EQUITY IMPACT OF INCORPORATING UNCERTAINTY IN TRAVEL TIMES IN MEASUREMENT OF ACCESSIBILITY

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ABSTRACT

Travel time uncertainty is usually not incorporated into measurements of accessibility. Consequently, assessments of equity, based on travel times to work, may differ when travel time uncertainty is taken into account, compared to the commonly used approach based on free flow travel times. To empirically investigate this issue, this paper presents the results of an analysis of social equity based on travel time as a measure of accessibility for the Brainport area, the Netherlands in the context of the work commute by car. GPS data, recording over a multi-week period, were used to measure travel time variability, assumed to capture uncertainty, during the work commute. Results indicate that society equity, measured in terms of the Gini coefficient, is influenced by the decision to include travel time uncertainty in the measurement of accessibility.

Keywords: Gini coefficient; GPS; Travel time; Equity

INTRODUCTION

Accessibility is viewed as an important ingredient of quality of life. It is therefore not surprising that over the years hundreds of studies have been concerned with measurement and application of the accessibility concept (e.g., Pirie, 1979; Kwan, 1998, 1999; Dijst, et al., 2002; Miller, 2007; Neutens, et al., 2007a, 2007b). Definitions have been very consistent in the sense that accessibility has been conceptualized to show how easy an activity location can be reached from other locations and to indicate how easy people can reach a set of potential destinations (e.g., Dijst, et al., 2002). The measurement of accessibility has taken on different forms. Many indicators are based on a definition of accessibility as the amount of effort needed to reach available services to conduct particular activities (e.g. Pooler, 1987; Kwan, et al., 2003).

Among geographers and urban planners, measures that identify a set of opportunities (e.g. jobs, stores or services), and a distance decay function to represent the amount of effort involved in travelling the distance between locations have been popular. The best known of such measures are distance or travel time, cumulative opportunity measures, and gravity-based measures (e.g., Vickerman, 1974; Wachs and Kumagai, 1973). Distance and travel time directly focus on the physical separation of places, expressed as travel costs, distance (Cartesian, on the network or topological) or time. The latter measure is most direct as time can be seen as a measure of effort. In contrast, topological distance as for example expressed in space syntax does not seem a valid measure of effort. Cumulative opportunity measures count the (attractiveness of the) opportunities within some arbitrarily defined distance or travel time. In some sense, it represents a simple, dichotomous distance function. Within this reach, increasing distance or travel time does not result in any reduced accessibility. In that sense, distance decay measures are more sensitive as they measure accessibility as a trade-off between supply and effort to reach that supply (e.g., Hansen, 1959).

Kwan and Weber (2003) criticized these measures. First, these measures usually assume that all people are concentrated in the centroids of the identified zones. Thus, within-zone differences in accessibility are not taken into account, making the measures inaccurate in some cases. Second, because a spatial zoning system is used, the measures depend on the arbitrary delineation of the urban system and definition of the zones. Thus, there has been a strong tradition in geography to develop space-time accessibility measures, which do not only fully capture individual-level differences in accessibility, but also take into account a multitude of space–time constraints the people face in their everyday life (e.g., Kwan, 2004).

All these measures, however, lack a sound theoretical basis in consumer choice theory. Regional scientists and transportation researchers have, therefore, preferred the use of the logsum measure because it can be shown that the logsum is related to the concept of consumer surplus.

Spatially, accessibility by definition will not be the same to every point or zone in a city. In general, people living in suburbs and the countryside will need to travel further to central locations where most jobs and other activity destinations are located. It implies that equity in accessibility will not be present in urban systems. Considering equity in the discussion of accessibility is extremely important in the context of the social inclusion and social justice policy agenda, which is often centered on the requirement of equal access to a range of urban services for disadvantaged groups. Well-known early examples of equity in accessibility include Talen (1998) and Nicholls (2001).

All these measures are thus based on distance or travel time. Regardless of the specific measure, uncertainty in travel times has rarely been taken into account in measuring accessibility. Because uncertainty in travel times may vary considerably within cities, ignoring such uncertainty may imply that the resulting accessibility measures are flawed, in turn impacting assessments of equity.

Considering this gap in the literature, this paper reports the results of an analysis to examine equity implications of incorporating uncertainty in travel times in the measurement of accessibility, taking work activities as an example. Specifically, it is investigated to what extent such improved representation of accessibility has a diverging impact on equity assessments.

To that end, the rest of the paper is structured as follows. First, we will report the data that were used for the analysis. Next, the measurement of spatial equity of accessibility will be briefly introduced. Then, we will represent some results with a special emphasis on the uncertainty of accessibility and equity. After that, we will summarize and conclude this paper by pointing out some future directions.

DATA

Data on daily activity-travel patterns were collected for two consecutive samples of approximately 100 respondents in the Brainport Region, a top technology breeding ground for innovation and home to world-class businesses, knowledge institutes and research institutions (Figure 1). Various agencies in this area design and manufacture the technology of the future to ensure a safe, green and caring society and sustainable economic development of the Netherlands. The five focal sectors of Brainport Eindhoven region are High Tech Systems & Materials, Food, Automotive, Lifetec and Design.

A total of 235 individuals carried a GPS device for three months. These devices recorded the timing and position of respondents. Such information can be used to derive activity-travel patterns. The ease of imputation depends on the facets that are derived from the traces. Classification of transport mode is commonly based on speed and acceleration information extracted from the GPS devices. Different transport modes can be identified based on corresponding profiles. Activity type is more difficult to impute. Usually, databases on locations that people mostly visit and land use are used to infer the activity that is conducted at certain stops made during the trip. It goes without saying that such imputation is not perfect and more difficult for the imputation of activity type than for transport mode.

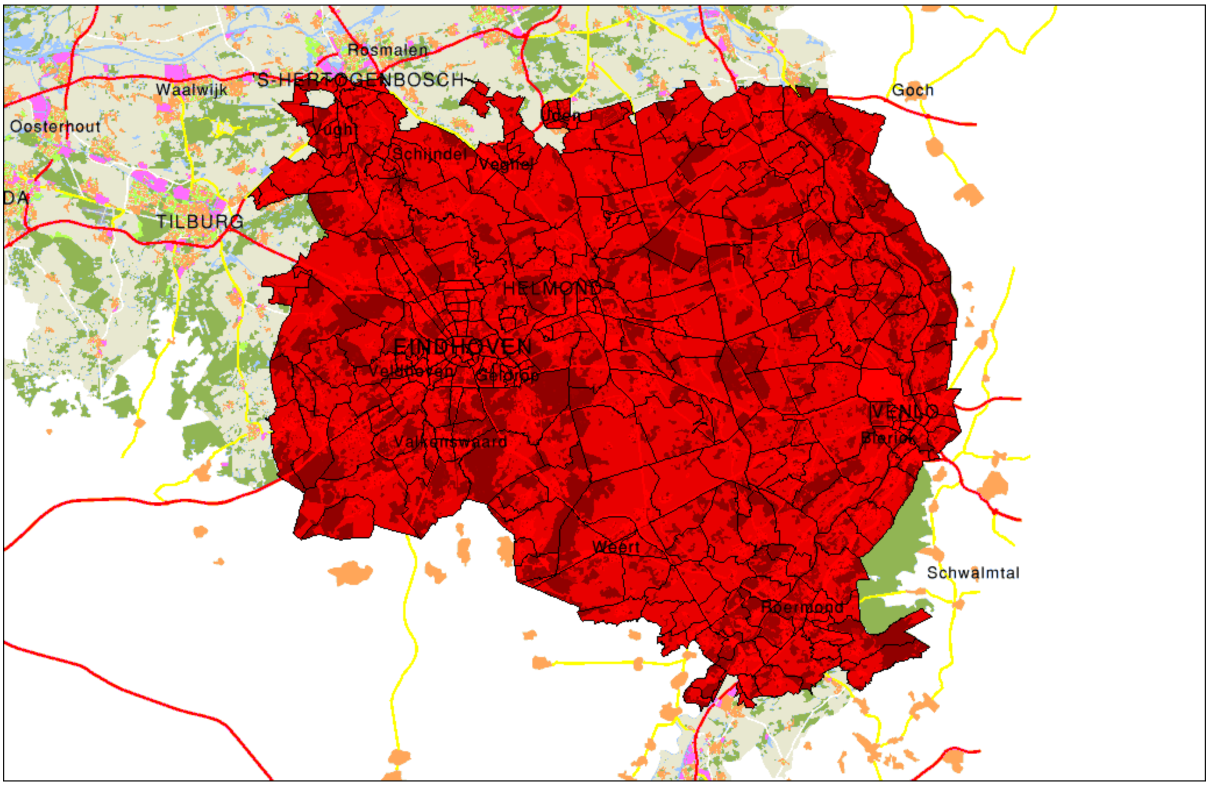


Figure 1 - The Brainport region

In the present study, a naïve Bayesian classifier was used to impute transport mode and activity type as a function of the information provided by the GPS device, including the variables describing its status. A BBN represents all factors deemed potentially relevant for observing a particular outcome and thus can be used to predict the conditional probability of observing a particular outcome. It means that with BBN it is possible to articulate expert beliefs about the dependencies between different variables. The network is represented as a directed graph, together with an associated set of probability tables. The nodes of this graph represent causal relationships between variables. The input variables include: distance to the railway track, metro track and tram track, average and maximum acceleration, speed average, speed max and deviation from the average speed, accumulated distance in a 3 minute time interval, possession of car, bike and motorbike, number of satellites that the GPS device used for recording (USEDSAT), number of amount of satellites that were available at that time (VIEWSAT), position accuracy of 3d coordinate (PDOP) and horizontal accuracy of 2d coordinate (HDOP). The output variable is one of the transport modes or the activity episode. Figure 2 gives the structure of the network used for imputation.

The conditional probabilities of the Bayesian Belief network capture the probabilities of whether it is a transport mode or activity episode. They depend on the interrelationship between the input variables mentioned and the pattern of output of transportation modes and activity episodes. The conditional probabilities pre-obtained from the training dataset are used for prediction.

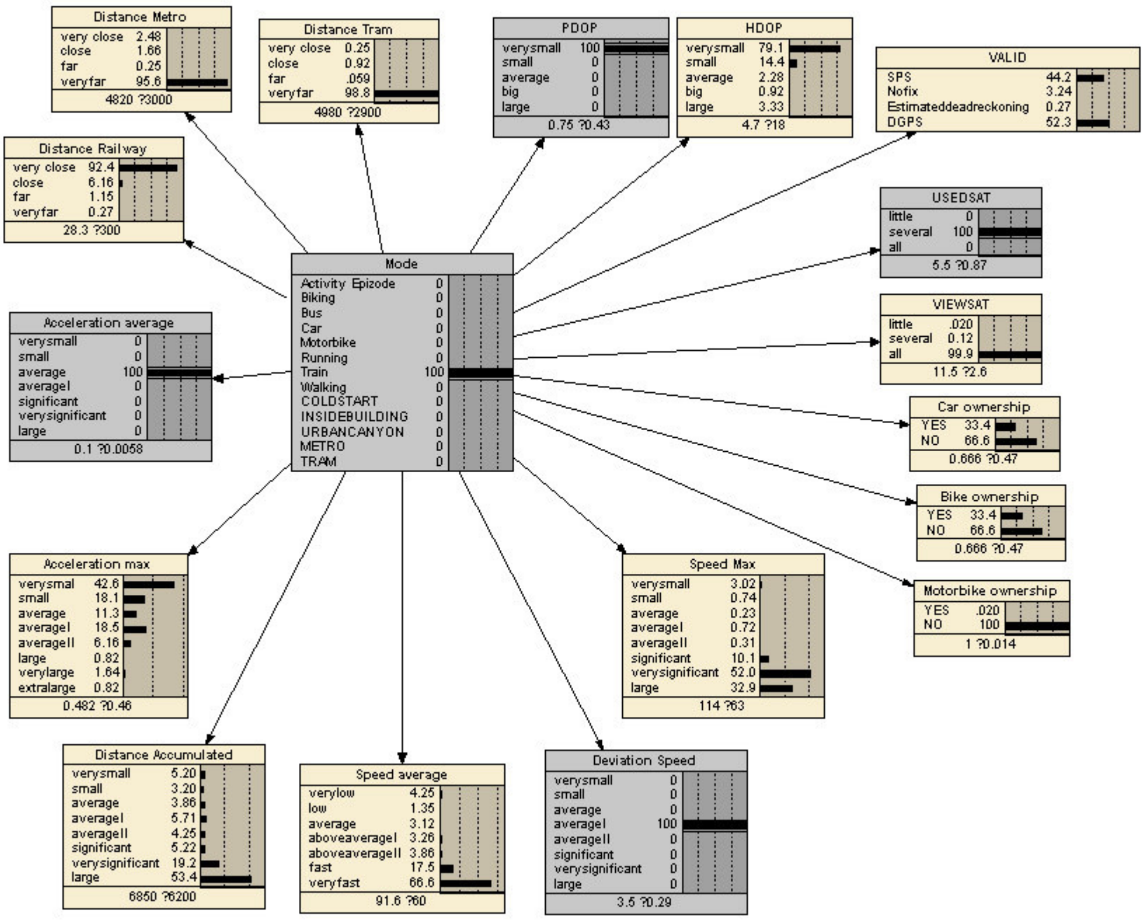


Figure 2 - Bayesian Belief network: Transportation Mode and Activity Episode Identification

The application of the Bayesian network to process the GPS traces results in a sequence of travel episodes, with an imputed transport mode, interrupted by activity episodes. To impute the type of activity, data of personal locations that people frequently visit and the point of interest database in the whole of the Netherlands were used. First, the coordinates, which appear most frequently within a spatially defined rectangular filter, were treated as the activity location. Then, the coordinates were used to match with the personal database and land use data sequentially taking 200 meters as a search diameter. The closest land use type was taken as the activity type.

In addition to the imputation, respondents were invited to complete a Web-based prompted recall instrument to validate the imputed activity-travel diaries and correct any mistakes made. A web-based user-friendly interface was developed to help people validate their travel and activity data (Figure 3). Because the data collection continued for three months, GPS traces of the same individuals can be used to measure variability in travel times from home to the same destination. Corresponding probability distributions were derived and used to calculate uncertainty-weighted travel times.

FIGURE 3 - The Web-based prompted recall page

3. MEASUREMENTS

Equity in accessibility was measured in terms of the Gini coefficient considering its popularity. For a discrete probability function, let $f(y)$, y_i , $i-1,...,N$ denote the points (individuals, zones) with nonzero probabilities, indexed in increasing order $y_i < y_{i+1}$. Then, the Gini coefficient can be expressed as:

$$G = 1 - \frac{\sum_{i=1}^{N} f(y_i)(S_{i-1} + S_i)}{S_n} \quad \textbf{(1)}$$

where

$$S_i = \sum_{j=1}^{N} f(y_j) y_j \quad \textbf{(2)}$$

and

$$S_o = 0 \quad \textbf{(3)}$$

The Gini coefficient (*G*) is defined to be in a range from 0 to 1. A low Gini coefficient indicates a more equal distribution, while higher Gini coefficients indicate more unequal distributions, with 0 and 1 corresponding to complete equity and complete inequity, respectively. In the equity measurement of accessibility, y_i indicates the travel time between different zones. A larger value of *G* will thus indicate less equitable distribution of travel times. Likewise, a value closer to 0 means a more equitable distribution of travel times.

4. RESULTS

The travel related data was drawn from the whole validated dataset of activity-travel agendas. To better represent the variability and uncertainty of travel time, trips made by car for a work activity were selected. Unrealistic trips were filtered out in advance. Moreover, cases with a single record only were removed. Assuming a single work address, variability (uncertainty) in travel times was calculated for a single origin-destination pair for each respondent, that was observed most frequently across the observation time period. To represent travel time across zones at an aggregate level, the location information was matched with the postcode area data of The Netherlands.

Frequency Distribution

Figure 4 represents the frequency distribution of the shortest, longest and the uncertainty-weighted average travel times. As shown in Figure 4(a), 17.86% of the average travel time is in the range of 0 to 15 minutes, while the majority of travel times (35.71%) falls in the range between 15 to 30 minutes. Few trips have a travel time longer than an hour.

Figure 4(b) shows the frequency of the shortest travel time. Different from the average travel time, the shortest travel time indicates the minimum time for that trip in the data. It is considered to be an approximation of the travel time in the free flow state. As shown in Figure 4(b), about 33.33% and 35.71% of the work trips have a shortest travel time in the range 0 to 15 minutes and 15 to 30 minutes respectively. If we compare this result with that in Figure 4(a), which gives the average uncertainty-weighted travel time, the percentage in the range of 0 to 15 minutes for the shortest travel (33.33%) is higher than that of average uncertainty-weighted travel time (17.86%). The difference is 15.47%. This means that the level of uncertainty is about 15% relative to the shortest travel time.

Figure 4(c) shows the frequency of the longest travel time. The longest travel time is the maximum travel time between an origin-destination pair. To some extent, it also gives an indication of traffic obstacles, like congestion, accident, road construction, etc. As shown in the bar chart, the highest frequency (38.1%) is also in the range 15 to 30 minutes. In addition, only 3.57% of the longest travel time is between 0 to 15 minutes. This is significantly different from distributions of average and shortest travel times, which are 17.86% and 33.33%, respectively.

Spatial Uncertainty

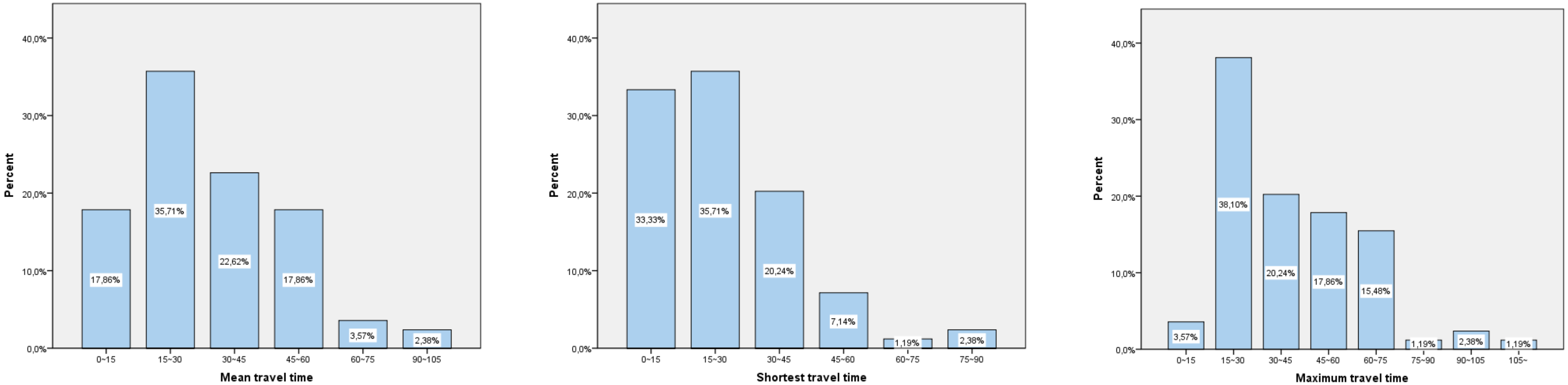
To better represent the spatial difference in accessibilities, we projected the travel times at the scale of postcode areas, as shown in Figure 5. The postcode zones were matched with the locations of start activities. It is evident that the levels of accessibility differ across the zones in cases of all three types of travel times. Compared to the average and longest travel time, shortest travel time has more zones in light yellow colour which is congruent with the expectation.

Equity of accessibility

In order to measure the equity of travel time in the aspect of spatial and horizontal dimension, Gini coefficients were calculated for all three cases. The coefficients were calculated according to the travel time across zones and across all individuals, for the uncertainty-weighted average travel times, shortest travel time and the longest travel time respectively. Results are shown in Table 1 and Table 2.

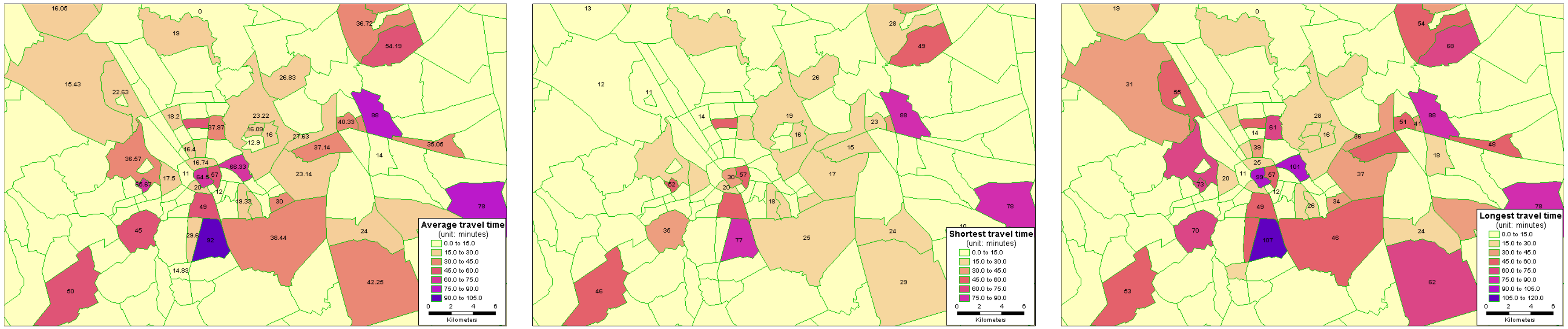
In the case of individual level (Table 1), the most equitable distribution of travel time is the longest travel time (0.306), while the most inequitable distribution is the shortest travel time (0.324). This suggests that the spatial distribution of job relative to home locations varies substantially in the Brainport area. Differences become smaller if travel time uncertainty is taken into account.

Unlike equity at individual level, equity at the zonal level measures differences in a spatial dimension. As shown in Table 2, the most equitable distribution is obtained for from the uncertainty-weighted average travel time (0.163), while the most inequitable distribution is the longest travel time (0.296).



(a) Average travel times (b) shortest travel times (c) Longest travel times

Figure 4 - Frequency of the travel times



(a) Average travel times (b) Shortest travel times (c) Longest travel times

Figure 5 – Travel times across zones

Table 1 Equity at individual level

Type	Gini coefficient
Shortest travel time	0.324
Longest travel time	0.306
Uncertainty-weighted average travel time	0.309

Table 2 Equity at zone level

Type	Gini coefficient
Shortest travel time	0.182
Longest travel time	0.296
Uncertainty-weighted average travel time	0.163

CONCLUSIONS AND DISCUSSION

In general, transportation researchers commonly adopt the shortest or free flow travel time to calculate measures of accessibility. However, these may fluctuate substantially due to differences in day-to-day traffic volumes. Such fluctuations give rise to uncertain times. Including such uncertainty in measuring accessibility will therefore improve the sensitivity and accuracy of these measures for urban planning and policy decision-making. This paper sheds some light on this important issue. Multi-week GPS data collection recently in the Brainport region was used to extract travel times by car to work. Three types of travel time were investigated: the uncertainty-weighted average travel time, shortest travel time and longest travel time. The uncertainty of travel times was measured using the frequency distributions of travel time. Furthermore, the Gini coefficient was used as a measure of equity.

Results show that the level of uncertainty is about 15% relative to the shortest travel time. If there is any congestion, in most cases, the travel time is longer than 15 minutes. Compared to the cases of average and longest travel time, the case of the shortest travel time has more zones with less travel time.

Results of equity of travel times at the individual level show that the difference in travel time among individuals in the situation of traffic jams is not larger than that of the shortest and average travel time. In addition, the most equitable distribution at the zonal level is based on the uncertainty-weighted average travel time and the most inequitable distribution is obtained for the longest travel time.

Although this paper shows some interesting results in the measurement of uncertainty and equity of travel times, there is still some potential to improvement and elaboration. As the GPS data collection is still ongoing now, we expect to get more data samples to validate the analysis. Moreover, future emphasis could be directed at differences between socio-economic groups and temporal aspects such as time of day and day of the week. In additional, a similar analysis can be conducted for other activity types, i.e. shopping, social activities, in future research.

REFERENCES

Dijst, M., De Jong, T., & Ritsema van Eck, J. (2002). Opportunities for transport mode change: An exploration of a disaggregated approach. Environment and Planning B, 29, 413-430.

Hansen, W. G. (1959). How accessibility shapes land use. J. of the Am. Plann. Inst., 25, 73–76.

Kwan, M.-P. (1998). Space–time and integral measures of individual accessibility: A comparative analysis using a point-based framework. Geo. An., 30, 191–216.

Kwan, M.-P. (1999). Gender and individual access to opportunities: A study of space–time measures. The Prof. Geo., 51, 210–227.

Kwan, M.-P., Murray, A. T., O'Kelly, M. E. and Tiefelsdorf, M. (2003). Recent advances in accessibility research: Representation, methodology and applications. J. of Geo. Syst., 5, 129–138.

Kwan, M.-P., and Weber, J. (2003). Individual accessibility revisited: Implications for geographical analysis in the twenty-first century. Geo. An., 35, 341–353.

Miller, H. J. (2007). Place-based versus people-based geographic information science. Geo. Compass, 1, 503–535.

Neutens, T., Witlox, F., Van de Weghe, N., & De Maeyer, Ph. (2007a). Human interaction spaces under uncertainty. Transp. Res. Rec., 2021, 28–35.

Neutens, T., Witlox, F., Van de Weghe, N., & De Maeyer, Ph. (2007b). Space–time opportunities for multiple agents: A constraint-based approach. Int. J. of Geo. Inf. Sci., 21, 1061–1076.

Nicholls, S. (2001). Measuring the accessibility and equity of public parks: A case study using GIS. Managing Leisure: An Int. J., 6, 201-219.

Pirie, G. H. (1979). Measuring accessibility: A review and proposal. Env.and Plan. A, 11, 299–312.

Pooler, J. (1987). Measuring geographical accessibility: A review of current approaches and problems in the use of population potentials. Geof., 183, 269–289.

Talen, E. (1998). Visualizing fairness: Equity maps for planners. J. of the Am. Plann. Ass., 64, (1), 22-38.

Talen, E. and Anselin, L. (1998). Assessing spatial equity: An evaluation of measures of accessibility to public playgrounds. Env. and Plann. A, 30, 595-613.

Vickerman, R.W. (1974). Accessibility, attraction and potential: a review of some concepts and their use in determining mobility. Env. and Plann. A, 6, 675–691.

Wachs, M. and Kumagai, T.G. (1973). Physical accessibility as a social indicator. Soc. Plann. Sci., 7, 327–456.