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## Exploring transport carbon futures using population microsimulation

## and travel diaries: Beijing to 2030

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## Exploring transport carbon futures using population microsimulation and travel diaries: Beijing to 2030

Abstract

Evaluating transport policy for cities in developing countries is often constrained by data availability that limits the use of conventional appraisal models. Here, we present a new 'bottom-up' methodology to estimate transport  $CO_2$  emission from daily urban passenger travel for Beijing, a megacity with relatively sparse data on travel behaviour. A spatial microsimulation, based on an activity diary survey and two sample population censuses, is used to simulate, for Beijing's urban districts, a realistic synthetic population, and their daily travel and  $CO_2$  emission over 2000-2010. This approach provides greater insight into the spatial variability of transport  $CO_2$  emission than has previously been possible for Beijing, and further, enables an examination of the role of socio-demographics, urban form and transport developments in contributing to emissions over the modelled period.

Using the 2000-2010  $CO_2$  emission estimates as a baseline,  $CO_2$  emissions from passenger travel are then modelled to 2030 under scenarios exploring politically plausible strategies on transport (public transport infrastructure investment, and vehicle constraint), urban development (compaction) and vehicle technology (faster adoption of clean vehicle technology). The results showed that, compared to the trend scenario, employing both transport and urban development policies could reduce total passenger  $CO_2$  emission to 2030 by 24%, and by 43% if all strategies were applied together. The study reveals the potential of microsimulation in emission estimation for large cities in developing countries where data availability may constrain more traditional approaches.

Keywords: Spatial microsimulation; Transport CO<sub>2</sub> emission; Travel behaviour; Beijing

#### **1. Introduction**

China has experienced rapid urbanisation and spatial restructuring since the 1980s, accompanied by major growth in travel, and the associated issues of energy consumption and greenhouse gas emission, traffic congestion and local air pollution (Feng et al., 2013). The IFEU (2008: 10) estimate that between 1990 and 2006, the stock of vehicles in China increased ten-fold, total vehicle kilometres (vkms) travelled increased five-fold, and energy and carbon dioxide emissions have increased four-fold. Even after such growth, the transport sector in China still accounts for a considerably lower share of final energy use than observed in Europe (Ibid: 6). However, as the Chinese economy develops, there is an anticipated further growth in transport carbon emissions in the future. The IFEU (2008: 6) highlights the uncertainty associated with such transport carbon emission estimates for China. Unofficial estimates of transport energy use are about a third higher than official estimates, with the discrepancies attributed to the way that official statistics report energy use (e.g. freight transport).

Accurately estimating transport  $CO_2$  emission at the national level is evidently challenging. Estimating at the urban level presents more difficulties, yet is an important task, as cities account for a disproportionately large share of energy use and emissions. Chinese cities are also growing rapidly; evaluation of the impact of planning policy on travel  $CO_2$ emissions is therefore particularly important. Dhakal (2009) estimates that Chinese urban areas account for 84% of energy use, and whilst this demand is from all sources, the share attributed to transport is growing rapidly. Estimates of transport carbon emission in China have to date employed aggregate data on total energy consumed or vehicle population registered, and tend to neglect the influence on emission of factors that operate at a more

resolved functional level, such as socio-demographic attributes or land use characteristics (e.g. Cai et al., 2012). Using less aggregate travel attributes (such as trip frequency, mode choice, and vehicle kilometres travelled) in  $CO_2$  emission estimation has major advantages over the former aggregate approach (He et al., 2013), but few studies of transport  $CO_2$  emission in transitional economies use such an approach, largely due to a lack of the data needed to support such disaggregate models; this is certainly the case for China.

However, microsimulation offers the potential to develop such models using the more limited data availability that is often a feature of developing economies. The key advantages offered by this approach are that emission estimates can be developed for more constrained geographies (such as cities), and that a more functionally resolved model results which enables exploration of development scenarios and policy or plan interventions. Thus microsimulation offers the potential, for example, to go beyond policy scenarios that estimate emission response to aggregate changes in vehicle characteristics (e.g. total number, average vkms) and to additionally consider how travel characteristics (e.g. trip frequency, travel distance, mode choice) of individuals influence carbon emission.

Spatial population microsimulation uses individuals or households as the basic analytical unit, and represents a useful tool for generating disaggregate forecasts over a long period (Ballas et al., 2005). On the basis of deterministic reweighting, synthetic reconstruction or combinatorial optimisation techniques, microsimulation models can synthesise much individual-level data for large populations by combining surveys and census data. It can also perform static what-if simulations to explore the impacts of alternative policy scenarios on the synthetic population for a base year, and perform future-oriented 'what-if' simulations by updating the basic microdata set over a long period (Ballas and Clarke, 2001). The spatial microsimulation approach has been widely used in the fields of geography, transport and social sciences in advanced economies (e.g. Birkin and Clarke, 1988; Beckman

et al., 1996; Kitamura et al., 2000; Miller et al., 2004; Lovelace et al., 2014), but there is little research on its application to urban transport CO<sub>2</sub> emission, particularly for developing countries.

Here, we present a new bottom-up methodology to provide an improved transport CO<sub>2</sub> emission estimate from individual's daily urban travel in Beijing from 2000 to 2030. On the basis of an activity diary survey and demographic data from the 2000 and 2010 population censuses (a 10% sample of Beijing's population), we employ spatial microsimulation to simulate for the city a realistic synthetic population, their daily travel behaviour and CO<sub>2</sub> emission at a fine geographical resolution (urban sub-district) between 2000 and 2010. We compare and analyse the changes in travel behaviour and transport CO<sub>2</sub> emissions over this decade, and examine the role of socio-demographics and change in urban form in contributing to this modelled trend. Next, the transport CO<sub>2</sub> emission from passenger travel behaviour is projected to 2030 under four scenarios, to illustrate the utility of the approach. The four scenarios are (i) transport policy trend, (ii) land use and transport policy, (iii) urban compaction and vehicle technology, and (iv) combined policy, and are developed to explore travel behaviour and transport CO<sub>2</sub> emission under current and politically plausible strategies on transport, urban development and vehicle technology.

#### 2. Methodology

#### 2.1. Case study city

We developed our microsimulation for Beijing, China's capital city that is a major source of transport related  $CO_2$ . Beijing is undergoing rapid change, yet lacks the resolved data to support more conventional emission estimation approaches. Beijing has experienced an increase in its urban area of 168% in the decade since 1998 (National Bureau of Statistics of China, 2009), an expansion that has been accompanied by suburban sprawl characterised by low density and mono-functional land use, while the traditional inner city urban space retains a high density, mixed land use (Zhao et al., 2010; Wang et al., 2011). Beijing can be divided into three broad zones: the central urban, inner suburban and outer suburban. The central urban zone (Fig. 1) comprises the urban districts of Dongcheng, Xicheng, Chongwen and Xuanwu, located in the inner city and representing the traditional business districts. The inner suburban zone includes the districts of Chaoyang in the northeast, Haidian in the northwest, Fengtai in the southwest and Shijingshan in the far west. These two central urban and inner-suburban zone accounted for approximately 63% of all households in 2000, with the inner suburban zone experiencing most of the post 1980s urban expansion. Most of the northern sub-districts are characterised by a high population density, in contrast to the lower density towards the periphery (Fig.1). The outer suburban area refers to the remote counties and villages in the Beijing municipality.

#### Figure 1 about here

Beijing lacks any publicly available travel survey data, hence to develop a representation of the travel behaviour of the Beijing population, a microsimulation model was developed that draws on both a travel diary survey designed and implemented by the behavioural geography research group of Peking University in 2007 (see Ma et al. 2014a for a detailed description) and the government national population census. This incorporated travel diary survey data for the 1,026 individuals (aged > 15) for whom there is a valid and continuous activity-travel record for the weekday, whilst census data is drawn from the fifth and sixth population census of Beijing in 2000 and 2010 respectively. The census has a stratified sample covering all districts, counties and villages. All people are required to

answer the short census form, which contains basic information on the household and individual socio-demographic attributes, while a 10% population sample in each sub-district was randomly selected to complete the long census form, which elicits additional information on demographic and economic attributes, including employment, occupation, housing tenure and household expenditure. Here, we use the 10% population sample in the microsimulation model as it comprises a richer socio-demographic data set. The 10% sample addresses 721,894 residents (aged >15) in the eight urban districts of Beijing in 2000, and 1,006,036 residents (aged >15) in urban Beijing in 2010 (Table 1).

#### Table 1 about here

#### 2.2. Calculating individual CO<sub>2</sub> emission

In our study,  $CO_2$  emission is estimated through a bottom-up approach in which we estimate  $CO_2$  emission for individuals with a known set of socio-demographic characteristics, based on a complete account of their travel activities during the weekday. Those individual level emission estimates, which collectively address all people in the city, are then scaled to the city using spatial microsimulation (see below) and census data for the corresponding socio-demographic groups. Individual level emission estimates are a function of travel distance by travel mode and a mode specific  $CO_2$  emission factor:

$$CARBON = \sum_{i=1}^{m} Distance_i \times Factor_i$$
(1)

where, CARBON refers to individual  $CO_2$  emission from urban travel on a typical workday, Distance<sub>i</sub> is the distance travelled in trip i during the day, m the number of trips made during the day, and Factor<sub>i</sub> the emission factor associated with the travel mode used in trip i (gCO<sub>2</sub> per person per km, derived from Grazi et al (2008)). There remains uncertainty in the aggregate emission factors, mainly due to uncertainty over the composition of the different vehicle fleet (e.g. vehicle class, engine size, weight and age) and a range of other factors, such as travel speed, road condition, and driving style. However, as China does not officially publish vehicle-use data on  $CO_2$  emission factors for all transportation modes, the analysis here makes use of fleet-averaged emission factors taking no consideration of travel speed variation on  $CO_2$  emission in China.

#### 2.3. Population synthesis

Having developed individual level emission estimates, these were applied to all people in the city, according to the corresponding demographic attributes. As the short form census lacks the required functional resolution of census data to achieve this, and the long form census, which does not, is only a 10% population sample, a spatial microsimulation model was developed in which the population was synthesised with all the characteristics of the 10% sample. The Flexible Modelling Framework (FMF), a generic software framework that facilitates the construction of population microdata was used to build a realistic population (Harland, 2013). The FMF incorporates a static spatial microsimulation algorithm based on Simulated Annealing (see Harland et al 2012 for a critical review of several different synthesising algorithms). Simulated Annealing (SA) has been demonstrated to provide the most promising results in the generation of synthetic spatial microdata at different geographical scales (e.g. Voas and Williamson, 2000; Hermes and Poulsen, 2012), and is a refinement over the basic combinatorial optimisation approach of hill climbing. It incorporates the Metropolis Algorithm allowing both backward and forward steps in its search of an optimal population configuration, which is selected from a small sample population (i.e. activity diary survey in this study) constrained by observed aggregate

population counts (i.e. population census). The optimisation process operates on known values common to both sample and constraint dataset, and the generated population is a realistic representation of the observed population aligning closely to the constraint totals while maintaining the rich variety of attributes contained in the survey samples. The weight for each individual in the sample population can be 0 representing exclusion or any number up to the total population count representing the number of times a particular individual has been selected in a specific geographical zone. The replacement criteria could be displayed as (Williamson et al., 1998):

$$p(\delta E) = exp(-\delta E / T)$$
<sup>(2)</sup>

where  $\delta E$  represents the potential change in combination performance, and T refers to the maximum level of performance degradation acceptable for the change of one element in a combination. Regarding the replacement elements randomly selected and evaluated, those improving combination performance are automatically accepted, while those degrading performance are only accepted if  $p(\delta E)$  is greater than a randomly generated number between 0 and 1.

#### 3. Simulating Beijing transport CO<sub>2</sub> emission, 2000-2010

#### 3.1. Estimating CO<sub>2</sub> emission in 2000

Using the activity diary survey and 2000 population census, firstly, a realistic synthetic population is generated using the SA algorithm. The constraining variables in the microsimulation are several household and individual socio-demographics, including gender, age, education, employment, occupation, housing tenure and area (Table 1), which are known to be significant influences on the travel behaviour of the study population (e.g. Wang et al., 2011; Ma et al., 2014b). As the travel information (e.g. travel distance, mode choice) can be derived from the activity diary survey, the next stage involves linking the travel behaviour elicited from the travel survey data to corresponding population sub-groups within the microsimulated synthetic population to spatially simulate the population's travel behaviour, and estimate their transport  $CO_2$  emissions at the sub-district level across urban Beijing for 2000. Simulated annealing is a stochastic process hence the sensitivity of the simulation outputs was tested by using different randomised number (seed value) to generate 10 synthetic populations. Variability in output variables by sub-district was low (standard deviation < 0.05 for trip frequency and < 0.8 for travel distance), demonstrating that the optimisation process is robust, and insensitive to the randomised seed value.

On average, the transport  $CO_2$  emission from people's daily travel in urban Beijing is 1.44 kg per person per day. People resident in most of Haidian and northwest Chaoyang subdistricts emit more  $CO_2$  (>1.55 kg per person per day), as people resident here travel further and make greater use of the car. In contrast, residents of the more compact central urban area (e.g. Dongcheng, Chongwen) have lower  $CO_2$  emissions in 2000 (Fig. 2). Further details on the population synthesis and simulation analysis for 2000 are given in Ma et al (2014a).

#### Figure 2 about here

#### 3.2. Estimating CO<sub>2</sub> emission in 2010

#### 3.2.1. Simulation by socio-demographic attributes

Using the 2000 base case as the starting point, a synthetic population was then generated for 2010 using spatial microsimulation, and the population's daily travel behaviour

and  $CO_2$  emission are examined across Beijing for 2000-2010. Table 1 presents socioeconomic data from the censuses, which was used to constrain the microsimulation models. Many of the constraining categories reveal much variation over this period, particularly for people aged 50 and over, those with different education levels, and the employed or retired. These data are indicative of the dynamic changes taking place in the city over this period. With such changing socio-demographics, we might expect that aggregate travel distance and transport  $CO_2$  emission will change as people with different socio-demographic attributes have different trip or tour (trip chain) characteristics.

Using the activity diary survey and census data, the FMF was used to create a synthetic yet realistic population for Beijing in 2010, constrained by the socio-demographic attributes derived from the 2010 census (Table 1). The population synthesis was undertaken at a fine geographical scale (urban sub-district level) and contains 1,006,036 individuals aged 15 and over across eight districts of Beijing. The goodness-of-fit evaluation statistics (e.g. Total Absolute Error, Percentage Error, Standardised Root Mean Square Error) show a very close match to the observed 2010 census data within the reconstructed population. Most of the constraining tabulations and cross-tabulations are reproduced with no or very little misclassification, which is a very good overall fit.

Travel attributes (trip frequency, mode etc) from the travel survey are then linked to the corresponding demographic groups in the synthetic population, and the population's daily travel behaviour is simulated spatially for Beijing in 2010. Fig. 3 illustrates the average travel distance for several transportation modes from the synthetic population across districts<sup>1</sup>. For motorised travel, the average trip distance by subway is highest (about 21 km per trip), followed by bus, car, taxi, and other transportation modes, like motorcycle. This simulation is

<sup>&</sup>lt;sup>1</sup> We simulate the population at a fine spatial (sub-district) scale, but only present and compare the results at the district level. This is mainly because some sub-districts experienced changes from 2000 (total 146 sub-districts) to 2010 (total 133 sub-districts), and the data of urban form and public/private transport developments to adjust the simulation results (see below) is only available at the district level.

in good agreement with the Beijing 2010 household travel survey (Beijing Transportation Research Centre, 2011), which found people travel furthest by subway, followed by bus and car, with the non-motorised travel shortest (about 3 km per trip for bicycle). It also reveals some geographical variability. By and large, the average trip distance for most transportation modes in the inner-suburban area is longer than that in the central urban area, possibly due to differences in socio-demographics, or urban form characteristics, which we address next.

#### Figure 3 about here

#### 3.2.2. Adjustment for changes in urban form and transport developments

So far, the microsimulation is only constrained by socio-demographics, and the simulation needs to be adjusted to account for urban form changes, and public and private transport development which are known to have had a significant impact on mode choice over the period in question (e.g. Zhao et al., 2010; He et al., 2013). Beijing's recent growth and urbanisation has been characterised by significant spatial restructuring with high-tech industry zones and housing established mainly in the suburbs, whilst employment opportunities arising from the substantial redevelopment of industrial land for tertiary industries has remained largely in the inner city, resulting in a spatial mismatch of jobs and housing (e.g. Wang et al., 2011), with obvious implications for travel.

Meanwhile, public transport has developed quickly, particularly the subway service, which is the focus of municipal policies for encouraging public transport in Beijing. The Beijing subway is the oldest and now busiest in China (Xu et al., 2010), with 16 lines comprising 442 km of track (second in extent only to the Shanghai Metro), compared to only 2 lines and 54 km of track in 2000 (Beijing Statistical Bureau, 2013). However, with urban expansion and rising incomes, motor vehicles ownership has also increased greatly, with

people becoming increasingly dependent on automobiles. Private car ownership doubled to three million over the period 2004-2009, and traffic congestion, air pollution, energy consumption and carbon emission, are now pressing problems in the city.

These urban form changes and public/private transit developments could be important factors of an elevated preference for motorised travel, so some measures are taken to adjust the simulated mode share by bicycle, car and subway. The most significant change to address is the sharp decline in mode share of non-motorised travel (NMT, e.g. walking, bicycle), which decreased from approximately 70% in the early 2000s to 30-40% in the later 2000s in many Chinese cities, with an average fall of 3% per year (He et al., 2013). In Beijing, the NMT share fell by approximately 25% from 2000-10, and this observation is used here to adjust the simulated mode share for bicycle. As actual car ownership (ACO) for each district is available in the Beijing statistical Yearbook and the simulated car ownership (SCO) can be derived from the microsimulation model, a simple equation is adopted to estimate the modified car share:

$$MCS_{i} = SCS_{i} \times (ACO_{i} / TP_{i}) / (SCO_{i} / SP_{i}) \times 100\%$$
(3)

where  $MCS_i$  represents the modified car share for the district i and  $SCS_i$  represents the simulated car share for the district i,  $TP_i$  and  $SP_i$  refer to the total population and sample population for the district i from the 2010 population census. The modified mode share for the subway (MSS) is calculated as 1 minus the share of other modes:

$$MSS_i = 1 - MNS_i - MCS_i - SBS_i - STS_i - SOS_i$$
(4)

where MNS<sub>i</sub> represents the modified mode share for non-motorised travel for the district i, and SBS<sub>i</sub>, STS<sub>i</sub> and SOS<sub>i</sub> refer to the simulated mode share for bus, taxi and other transportation modes (mainly motorcycle) for the district i, respectively.

Table 2 presents the final estimated mode share for each transportation mode in urban districts of Beijing for 2010. On average, about 43% of trips in urban Beijing are made by public transportation modes (i.e. bus, subway), with nearly 30% made by private vehicles. This agrees well with the 40% value for public transit, and 34% for car, reported in an independent household travel survey conducted by the Beijing government in 2010 (Beijing Transportation Research Centre, 2011). The simulation results also show the variability in different travel modes by area. Residents of inner-suburban districts have a higher share of subway travel; with car travel below that of the central urban area. This may be because residents of inner-suburban zones, who have longer travel distances, prefer subway travel as it is fast, inexpensive and uncongested. In contrast, with rising car ownership and changing urban form (industrial suburbanization, falling residential density, and a job-housing spatial mismatch), the share of car travel in the central urban area has increased greatly.

#### Table 2 about here

#### 3.3. Comparing CO<sub>2</sub> emission over 2000-2010

Using the simulated trip distance, mode share, and emission factors, the transport  $CO_2$  emission from the travel of the synthetic population is estimated for each district for 2010 (Fig. 4). On average, the transport  $CO_2$  emission from people's daily urban travel in Beijing is about 2.21 kg per person per day, which is in good agreement with the value reported in a Beijing household carbon emission survey conducted in 2010 by Qin and Han (2013). They estimated the housing and transport carbon emissions for selected neighbourhoods in Beijing,

and observed that transport  $CO_2$  emission from people's daily travel varied widely (from 14.8 to 1,734.8 kg per person per year), with an average of 2.11 kg per person per day. Compared to the average  $CO_2$  emission in 2000, this shows that  $CO_2$  emission per capita from travel has increased significantly (by about 54%) in Beijing, with that in the central urban districts (except Xuanwu) experiencing an increase since 2000 of more than 70%.

#### Figure 4 about here

Total CO<sub>2</sub> emission for each urban district was derived by estimating emission from the synthetic population (a 10% sample of all people aged >15) for 2010 (Fig. 4). The total CO<sub>2</sub> emissions in Chaoyang and Haidian districts are very high, more than 630 tonnes on a typical workday, followed by Fengtai district with 400 tonnes or so. The emission in the central urban area is much lower than that in the inner suburban area; this is possibly due to the decreasing population density in the central area, as the average CO<sub>2</sub> emission in 2010 displays small variation across districts. Moreover, compared to the emission in 2000, the total transport CO<sub>2</sub> emission from people's daily travel has experienced significant increase over 2000-2010, with the growth rate approximately 114%, much higher than the population growth rate (about 39%) in urban Beijing during this period.

#### 4. Scenario development

#### 4.1. Overview

The work above presented a spatially resolved passenger transport  $CO_2$  emission baseline for Beijing 2000-10, whose emissions are consistent with the limited verification data available from independent studies. The next stage is to demonstrate how the model can be used to explore possible carbon futures. To do this we use a scenario approach, exploring the impact of trends and possible management strategies on transport CO<sub>2</sub> emission from people's daily travel to 2030. Below, four scenarios (Table 4) are developed to explore travel behaviour and transport CO<sub>2</sub> emission under current and politically plausible strategies on transport, urban development and vehicle technology, all of which are of interest to Beijing city planners, and which are politically feasible. The first, Transport Policy Trend (TPT) scenario examines emissions under a continuation of current transport policy, with continuing investment in public transport provision coupled with car constraint. The second, Land Use and Transport Policy (LUTP) scenario examines the impact on emission of the transport policy trend (TPT) combined with urban development strategies that promote densification and compaction. The third, Urban Compaction and Vehicle Technology (UCVT) scenario examines the impact of technological change in the vehicle fleet combined (a faster uptake of lower emission vehicles) with compact urban development. The final scenario, Combined Policy (CP) examines the impact of combined transport policies, urban development strategies and vehicle technologies.

All four scenarios are reasonable reflections of possible strategies for Beijing, and incorporate dynamic changes in Beijing's population, as these influence travel demand and ultimately emissions (Li et al., 2010). We could explore a range of population scenarios in our analysis, but here we apply a common demographic change to our four scenarios introduced above. Table 3 illustrates observed population change 2000-2010 (Beijing Statistical Bureau, 2011). Average annual growth rate has been high at 3.3%, and is expected to remain so (falling slightly over the next two decades), primarily due to internal, principally rural-urban, migration in China (Yuan et al., 2008).

Table 3 about here

Two city plans have been implemented to control population growth, the "Beijing City Master Plan (2004-2020)" and the "12th Five Year Plan (2010-2015)". These plans require the local government to limit the total population in Beijing and slow its annual growth rate. Our scenarios adopt the average annual growth rate of the eight districts of the central urban and inner suburban areas for the modelled population, which is projected to be 2.4% 2010-2020, and 2.2% 2020-2030 (Table 3). Using the estimated urban population share, the total population in Beijing is projected to be 23.96 million in 2020 and 29.79 million in 2030, which is in good agreement with the predicted 29.82 million in 2030 reported by Feng et al (2013).

### 4.2. Transport Policy Trend

The Transport Policy Trend (TPT) scenario represents a continuation of current transport policies that aim to encourage public transit use and reduce travel by private vehicle. Primary measures include restrictions on private vehicle usage through regulation, rationing of car licenses, and development of a Bus Rapid Transit (BRT) system and a subway extension (Table 4).

#### Table 4 about here

Throughout the Beijing Olympics period (July-September 2008), where concerns over poor air quality were paramount, the municipal government restricted vehicle use via a last digit license plate ban, where on alternating days only vehicles with the permitted odd or even last digit could be used (Hao et al., 2011). This 50% ban was relaxed to a 20% ban in October 2008 (using the last two licence plate digits vehicles are restricted on weekdays in the urban area, which is within the 5th ring road). To control growth in private vehicles in Beijing limitations on issue of car license plate were introduced in December 2010. The government information on the control and management of Beijing small passenger vehicles can be found at http://www.bjhjyd.gov.cn/. Normally, licence applicants need to go through some stages before they could purchase private cars. First of all, licence applicants must meet some requirements (e.g. have a Beijing hukou or have a Beijing Work and Residence Certificate) and register at the official website to apply an account. Next, they are randomly selected in a lottery and only then can they purchase a private vehicle with a valid number. From 2011-13, the total lottery quota was 0.24 million; this is reducing to 0.15 million for the period 2014-2017. For those who have been successfully selected in a lottery, they must complete the registration procedures for vehicles within six months; otherwise they will be regarded as giving up their qualifications for car ownership.

Policies on improving public transit are set out in the "12th Five Year Plan (FYP) for Public Transit Development in Beijing". The government aims to improve the BRT network from one line (in 2007) to nine lines between the central city and suburban towns, and 18 BRT lines in the central city, by 2020 (Ma et al., 2008). Compared to regular buses, BRT buses have dedicated lanes with exclusive access, which can double operational speed from 10 to 20 km/h in the rush hour, and effectively doubles the bus system capacity, potentially adding eight million passengers a day, with no increase in the number of vehicles (Creutzig and He, 2009). The city government is also developing the subway system with plans to extend the network to 660 km by 2015.

Faster public transit can induce a significant modal shift. For example, in Seoul, a 10% increase in public transport speeds induced 5% of car drivers to switch to bus and subway (Lee et al., 2003). This is the expectation of the Beijing 12th FYP which aims to raise the share of public transit travel in urban areas to 50% by 2015, decrease the car share to 25%

and achieve a bicycle share of 18%. Based on these parameters, the share of public transit under the TPT scenario is assumed to reach 52% (c. 34% bus, 18% subway) in 2020, and 57% (c. 36% bus, 21% subway) by 2030 (Table 5). Travel by private vehicles is assumed to decrease to 25% in 2020, and 23% in 2030, with cycling at 16%. Average trip distance by vehicle types, personal trip frequency, and the vehicle emission factor under the TPT scenario follow the 2010 simulation results and are assumed to be constant during the period 2010-2030.

#### 4.3. Land Use and Transport Policy

The Land Use and Transport Policy (LUTP) scenario assumes, in addition to the transport measures described above, that travel growth will also be tackled using urban planning and design policies. Recent urban development has followed a planning model, familiar in the western world, of land use zoning, with single use, large-lot residential development and auto-oriented street design. The urban form of Beijing is now characterised by low density development with little mixed use (Zhao et al., 2010). Alternative planning strategies have been tried elsewhere that have proved effective in encouraging non-motorised travel and reducing vehicle kilometres travelled (VKT) (e.g. Grazi et al., 2008; Qin and Han, 2013). These 'new urbanist', 'smart growth', and 'transit-oriented development' strategies seek to develop a more compact urban form characterised by high density and mixed land use, with ready access to work and services facilitated by prioritisation of public transit (Mitchell et al., 2011).

In the LUTP scenario, we assume that compact urban development is pursued by the Beijing government, together with the transport policies described above that promote mass public transport and strictly control private cars. Primary compaction measures include urban redevelopment in the old urban residential area, infill, densely developing neighbourhood

centres accommodating a range of household types and land uses, increasing population density by 50% in the suburban districts, constructing basic services and facilities near residences to put the activities of daily living within walking distance, and developing a pedestrian-friendly street network in the suburbs (Table 4).

Such measures are assumed to have significant impacts on travel and mode choice if adopted for Beijing. Reviewing 85 land use-VKT scenarios in the US, Bartholomew and Ewing (2009) found that vehicle kilometres travelled (VKT) under different planning scenarios ranged from 5% above the regional trend to 32% below it; and that the difference is larger for longer planning horizons. Comparing the travel distance in different (traditional and commodity housing) neighbourhoods from the Beijing 2007 travel survey, with adopting compact urban development (e.g. mixed land use, increasing population density), the average trip distance by vehicle types is assumed to have a 15% reduction in the LUTP scenario by 2020 and have a further 5% reduction by 2030, respectively (Table 5). Regarding the mode share, 3% car travel in the TPT scenario is assumed to be shifted to bus, subway and bicycle with a 1/3 split each, as suggested in some prior studies (e.g. He et al., 2013). Vehicle emission factors are assumed to be the same as the TPT scenario over 2010-2030.

#### 4.4. Urban Compaction and Vehicle Technology

In the Urban Compaction and Vehicle Technology (UCVT) scenario, densification or compaction policies are pursued, with the addition of aggressive promotion of clean vehicle technology, which mainly includes strengthening emission standards of in-use and new vehicles, improvement of fuel efficiency, and substitution of alternative clean fuel types (Table 4). In China, both central and local governments have made substantial efforts to promote development and use of clean vehicle fuels, such as liquefied petroleum gas (LPG), compressed natural gas (CNG), electric vehicles (EV), hybrid electric vehicles (HEV) and

fuel cell vehicles (FCV), through policies and legislations, including the 'National Clean Vehicles Action' (1999), 'Renewable Energy Law' (2005), and 'Rules on the Production Admission Administration of New Energy Automobiles' (2007) (Hu et al., 2010).

With these government interventions, LPG and CNG vehicles increased rapidly in bus and taxi fleets. By 2005 Beijing had more than 2,000 CNG buses and 600 LPG taxis and about 32,000 gasoline/LPG bi-fuel taxi, which were demonstrated to have better performance on the road than the conventional vehicles (Hao et al., 2006). However, compared to global HEV sales, which grew rapidly from 40,000 in 2002 to 509,000 in 2007, growth in clean fuel vehicles in China has been slow, although there has been considerable investment in EV/HEV/FCV research and development projects (Hu et al., 2010). This scenario assumes that the government will continue to encourage new energy projects, and subsidise HEV and FCV vehicle purchases, so that the share of new clean vehicles in use increases to match EU's current level by 2030.

Policies to improve fuel efficiency and emission standards are also included in this scenario. China issued its first two-phase vehicle fuel-economy standards for passenger vehicles in 2004, in order to improve the fuel efficiency of the fleet by 15% (Huo et al., 2012). The average fuel consumption rates were reduced from 9.11 L/100km in 2002 to 8.06 L/100km in 2006 and 7.87 L/100km in 2009 (Wagner et al., 2009; Wang et al., 2010). The third phase fuel-economy standard, similar to the US CAFE standard, has been designed and will be adopted to improve fuel efficiency to 6.9 L/100km by 2015 and 4.5-5 L/100km by 2020 (Huo et al., 2012). Moreover, the Beijing government also tightened the vehicle emission standards and implemented the Euro 4 standard for light-duty vehicles in 2008. It plans to catch up with the EU in future by introducing more stringent emission standards, i.e., Euro 5 in 2012 and Euro 6 in 2016, to control emissions (Wu et al., 2011).

Estimates of aggregate reduction in  $CO_2$  emission factors for Chinese passenger transport from fuel efficiency improvements and clean fuels vary, including 17% (Liu et al., 2007), 22% (Ou et al., 2010) and 25% (Zhang et al., 2005). This scenario assumes a midlevel values for 2020 of 20%, rising to 25% in 2030, compared to the trend value. VKT is assumed to be the same as the LUTP. Regarding the mode share, as no major transport policies are implemented, the mode share by car is assumed to follow the historical trend (2000-2010), accounting for approximately 37% in 2020 and 45% in 2030, whereas the share by public travel and NMT reaches 56% in 2020 and 49% in 2030, respectively (Table 5).

#### 4.5. Combined Policy

While the three scenarios above (i.e. TPT, LUTP, and UCVT) address specific measures in different aspects in isolation, the final scenario, Combined Policy (CP), assumes all these measures discussed above are considered altogether to reduce the transport  $CO_2$ emissions from people's daily travel, including the transport policies, compact urban development and vehicle technologies (Table 4). A complete combination of these measures is assumed to have significant impacts on travel distance, mode choice and emission factor at the same time (Table 5). Results and analysis of these four scenarios on future transport  $CO_2$ emissions in urban Beijing are presented below.

#### 5. Results

#### 5.1. Average CO<sub>2</sub> reduction potential

Based on the assumptions above, we first compute an average per capita  $CO_2$ emission for passenger transport under the four scenarios to 2030. This is calculated from mode share by trip frequency by travel distance and mode specific  $CO_2$  emission factor, as:  $AverageCO_2 = \sum MS_i \times ATF \times ATD_i \times EF_i$ (5)

where  $MS_j$  refers to the mode share by vehicle type j ( j = bicycle, bus, subway, car, taxi, and other), ATF represents the average trip frequency on a typical workday (i.e. 2 trips per person per day),  $ATD_j$  is the average trip distance by vehicle type j, and  $EF_j$  the emission factor associated with the vehicle type j.

Fig. 5 presents the results from 2000 to 2030. Compared to the sharp increase from 2000-2010, transport  $CO_2$  emission under the TPT scenario will grow more slowly to 2.30 kg per person per day in 2020 and 2.24 kg in 2030, as a continuation of current transport policies is considered effective in encouraging public transit use and reduce private car travel. When both transport and urban development policies are employed (i.e. LUTP),  $CO_2$  emission falls to 1.85 kg per person per day by 2020 and 1.70 kg by 2030, mainly due to the lower VKT.

#### Figure 5 about here

Under the UCVT scenario, where vehicle technology is aggressively promoted with compact urban development, average CO<sub>2</sub> emission reaches 1.96 kg per person per day in 2020 and 1.89 kg in 2030, falling 14% relative to 2010. However, when transport policies, compact urban development and vehicle technologies are employed together (i.e. CP), CO<sub>2</sub> emission falls sharply to 1.48 kg per person per day by 2020 and 1.27 kg by 2030, reducing 43% relative to 2010. It suggests that, although transport policies, urban compaction and vehicle technology are feasible tools, they cannot significantly reduce transport CO<sub>2</sub> emissions from people's daily travel in isolation. The most effective solution to mitigate

transport carbon emission in the future is the combination of those solutions concerning travel behaviour, urban planning and vehicle technologies.

#### 5.2. Total CO<sub>2</sub> emission comparison

Total  $CO_2$  emission from people's daily travel is calculated by the total population (see Table 3, the projected full population in eight urban districts in 2020 and 2030) multiplied by the average  $CO_2$  emission, as:

$$TotalCO_2 = \sum MS_j \times (ATF \times TP_t) \times ATD_j \times EF_j$$
(6)

where  $TP_t$  refers to the total population in year t (t = 2020 or 2030).

Fig. 6 presents the total transport  $CO_2$  emission in urban Beijing in 2020 and 2030, and shows that, under the trend scenario (TPT), total transport  $CO_2$  emission reaches about 34,200 tonnes per day in 2020 and 41,400 tonnes per day in 2030, with car travel accounting for half of all transport emissions (Fig. 7). Together with urban compaction strategies to decrease VKT, total transport  $CO_2$  emissions under the LUTP scenario are about 20% below the trend scenario in 2020, and 24% less in 2030, with the proportion of total  $CO_2$  from public transit rising to 46% by 2030 (Fig. 7).

In contrast, with compact urban development and vehicle technology taken into account, total transport  $CO_2$  emission under the UCVT scenario is 16% below the trend scenario in 2030, with the car accounting for more than 70% of the total  $CO_2$  emission (Fig.7). This is mainly due to the larger vehicle population and increasing car travel, which suggests

that continuing to encourage public transit use and constrain car travel in Beijing through transport policies is a priority solution for reducing transport carbon emission. However, these measures will be more effective if developed in conjunction with travel sensitive land use policies and advanced vehicle technologies, as total transport  $CO_2$  emissions under the CP scenario decrease sharply, about 36% below the trend scenario in 2020, and 43% less in 2030 (Fig. 6).

### 6. Conclusions

Climate change is widely recognised as a real threat to urban development and a key global challenge of the 21st century (IPCC, 2013). How to reduce energy consumption and carbon emissions has been on the top of a number of political agendas and scientific research. While cities are responsible for 80% of global greenhouse gases, three urban sectors (industry, transport and housing) constitute the main sources of carbon dioxide emissions (Dhakal, 2009). One of the biggest sources, with the fastest growth in CO<sub>2</sub> emission of any sector is the transport sector (Yan and Crookes, 2009). With increasing travel demand and car usage, transport CO<sub>2</sub> emissions globally will continue to grow rapidly contributing further to climate change its damaging impacts (Stern, 2007). A combination of measures, such as improving public transit development, promoting sustainable urban form, and developing new clean fuels, are urgently needed to achieve the energy saving and carbon emission reduction goals of national governments (e.g. an 80% reduction of CO<sub>2</sub> emissions by 2050 recommended by the UK Committee) and the wider international community (e.g. Kyoto protocol).

To achieve those goals above, a number of studies have investigated strategic pathways to large-scale reductions in  $CO_2$  emissions from the transport sector (e.g. Warren, 2007; Bristow et al., 2008; Brand et al., 2012). These studies found that technological

development alone cannot deliver the significant reductions in transport  $CO_2$  emissions and that behavioural change is required (Hickman and Banister, 2007). However, using the 'IPAT' type decomposition analysis, Kwon (2005) projected  $CO_2$  emissions from car travel in the UK over 2000-2030 through the development of various scenarios upon changing car driving distance and  $CO_2$  efficiency of car driving. The results showed that it was very difficult to achieve the  $CO_2$  reduction target even under the most optimistic scenario of changes in Affluence (e.g. driving distance, trip rates) and Technology factors. By and large, most of those studies used 'top-down' models to project transport carbon emissions at the aggregate level, which were unable to directly link individuals' daily travel behaviour with household socio-demographics and urban form characteristics operated at the micro scale.

In contrast to prior studies which estimate transport  $CO_2$  emissions using aggregate vehicle population statistics, this paper presents a new 'bottom-up' methodology to simulate and project transport  $CO_2$  emissions from people's daily urban travel using disaggregate travel attributes for a Chinese mega-city to 2030, where published travel survey, energy statistics or census data are usually very poor. Using a spatial microsimulation approach, we firstly estimate transport  $CO_2$  emission from people's daily travel behaviour at disaggregate level in urban Beijing over 2000-2010. The microsimulation results show that the average  $CO_2$  emission from urban travel has increased significantly from 2000-10, reaching 2.21 kg per person per day in 2010. It also suggests that the total mass transport  $CO_2$  emission in urban Beijing has increased by 114% since 2000, with the Chaoyang and Haidian districts being particularly high emitters.

Next, on the basis of the estimated historical emissions, we also develop four major scenarios concerning transport policies, urban planning and vehicle technology to examine how changes in people's daily travel behaviour (e.g. trip distance, mode share, etc) may impact upon transport carbon emission in urban Beijing to 2030. These four scenarios (i.e.

transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy) are developed to illustrate the capability of the modelling approach taken, and they are reasonable reflections of possible strategies for Beijing. The modelling results show that compared to the trend scenario, employing both transport and urban development policies could contribute a further 24% reduction of the total carbon emission to 2030. Moreover, when transport policies, compact urban development and vehicle technologies are combined, the total transport CO<sub>2</sub> emission falls sharply, about 36% below the trend scenario in 2020, and 43% less in 2030. It shows that the most effective solution to mitigate transport carbon emission in the future is the combination of those solutions concerning travel behaviour, urban planning and vehicle technologies.

This study combines the spatial microsimulation approach from geography with activity travel research from the transport field, and applies them to simulate and forecast long run CO<sub>2</sub> emission for a developing country where detailed data to undertake such fine scale analysis using more conventional model is very scarce. Whist the case is particularly relevant to urban Beijing, this analysis could be applied in other big cities to microsimulate urban travel and estimate transport carbon emission effectively and dynamically. The methodology presented here could allow a more detailed assessment of travel behaviour at the disaggregate level and allow the effect of different policies, strategies or technologies to be more realistically evaluated. In addition, whilst transport CO<sub>2</sub> is our focus here, the methodology could also be useful for estimating emissions of other pollutants relevant to local air quality (such as fine particulates or oxides of nitrogen), or identifying where congestion may become more serious in future.

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#### References

- Ballas, D., Clarke, G., Dorling, D., Eyre, H., Thomas, B., Rossiter, D., 2005. SimBritain: a spatial microsimulation approach to population dynamics. Population, Space and Place 11, 13-34.
- Ballas, D., Clarke, G.P., 2001. The local implications of major job transformations in the city: a spatial microsimulation approach. Geographical Analysis 33, 291-311.
- Bartholomew, K., Ewing, R., 2009. Land use-transportation scenarios and future vehicle travel and land consumption: a meta-analysis. Journal of the American Planning Association 75, 13-27.
- Beckman, R.J., Baggerly, K.A., McKay, M.D., 1996. Creating synthetic baseline populations. Transportation Research Part A 30, 415-429.
- Birkin, M., Clarke, G., 1988. SYNTHESIS–a synthetic spatial information system for urban and regional analysis: methods and examples. Environment and Planning A 20, 1645-1671.
- Beijing Statistical Bureau, 2011, 2013. Beijing Statistical Yearbook. Beijing: China Statistical Press.
- Beijing Transportation Research Centre, 2011. Beijing Transport Development Yearbook. Beijing: China Statistical Press.
- Brand, C., Tran, M., Anable, J., 2012. The UK transport carbon model: An integrated life cycle approach to explore low carbon futures. Energy Policy 41, 107-124.
- Bristow, A.L., Tight, M., Pridmore, A., May, A.D., 2008. Developing pathways to low carbon landbased passenger transport in Great Britain by 2050. Energy Policy 36, 3427-3435.
- Cai, B., Yang, W., Cao, D., Liu, L., Zhou, Y., Zhang, Z., 2012. Estimates of China's national and regional transport sector CO<sub>2</sub> emissions in 2007. Energy Policy 41, 474-483.
- Creutzig, F., He, D., 2009. Climate change mitigation and co-benefits of feasible transport demand policies in Beijing. Transportation Research Part D 14, 120-131.
- Dhakal, S., 2009. Urban energy use and carbon emissions from cities in China and policy implications. Energy Policy 37, 4208-4219.
- Feng, Y.Y., Chen, S.Q., Zhang, L.X., 2013. System dynamics modelling for urban energy consumption and CO<sub>2</sub> emissions: a case study of Beijing, China. Ecological Modelling 252, 44-52.

- Grazi, F., van den Bergh, J.C., van Ommeren, J.N., 2008. An empirical analysis of urban form, transport, and global warming. The Energy Journal 29, 97-122.
- Hao, H., Wang, H., Ouyang, M., 2011. Comparison of policies on vehicle ownership and use between Beijing and Shanghai and their impacts on fuel consumption by passenger vehicles. Energy Policy 39, 1016-1021.
- Hao, J., Hu, J., Fu, L., 2006. Controlling vehicular emissions in Beijing during the last decade. Transportation Research Part A 40, 639-651.
- Harland, K., 2013. Microsimulation Model User Guide (Flexible Modelling Framework). National centre for research methods working paper.
- Harland, K., Heppenstall, A., Smith, D., Birkin, M., 2012. Creating realistic synthetic populations at varying spatial scales: a comparative critique of population synthesis techniques. Journal of Artificial Societies and Social Simulation 15(1), 1-15.
- He, D., Liu, H., He, K., et al, 2013. Energy use of, and CO<sub>2</sub> emissions from China's urban passenger transportation sector Carbon mitigation scenarios upon the transportation mode choice.
   Transportation Research Part A 53, 53-67.
- Hermes, K., Poulsen, M., 2012. A review of current methods to generate synthetic spatial microdata using reweighting and future directions. Computers, Environment and Urban Systems 36, 281-290.
- Hickman, R., Banister, D., 2007. Looking over the horizon: Transport and reduced CO<sub>2</sub> emissions in the UK by 2030. Transport Policy 14, 377-387.
- Hu, X., Chang, S., Li, J., Qin, Y., 2010. Energy for sustainable road transportation in China: Challenges, initiatives and policy implications. Energy 35, 4289-4301.
- Huo, H., He, K., Wang, M., Yao, Z., 2012. Vehicle technologies, fuel-economy policies, and fuelconsumption rates of Chinese vehicles. Energy Policy 43, 30-36.
- IFEU, 2008. Transport in China: Energy Consumption and Emissions of Different Transport Modes. Final Report. Institute for Energy and Environmental Research, Heidelberg in Cooperation with Institute of Comprehensive Transportation of National Development and Reform Commission of China (ICT).

- IPCC, 2013. Summary for policymakers: in climate change 2013: The physical science basis. Contribution of working group I to the Fifth Assessment report of the Intergovernmental Panel on climate change. Cambridge: Cambridge University Press.
- Kitamura, R., Chen, C., Pendyala, R.M., Narayanan, R., 2000. Microsimulation of daily activitytravel patterns for travel demand forecasting. Transportation 27, 25-51.
- Kwon, T., 2005. A scenario analysis of CO<sub>2</sub> emission trends from car travel: Great Britain 2000-2030. Transport Policy 12, 175-184.
- Lee, S., Lee, Y.H., Park, J.H., 2003. Estimating price and service elasticity of urban transportation demand with stated preference technique: Case in Korea. Transportation Research Record 1839, 167-172.
- Li, L., Chen, C., Xie, S., et al, 2010. Energy demand and carbon emissions under different development scenarios for Shanghai, China. Energy Policy 38, 4797-4807.
- Liu, J., Wang, R., Yang, J., 2007. A scenario analysis of Beijing's private traffic patterns. Journal of Cleaner Production 15, 550-556.
- Lovelace, R., Ballas, D., Watson, M., 2014. A spatial microsimulation approach for the analysis of commuter patterns: from individual to regional levels. Journal of Transport Geography 34, 282-296.
- Ma, H., Hadden-Loh, T., Yang, X., Sun, Z., Shi, Q., 2008. Evolution and effect of transportation policy on public transit: Lessons from Beijing. Transportation Research Record 2063, 176-182.
- Ma, J., Heppenstall, A., Harland, K., Mitchell, G., 2014a. Synthesising carbon emission for megacities: a static spatial microsimulation of transport CO<sub>2</sub> from urban travel in Beijing. Computers, Environment and Urban Systems 45, 78-88.
- Ma, J., Mitchell, G., Heppenstall, A., 2014b. Daily travel behaviour in Beijing, China: an analysis of workers' trip chains, and the role of socio-demographics and urban form. Habitat International 43, 263-273.
- Miller, E.J., Douglas Hunt, J., Abraham, J.E., Salvini, P.A., 2004. Microsimulating urban systems. Computers, Environment and Urban Systems 28, 9-44.

- Mitchell, G., Hargreaves, A., Namdeo, A., Echenique, M., 2011. Land use, transport, and carbon futures: the impact of spatial form strategies in three UK urban regions. Environment and Planning A 43, 2143-2163.
- National Bureau of Statistics of China, 2009. China Statistical Yearbook. Beijing: China Statistical Press.
- Ou, X., Zhang, X., Chang, S., 2010. Scenario analysis on alternative fuel/vehicle for China's future road transport: Life-cycle energy demand and GHG emissions. Energy Policy 38, 3943-3956.
- Qin, B., Han, S., 2013. Planning parameters and household carbon emission: evidence from high- and low-carbon neighbourhoods in Beijing. Habitat International 37, 52-60.
- Stern, N., 2007. The Economics of Climate Change: The Stern Report. Cambridge: Cambridge University Press.
- Voas, D., Williamson, P., 2000. An evaluation of the combinatorial optimisation approach to the creation of synthetic microdata. International Journal of Population Geography 6, 349-366.
- Wagner, D.V., An, F., Wang, C., 2009. Structure and impacts of fuel economy standards for passenger cars in China. Energy Policy 37, 3803-3811.
- Wang, D., Chai, Y., Li, F., 2011. Built environment diversities and activity-travel behaviour variations in Beijing, China. Journal of Transport Geography 19, 1173-1186.
- Wang, Z., Jin, Y., Wang, M., Wei, W., 2010. New fuel consumption standards for Chinese passenger vehicles and their effects on reductions of oil use and CO<sub>2</sub> emissions of the Chinese passenger vehicle fleet. Energy Policy 38, 5242-5250.
- Warren, J.P. ed., 2007. Managing Transport Energy. Power for a Sustainable Future, 3. Oxford: Oxford University Press, in association with The Open University.
- Williamson, P., Birkin, M., Rees, P.H., 1998. The estimation of population microdata by using data from small area statistics and samples of anonymised records. Environment and Planning A 30, 785-816.
- Wu, Y., Wang, R., Zhou, Y., Lin, B., Fu, L., He, K., Hao, J., 2011. On-Road vehicle emission control in Beijing: past, present, and future. Environmental Science & Technology 45, 147-153.

- Xu, M., Ceder, A., Gao, Z., Guan, W., 2010. Mass transit systems of Beijing: governance evolution and analysis. Transportation 37, 709-729.
- Yan, X., Crookes, R.J., 2009. Reduction potentials of energy demand and GHG emissions in China's road transport sector. Energy Policy 37, 658-668.
- Yuan, X., Ji, X., Chen, H., Chen, B., Chen, G., 2008. Urban dynamics and multiple-objective programming: a case study of Beijing. Communications in Nonlinear Science and Numerical Simulation 13, 1998-2017.
- Zhang, J.T., Liang, S.R., Ding, L.Q., 2005. Clean alternative fuels for vehicle engines and development prospect. Advances in Fine Fetrochemicals 6, 43-47.
- Zhao, P., Lü, B., de Roo, G., 2010. Urban expansion and transportation: the impact of urban form on commuting patterns on the city fringe of Beijing. Environment and Planning A 42, 2467-2486.

Constraints		2000 Population census		2010 Population census	
Individual-level	Categories	Count	Share (%)	Count	Share (%)
Gender	Male	379,227	52.53	503,865	50.08
Genuer	Female	342,667	47.47	502,171	49.92
	15-29	241,159	33.41	327,823	32.59
Age	30-39	162,300	22.48	195,109	19.39
	40-49	142,009	19.67	178,594	17.75
	50-59	68,672	9.51	148,521	14.76
	>= 60	107,754	14.93	155,989	15.51
	Primary	314,669	43.59	343,015	34.10
Education	Secondary	217,302	30.10	242,569	24.11
	Tertiary	189,923	26.31	420,452	41.79
Employment	Employed	500,782	69.37	662,171	65.82
	Jobless	71,415	9.89	101,667	10.11
	Retired	138,759	19.22	222,757	22.14
	Other	10,938	1.52	19,441	1.93
Occupation	Students	78,294	10.85	93,642	9.31
	Workers TP1	181,548	25.15	267,379	26.58
	Workers TP2	240,940	33.38	301,150	29.93
Total	Individuals	721,894	100.00	1,006,036	100.00
Household-level	Categories	Count	Share (%)	Count	Share (%)
Housing area	<= 29	155,299	61.13	240,207	60.56
(m <sup>2</sup> /capita)	>= 30	98,767	38.87	156,447	39.44
Housing tenure	Owner	134,048	52.76	218,226	55.02
	Tenant	120,018	47.24	178,428	44.98
Total	Households	254,066	100.00	396,654	100.00

# Table 1.Comparing the distribution of constraining variables between 2000 and 2010<br/>census samples

Note: Workers TP1 are workers in government or public institutions; Workers TP2 are workers in factories, service companies and other.

Table 2.Estimate	d mode share in urba	n districts of Beijing for 2010
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Mode share (%)	Bicycle	Bus	Subway	Car	Taxi	Other	Total
Dongcheng	20.6	30.1	6.0	34.1	6.0	3.3	100.0
Xicheng	18.4	30.3	4.7	37.2	6.0	3.3	100.0
Chongwen	24.5	29.9	5.3	30.9	5.8	3.6	100.0
Xuanwu	20.8	31.0	10.2	28.7	5.8	3.6	100.0
Chaoyang	17.9	31.4	14.4	26.9	5.5	4.0	100.0
Fengtai	21.9	31.8	6.8	29.7	5.6	4.2	100.0
Shijingshan	24.1	30.2	12.1	23.9	5.9	3.8	100.0
Haidian	14.0	32.3	16.7	28.5	5.3	3.2	100.0
Estimated	18.3	31.4	11.9	29.1	5.6	3.7	100.0
Surveyed	16.4	28.2	11.5	34.2	6.6	3.1	100.0

#### Table 3. Population growth in Beijing over 2000-2030

Variables	2000	2005	2010	2020	2030
Population in eight urban districts (million)	8.50	9.53	11.72	14.86	18.47
Total population (million)	13.57	15.38	19.61	23.96	29.79
Urban population share <sup>a</sup> (%)	62.64	61.96	59.77	62.00	62.00
Population growth rate <sup>b</sup> (%)	2.61	2.30	3.26	2.40	2.20

<sup>a</sup> Urban population share = Population in eight urban districts / Total population \*100% <sup>b</sup> Population growth rate refers to the average annual growth rate of population in eight urban districts; 2.61 was the average annual population growth rate during 1990-2000
Measures	TPT	LUTP	UCVT	СР	
Improve public transport development and constrain private vehicle use	20%-off driving restrictions; maximum 150,000 car license plate release over 2014- 2017; 18 BRT lines in the central city and 9 BRT lines to the suburbs by 2020; 660 km of subway by 2015	As TPT	None	As TPT	
Promote urban compaction to reduce vehicle kilometres travelled (VKT) and motorised travel	None	Urban redevelopment; infill; densely developing neighbourhood centres; increasing population density by 50% in the suburbs; constructing basic services and facilities near residences; developing pedestrian- friendly street network, etc.	As LUTP	As LUTP	
Develop vehicle None technology to provide new clean vehicles and improve fuel efficiency		None	Promote emission standards, e.g. Euro 5 in 2012, Euro 6 in 2016; substitution of clean fuel vehicles, e.g. CNG buses, LPG taxis, HEV, FCV; improve fuel efficiency, e.g. 6.9 L/100km by 2015 and 4.5-5 L/100km by 2020	As UCVT	

## **Table 4.**Transport, land use and technology measures in the four scenarios

Control factors	Category	TPT		LUTP		UCVT	UCVT		СР	
		2020	2030	2020	2030	2020	2030	2020	2030	
Mode share (%)	Bicycle	17.0	15.0	18.0	16.0	11.0	8.0	18.0	16.0	
	Bus	33.5	35.6	34.5	36.6	32.4	28.0	34.5	36.6	
	Subway	18.4	21.4	19.4	22.4	12.9	13.0	19.4	22.4	
	Car	25.0	23.0	22.0	20.0	37.3	45.5	22.0	20.0	
	Taxi	4.5	4.0	4.5	4.0	5.6	4.6	4.5	4.0	
	Other	1.6	1.0	1.6	1.0	0.8	0.9	1.6	1.0	
Average trip distance (km)	Bicycle	3.3	3.3	2.8	2.6	2.8	2.6	2.8	2.6	
	Bus	16.5	16.5	14.0	13.2	14.0	13.2	14.0	13.2	
	Subway	22.6	22.6	19.2	18.1	19.2	18.1	19.2	18.1	
	Car	13.8	13.8	11.7	11.0	11.7	11.0	11.7	11.0	
	Taxi	9.7	9.7	8.2	7.8	8.2	7.8	8.2	7.8	
	Other	6.1	6.1	5.2	4.9	5.2	4.9	5.2	4.9	
Emission factor (g/person/km)	Bicycle	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	Bus	73.8	73.8	73.8	73.8	59.0	55.4	59.0	55.4	
	Subway	9.1	9.1	9.1	9.1	7.3	6.8	7.3	6.8	
	Car	178.6	178.6	178.6	178.6	142.9	134.0	142.9	134.0	
	Taxi	178.6	178.6	178.6	178.6	142.9	134.0	142.9	134.0	
	Other	113.6	113.6	113.6	113.6	90.9	85.2	90.9	85.2	

## **Table 5.**Key parameters of travel behaviour under four scenarios



Figure 1. Study area and population density in the sub-districts of urban Beijing for 2000

## (Note: The colour figures are used for online version only)



Figure 2. Average CO<sub>2</sub> emission from the synthetic population in each sub-district for 2000



Figure 3. Average trip distance for each mode by the synthetic population in 2010



Figure 4. Average and total  $CO_2$  emission from the synthetic population in 2010



Figure 5. Average CO<sub>2</sub> emission from people's daily urban travel over 2000-2030



Figure 6. Total transport CO<sub>2</sub> emission from daily travel in urban Beijing



Figure 7. Transport CO<sub>2</sub> emission by vehicle types in 2020 and 2030



The following black-and-white figures are used for printed version:

Figure 1. Study area and population density in the sub-districts of urban Beijing for 2000



Figure 2. Average CO<sub>2</sub> emission from the synthetic population in each sub-district for 2000



Figure 3. Average trip distance for each mode by the synthetic population in 2010



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Figure 5. Average CO<sub>2</sub> emission from people's daily urban travel over 2000-2030



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