CO_2 emission from passenger travel in Guangzhou, China: A small area simulation

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Abstract: Urban passenger travel is a major source of greenhouse gas emission. For China, understanding how passenger transport CO_2 emission varies within cities is constrained by data availability, which limits development of mitigation policies and interventions targeted at specific areas or populations. We address this problem by applying an improved bottom-up methodology to provide temporal and spatially resolved estimates of daily passenger transport CO_2 emission for urban Guangzhou. Drawing on sample census data we develop a spatial microsimulation of the population, which applied with an activity diary survey allows spatial simulation of the synthetic population's daily travel and transport CO_2 emission at the sub-district scale for workday and weekend, respectively. Point-of-interest (POI) data is used to quantify the connection between urban form, passenger travel and transport CO_2 emission. Results show that people residing in the compact city centre make shorter trips, have more non-motorised travel and emit less CO_2 on both workday and weekend. In contrast, residents of newly developed urban areas and remote districts, characterised by low population and employment density, and poor accessibility to facilities and services, travel further generating more CO_2 emission on a typical workday, but exhibit significant variation between workday and weekend. The microsimulation approach presents greater insight into the micro-scale spatio-temporal variability of passenger transport CO_2 emission in a Chinese mega-city than has previously been possible.

Keywords: Spatial microsimulation, urban passenger travel, transport CO_2 emission, small area simulation, urban form, Guangzhou

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Introduction

China's rapid urbanisation and motorisation have led to serious problems over the last decade, including dramatic growth in energy consumption, CO_2 emission, and air pollution (e.g. persistent smog) and its associated health impacts. The road transport sector represents the fastest growing source of greenhouse gases (GHG's) in China, mainly due to a rapid growth of vehicle population, travel demand and inefficient fuel combustion (Wang et al., 2007). Zheng et al. (2015) estimated that China's road transport CO_2 emissions increased more than seven-fold from 1990 to 2013, compared to an average five-fold increase for other economic sectors. Zhang and Nian (2013) forecast a 43% increase in global transport energy to 3260 million tonnes of oil equivalents (Mtoe) in 2035, of which China will account for more than 30%. Urban passenger travel is the main source of the transport-related CO_2 emissions. Hao et al. (2014) estimated that in 2010 China's urban passenger transport accounted for 2815 billion passenger kilometres of motorised travel, 77 Mtoe fuel use, and 335 Mt CO_2 equivalent lifecycle GHG emission. Moreover, as China expects continuous urbanisation and increase in car use over the next few decades, passenger travel will grow rapidly with effects on energy consumption and CO_2 emission, and the road transport sector will in future dominate China's emission inventory (Wang et al., 2007).

Reducing transport CO_2 emission is thus a major challenge for China, one that can be more easily tackled with a better understanding of the spatial distribution of carbon emission and the travel behaviour that shapes it (Ma et al., 2015). However, as China has no national travel survey, and energy data are published at a relatively coarse geography, prior studies have resorted to aggregate data, such as total energy use or registered vehicle population reported in the Chinese Statistical Yearbook, to estimate transport CO_2 emission, at national and regional level (e.g. Dhakal, 2009; Hao et al., 2014). Little research has used disaggregate travel attribute data to estimate transport

CO_2 emission for finer geographical scales, although such analyses are clearly important in supporting targeted interventions to reduce emissions.

Spatial microsimulation creates large-scale synthetic populations that realistically match attribute profiles of real populations at various geographical levels, and thus represents a useful technique to overcome limitations imposed by a lack of geo-coded micro datasets (e.g. Harland et al., 2012; Hermes & Poulsen, 2012). It offers great potential for transport planners and policy makers who lack access to travel survey data, or individual-level data at fine geographic resolution (Lovelace et al., 2014). Using individuals or households as the basic analytical unit, a spatial microsimulation model can generate disaggregate estimates or forecasts at a micro scale, and can also perform 'what-if' simulations to assess the impacts of policy or planning interventions in specific areas or on targeted populations (Ballas & Clarke, 2001). Spatial microsimulation has been applied in geography and social sciences in developed countries, but has been little used to simulate urban passenger travel and its emissions, or to explore geographic variation and evaluate transport policies (Lovelace & Philips, 2014; Ma et al., 2015). Partly due to a lack of supporting data, microsimulation studies are rare in developing countries, including China, where travel patterns are often highly complex and where problems of traffic congestion, carbon emission and air pollution are particularly serious (Ma et al., 2014).

To address this challenge, this paper shows how microsimulation can be applied to provide improved spatially resolved estimates of urban passenger transport CO_2 emission. Drawing on sample census data we develop a spatial microsimulation of the population, which applied with an individual-level activity diary survey allows the spatial simulation of the synthetic population's daily travel and CO_2 emission at the sub-district scale, for both workday and weekend. Data limitations have meant prior studies have relied on a 'top-down' approach to estimate national and regional scale transport emissions. In contrast, the microsimulation based 'bottom-up' approach enables greater insight into the micro-scale spatio-temporal variability of transport CO_2 emission for a Chinese mega-city than has previously been possible. It also provides a basis from which to improve understanding of the relationship between transport CO_2

emission and urban form characteristics that can better inform planning of Chinese cities.

Background

Travel behaviour and GHG emission

People's travel behaviour, including mode choice and distance travelled, is an important influence on passenger transport CO_2 emission. There is growing emphasis on the connections between individual's daily travel behaviour, GHG emission and global climate change (Barr & Prillwitz, 2012), with some research analysing variation of individual daily travel behaviour and associated carbon emission at the disaggregate level. For instance, using a travel survey with a sample of 456 individuals in Oxfordshire, UK, Brand and Boardman (2008) proposed a method to profile annual GHG emission from personal daily travel across various transport modes. Results showed that air and car travel dominated GHG emissions, and that emissions from the population were unequally distributed, with the top 10% of emitters responsible for 43% of emissions and the bottom 10% for only 1%. Brand and Preston (2010) further profiled UK GHG emissions for non-business-related passenger travel across multiple modes, and found a "60-20 emission" rule operated, stable across several scales, with the top 20% of emitters producing 61% of emissions.

Studies investigating the impact of urban form on travel behaviour and carbon emission are widespread (Anderson et al., 1996; Ewing & Cervero, 2010). For example, using a 1998 Dutch housing survey, Grazi et al. (2008) examined the impact of urban density on commuting behaviour and CO_2 emission, and found that higher density areas had lower car based carbon emissions. Lee and Lee (2014) investigated the relationship between urban form and household carbon emission in the 125 largest urbanised areas of the U.S., and found that doubling population-weighted density reduced CO_2 emission from household travel by 48%, while doubling per capita transit subsidy could reduce vehicle miles travelled (VMT) by 46% and transport carbon emission by 18%. Such studies are illustrative of prolonged efforts to understand the role of urban form in urban travel and emissions, and in particular to demonstrate the advantages of the compact urban form, yet the effect of form remains contested. For example, based on the 2001 National Household Travel Survey data in the U.S., Brownstone and Golob (2009) explored the impact of residential density on vehicle use and energy consumption in California, and reported significant correlations between density, travel and energy use, yet using the same data, Liu and Shen (2011) found urban form did not significantly affect VMT or energy use. Debate over the relationship between urban form and travel remains vigorous and contested (see e.g. Ewing & Cervero, 2017; Stevens, 2017).

In addition to daily travel behaviour, studies also analyse how leisure and holiday travel affects transport carbon emission. Drawing on the German national transport survey, Reichert et al. (2016) examined the variation in GHG emissions from daily and long-distance travel. Results showed that residents in rural and suburban areas had higher GHG emissions from daily travel, but lower for long-distance travel than urban residents; however, people living in densely populated cities cumulatively emitted less CO_2 from all trips than their counterparts. Using focus groups and a survey of 1500 residents in Southwest England, Barr and Prillwitz (2012) explored attitudes and decisions explaining daily, leisure and holiday travel. Different lifestyle groups had very different travel behaviour, particularly with respect to holiday travel, hence they concluded that measures intended to reduce travel carbon must be adapted to fit lifestyle groups.

Much passenger travel carbon research adopts a 'bottom-up' approach in which emissions are estimated from disaggregated attributes, such as trip frequency, travel distance, mode choice and mode specific emission factor (Liu et al., 2017). Studies mainly investigate the relationships between travel behaviour and GHG emission at the individual level, and thus can differentiate emissions by mode and social group. However, sample sizes in these studies are relatively small, hence unsuited to estimation of spatial variation in passenger transport CO_2 emission within cities. Detailed travel information for larger populations is often unavailable in many countries, particularly in developing economies such as China.

Spatial analysis of GHG emission

Due to data limitations at a micro scale, studies often adopt a 'top-down' approach to estimate total energy consumption and GHG emission at the national scale, or to examine the spatial and temporal distribution of GHG emission by region or metropolitan area. Typically, aggregate VMT statistics, fuel consumption and total population at broad (national or regional) scales are used to produce generalised emission estimates (Hillmer-Pegrama et al., 2012). For instance, based on national statistics for the vehicle fleet, VMT and fuel economy, He et al (2005) explored the current and future energy consumption and GHG emission from road transport at the national scale for China. For the provincial scale, Huang and Meng (2013) estimated total energy use and carbon emission using National Bureau of Statistics of China national and provincial energy data. They then downscaled these emission estimates to distribute them to urban areas, using regression models. However, results are tentative due to uncertainty in the statistical yearbooks' data and for the assumption of a linear relationship between GDP and GHG emission used for each province (Huang & Meng, 2013).

Loo and Li (2012) found that the spatio-temporal distribution of road transport CO_2 emission in China had become more uneven from 1988 to 2008, with most emission concentrated in the more developed provinces (e.g. Beijing and Guangdong), with much lower emission growth in the less developed western regions (e.g. Qinghai and Ningxia). Clarke-Sather et al (2011) supported this conclusion of geographical disparity across China, finding that GHG emissions from the eastern regions are much higher than from westerns regions and inequality in per capita CO_2 emission reflects the inequality in per capita GDP at the interprovincial scale.

Some studies have applied remote sensing to investigate the spatio-temporal evolution of carbon emission fluxes induced by land use and land cover change (Evrendilek et al., 2011; Sohl et al., 2012). However, as spatially resolved travel data for large populations is generally unavailable in many developing countries, including China, these, like other 'top-down' analyses continue to focus on the spatial distribution of GHG emission at aggregate national or regional scales, and so are unable to provide a more incisive analysis at finer geographic resolution needed to inform urban planning and specific development policies (Güneralp & Seto, 2012).

Spatial simulation at a micro level

Developing a more fine-grained understanding of the spatial distribution of individual travel and carbon emission and the spatial effects of interventions is important for research and policy. However, due to confidentiality issues, spatially resolved microdata sets with a wide range of individual characteristics are rarely publicly accessible in many countries (Ballas & Clarke, 2001). Mining of 'Big Data' offers promise in terms of a more disaggregate analysis of travel behaviour (Cai & Xu, 2013; Cai et al., 2014), yet issues of partial, incomplete and inconsistent data, data standards and integration, and privacy continue to pose challenges. There remains a strong demand for the development of small area estimates of individual behaviour and the potential effects of urban planning and transport policies, which could guide government acquisition of detailed information at fine geographic scale, better allocate limited resources to specific places, and evaluate the impacts of policy decisions (Harland et al., 2012).

Spatial microsimulation, aimed at generating large-scale microdata sets on individual or household attributes at fine geographic scale, allows the investigation of spatial heterogeneity of the distribution of individual-level populations and of potential policy impacts (Ballas & Clarke, 2001). It has been used to generate small-area income distributions (e.g. Birkin & Clarke, 1989; Tanton, 2011), forecast activity-travel demand (e.g. Veldhuisen et al., 2000; Miller et al., 2004), and simulate small area health-related behaviour or outcomes, such as smoking or obesity respectively (e.g. Tomintz et al., 2008; Koh et al., 2015). Using the person or household as the basic analytical unit, microsimulation represents an effective method for explicitly replicating disaggregated travel behaviour for travel demand forecasting and transport policy analysis, with various models developed since the 1990s simulating the temporal, spatial and modal decisions of individual-level populations (Kitamura et al., 2000).

Understanding the combined effects of land use and transport on energy use and GHG emission is of particular interest in urban planning and policy development. For two decades, there has been growing attention on the use of microsimulation in this area, including the models UrbanSim in the U.S. (Waddell, 2002) and ILUTE (integrated land use, transportation, environment) in Canada (Miller et al., 2004). ILUTE has been developed to simulate regional energy use and carbon emission from the transport sector through integration with TASHA (Travel/Activity Scheduler for Household Agents) (Hao et al., 2010), and illustrates how microsimulation of urban individual and household agents offers a means of predicting energy use and carbon emission. Recent spatial microsimulation models estimate energy use and emission at finer geographic resolution. For instance, Lovelace and Philips (2014) simulated the geographic and social distribution of the threats posed by peak oil on commuters in Yorkshire, UK, and found that rural areas had the highest vulnerability to oil scarcity.

To conclude, due to data limitations, many studies adopt a ‘top-down’ approach to GHG emissions estimation at the aggregate national or regional scale. Research using a ‘bottom-up’ approach to estimate passenger transport CO_2 emission from a large population’s daily travel behaviour at a micro scale has been scarce to date, particularly for developing countries, where transport and environmental issues are serious. Ma et al. (2014) developed the first spatial microsimulation model of passenger travel emission for a Chinese mega-city. Using a 2007 activity diary survey and 2000 population census data, a spatial microsimulation model was used to estimate a realistic synthetic population’s daily travel behaviour and transport CO_2 emission at the sub-district scale in 2000 for urban Beijing. However, the study has some limitations in that only workday travel was simulated (thus neglecting important weekend leisure and other trips), hence the temporal variation of passenger travel emission could not be investigated, as residents differ in their activities and travel patterns between workday and weekend. Moreover, variables on spatial location that can be expected to significantly influence urban passenger travel were not considered, which might lead to biased estimation of transport CO_2 emission at the disaggregate level.

In this study we make methodological advances on previous work, and further develop the spatial microsimulation framework by taking into account housing variables (e.g. building age as a proxy for spatial location) as the constraints in the microsimulation model, as housing of different types and age are mainly located in different areas in Chinese mega-cities (Liu et al., 2017). Controlling for these variables should generate a more accurate simulation of urban passenger travel and an improved estimation of transport CO_2 emission at the disaggregate level. Moreover, in recognising differences between workday and weekend travel patterns, we simulate a large synthetic population's daily travel behaviour and passenger transport CO_2 emission at the urban sub-district level at finer geographic and temporal scale than has previously been possible. This provides a more incisive analysis of the integration of urban form, transport and emission at a micro scale to inform low carbon city planning and transport policies in Chinese mega-cities.

Methodology

Study area

We develop our spatial microsimulation model for Guangzhou the capital of Guangdong province, and China's third largest city. Its proximity to Hong Kong, Shenzhen, and access to international markets via the Pearl River meant that Guangzhou was able to quickly benefit from Deng's Economic reforms and openness policy initiated in the 1970s. Guangzhou has undergone land and housing marketisation, and rapid urbanisation with increasing travel and emissions, yet lacks publicly available spatially resolved data from which to estimate transport emission at intra-urban scale. We focus on urban Guangzhou (Fig.1) which comprises historical and urbanised districts including Liwan and Yuexiu within the inner ring road, new urban districts of Tianhe and Haizhu where industrial enterprises, foreign investment, hi-tech firms and housing development have mainly located since 2000, and the inner suburban and remote urban districts including Baiyun, Huadu, Panyu, and Huangpu[1] (Xie & Ning,

[1] In 2014, Luogang and Huangpu districts were merged into new Huangpu district by the Guangzhou government.

2004). These areas accounted for 80% of all registered households in 2010 (Guangzhou Statistical Yearbook, 2011), and include the neighbourhoods where activity travel survey participants were mainly drawn from (Fig.1).

[Insert Figure 1 about here]

Data

To overcome the lack of national travel data we draw on a 2013 travel diary survey. Eighteen neighbourhoods were surveyed (Fig.1) providing a representative sample based on location characteristics, household and individual level socio-demographic attributes, and a wide range of historical, institutional and spatial features of Guangzhou's urban districts. This includes all the housing types in the city, comprising self-built housing, *danwei* compounds, commodity housing, affordable housing, and mixed residential areas. Continuous activity-travel records were collected for a Monday (representing a workday) and a Sunday (representing the weekend), measured by a set of questions on travel behaviour characteristics, such as "how many trips did you make last Monday or Sunday?", "what was the start and end time for each of your trips?", "which transportation mode (e.g. walking, bus, subway, private car) did you use for each trip?" and "what is the address of each trip destination or activity location?". Our analysis addresses 1605 randomly selected individuals who returned a valid self-administered questionnaire, which contains information on housing, household and individual socio-demographics, and complete activity-travel records, including activity type, trip frequency, mode choice, and travel distance calculated by the Euclidean distance between two consecutive activity locations.

A second major data set used is the 2010 sixth population census of Guangzhou, which comprises the short form census all people must complete, addressing household and individual socio-demographics, and the long form census that is a 10% stratified sample (comprising 927,855 residents aged >15 in the urban districts), randomly selected in each area, that adds data on economic attributes, housing characteristics, employment, occupation, housing area and tenure. We use the 10% sample, which has richer demographic data, as our target population in the spatial microsimulation model. Table 1 summarises data for the key socio-demographic and housing variables common to the travel survey and population census. These variables have previously proved to be important predictors of daily travel behaviour and transport emission (e.g. Ma et al., 2014).

[Insert Table 1 about here]

Finally, fine-grained point-of-interest (POI) data on diversified urban form characteristics are also employed to quantify connections between spatial location, urban passenger travel and transport CO_2 emission. The POI data for Guangzhou in 2014 was purchased (from Daodaotong who provide map data for Baidu, China's most used search engine) and geocoded, which details the location and attributes of 15 major economic activities and 65 sub-categories, including factories, offices, restaurants, shops, hospitals, health care centres, research institutions and so on. These data were used to derive multi-dimensional measures, including population and employment densities, road density, and land use mix, to represent the diversified urban form features at fine (sub-district) scale (Fig.2). They enable the association of built environment characteristics and travel behaviour and transport emission to be explored (see below).

[Insert Figure 2 about here]

CO_2 emission calculation and comparison

Drawing on the travel diary data, we employ a bottom-up approach to estimate transport CO_2 emission for each of the 1605 individuals for both workday and weekend. An individual's travel CO_2 emission is a function of travel distance by travel mode and a mode specific CO_2 emission factor:

$$Carbon_w = \sum_{i=1}^{m} Distance_{iw} \times Factor_i \quad (1)$$

where $Carbon_w$ represents individual CO_2 emission from travel on a typical day (w refers to workday or weekend), $Distance_{iw}$ is the distance travelled in trip i during the workday or weekend, m the number of trips, and $Factor_i$ the emission factor for the travel mode in trip i (g CO_2 per person per km, derived from Grazi et al (2008)). China has not officially published vehicle CO_2 emission factors hence we acknowledge the uncertainty in these fleet-averaged emission factors, which take no account of travel speed variation or road condition (Ma et al., 2015).

We next compare travel behaviour and emission by socio-demographic group and housing category on the basis of the travel diary survey (Table 2). Generally, men, people with high educational attainment, and the employed travel further, make fewer non-motorised trips and emit more CO_2 on a typical workday, whilst at the weekend it is men, older people (aged 65 and above), people with high education attainment and the unemployed who travel longer distances and emit more CO_2 than their counterparts. Differences in travel behaviour and emission by socio-demographic group are more substantial and significant on a workday than at the weekend (Table 2).

[Insert Table 2 about here]

Considering household level attributes, we find that people with a larger home, or in purchased commodity housing have a longer travel distance and generate higher emissions than their counterparts; such differences are substantial and significant both on workday and at weekend. With respect to building age, people resident in housing built after the 1990s generally travel further, have fewer non-motorised trips and higher emission on both workday and weekend. This is probably because old housing, particularly which built before 1979, primarily has an inner city location, characterised by a high population density, mixed land use and proximity to various facilities (Fig.2). In contrast, housing built after the market reform of the 1990s is mainly located in the suburbs and outer urban districts with relatively low job density and accessibility to public transit (Zhou et al., 2015; Liu et al., 2017). Building age thus partly reflects the geographical and locational features of the residents.

Synthesising small area population

The estimates of individual level CO_2 emission are then scaled to the target population in urban Guangzhou, according to corresponding household and individual level socio-demographic attributes. As observed data on the full population is unavailable, we use spatial microsimulation to synthesise the population, drawing on the long form 10% sample census. Before running the spatial microsimulation model, we conduct a series of correlation analyses and regression models to examine associations of household and individual socio-demographic attributes and travel behaviour, including travel distance and carbon emission. Variables in Table 2 have significant influences on travel behaviour and transport CO_2 emission. They are common to the travel survey and population census which allows the use of tabulations at the urban sub-district (*jiedao*) scale to act as constraints of the microsimulation model which synthesises Guangzhou's population by small area, each with all the characteristics of the target population.

Established techniques used to create small area synthetic populations comprise deterministic reweighting, conditional probabilities (Monte Carlo sampling) and simulated annealing (see Harland et al (2012) for a critical review). Our population microsimulation used the Flexible Modelling Framework (Harland, 2013), which incorporates a static spatial microsimulation algorithm based on simulated annealing, a combinatorial optimisation approach shown to more accurately reproduce population microdata at various geographical scales (Voas & Williamson, 2000; Hermes & Poulsen, 2012). This framework incorporates the Metropolis Algorithm allowing both backward and forward stepping in the search for an optimal population configuration, selected from the travel survey data constrained by observed aggregate population census counts. The synthesised population is thus a realistic spatial representation of the target population aligning closely to the constraining tabulations while maintaining the rich variety of attributes contained in the travel survey samples (Ma et al., 2015).

As the outputs of the spatial microsimulation model are estimates of unknown data, the generated synthetic population is evaluated via goodness-of-fit testing. Absolute and relative measures include Total Error (TE), Percentage Error (PE), Cell Percentage Error (CPE) and Standardised Root Mean Square Error (SRMSE) (Smith et al., 2009; Harland et al., 2012), whilst the most frequently used statistic is the Total Absolute Error (TAE), which is easily calculated and understood, and subject to the total population sample (Voas & Williamson, 2001):

$$\text{TAE} = \sum_i \sum_j | T_{ij} - E_{ij} | \tag{2}$$

where T_{ij} and E_{ij} are the observed and simulated counts respectively for the cell at ij.

Table 3 presents the goodness-of-fit statistics for the Guangzhou population microsimulation, which reveals a very good overall fit. Most of the constraining tabulations at the sub-district level are reconstructed with very little or no misclassification, demonstrating the synthetic population very closely matches the observed census data.

[Insert Table 3 about here]

Finally, we link travel attributes (e.g. distance, mode choice) from the diary survey to the corresponding population sub-groups in the synthesised population to spatially simulate the population's travel behaviour on both workday and weekend, and hence estimate their transport CO_2 emissions at the sub-district scale for 2010. However, as information on modal split is not included in the population census data and thus cannot be used as a constraint in the microsimulation model, it is unable to provide accurate estimation of mode-specific CO_2 emission at the fine geographic level. We focus on simulating the individual-level CO_2 emission from urban travel based on a complete account of travel activities and mode choice during the workday and weekend for a large synthetic population at the urban sub-district scale in Guangzhou.

Results

Travel behaviour

The simulated travel behaviour of the synthetic population agrees well with observed data and additionally provides insight into geographic variability at the sub-district scale. Our simulation shows that the average travel time is approximately 62 minutes per person on a typical workday (56 minutes at weekend) in 2010, consistent with the 65 minutes per person per day reported by Jiang et al. (2014) using a 2011 household travel survey of Guangzhou. Figs. 3-5 show (by quartile) the average travel distance of the population in each sub-district, and their average and total transport CO_2 emission. Significant variation in travel behaviour and carbon emission is evident across Guangzhou, and between workday and weekend.

For Guangzhou as a whole, travel distance is approximately 7.6 km per person on a typical workday compared to 6.2 km per person at weekend, suggesting that work based commuting trips exceed leisure and retail based travel. Residents of the traditional old town city centre sub-districts (Yuexiu and Liwan) do not travel as far (Fig. 3) presumably as the centre has a high density of people and jobs, mixed land use, and good accessibility to facilities and services (Fig. 2). A higher than average percentage of trips are taken by public transit and non-motor modes (walk and bicycle). These observations are consistent with those for another of China's mega-cities, Beijing, where inner city resident's daily travel is also shorter than that of suburbanites (Qin & Han, 2013; Ma et al., 2014). Effects of such urban compaction, in terms of travel behaviour, have similarly been identified in developed countries (e.g. Ewing & Cervero, 2010, 2017).

[Insert Figure 3 about here]

In contrast, residents of new urban districts, such as Tianhe and northern Haizhu, travel further on a workday, with a slight variation at weekend from the workday. Residents of Tianhe, developed as Guangzhou's new CBD are mostly white-collar workers highly reliant on private cars, while residents in northern Haizhu, where many high priced river-view houses are located, work in the traditional city centre or Tianhe. Residents of these new urban districts tend to travel further than those of the inner city on both workday and weekend (Fig. 3). An above average share of trips are taken by motor vehicles.

People living in more distant urban areas, such as Huadu, Huangpu and northern Panyu, travel further on a typical workday, but exhibit significant variation between workday and weekend. For instance, people from Huangpu do not travel as far at weekend, while those resident in many sub-districts of Huadu travel further on workdays and particularly at the weekend. This is possibly because with rapid urban expansion and spatial restructuring, Huangpu has developed as a new sub-centre of Guangzhou (Zhou et al., 2015). Thus although people resident here must travel further to the city centre for work during the weekdays, they can meet their non-work needs (shopping, leisure) nearby at weekend. This situation is quite different in the remote district of Huadu, which only became an urban district of Guangzhou in 2000. This area has low employment density, mono-functional land use (e.g. dormitory development) and poor access to various facilities and services (Fig.2), with residents having to travel further to other areas for both work and non-work activities (Fig. 3).

Carbon emission

Modelled CO_2 emission from urban travel in 2010 at the sub-district scale is shown in Fig. 4. On average, travel-related CO_2 emission is 420 g per person on a typical workday and 407 g per person at weekend. Geographic variation in transport CO_2 emission is also evident. Residents of Yuexiu and Liwan in the compact central area have lower CO_2 emission on both workday and weekend, as trips are shorter with a higher share of non-motorised trips. In contrast, residents of the new urban districts, including Tianhe and Haizhu, and the remote districts of Huadu, Baiyun, and northern Panyu, have higher CO_2 emission on a typical workday (with slight variation at weekend), mainly due to their longer travel distance and greater use of motor vehicles. For the sub-centre of Huangpu and the southern areas of Panyu, average CO_2 emission is much lower at weekend than on workday, probably as residents need to travel less for non-work weekend activities.

[Insert Figure 4 about here]

Total CO_2 emission from the synthetic population is calculated across the urban sub-districts of Guangzhou for 2010, through multiplying the total population (a 10% sample of all people aged 15 or above) by the average CO_2 emission in each area. This further helps to identify areas where spatial planning or transport interventions are needed to encourage lower carbon city development. As shown in Fig.5, the total CO_2 emission from urban passenger travel in the compact central area of Yuexiu and Liwan is much lower than other districts on both workday and weekend, although the population density in these urban districts is relatively high (Fig.2). In contrast, total CO_2 emission from urban travel in the south of Tianhe and west of Haizhu is very high, more than 3,510 kg on a typical workday, which is possibly as the population density and average CO_2 emission are both high in these geographic zones. With respect to other districts, the total transport CO_2 emission from the synthetic population in sub-districts of Huadu, Baiyun, and Panyu is also very high on both workday and weekend. This is possibly because people living here travel further and generate more CO_2 emission both on workday and at weekend, as the population density in these remote urban districts is relatively low.

[Insert Figure 5 about here]

Discussion and conclusion

China is currently experiencing a rapid increase in its motor vehicle fleet and travel demand, and emissions from passenger transport represents one of the fastest growing GHG sources in China (Wang et al., 2007). However, due to data limitations, most studies adopt a ‘top-down’ approach to estimate transport emission based on aggregate energy consumption data at a broad national or regional scale. Although using disaggregate travel attributes (e.g. VMT, mode choice) to analyse GHG emission at a micro scale offers major advantages over the aggregate approach, little research uses such a 'bottom-up' approach, including that in China, mainly due to a lack of the necessary data to support such fine-grained analysis (He et al., 2013). Developing mitigation policies and interventions targeted at specific areas or populations in China is commonly constrained by data availability which limits understanding of passenger transport CO_2 emission variation within cities.

Using an activity diary survey in 2013 and the population census data in 2010, we applied an improved bottom-up approach to provide an improved estimate of transport CO_2 emission from passenger travel on both workday and weekend for urban Guangzhou in 2010, and at finer geographic and temporal scale than has previously been possible. This was achieved through a sub-district spatial microsimulation model of the synthetic population's daily travel. Our microsimulation provides insight into the geographic variability of people's urban travel and carbon emission on both workday and weekend, and the associations with sub-district level built environment characteristics. This approach enhances the potential for low carbon land use and transport planning and policy targeted at specific areas and populations.

Given the absence of travel or energy consumption data at small area scale in China, our study develops a spatial microsimulation model, but uses limited data which introduces some constraints. The travel survey does not cover all districts, and we assume that travel behaviour in the remaining outlying districts (Zengcheng, Conghua, and Nansha) is not well represented by travel in the urban districts, hence we limit our microsimulation to urban Guangzhou, rather than the entire urban region. Furthermore, the travel distance derived from the activity diary survey is calculated for out-of-home activities based on Euclidean distance, which likely underestimates trip distances, and hence transport emissions. GPS survey data could in future be used to derive travel distance sensitive to the road network.

As the spatial microsimulation outputs are estimates of unknown data, it is difficult to validate the simulated results at the disaggregate level, as reported in prior studies (e.g. Smith et al., 2009). However, we use a wide range of goodness-of-fit statistics to compare the combinations of constraining variables between the synthetically constructed population and census count, and find that the generated synthetic population represents the observed target population well. Moreover, we have also validated the simulation results against available external information, by comparing the simulated travel behaviour with the independently observed travel survey of Jiang et al. (2014). This shows that the microsimulation results are consistent with observations of other studies, and hence that the insights into the geographic and temporal variability of the transport CO_2 emission appear robust.

Whilst urban transport is widely regarded as an important and rapidly growing source of GHG emissions, its growth is mainly driven by behavioural factors, such as increasing travel distance (often as a consequence of a desire for more living space), and a shift towards motorised, higher-carbon travel modes (e.g. Salonen et al., 2014). These changes in travel behaviour are influenced by urban form characteristics. Our simulation results show that people residing in the more compact city centre travel shorter distances, make fewer motorised trips and emit less CO_2 on both workday and weekend. In contrast, people living in newly developed urban areas and remote districts, characterised by low population and employment density, and mono-functional land use, travel further and generate more CO_2 emission than their counterparts. This suggests that policies to combat dispersal are needed, whether through compaction of the urban core or further development of mixed use connected sub-centres beyond the core (polycentrism).

In addition to urban planning measures, a set of transport policies to promote behavioural changes (e.g. adoption of fuel-efficient vehicles) have been regarded as important instruments to reduce carbon emission from the road transport sector (Knuth, 2010; Graham-Rowe et al., 2011). However, the potential of these technology strategies has been questioned on grounds of the rebound effect, where emission reduction from greater fuel efficiency might be offset by increased car travel (Greene, 2012). Therefore, demand management policies to encourage modal shift towards low-carbon transportation modes, e.g. reducing car use and VMT, should be actively implemented to support sustainable transport (Loo & Li, 2012). For instance, parking policies such as parking fees, parking space management and car-free zones, particularly in workplaces, are known to have significant effects on mode choice, reducing car travel from 5% to 30% in urban areas (Cuenot et al., 2012). Road pricing can also discourage car travel, reducing congestion and emissions (Cavallaro et al., 2018). Moreover, long-term investment in public transport, particularly subway development in Chinese mega-cities, and promotion of walking and cycling could also make a substantial contribution to reducing car travel in the future (Banister, 2011).

Hankey and Marshall (2010) suggest there are three main options to reduce transport CO_2 emissions: low-carbon fuels, more-efficient vehicles, and VMT reduction, particularly of car travel. In China, there is not yet a comprehensive strategy for promoting low carbon transport (Zhang & Nian, 2013), hence government engagement to encourage uptake of all these measures is needed. Informed urban and transport policy and planning is clearly needed to effect fundamental behavioural changes to promote sustainable mobility and low carbon travel. However, China has an anticipated urban population of a billion people by 2030, including 221 cities over a million people each by 2025 (McKinsey, 2009), but a deficit of observed travel data. Microsimulation thus offers a means to better understand the travel behaviour that underpins the traffic flows and transport emission of China's cities and mega-cities, and hence to support lower carbon transport and city development.

Acknowledgements

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Figures

(The color figures are used for online version only, while the black-and-white figures are used for the production in print)

Fig.1. Study area of Guangzhou.

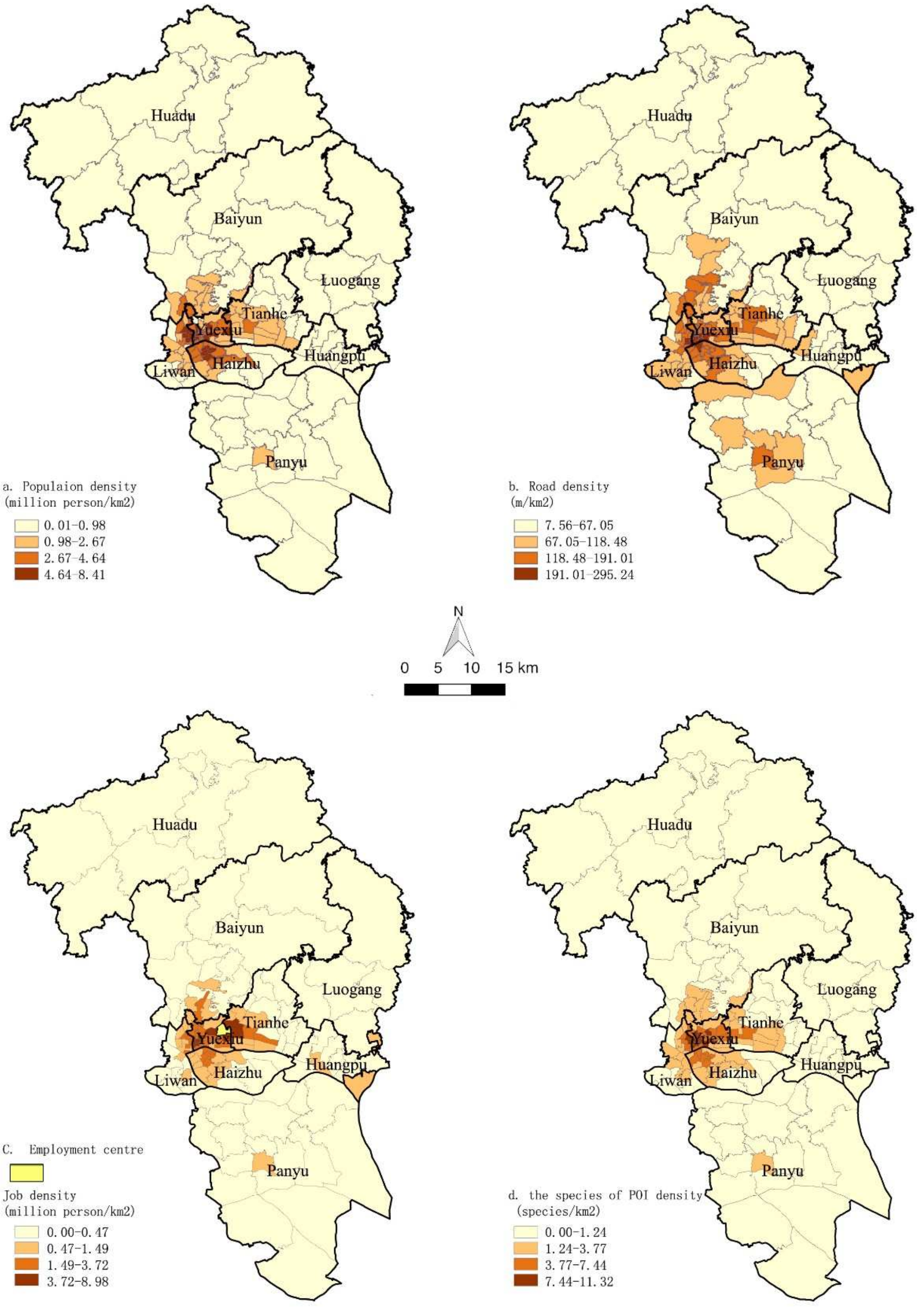


Fig.2. Sub-district level built environment characteristics in urban Guangzhou. (a. population density; b. road density; c. employment density; d. land use mix represented by the diversity of POI data)

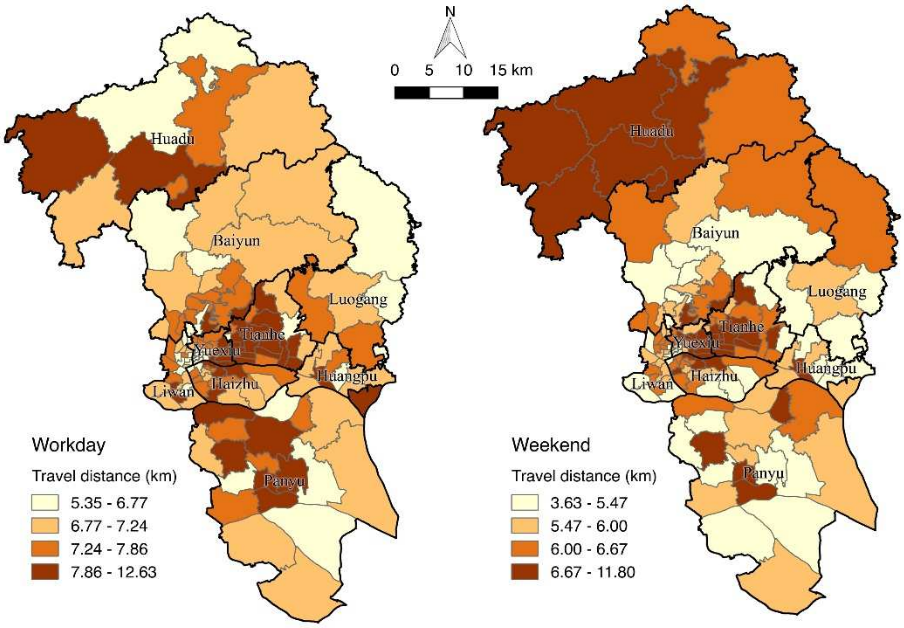


Fig.3. Average distance travelled by the synthetic population in each sub-district.

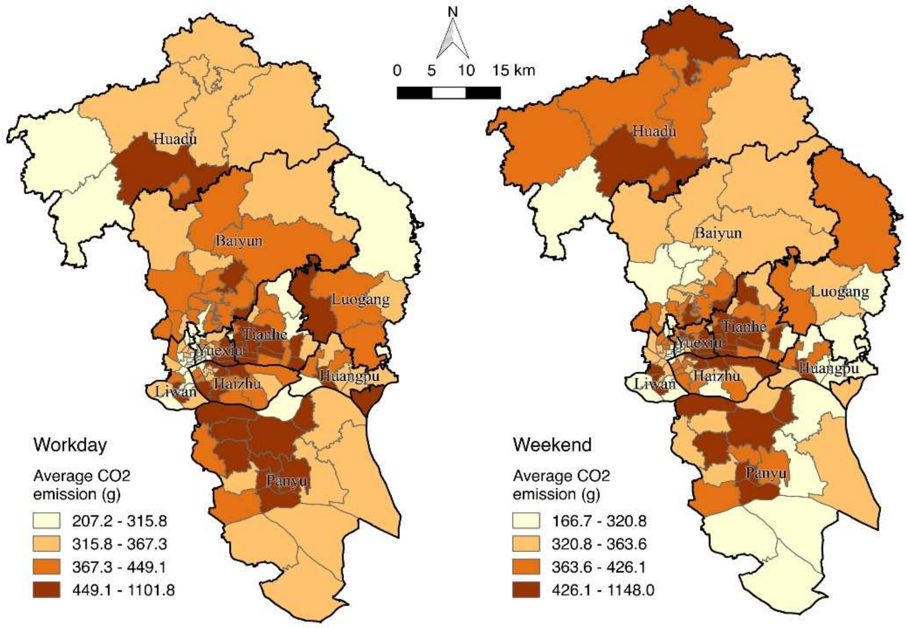


Fig.4. Average CO_2 emission from the synthetic population in each sub-district.

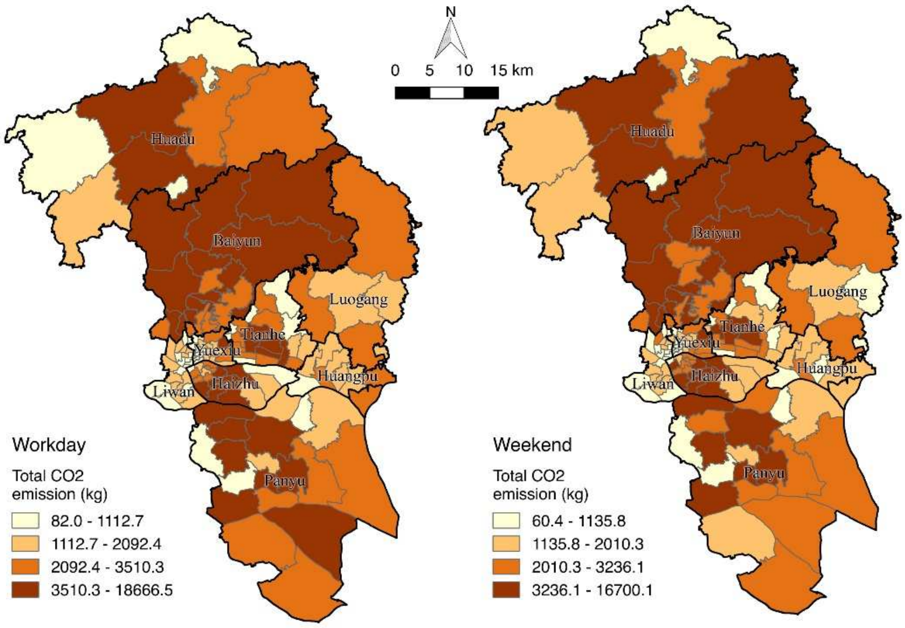
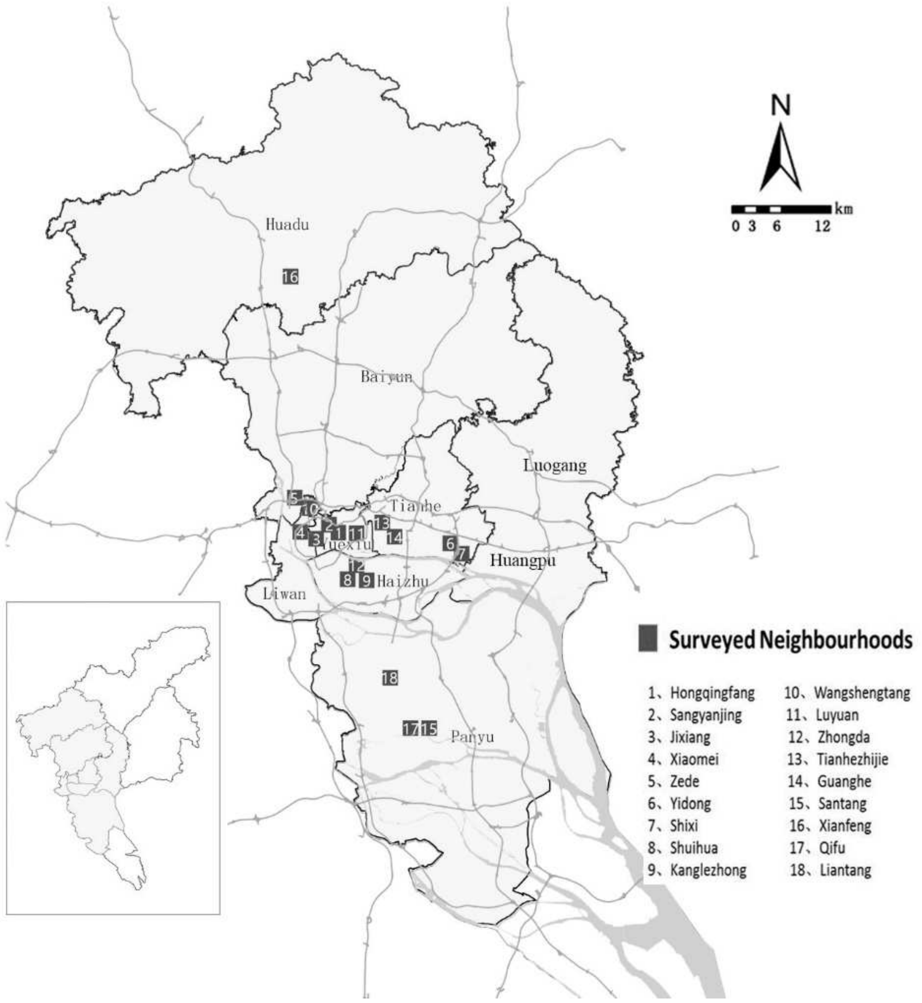


Fig.5. Total CO_2 emission from the synthetic population in each sub-district.



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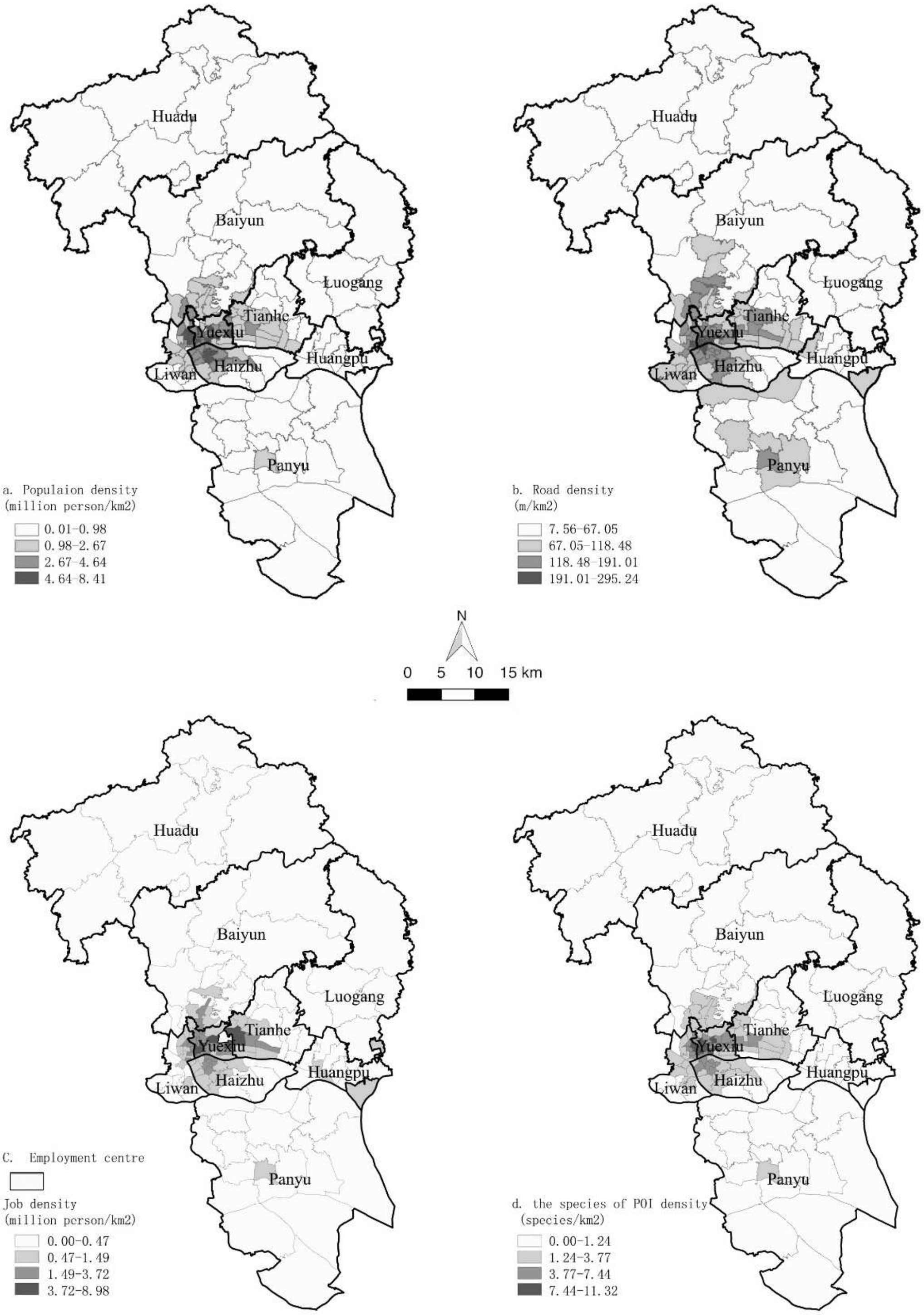

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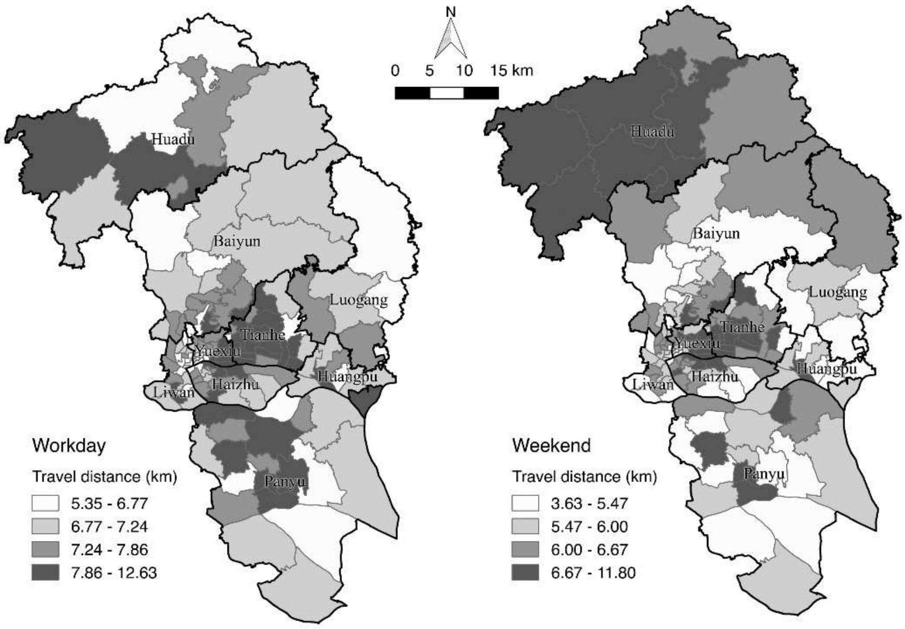

Fig.3. Average distance travelled by the synthetic population in each sub-district.

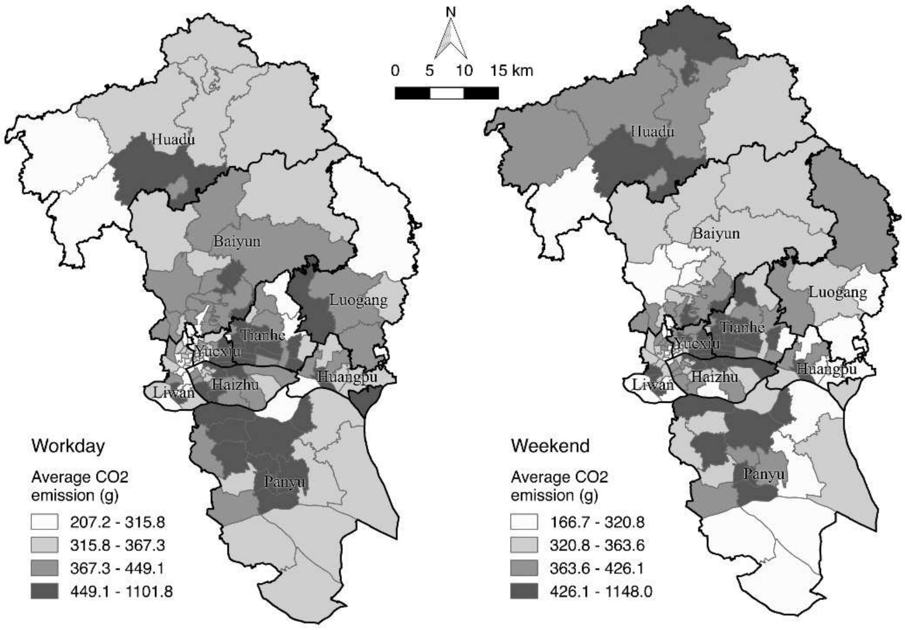

Fig.4. Average CO_2 emission from the synthetic population in each sub-district.

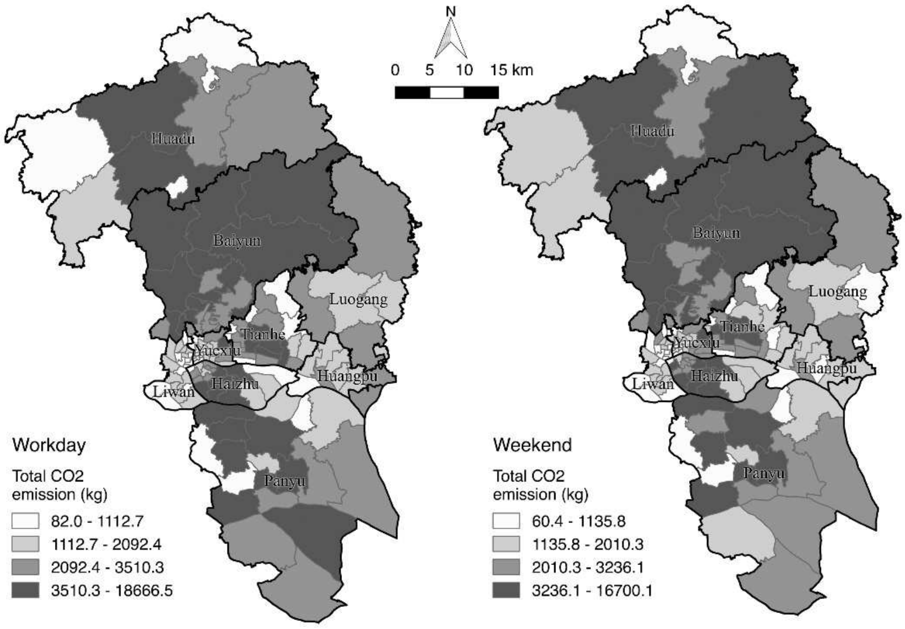

Fig.5. Total CO_2 emission from the synthetic population in each sub-district.

Tables

Table 1 Summary of key variables in the population census and travel survey.

Variables	Categories	Population census (%)	Travel survey (%)
Gender	Male	51.95	41.18
	Female	48.05	58.82
Age	15-30	37.31	23.86
	30-45	32.84	40.50
	45-65	22.44	34.70
	65+	7.41	0.94
Education	Primary	48.90	29.28
	Secondary	27.29	42.37
	Tertiary	23.81	28.35
Employment	Employed	64.36	86.04
	Unemployed	35.64	13.96
Occupation	Workers in service companies (WTP1)	39.70	59.09
	Workers in government and public institutions (WTP2)	17.26	21.65
	Other	43.04	19.26
Housing area (m^2)	<50	39.30	31.35
	50-80	23.17	36.88
	80-110	20.13	20.06
	110+	17.40	11.71
Housing tenure	Rent	40.85	33.83
	Self-built	19.17	16.14
	Buy commodity housing	23.44	28.35
	Buy affordable or Danwei housing	16.54	21.68
Building age	Before 1979	7.99	5.73
	1980-1989	16.27	32.52
	1990-1999	39.31	47.60
	After 2000	36.43	14.15

Table 2 Comparing travel and CO_2 emission between workday and weekend.

		Workday			Weekend		
Household and individual socio-demographic attributes		Travel distance (km)	Non-motor trips	CO_2 emission (g)	Travel distance (km)	Non-motor trips	CO_2 emission (g)
Gender	Male	8.77	2.27	568.50	5.59	1.81	423.18
	Female	7.36	2.69	354.89	5.27	2.28	261.52
	F	10.48+	30.39+	23.04+	0.77	37.80+	14.65+
Age	15-30	7.99	2.44	393.98	6.22	1.72	363.91
	30-45	8.93	2.30	555.16	5.55	2.09	359.64
	45-65	6.70	2.75	350.10	4.46	2.32	251.63
	65+	9.98	3.53	268.88	12.79	2.93	886.06
	F	7.08+	9.06+	6.19+	10.73+	13.69+	4.35+
Education	Primary	5.27	2.84	225.60	4.82	2.29	236.84
	Secondary	8.05	2.49	413.97	4.76	2.15	243.77
	Tertiary	10.54	2.16	710.46	6.96	1.79	548.38
	F	46.07+	19.10+	37.04+	15.78+	13.96+	22.64+
Employment	Employed	8.38	2.43	487.80	5.33	2.03	326.41
	Unemployed	5.28	2.89	165.83	5.84	2.48	338.51
	F	25.36+	14.26+	26.00+	0.99	17.24+	0.04
Occupation	WTP1	7.73	2.58	432.05	5.12	2.10	282.85
	WTP2	8.67	2.17	507.83	5.48	1.98	405.56
	Other	10.03	2.29	636.28	5.80	1.86	371.04
	Unemployed	5.28	2.89	165.83	5.84	2.48	338.51
	F	13.58+	10.23+	12.43+	1.02	7.60+	1.90
Housing area (m^2)	<50	5.79	3.03	225.67	4.15	2.47	174.19
	50-80	7.86	2.46	399.82	4.96	2.10	264.79
	80-110	10.17	2.16	615.37	6.67	1.88	481.44
	110+	10.16	1.81	864.05	7.97	1.41	676.57
	F	22.77+	33.34+	30.54+	18.30+	25.74+	22.15+
Housing tenure	Rent	6.35	2.82	286.25	4.70	2.26	241.26
	Self-built	6.76	1.84	367.33	5.48	1.55	310.97
	Commodity	11.11	2.32	746.11	6.60	2.14	459.18
	Affordable	7.17	2.73	346.96	4.86	2.17	304.95
	F	31.03+	24.91+	26.79+	6.89+	13.87+	5.86+
Building age	Before 1979	5.73	3.02	262.38	4.58	2.21	164.63
	1980-1989	6.38	2.93	288.55	4.18	2.61	191.76
	1990-1999	9.39	2.28	559.77	6.37	1.87	439.26
	After 2000	7.57	2.04	477.38	5.26	1.59	333.72
	F	15.49+	25.71+	11.38+	10.55+	36.22+	10.48+

Note: '+' indicates the p value associated with the F is below 0.01 in the ANOVA analysis.

Table 3 Representation of the model constraints at the sub-district level.

Constraints	SRMSE	TAE	PE	TE	CPE
Gender	0.00	0	0.00	0	0.00
Age	0.00	24	0.00	12	0.00
Education	0.00	0	0.00	0	0.00
Employment	0.00	0	0.00	0	0.00
Occupation	0.00	0	0.00	0	0.00
Housing area	0.00	0	0.00	0	0.00
Housing tenure	0.01	672	0.04	336	0.07
Building age	0.00	264	0.01	132	0.03