Trips and their CO₂ emissions induced by a shopping center

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Abstract

Most of previous studies have focused on the entire trips in a geographic region, while few of them addressed those induced by a city landmark. To address it, this paper explores the trips and their CO₂ emissions induced by a shopping center from a time-space perspective and their usage in relocation planning. This is done by the mean of a case study in the city of Borlänge in mid-Sweden, where the trips, to the town’s largest shopping mall in its center, are examined. To do so, we adopt GPS tracking data of car trips that end and start at the shopping center. Thereafter, (1) we analyze the traffic emission patterns from a time-space perspective, where temporal patterns reveal an hourly-based traffic emission dynamics and spatial patterns uncover a heterogeneous distribution of traffic emissions in spatial areas and individual street segments. Further, (2) this study reports that most of the observed trips follow an optimal route in terms of CO₂ emissions. In this respect, (3) we evaluate how well located the current shopping center is through a comparison with two competing locations, and we conclude that the two suggested locations, which are close to the current shopping center, do not show a significant improvement in term of CO₂ emissions.

Keyword: GPS tracking data, trips, CO₂ emissions, relocation planning

Jel codes: L81, R11, Q51

1. Introduction

Studies on human trips have been revived during the recent years from many aspects. From the aspect of their relationship with the urban environment, geographers or urban planners have argued that a sustainable urban design or planning could reduce the number of trips or the miles travelled in order for an environment-friendly society (Barton et al. 1995, Banister and Marshall 2000, Stead and Marshall 2001). Particularly, using travel diary data, Giuliano and Narayan (2003) examined their relationship in the US and Great Britain, and they found that daily trip patterns are highly related to urban form. From the aspect of human mobility, physicists or statisticians have reported the scaling property or Levy flight characteristic of human travel length with respect to different modes of transportation (Brockmann et al. 2006, Rhee et al. 2011, Jia et al. 2012). From the aspect of human activity, geographers or statisticians have paid extensive attention to the investigation of urban dynamics via the mining of trip data. For example, Reades et al. (2009) examined the space-time dynamic of urban life for a better understanding of how a city functions, whereas Ahas et al. (2010) found the diurnal rhythm of city life and its spatial difference in Tallinn. Recently, Jia and Jiang (2012a) have explored the rhythm of urban area in Sweden using static points of GPS tracking data.

It is well known that trips consume energy regardless of transportation mode such as walking, biking or travelling by car or bus. The amount of energy cost is further related to the emissions of environmental pollutants, such as carbon-dioxide, nitrogen-oxide and particulates. Hence, to fulfill a low emission of pollutants, several studies have tried to
establish the relationship between trip patterns and transport emissions. For example, Redsell et al. (1988) reported that an average vehicle speed of 65 km/h could lead to the lowest consumption of energy for petrol cars. Besides, using data from the 1989/91 National Travel Survey, Stead (1999) suggested the usage of travel length as a proxy of environmental indicator or vehicle emissions because of its simplicity in collection and calculation, whereas Carling et al. (2012) have adopted the travel length as a proxy of CO₂ emission to examine the relocation of retail stores. These methodologies to estimate the traffic emissions are so simple that they do not consider other factors included in a trip, such as the travel speed, travel time, acceleration, or deceleration. Therefore, to meet these requirements, a few on-road vehicle emission models have been proposed in the literature, such as the IVE model (Davis et al. 2005), the LIISA model (Määttä-Juntunen et al. 2011), and the eco-driving model (Ando and Nishihori 2012).

The above studies are accompanied by advancements in the Internet and telecommunication, which witness the usage of digital media or mobile devices with GPS units for recording movement locations. With the availability of these GPS tracking data, we are granted a new chance to investigate the trips, which poses a significant difference from the conventional methods relying on questionnaires or diaries. The GPS tracking data not only allow us to perform a micro-analysis of the movement patterns, for example, an accurate measurement of CO₂ emissions, but also suggest a new way to assess the problem of relocation planning, which has attracted the attention of geographers or urban planners using many location models (Mirchandani 1990, Daskin 1995, Klose and Drex1 2005, Francis et al. 2009, Carling et al. 2012). Importantly, this thinking is in line with the novel idea on urban code (Mikoleit and Pürckhauer 2011) which aims to acquire knowledge from massive crowdsourced data for promoting a more sustainable urban development.

Most of the previous studies have focused on the trips in a geographic area, but few of them addressed those resulted from a city landmark and their usage on relocation planning. Therefore, this paper puts an emphasis on trips induced by a shopping center in an edge-of-town location in Borlänge, Sweden. Using GPS tracking data, it firstly analyzes the time-space patterns of CO₂ emissions induced by a shopping center, and then it puts an emphasis on evaluation of the location of the current shopping center from an energy-efficient perspective. Particularly, this paper aims to examine the following questions. (1) How do the CO₂ emissions induced by the shopping center change over time? (2) What is the spatial distribution of CO₂ emissions induced by the shopping center? And (3) how well is the current location of the shopping center in terms of CO₂ emissions? Or, are there other alternative locations that perform better than the current one? The answers to the above questions constitute the main findings of this paper, and they will definitely benefit to the studies in many other fields, such as landmark relocation planning, urban planning, and transportation design and management.

This paper is structured as follows. In Section 2, we introduce the trip data adopted and the measurements of their CO₂ emissions. In Section 3, we report the findings around the time-space dynamics of the CO₂ emissions induced by the shopping center. In section 4, we compare the observed trips with the optimal ones in terms shortest network distance and further evaluate how well located the current shopping center is in terms of CO₂ emissions. Finally, we draw conclusions in Section 5.

2. Trips and CO₂ emissions measurement
2.1 Trips
In this study, GPS tracking data were collected by volunteers equipped with BT-338X, a Bluetooth GPS data logger that is the combination of a GPS receiver and data logger with Bluetooth interface, from March 29 to May 15 in 2011 in three sites of Borlänge. Volunteers were recruited from four large sports associations dispersed in our study area with a high compliance and participation rate, and they attached the BT-338X to their private cars for around one week. This leads to a total number of 262,021 movement recordings contained in 258 GPS logger files with the removal of 5,402 invalid records due to the loss of GPS signal. Each volunteer records her/his information every 5 or 30 seconds when the GPS signal is received, and the information includes longitude (x), latitude (y), time (t), and velocity (v). The longitude and latitude are referenced by the World Geodetic System 84 (WGS 84) and measured with the accuracy of 5 meter according to the BT-338X user manual, whereas the velocity is measured with the unit of m/s.

To obtain the trip data, we have conducted three steps as follows. Firstly, we derive the purposive locations (Jia et al. 2012) from the GPS tracking data. Purposive locations refer to the locations with drastic change in time, distance or angle along the movement trajectories of individual volunteers. They can be identified as two categories including the large time interval locations and the tortuous locations. Secondly, a trip can be obtained by connecting one large time interval location or starting location to the next large time interval location or ending location (Figure 1). Thirdly, we extract the trip samples that start or end at the shopping center, from the entire trip data. Thereafter, we obtain a total number of 498 trips induced by the shopping center, which have a total travel length of about 2,481 Km from 151 volunteers. Further, we show a linear kernel density map of the trips induced by the shopping center in Figure 2, where the shopping center (known as Kupolen) is marked as a black triangle.

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![Figure 1: Illustration of identifying trips in a volunteer movement trajectory](image-url)
We further take a look at the statistical descriptions for the trip data. For the number of trips taken by one volunteer, we found that most of the volunteers have two trips during this period, which is fairly reasonable since most of the people would like to go to the shopping mall once a week. As shown in Table 1, during this period, around 50% of the volunteers have three trips or less, whereas 95% of the volunteers have seven trips or less. For the number of halts (tortuous locations which are short-time breaks during a trip to the shopping mall) and street intersections in a trip, we reported that 70% of the trips are direct trips to the shopping mall with an average number of 11 street intersections visited (Table 2), which is pretty reasonable since most of the people would prefer to optimize their trips with lower consumption of gas by having less stops and crossing less street intersections. In addition, as shown in Table 2, we found that few tips have a large number of halts and the corresponding large average number of street intersections. Therefore, it is assumed that most of the volunteers seemed to have a wise strategy in managing their trips to the shopping center in terms of low energy cost.

### Table 1: Distribution of the number of trips per volunteer

<table>
<thead>
<tr>
<th>Percentile</th>
<th>5</th>
<th>25</th>
<th>50</th>
<th>75</th>
<th>95</th>
<th>Mode</th>
<th>Min</th>
<th>Max</th>
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<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>7</td>
<td>2</td>
<td>1</td>
<td>12</td>
<td></td>
</tr>
</tbody>
</table>

### Table 2: Number of halts (tortuous locations) and street intersections per trip (Note: for the first column in this table, we can observe that 351 trips have zero halt with an average number of 11 street intersections visited)

<table>
<thead>
<tr>
<th>Number</th>
<th>Trips</th>
<th>Halts</th>
<th>Intersections</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>351</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>Number</td>
<td>126</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>Number</td>
<td>11</td>
<td>1</td>
<td>41</td>
</tr>
<tr>
<td>Number</td>
<td></td>
<td>2</td>
<td>49</td>
</tr>
<tr>
<td>Number</td>
<td></td>
<td>3</td>
<td>86</td>
</tr>
</tbody>
</table>

### 2.2 CO₂ emissions measurement

To estimate the energy cost of each trip quantitatively, we adopt the amounts of CO₂ emissions as a proxy in this study. CO₂ emission, as the most important greenhouse gas, is the
main causing factor of global warming and the consequent climate change. It is primarily caused by the combustion of gasoline fuels (Steed 1999), and hence, the more energy being consumed the more amounts of CO$_2$ being emitted. In addition, there are several models existing in the literature (Stead 1999, Oguchi et al. 2002, Davis et al. 2005) that can be used for the estimation of CO$_2$ emissions of vehicles. For instance, Stead’s model (1999) is so simple that it only considers the travel length, whereas Davis’ model (2005) is so complex that it adopts the binning technology with consideration of both the micro-working conditions of vehicles and the surrounding environmental factors like wind direction and road slope. Through comparison, Oguchi’s model is adopted in this study due to its neither simplicity nor complication, and importantly it is highly suitable for the GPS tracking trip data.

This model considers the instantaneous working conditions of an on-road vehicle, such as the speed change in terms of acceleration or deceleration, total travel time, and total travel length (Equation [1]), and it is specifically used for the gasoline-powered vehicles which also agree well with the situation in this study.

$$E(trip) = K_C \times (0.3T + 0.028D + 0.056\sum_{i=2}^{n}\delta_i \times (v_i^2 - v_{i-1}^2))$$

[1]

Where $E$ is the estimated CO$_2$ emission amount (Kg), $K_C$ is the CO$_2$ emission coefficient with the value 0.002322, $T$ is the total travel time (second), $D$ is the total travel length (meter), $v_i$ is the velocity at GPS location i (m/s), $n$ is the number of GPS locations in the trip, and $\delta_i$ is an indicator with value 1 ($v_i > v_{i-1}$) or 0 ($v_i <= v_{i-1}$). By applying this model to the trip data, we can calculate the amounts of CO$_2$ emitted by each trip, which is explored from a time-space perspective in the following section.

3. Time-space patterns of CO$_2$ emissions

In this section, we present the time-space patterns of CO$_2$ emitted from the trips induced by the shopping centre. Temporal patterns are examined through the changes of CO$_2$ emissions over time. Spatial patterns are investigated with the distribution of CO$_2$ emissions in spatial areas and street segments respectively.

3.1 Temporal patterns

Trips induced by the shopping centre may have dynamic properties in terms of the traffic CO$_2$ emissions occurred on street network over time. To examine this dynamic, the CO$_2$ emissions of trips are chopped and aggregated in a time slot, for example, one hour. Further, trips can be categorized as either in-trips to the shopping center or out-trips from the shopping center, and hence the corresponding CO$_2$ emissions are considered as in-traffic emissions and out-traffic emissions respectively. Therefore, we present the traffic emissions dynamics from the aspects of in-traffic emissions, out-traffic emissions and total traffic emissions on an hourly basis for both weekday and weekend.

On one hand, Figure 3a shows the temporal patterns on weekday, and the traffic emissions per hour are averaged over five weekdays from Monday to Friday. One observation from it demonstrates that there is a general pattern of the change of total traffic emissions over time. For instance, total traffic emissions start to rise around 10AM in morning and decline around 8PM in evening, among which there is one obvious peak occurred around 3PM in afternoon. Another finding is that there is a difference between the in-traffic emissions and out-traffic emissions with respect to the change over time. For example, in-traffic emissions come to a
peak around 3PM during afternoon, whereas out-traffic emissions go to a peak around 4PM during afternoon.

On the other hand, Figure 3b shows the temporal patterns on weekend, and the traffic emissions per hour are averaged over two weekends on Saturday and Sunday. Firstly, one common pattern shows that traffic emissions last from around 10AM in morning to around 5AM in afternoon regardless of total traffic, in-traffic or out-traffic. Secondly, for the emissions of total traffic and out-traffic, there are two clear peaks occurred around 12AM in noon and 4PM in afternoon respectively and one nadir appeared around 2PM in afternoon; for the emissions of in-traffic, the pattern seems to be relative stable compared with the other two patterns, and only one peak is observed around 4PM in afternoon. How the temporal patterns uncovered can be useful to the fields of traffic management or landscape design needs further investigation, but it is believed that they at least reflect the rhythm of the local residents to the shopping center which contributes to the study of human geography.

Besides, it is found that the temporal rhythm bears a remarkable resemblance with the real situation in terms of the opening hours for the shopping center. For instance, the shopping center opens from 10AM to 8PM during workdays, whereas it opens from 10AM or 11AM to 5PM for Saturday or Sunday. This suggests that the landmark or especially its marketing strategy has a non-trivial influence on the temporal dynamic of local traffic and the corresponding environmental emissions. However, they cannot tell us how the emission patterns induced by the shopping center distribute in space. To achieve this goal, spatial patterns are presented in the following section.

3.2 Spatial patterns
In this section, we continue to explore the patterns of CO₂ emissions in terms of their spatial distribution in areas and street segments respectively. It is important to identify the exact
potential market or service areas related to the location of a shopping mall or retail store in retailing or marketing research, but few researches have considered the CO\textsubscript{2} emissions from these potential areas. Similarly, in this study, due to the fact that CO\textsubscript{2} emissions are produced by vehicles traveling to the shopping center, it is also important to understand how CO\textsubscript{2} emissions distribute in individual street segments.

To investigate the distribution of CO\textsubscript{2} emissions in different areas, we firstly extract the origin and destination locations of all trips, and then we further remove the locations inside the shopping center. Secondly, using these locations, a kernel density map is produced to extract the spatial areas influenced by the shopping center. Thirdly, we assign the CO\textsubscript{2} emissions to each area by summing the emission values of the trips that start or end with this area. As shown in Figure 4, it is reported that a total of 32 areas with two landuse types are impacted by the shopping center, which includes residential landuse and commercial landuse (retail areas with a mixture of cars selling, restaurants, toy shops, and supermarkets). This indicates that two types of trips attracted to or from the shopping center can be identified, namely the ones directly coming from or going to home (note that most of the home locations of the volunteers are within the residential areas) and the others coming from or going to another interested place (e.g., retail stores). Besides, it is found that traffic emissions resulted from neighborhoods areas constitute around 67% of the total traffic emissions, whereas the ones resulted from retail areas constitute about 33%.

![Figure 4: Map of observed CO2 emissions from different areas visualized with three categories: low emission, medium emission, and high emission](image_url)

To explore the distribution of CO\textsubscript{2} emissions in individual street segments, we assign the emission value of each trip to the corresponding street segments according to Equation [2], which is similar to the process of a linear kernel density estimation.

\[
E(t_i, s_j) = \left(\frac{1}{\sum \text{dist}(t_i, s_j)} \ast (1-u) + \frac{\text{len}(s_j)}{\sum \text{len}(s)} \ast u\right) \ast E(t_i), \quad \text{dist}(t_i, s) < r
\]  

[2]
Where $t_i$ denotes a trip $i$, $s_j$ denotes a street segment $j$, $dist(t_i, s_j)$ is the nearest distance between $t_i$ and $s_j$, $len(s_j)$ is the length of $s_j$, $r$ is the bandwidth within which the street segments will be influenced by trip $t_i$, $u$ is a weight parameter to determine the relative importance of distance or length, $E(t_i)$ is the emission value of trip $t_i$, and $E(t_i, s_j)$ is the emission value assigned to the street segment $s_j$ by trip $t_i$.

Figure 5 displays a CO$_2$ emission map of the underlying street network. As the trips are induced by the shopping center, we can clearly observe that the emission values of street segments decrease gradually as their distances increasing from the shopping center. Besides, several roundabouts connecting streets with different directions are reported to have very large emission values. This map also gives us a scaling impression in terms of the distribution of the emission values among street segments, namely a majority of street segments have a very low emission value, whereas a minority of them have an extremely large emission value. Here, the heavy-tailed distribution of traffic emissions in street segments (Figure 6) is common to many other phenomena in the geographic space (Lämmer et al. 2006) or society (Jia and Jiang 2012a). These patterns may be interesting to the urban planners or marketing researchers. As for the urban planners, they may inspire another topic to evaluate the location of the current shopping center from an energy-efficient perspective, which will be elaborated in the following section.
Figure 6: Log-log plot of the CO₂ emissions (kg) in (a) trips (alpha=2.62, xmin=0.57, P=0.11) and (b) street segments (alpha=1.76, rate=1.10, xmin=0.053, P=0.90)

4. Optimal trips and evaluation of the shopping center
In this section, we primarily report the results on how well the current location of shopping center is from an energy-efficient perspective. To address this problem, two topics will be investigated sequentially. Firstly, the CO₂ emission of each trip is compared with the one of an optimal route in terms of shortest network distance. Secondly, based on the first result, the current location of shopping center is evaluated through a comparison with two alternative locations suggested in two scenarios.

4.1 Optimal trips with low energy cost
It is interesting to delve into the individual patterns of each trip, or we wonder if every trip is optimized by the volunteer. Optimization here means the trip should have a low emission of CO₂ or is energy-efficient. Our previous empirical findings (Section two) seem to suggest that most of the observed trips are optimized due to a small number of halts and street intersections visited. In reality, many other factors are considered to be important on shaping the optimization of trips, such as speed change like deep acceleration or deceleration, route choice in terms of travel time or length, and other extra physical factors including road slope and engine of car. However, in this study, we only consider the route choice behaviors of volunteers, and further we assume that volunteers would have a mental map to come up with a best route choice.

To test our assumption, we firstly calculate the shortest street network distance for each volunteer using the conventional Dijkstra algorithm, which is considered as an optimal route compared with the observed trip counterpart. Secondly, the CO₂ emission value of each optimal route is calculated with Equation [1], where the distance effect is updated and the speed and time effects are unchanged with respect to the observed trip. Finally, we conduct a correlation analysis between the emission values of observed trip and optimal route. The results are shown in Figure 7: Figure 7a shows a linear regression curve of their relationship with a high R-Square value equal to 0.96, and only five out of 498 trips are reported to be not energy-efficient; Figure 7b demonstrates a lognormal distribution of the deviated emission values from the regression curve, which suggests a way to select the top five outliers (Jiang 2012). Further, the top five observed trips are reported to have multiple halts. Therefore, we conclude that most of the observed trips are optimal ones.
4.2 Evaluation of the shopping center

As elaborated above, most of the trips are similar to the corresponding optimal ones in terms of CO$_2$ emissions. In other words, we can say that most of the volunteers follow a shortest network distance during their journeys to the shopping center. This guarantees that the shortest network distance can be adopted to model the human trips to a shopping center, which indicates to explore the relocation planning issue on the current shopping center. In particular, we need to know whether there are any other competing locations that the shopping center should be located to satisfy the demands of consumers so that the total CO$_2$ emissions are the minimum. This question is also the problem of evaluating the location of the current shopping center from an energy-efficient perspective. To cope with this problem, two strategies are proposed in this section.

The first strategy is to employ the p-median model (Mirchandani 1990) which aims to optimally allocate $P$ facilities among $Q$ demanding points such that the total distance from each demanding point to the nearest facility is minimized. In this context, it is to select one location $l$ among the street nodes $L$ (ending point of street segments) such that the total CO$_2$ emissions of the optimal trips induced from the observed 498 demanding points (origins or destinations of the trips) is minimized, and we give the objective function as follows.

$$\text{Min}_{l \in L} \left\{ \sum_{i=1}^{N} E(\text{trip}(q_i, l)) \right\}$$  \hspace{1cm} [3]

Where $l$ is the location of a street node, $L$ is the whole set of street nodes, $N$ is the number of demanding points which equal to 498, $q_i$ is the $i^{th}$ demanding point, $\text{trip}(q_i, l)$ is the shortest network distance from $q_i$ to $l$, and $E(\text{trip}(q_i, l))$ is the CO$_2$ emission of the trip. By applying this method to our 498 demanding points, we obtain the suggested location $\tilde{l}$ (black triangle in Figure 9) which is located very close to the current shopping center with about 300 meters. Besides, we assign CO$_2$ emissions of all simulated trips to the corresponding street segments using equation [2] (Figure 8). Compared with emissions from the current shopping center (Figure 5), the emissions from this new location are more concentrated in a small number of street segments although there is a 9% decrease in terms of the total CO$_2$ emissions ($(389 - 354) / 398$).
However, the street network is not homogeneous in its structure with respect to the importance of street node. For instance, some nodes may act a more important role than others in terms of the accessibility. Therefore, the second strategy is to adopt the weighted p-median model which considers the relative importance of the street node. Here, the importance of a street node is measured with a network metric Betweenness, which is defined as the number of shortest paths between any two nodes that pass through the current node and reflects the accessibility of the current node within the network (Jia and Jiang 2012b). Generally, it is defined as follows.

\[ b_i = \sum_{m \neq i \neq n} \frac{\text{Path}(m, i, n)}{\text{Path}(m, n)} \]  \[4\]

Where \( \text{Path}(m, i, n) \) is the number of shortest street network paths through node \( i \) from node \( m \) to \( n \), and \( \text{Path}(m, n) \) is the number of shortest street network paths from node \( m \) to \( n \). We show a kernel density map of the Betweeness value of each street node in Figure 9, where an observation is that the areas close to the current shopping center have the highest level of accessibility.
Hence, by taking into account of the accessibility of street nodes, the weighted p-median model is given as the following objective function.

\[
\min_{l \in L} \left( b_l \sum_{i=1}^{N} E(\text{trip}(q_l, I)) \right)
\]

[5]

Where \( b_l \) is the Betweeness value of a street node \( l \), and other parameters are the same as the ones in [3]. Again, by applying this method to the 498 demanding points, we found that the suggested location is also located very close to the current shopping center with about 320 meters. Further, we found that this new location is along the street of Gjutargatan where the urban land is now under construction for an IKEA shopping mall. Assigning the emissions of the simulated trips to the corresponding street segments, we can obtain an emission map shown in Figure 10 which displays an intermediate pattern between Figure 5 and Figure 8 in terms of the concentration of emission on the street segments. In addition, the total estimated \( \text{CO}_2 \) emissions is about 357 Kg which indicates an 8% \(((389 - 357) / 398)\) decrease compared with the current shopping center.
Figure 1: Map of CO₂ emissions in individual street segments induced by the new location obtained from weighted p-median model.

5. Conclusions

This study investigates the trips and their CO₂ emissions induced by a shopping center using GPS tracking data. The results uncover a time-space dynamic patterns of CO₂ emissions from the trips. Particularly, the temporal patterns suggest a rhythm of traffic emissions which coincides well with the opening hour of the shopping center; whereas the spatial patterns indicate an uneven proportion of traffic emissions from spatial areas with different landuse types and a heterogeneous emission distribution in individual street segments. On the other hand, it is reported that most of the observed trips seem to be the optimal ones in terms of the shortest network distance. In this respect, the shortest network distance is adopted as a proxy of human trip to simulate the trip patterns induced by other competing shopping locations. This motivates us to further explore the rational of the current shopping center location in terms of CO₂ emissions. Consequently, two competing locations are suggested by the applications p-median model and weighted p-median model, and both of them are close to the current location of shopping center with a decrease of 9% and 8% CO₂ emissions respectively.

This study suggests the usage of crowdsourced GPS tracking data to investigate the issues related to the dynamics of traffic CO₂ emissions and the relocation planning in urban systems. GPS tracking data show several advantages compared with the conventional human diary or questionnaire data in transportation research, for instance, they are time-saving and economical. In addition, this paper is inspired by the idea in urban code which aims to uncover novel urban patterns from massive crowdsourced geospatial data. As far as we know, this paper is the first to bear this idea to explore the patterns of traffic CO₂ emissions induced by a shopping center from a time-space perspective and their usage in relocation planning, which might establish an empirical benchmark in this field.

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