each group by summing the normal movement range value (Section 3.4). Two ARI series were calculated for the data of this study: normalizing the parameters together between weekdays and weekends (Table 4), and normalizing the parameters between weekdays and weekends separately (Table 7). As shown in Table 4, the InInWeekday has the lowest ARI and the InOutWeekend has the highest ARI among all eight groups.

4.2. Linearity of activity space

The avg. of each movement linearity parameter for the individuals in each group is presented in Figure 8 and Table 6. Also, the normalized movement linear parameters and the difference of values from average are shown respectively in Table 7 and Table 8 to compare the results better.

In all groups, the avg. of each of the linearity parameters of individuals' movements on weekdays is lower than that of the weekends (Figure 8). The InOut group has the lowest avg. in each linearity parameter on weekdays and the highest avg. on weekends (Table 6). Their movement linearity parameters are on average 29.72% above the avg. of avg. on weekends and 14.91% below the avg. of avg. on weekdays (Table 8). The OutOut group, on average, has the highest linearity parameters on weekdays (Table 6). On the other hand, on weekends, the InOut group has the highest linearity parameters on average (Table 6).

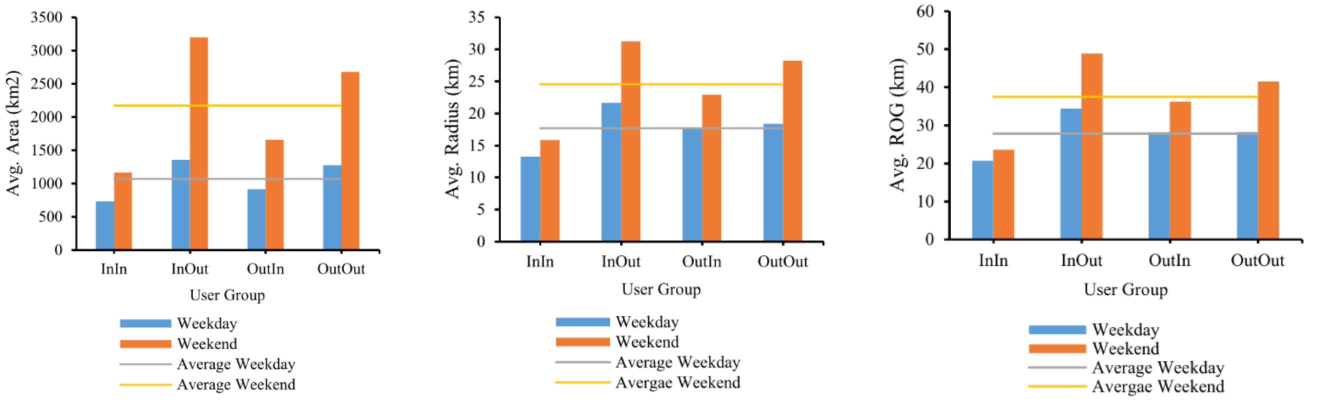

Figure 7. The average of each Movement Range Parameters of users in each group separately on weekdays and weekends: a) Area, b) Radius, and c) ROG.

Table 4. Activity Range Index calculated on Weekday and Weekend together.

User Groups	Activity Range Index
InInWeekday	0
InInWeekend	0.421
OutInWeekday	0.579
OutOutWeekday	0.772
InOutWeekday	1.207
OutInWeekend	1.462
OutOutWeekend	2.364
InOutWeekend	3

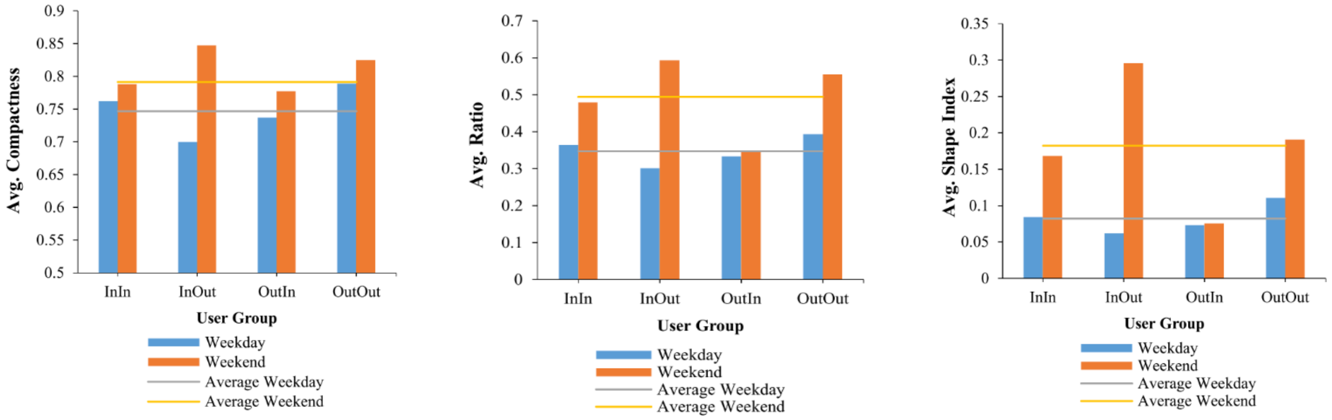

Figure 8. The average of each Movement Linearity Parameters of users in each group separately on weekdays and weekends: a) Compactness, b) Ratio, and c) Shape Index.

After determining the linearity parameters of movement, as described in Section 3.5, an index of ALI can be obtained by summing the normalized linearity parameters. Two ALI series were calculated for this study's data: Normalizing the parameters on weekdays and weekends together (Table 5) and normalizing the parameters separately between weekdays and weekends (Table 7).

Table 5 shows the ALI values for all four user groups ascendingly throughout the week. As can be seen in the InOut group, users on weekdays have the least value and thus have the highest linearity. Additionally, this group has the highest ALI value on weekends, and hence the movement of its group members on weekends is more circular than the others.

Table 5. Activity Linearity Index calculated on Weekday and Weekend together.

User Groups	Activity Linearity Index
InOutWeekday	0
OutInWeekday	0.411
InInWeekday	0.732
OutInWeekend	0.748
OutOutWeekday	1.125
InInWeekend	1.661
OutOutWeekend	2.266
InOutWeekend	3

Table 6. Movement Parameters: range, linearity, and entropy. The Highest value in each parameter. The Lowest Value in each parameter.

Day	User Group	Activity Range Parameters			Linearity Parameters			Entropy
		Avg. Area (km^2)	Avg. Radius (km)	Avg. ROG (km)	Avg. Compactness	Avg. Ratio	Avg. Shape Index	Avg. Entropy
Weekday	**InIn**	732.629	13.243	20.68	0.762	0.364	0.084	7.551
	InOut	1353.820	21.640	34.380	0.699	0.301	0.062	6.519
	OutIn	911.9340	17.553	28.144	0.737	0.333	0.073	6.653
	OutOut	1274.893	18.333	28.196	0.789	0.392	0.110	6.429
	Average	1068.321	17.692	27.832	0.747	0.348	0.0822	6.788
Weekend	**InIn**	1162.258	15.819	23.518	0.788	0.479	0.168	10.663
	InOut	3196.497	31.222	48.822	0.847	0.593	0.296	10.288
	OutIn	1653.151	22.913	36.148	0.777	0.349	0.075	10.657
	OutOut	2678.983	28.235	41.497	0.824	0.555	0.191	10.434
	Average	2172.722	24.547	37.496	0.809	0.494	0.182	10.511

Table 7. Normalized Activity Range Parameters and Normalized Linearity Parameters separately on weekends and weekdays.

Day	User Group	Normalized Activity Range Parameters			ARI	Normalized Linearity Parameters			ALI
		Area (km^2)	Radius (km)	ROG (km)		Compactness	Ratio	Shape Index	
Weekday	**InIn**	0	0	0	0	0.700	0.685	0.455	1.841
	InOut	1	1	1	3	0	0	0	0
	OutIn	0.289	0.513	0.547	1.349	0.419	0.349	0.233	1.002
	OutOut	0.873	0.606	0.551	2.030	1	1	1	3
Weekend	**InIn**	0	0	0	0	0.154	0.531	0.421	1.106
	InOut	1	1	1	3	1	1	1	3
	OutIn	0.241	0.461	0.499	1.2	0	0	0	0
	OutOut	0.746	0.806	0.710	2.262	0.676	0.843	0.524	2.043

4.3. Entropy

In all four groups, the average entropy of weekends is higher than that of the weekdays (Figure 9). Furthermore, users in InIn group have the highest entropy values both on weekdays and weekends. However, in general, there is a slight difference between groups, whether on weekdays or weekends. However, The OutOut group has the lowest entropy on weekdays, and the InOut group has the lowest entropy on weekends (Table 6). The mean value of entropy in all groups on weekdays is below the mean of avg, except for the InIn group that is higher (Table 8).

Table 8. The difference of avg. parameters of movement parameters (range, linearity and entropy) in each group from avg. of avg. of all groups (in percent). The Highest value in each parameter. The Lowest Value in each parameter.

Day	User Group	Activity Range Parameters (ARP) Area (%)	Radius (%)	ROG (%)	Avg. of avg. of each ARP (%)	Activity Linearity Parameters (ALP) Compactness (%)	Ratio (%)	Shape Index (%)	Avg. of avg. of each ALP (%)	Entropy (%)
Weekday	**InIn**	-31.42	-25.15	-25.95	-27.51	2.03	4.65	1.95	2.88	11.23
	InOut	26.72	22.32	23.53	24.19	-6.31	-13.40	-25.01	-14.91	-3.96
	OutIn	-14.64	-0.79	1.12	-4.77	-1.32	-4.19	-11.19	-5.57	-1.99
	OutOut	19.34	3.62	1.31	8.09	5.60	12.93	34.25	17.59	-5.29
Weekend	**InIn**	-46.51	-35.55	-37.28	-39.78	-0.48	-3.07	-7.90	-3.82	1.45
	InOut	47.12	27.19	30.21	34.84	7.03	19.98	62.15	29.72	-2.12
	OutIn	-23.91	-6.66	-3.60	-11.39	-1.85	-29.19	-58.81	-29.95	1.40
	OutOut	23.30	15.02	10.67	16.33	4.15	12.28	4.55	7.00	-0.73

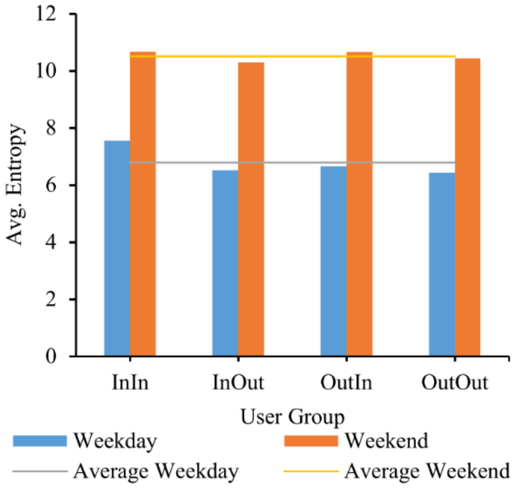

Figure 9. The average entropy of users in each group separately on weekdays and weekends.

5. Discussion and conclusions

In this paper, a method was proposed to examine the impact of users' home and workplace locations within or out of the city center on the users' activity space separately on weekdays and weekends. In the proposed method, the high-density road network was considered the city center and defined using the kernel density estimation. Next, users' movement data were grouped into eight sets based on their home and workplace location relative to the city center and considering weekends and weekdays. Moreover, the standard deviation ellipse was used to model the users' activity space. Therefore, area, radius, and radius of gyration were considered as the range movement parameters, and compactness, ratio, and shape index as the linearity movement parameters. In addition to the mentioned range and linearity movement parameters, entropy was used to compare users' variety of the visited locations. After calculating the mean value of each mentioned parameters for each group, to compare the means of group variables, the t-test was used. Furthermore, in this paper, two new indices were introduced: the sum of min-max normalized movement range parameters as the ARI; and the sum of min-max normalized linearity movement parameters as the ALI. Eventually, interpreting the mentioned parameters makes it possible to compare groups. Thus, the higher the ARI of a group, the more extensive and dispersed its activity space. The closer the value of ALI to 0, the more linear the activity space, and the closer to 3, the more circular the movement. Moreover, the higher the entropy, the greater the irregularity and the less predictability of the movement.

The MDC dataset of canton Vaud of Switzerland was used as a case study to implement the proposed method. By interpreting the results of ARI, ALI, and entropy in all groups, on average, people tend to have broader, more non-linear, and more random movements on weekends rather than on weekdays. This might be because of people's free time and their tendency to go to picnics and campsites on weekends rather than on weekdays. As shown in Figure 10a, the density of campsites is higher in the suburbs of canton Vaud shows that to reach these places, people have to travel longer distances. Moreover, interpreting the ARI values specified that people whose homes and workplaces are inside the city center have the lowest range of movement. This might be due to the unequal distribution of the urban facilities, e.g., stores, parks, restaurants, hospitals, etc., between the central and the non-central urban areas (Figure 10b). Hence, people who live or work outside the city center have to travel more to provide life and work necessities. Furthermore, comparing the ALI values showed that InOutWeekday and OutInWeekday have the lowest ALI. Accordingly, a user whose home (or workplace) is within the city center and the other (either home or workplace) is within the suburbs and has more linear movements. Therefore, because of the distance between their home and workplace, there might be no time left for the users to go to other places rather than their workplaces and homes. Moreover, InInWeekday group has the most entropy value that shows its users go to more diverse places which might be due to easy access to the various stores in the city center. And among these groups, those who live in the city center and work outside the city center have the most movement range and linearity on weekdays. This might be due to the higher distance between home and workplace in this group, which allows them to only move between work and home on weekdays. And also they have the most movement range and least movement linearity (highest ALI) on weekends. this might be due to their free time on weekends that allows them to go further places that they couldn’t go during weekdays. However, the lower amount of entropy in this group shows that even on weekends they move between certain places.

However, in this paper, a method was proposed to analyze range, linearity, and entropy of individuals’ activity spaces based on their homes and workplaces relative to the city center. Implementing the proposed method on another canton or another city in another country may produce different results. Because each city has a different city structure, city center size, and may have different behavior in the society and thus different movement patterns. Also, there are various methods to determine the city center. Therefore, different methods can produce different city centers in shape and size, even for the same city. Hence, the impact of different methods for defining city centers on the results could be considered in future works.

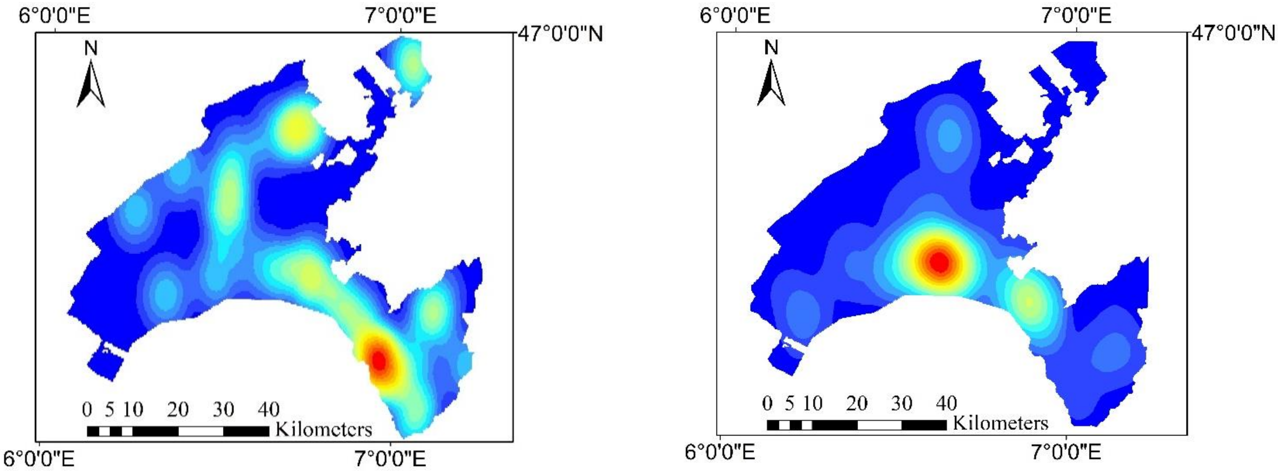

Figure 10. a) campsites density map; b) urban infrastructures density map.

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