



# Investigating the comparative roles of multi-source factors influencing urban residents' transportation greenhouse gas emissions

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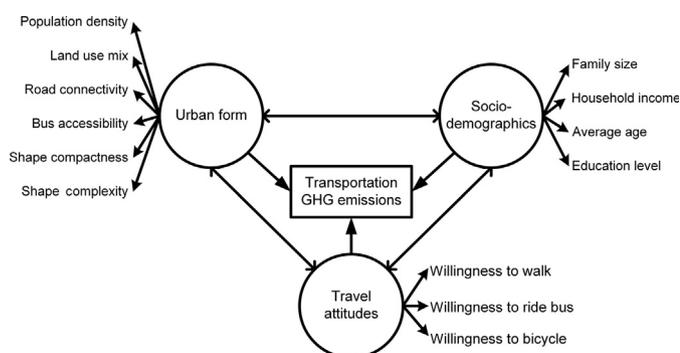
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## HIGHLIGHTS

- Effects of urban form, socio-demographics and travel attitudes on transportation GHG
- Factors are interacted, producing direct and indirect effects on transportation GHG.
- Urban form plays a leading role compared with socio-demographics and travel attitudes.
- Population density is a primary factor due to its solid direct and indirect effects.
- Interrelationships existed in factors should be fully considered in decision-making.

## GRAPHICAL ABSTRACT



## ARTICLE INFO

### Article history:

Received 23 April 2018

Received in revised form 18 June 2018

Accepted 6 July 2018

Available online xxxx

Editor: P. Kassomenos

### Keywords:

Urban form

Socio-demographics

Travel attitudes

residents' transportation GHG

Path analysis

## ABSTRACT

The current growth in transportation-related greenhouse gas (GHG) emissions has been largely attributed to rapid urbanization, particularly for cities in developing countries. Studies on the contributing factors and analysis of the mechanisms by which they influence transportation GHG emissions could aid in better achievement of mitigation goals. Yet, comparative contributions of the different sources of these drivers have not been well quantitatively investigated. This study employs a wide range of indicators across urban form, socio-demographic characteristics and residents' travel attitudes. By integrating a questionnaire-based survey of 1125 household in 45 communities in Xiamen City, China, land-use-based urban form quantification, inventory-based GHG calculation, a path analysis model is built to identify the interactions among these indicators and investigate their comparative direct and indirect effects on residents' local transportation GHG emissions. It was found that many variables interactively influence the transportation GHG emissions, producing considerable effects, both direct and indirect. Urban form plays a leading role in transportation GHG emissions, in comparison to socio-demographics and travel attitudes. Population density, land use mix, road connectivity and bus accessibility, in urban form; education, in socio-demographics; and willingness to ride the bus, in travel attitudes; were found to have significant positive effects on reducing residents' local transportation GHG emissions. Urban density—characterized by population density here—is the primary influential factor, due not only to its large direct effects, but also to its wide indirect effects through its influence on other variables. The results of this study may help policy makers consider how they can effectively utilize these key indicators to formulate mitigations in the transportation sector, and particularly, how to design low-carbon-friendly urban forms, in urban planning.

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## 1. Introduction

### 1.1. Motivation

Cities are facing compound challenges from climate change mitigation and urbanization (Pancost, 2016; Rosenzweig et al., 2010). The transportation sector is one of the most important sources of greenhouse gas (GHG) emissions contributed by human activities in the urban environment, and was responsible for 23% of CO<sub>2</sub> emissions from fuel combustion in 2014, with three quarters of this amount coming from road vehicles (IEA, 2016). Further concern over this issue has arisen because of rapid urbanization, with large populations migrating from rural to urban societies, leading to massive growth in transportation demand and vehicle kilometers traveled (VKT). This pattern is likely to continue in most cities, over the next few decades (Forman and Wu, 2016; United Nations, 2018), suggesting an overall increasing trend of transportation-related GHG emissions in the future. This trend may increase the pressure for countries to meet their targets set by the 2015 Paris Climate Agreement (McPhearson, 2016), and compromise the on-going international efforts to meet the Climate Action in Sustainable Development Goals (SDGs). Developing countries like China have more urgent need for these actions, as well as the greatest potential for reducing future emissions, because they are in the accelerating stage of urbanization, and the drivers of transportation GHG, such as urban form, socio-demographics and residents' travel attitudes, have been changing dramatically. Therefore, comprehensive study of the factors and understanding their mechanisms of influence on transportation GHG emissions could aid in better planning of climate actions designed to achieve the transportation sector's mitigation goals, in the context of climate change and urbanization.

### 1.2. Literature review

An increasing body of research has investigated the factors influencing residents' transportation behaviors and the resulting GHG emissions. Generally, variables in these studies refer: (1) urban form, (2) socio-demographics, and (3) travel-attitude-based residential self-selection. Previous travel research has demonstrated the considerable potential of changing the built environment to reduce travel demand. In these studies, built environment usually refers to the urban form characteristics, and was measured by the "D Variables"—including density, diversity of land use, design of street, destination accessibility and distance to transit (Cervero and Kockelman, 1997; Ewing and Cervero, 2001; Ewing et al., 2009). Urban form is the physical patterns, layouts, and structures that make up urban environment (Muscatò, 2017). It is well known that urban form affects GHG emissions, primarily in the transportation sector (Hankey and Marshall, 2010; Ishii et al., 2010; Liu and Sweeney, 2012). Density, land use mix, accessibility and connectivity are the major urban form drivers of transportation energy use and GHG emissions (Banister, 2011; Seto et al., 2014). There is consistent evidence that urban forms characterized by high density, mixed land uses, and adequate transit connectivity and accessibility are appropriate for encouraging non-vehicle travel and reducing VKT, leading to greater emissions savings in the transportation sector (Creutzig et al., 2016; Lee and Lee, 2014). As a result, land use planning has focused on compact city design that aims to limit sprawl and reduce automobile dependence—and thus VKT, energy consumption, and GHG emissions (Zhao et al., 2011).

Incorporating the socio-demographic factors in empirical studies on travel behavior is necessary, because different socio-demographic groups have different activity patterns (Chapin, 1974; Van Acker et al., 2010). Previous studies have demonstrated that—besides urban form—transportation GHG emissions also vary in relation to socio-demographic characteristics. Gross domestic product (GDP)—perceived as a vital metric of income—is the main driving factor for the growth of per capita CO<sub>2</sub> emissions from transportation on the

national scale, as demonstrated by the works of Lakshmanan and Han, 1997; Mazarino, 2000; Yang et al., 2015 in the U.S., Italy and China, respectively. When looking at the household scale, socio-demographics such as household size, income, education, employment, age, car ownership, et al. may affect residents' travel behavior and the resulting transportation GHG emissions, in varying degrees (Büchs and Schnepf, 2013; Bhat et al., 2009).

More recently, the role of citizens' travel attitude on travel behavior has been receiving increasing attention. Milakis et al., 2017 employed three indicators: walking preference, car preference and travel attitude to trip convenience to investigate the effect of travel attitude on travel behavior in Greece. Travel attitude affects residential self-selection which is defined as "the trend of residents to select locations on the basis of their travel preferences, needs and abilities" (Litman, 2005). For example, residents who prefer driving may consciously choose to live in remote and spacious neighborhood, while residents who prefer public transit and walking are of more possibility to live in neighborhood accessible to bus stations and conducive to walking (Bohte et al., 2009). Cao et al., 2009; Mokhtarian and Cao, 2008 examined the impacts of residential self-selection on travel behavior by reviewing empirical studies relating to this topic, and concluded that the travel attitudes accounted for a predominant role in travel behavior. However, Naess, 2014 argues that residential self-selection is hardly influence travel behavior. This shows that the effect of travel-attitude-based residential self-selection on travel behavior is not quite clear yet.

Generally, many sources of variables may affect residents' travel behavior and the consequent GHG emissions, and previous studies have tried to investigate the contributions of urban form, socio-demographics and travel attitudes. One concern is that these factors may interact, thereby leading to both direct and indirect casual effects on residents' GHG emissions. The interactions may exist between the same category of factors or between the different category of factors. For example, high density of urban form is generally associated with mixed land use, high accessibility and sufficient road connectivity (Song et al., 2017); household income is associated with education level, employment, car ownership, etc. (Diener, 1993); urban form such as density, accessibility and road connectivity may associate with socio-demographics like car ownership (Cao et al., 2007). As a form of Structural Equation Modeling (SEM), path analysis is a statistical technique used to evaluate causal models by examining the relationships between a dependent variable and two or more independent variables (Streiner, 2005). Unlike other techniques, path analysis is expert in examining the comparative strength of direct and indirect effects from independent variables to a dependent variable because it specifies relationships among all of the independent variables, and therefore the method has been adopted in physical sciences, medical science and social sciences for complex planning problems (Crossman, 2017). Several previous literatures attempted to apply path analysis to investigate the factors influencing travel behavior or its energy consumption. Using the path analysis, Bagley and Mokhtarian, 2002 examined the relationship of residential neighborhood type to travel behavior, incorporating attitudinal, lifestyle, and demographic variables in the San Francisco Bay Area; Eboli et al., 2012 explored the relationship among some spatial variables regarding geographical features, activity location, demographic and economic characteristics, and transportation variables such as trip production; Liu and Shen, 2011 examined the effects of urban land use characteristics on household travel and transportation energy consumption in the Baltimore metropolitan area. However, the comparative contribution of different sources of factors have not been comprehensively investigated in one model, and there is a lack of case studies in cities of developing countries.

### 1.3. Contribution

In the present study, by integrating a questionnaire-based survey of 1125 household in 45 communities in Xiamen City, China, land-use-

based urban form quantification, inventory-based GHG calculation, a path analysis model was built to identify the interactions among factors from urban form, socio-demographics and travel attitudes, and investigate their comparative direct and indirect effects on urban residents' local transportation GHG emissions.

## 2. Study area and methods

### 2.1. Study area and sampling

Xiamen City, with 3,860,000 population in 2015 and 1573 km<sup>2</sup> land area located on the southeastern coast of China, is a Special Economic Zone in China. Over the past three decades, the booming economy and rapid urbanization of Xiamen City have greatly altered urban land use, spatial form and socio-economic level, which have not only increased the demand for transportation, but also changed the residents' transportation modes (Cui et al., 2011). According to the residents' travel survey by Xiamen Institute of City Planning, residents in Xiamen City are increasingly relying on private car with its proportion increasing from 4.90% in 2003 to 8.21% in 2009, nevertheless proportion of non-motorized modes (including walking and bicycling) decreasing from 50% to 40.72% (Wu et al., 2009). As a result, GHG from the transportation sector have been increasing rapidly.

In this study, to obtain the required information on urban form, socio-demographics, travel attitudes, and residents' transportation GHG emissions, the stratified random sampling method was employed to determine 45 urban communities, and their location are depicted in Fig. 1. The stratified random sampling takes full account of the diversity of the samples, and therefore the data of the samples is more representative than the simple random sampling (Särndal et al., 2003). Twenty-five volunteer families for each community were randomly selected to take part in this research; hence the original sample consisted of 1125 households.

### 2.2. Measurements

In October 2015, trained interviewers visited the selected urban families and carried out a face-to-face questionnaire survey for each household. Three aspects of information were collected: (1) family socio-demographic characteristics; (2) family members' attitudes on transportation modes; and (3) family members' local transportation activity details from Monday to Sunday within one week, including destinations, modes, frequency, and distance. In the survey, destinations

include workplace/school, shopping center/supermarket, public service agencies (e.g., hospital, library, administration and services centre), service establishments (e.g., banks, restaurant, cafe shop, laundromats, barber shops), entertainment venues (e.g., parks, sports stadiums, theaters, concert halls). Transportation models include walking, bicycling, private car, taxi, bus, and motorcycle.

#### 2.2.1. Residents' transportation GHG emissions

GHG emissions from residents' transportation activity were calculated by multiplying each local activity level by its corresponding emission factor. In this study, only direct emissions are calculated. Indirect emissions from fuel production and infrastructure are excluded due to data limitation. Activity level was quantified according to each family member's transportation details, including destinations, modes, frequency, and distance. By referring to the IPCC's methods (IPCC, 2006) and local emission factors, GHG—including CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O—for private car, taxi, bus and motorcycle was calculated (details in Supplementary Information). In this analysis, emissions for CH<sub>4</sub> and N<sub>2</sub>O were converted to carbon dioxide equivalent value (CO<sub>2</sub>e).

#### 2.2.2. Socio-demographics

Socio-demographics including family size, income, age, and education were recorded in the questionnaire. Family size refers to the number of family members. Household income was taken as monthly family income. Age is the average age of family members. During the interview, the educational background for each family member was recorded. To quantify the household educational level, the educational background was measured using a 1 to 5 scoring scale: primary education or below = 1, junior high school education = 2, high school education = 3, undergraduate or specialist qualifications = 4, and graduate degree = 5, and the average value represents the household educational level.

#### 2.2.3. Travel attitudes

In the questionnaire, three queries: (1) willingness to walk instead of traveling by car if possible; (2) willingness to ride the bus instead of traveling by car if possible; and (3) willingness to bicycle instead of traveling by car if possible, were designed to gain information on residents' attitudes on transportation options. The Likert scale was applied to quantify the response: strongly disagree = 1, disagree = 2, neutral = 3, agree = 4, strongly agree = 5. The average value for each question for all family members was calculated, to represent the household's attitudes to walk, ride the bus, and bicycle.

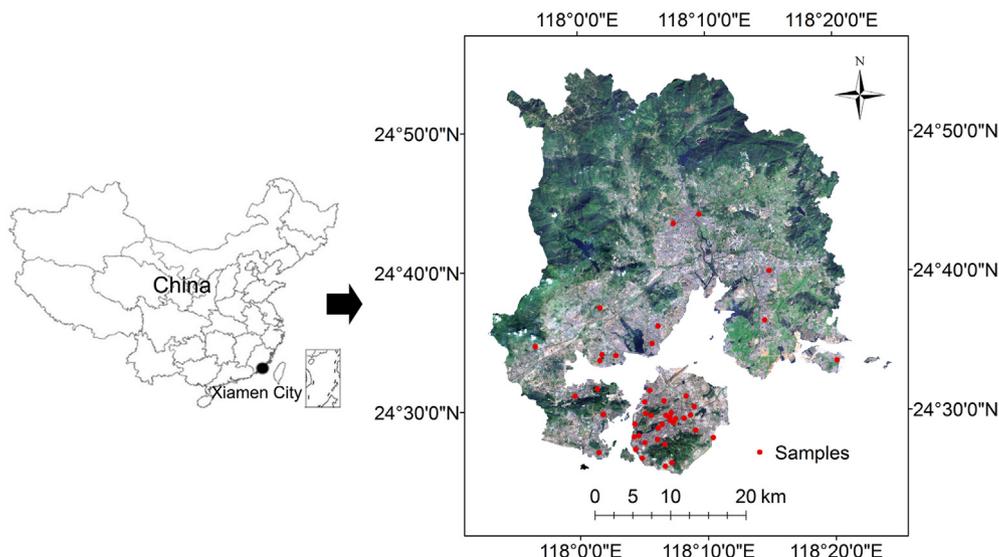


Fig. 1. Study area and sampling sites.

### 2.2.4. Urban form

To characterize urban form, 10 × 10-meter high-resolution land use data of Xiamen City for 2014 was generated using the inversion of IKONOS satellite data and digitization of land use maps provided by the Xiamen Urban Planning and Design Institute. On this basis, the land use was reclassified into thirteen types (Table S3). For each sample of communities, the urban form is represented by employing a range of indicators including population density, land use mix, road connectivity, bus accessibility, shape compactness and shape complexity. These indicators depict many aspects of urban form, in which population density is the measurement of urban density; land use mix is the diversities and integration of different land use; road connectivity refers to street density; accessibility combines proximity and travel time, but here is measured by bus accessibility—distance from a community to the nearest bus stop—due to data limitation; shape compactness and shape complexity are the measurements of geometric shapes of built-up area. Their definitions and estimation are described in the Supplementary Information.

### 2.3. Data analysis

#### 2.3.1. Correlation analysis

Correlation analysis was employed to identify the correlations among urban form, socio-demographics, travel attitudes, and transportation GHG emissions. It helps to select the key factors and identify their interrelationships that will be involved in the path analysis model. Since educational level and travel attitudes indicators were measured using an ordinal scale, Spearman correlation analysis was applied.

#### 2.3.2. Path analysis

According to the key factors and their interrelationships identified by correlation analysis, we built a path analysis to investigate the direct and indirect effects of urban form, socio-demographics and travel attitudes on residents' transportation GHG emissions. In path analysis direct effects occur directly from one variable to another, and indirect effects are effects that is mediated by other variables (Garson, 2013; Streiner, 2005). The standard path coefficient represents the strength of the effect, referring to the standard deviation changes of one variable when another variable rises 1 standard deviation (Kline, 2015). In empirical studies, absolute values of standard path coefficient < 0.10 imply a “small” effect; values around 0.30, a “medium” effect; and values >0.50, a “large” effect (Dessardo et al., 2012). After interrelationships among variables are identified based on general logic, previous researches and correlation coefficients, a hypothesized path analysis model is built. Its performance is assessed by indexes including the *P* value of  $\chi^2$ , root mean square error of approximation (RMSEA), comparative fit index (CFI), global fit index (GFI), and the normed fit index (NFI) (Bryman and Cramer, 1994; Jaccard and Wan, 1996; Schumaker and Lomax, 2004). AMOS 7.0 software was used to conduct the path analysis.

## 3. Results

### 3.1. Statistical descriptions

Statistical descriptions of GHG emissions, urban form, socio-demographics and travel attitudes are detailed in Table 1. The average GHG emissions of 45 sample communities was 1.699 kg CO<sub>2</sub>e household<sup>-1</sup>·day<sup>-1</sup> and 0.594 kg CO<sub>2</sub>e capita<sup>-1</sup>·day<sup>-1</sup>. CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O account respectively for 97.70%, 1.04%, and 1.26% of the total GHG emissions.

According to the questionnaire results, walking, bicycling, private car, taxi, bus, and motorcycle are the main modes of residents' transportation in Xiamen City, and their frequencies are 38.57%, 4.85%, 17.70%, 2.04%, 23.84% and 13.00%, respectively (Fig. 2). In this analysis, walking and bicycling represent the non-motorized modes of transportation,

**Table 1**

Statistical descriptions of urban residents' transportation GHG emissions, urban form, socio-demographics and travel attitudes, for 45 communities.

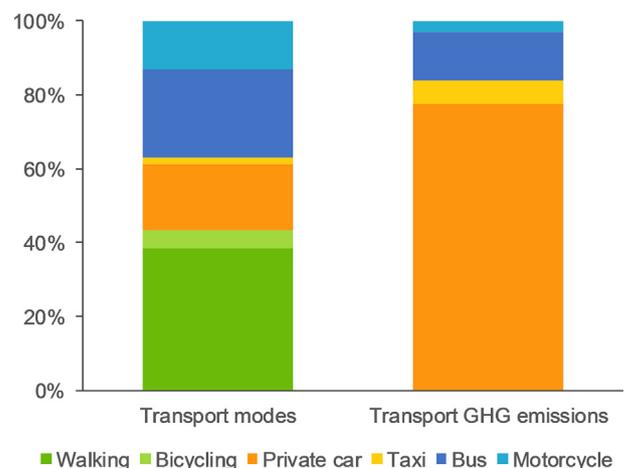
Variables	N	Min	Max	Mean	SD
Residents' transportation GHG emissions (kg CO <sub>2</sub> e/capita/day)	45	0.190	1.620	0.594	0.284
Population density (population/km <sup>2</sup> )	45	1168	60,529	22,473	17,737
Land use mix	45	0.01	0.72	0.49	0.15
Road connectivity	45	0.44	53.61	13.70	12.04
Bus accessibility	45	0.10	6.68	1.87	1.36
Shape compactness	45	0.03	0.50	0.22	0.14
Shape complexity	45	1.20	3.51	1.82	0.47
Family size	45	1.52	4.32	3.16	0.43
Household income (thousand RMB)	45	81.07	187.81	134.64	20.48
Average age of family	45	30.00	51.30	39.66	5.35
Household educational level	45	1.80	3.50	2.88	0.31
Willingness to walk	45	3.02	4.51	3.94	0.32
Willingness to ride the bus	45	2.77	4.24	3.66	0.33
Willingness to bicycle	45	2.71	4.24	3.44	0.30

and private car, taxi, bus, and motorcycle represent motorized modes of transportation. The two types of transportation account for 43.42% and 56.58%, respectively, indicating that the public is mainly dependent on motorized vehicles. As shown in Fig. 2, although in terms of travel frequency the bus is much higher than the private car, yet the private car dominates the GHG emissions, occupying 77.47%, followed by bus (13.14%), taxi (6.38%) and motorcycle (3.02%).

We compared the GHG footprint of transportation sector in Xiamen City with several mega cities worldwide. As shown in Table 2, per capita GHG of Xiamen is close to the level of New York City, which is less than Beijing, the capital city of China. However, intensity of transportation GHG of Xiamen is significant higher than cities in developed countries such as Tokyo Metropolitan, Great London and cities in developing countries like New Delhi. In addition, per capita GHG of Xiamen exhibits a stable increasing trend from 2009 to 2014. This implies that implementing low carbon strategies to mitigate GHG emissions in transportation sector is urgent and stressful.

### 3.2. Correlation analysis

Fig. 3 represents the correlations among residents' transportation GHG emissions, urban form, socio-demographics and travel attitudes. Urban form, except for shape compactness and shape complexity, displays a close correlation with residents' transportation GHG emissions, in which population density, land use mix, road connectivity and bus accessibility exhibit significant negative correlations. However, only educational level in the socio-demographics is significantly correlated



**Fig. 2.** Characteristics of urban residents' transportation modes and GHG emissions.

**Table 2**  
GHG footprint of transportation sectors in major cities.

City/mega metropolitan region	GHG (tons/capita)	Year	Source
Xiamen	1.14	2009	Xiamen Municipal Development and Reform Commission (2016)
	1.26	2010	
	1.45	2011	
	1.56	2012	
	1.71	2013	
	1.88	2014	
Beijing	1.68	2009	Gu et al. (2014); Jiang et al. (2013)
	1.89	2011	
Tokyo Metropolitan	0.92	2011	Bureau of Environment Tokyo Metropolitan Government (2017)
	0.86	2014	
New Delhi	0.77	2009	Ramachandra et al. (2015)
New York City	1.36	2011	New York City Mayor's Office of Sustainability (2017)
	1.82	2015	
Great London	0.91	2014	Department for Business, Energy, and Industrial Strategy (2017)
	0.90	2015	

with transportation GHG emissions. Similarly, willingness to ride the bus is the only factor in travel attitudes that displays significant correlation.

Inter-correlations also exist among the factors urban form, socio-demographics and travel attitudes, suggesting that these factors are not independent, but mutually influential. For example, population density is significantly positively correlated with road connectivity, bus accessibility and willingness to ride the bus. Road connectivity, bus accessibility, willingness to walk and willingness to ride the bus are significantly positively interrelated. Educational level is significantly positively correlated with household income, willingness to ride the bus and willingness to walk.

We built a regression model to further analyze the effects of these factors on residents' transportation GHG. Considering the potential multicollinearity induced by inter-correlations between variables,

ridge regression was employed. As shown in Table 3, population density, land use mix, road connectivity, bus accessibility, education level and the willingness to bus are the significant factors influencing residents' transportation GHG, which is consist with the results from correlation analysis. However, the ordinary regression model is incapable of revealing the direct and indirect causal relationships between influencing factors and GHG emissions.

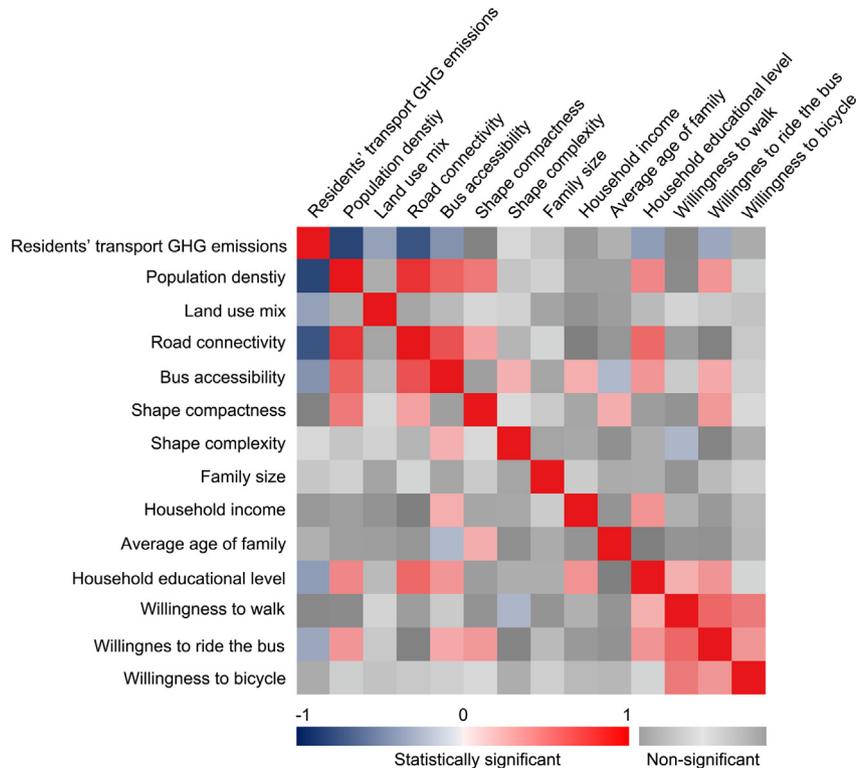
3.3. Path analysis model and validation

Referring to the results from correlation analysis, six key variables that significantly correlated with residents' transportation GHG emissions—including population density, land use mix, road connectivity, bus accessibility, educational level and willingness to ride the bus—are involved in the hypothesis path analysis model. Moreover, their paths affecting GHG emissions and interactions are identified according to general logic, previous studies and correlation coefficients that are significant at the 0.05 or 0.01 level. The hypothesized path analysis model is shown in Fig. 4. All variables are assumed to have direct effects on GHG emissions. Population density is assumed to have indirect effects on GHG emissions through road connectivity, bus accessibility and willingness to ride the bus. Road connectivity is assumed to have an indirect effect via bus accessibility, which also is assumed to have an indirect effect via willingness to ride the bus. In addition, educational level is assumed to have an indirect effect on GHG emissions through willingness to ride the bus.

The hypothesized model achieved good fit to data, as demonstrated by a non-significant  $\chi^2$  value ( $\chi^2 = 15.807, P = 0.071 > 0.05$ ), RMSEA =  $0.031 < 0.05$ , CFI =  $0.930 > 0.9$ , GFI =  $0.914 > 0.9$  and NFI =  $0.966 > 0.9$ .

3.4. Effects of influencing factors on GHG emissions

The final path model and standardized coefficients between variables are depicted in Fig. 4.



**Fig. 3.** Correlation matrix between variables (Statistically significant means that correlation coefficients are statistically significant at  $p < 0.05$ , while non-significant means not statistically significant at  $p < 0.05$  level.)

**Table 3**  
Ridge regression model of residents' transportation GHG with its influencing factors.

Independent variables	Unstandardized coefficients		Standardized coefficients	T	Sig
	B	SE(B)	Beta		
Population density	-0.000004	0.000001	-0.251711	-4.600850	0.000083
Land use mix	-0.314741	0.119179	-0.168729	-2.640920	0.013370
Road connectivity	-0.003081	0.001289	-0.130235	-2.390300	0.023804
Bus accessibility	-0.017020	0.013199	-0.071689	-1.289480	0.030778
Shape compactness	-0.086591	0.124427	-0.042470	-0.695915	0.492218
Shape complexity	0.033785	0.035438	0.055715	0.953370	0.348561
Family size	0.025535	0.057075	0.027853	0.447387	0.658037
Household income	0.055556	0.055245	0.059190	1.005623	0.323209
Average age of family	0.000813	0.003205	0.015012	0.253515	0.801722
Household education level	-0.045990	0.037844	-0.070516	-1.215246	0.034420
Willingness to walk	-0.048072	0.053528	-0.053411	-0.898058	0.376813
Willingness to bus	-0.079797	0.090653	-0.082990	-0.880244	0.028622
Willingness to bicycle	-0.040036	0.057751	-0.041638	-0.693256	0.493860
Constant	0.837025	0.444628	0.000000	1.882530	0.017019

Note: dependent variable is residents' transportation GHG; R Square = 0.693406; F value = 4.523284, Sig F = 0.000336.

3.4.1. Direct effects

As shown in Table 4, population density, land use mix, road connectivity, bus accessibility, educational level and willingness to ride the bus, to different extents, show negative direct effects on residents' transportation GHG emissions. In terms of the absolute values of standard path coefficients, the order of direct effects is: population density (-0.425) > land use mix (-0.303) > road connectivity (-0.255) > bus accessibility (-0.237) > educational level (-0.195) > willingness to ride the bus (-0.151). Obviously, urban form, especially population density, land use mix and road connectivity, prove to be the major factors influencing residents' transportation GHG missions directly, in comparison to socio-demographics and travel attitudes.

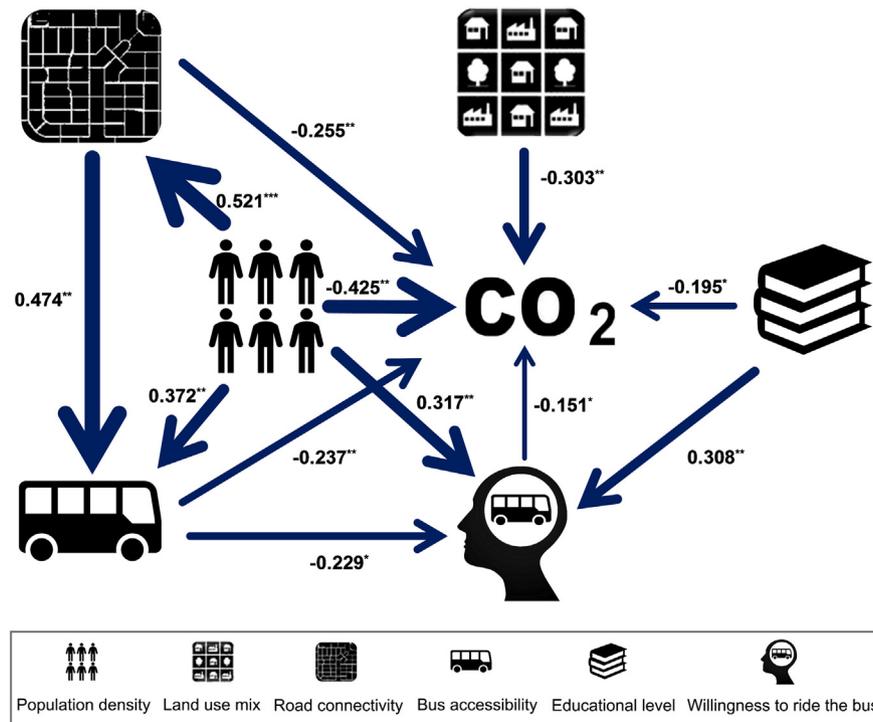
3.4.2. Indirect effects

Population density, road connectivity, bus accessibility and educational level exhibit different degrees of indirect effects as well. In

particular, population density, through road connectivity, bus accessibility and willingness to ride the bus, imposes wide and complex effects on GHG emissions. It also shows the largest total indirect effects among the studied factors, with a standard coefficient of -0.349. Although much lower than population density, indirect effects of other factors on GHG emissions are also significant. For example, road connectivity—through bus accessibility—also shows a negative indirect effect, with a standard coefficient of -0.129. Mediated by willingness to ride the bus, both bus accessibility and educational level show negative indirect effects, with coefficients of -0.035 and -0.047, respectively. Overall, the order of indirect effects is: population density (-0.349) > road connectivity (-0.129) > educational level (-0.047) > bus accessibility (-0.035).

3.4.3. Total effects

Total effects equal direct effects plus indirect effects, and the order of total effects is: population density (-0.774) > road connectivity



**Fig. 4.** Path analysis model with standardized coefficients (the thickness of the line indicates the magnitude of the effect; arrows indicate the direction of the effect. \*\*\* indicates coefficient is significant at the 0.001 level; \*\* indicates coefficient is significant at the 0.01 level; \* indicates coefficient is significant at the 0.05 level.)

**Table 4**

Direct, indirect and total effects of urban form, socio-demographics and travel attitudes on urban residents' transportation GHG emissions.

Variables	Direct effects	Indirect effects	Total effects
Population density	−0.425	−0.349	−0.774
Land use mix	−0.303		−0.303
Road connectivity	−0.255	−0.129	−0.384
Bus accessibility	−0.237	−0.035	−0.272
Household educational level	−0.195	−0.047	−0.242
Willingness to ride the bus	−0.151		−0.151

(−0.384) > land use mix (−0.303) > bus accessibility (−0.272) > educational level (−0.242) > willingness to ride the bus (−0.151). Among the studied influencing factors, the absolute value of the standard path coefficient of population density is above 0.5, indicating a large effect on urban residents' transportation GHG emissions. Both road connectivity and land use mix are >0.3, suggesting upper-middle total effects. The coefficients of bus accessibility, educational level and willingness to ride the bus are between 0.1 and 0.3, indicating lower-middle total effects.

#### 4. Discussion

##### 4.1. Comparative contributions of urban form, socio-demographics and travel attitudes

The factors studied, and the mechanisms whereby they influence urban residents' transportation GHG emissions, are diverse and complex, because they can come from different sources such as urban form and socio-demographics as well as from residents' travel attitudes, and may closely interact with each other. In the face of this puzzle, it is important for policy makers to understand the complex mechanisms and quantitatively assess their impacts, so as to formulate more efficient mitigation measures for transportation GHG emissions. The present study not only employed a wide range of indicators across urban form, socio-demographics and travel attitudes, but also took their interrelationships into consideration, making it possible to compare the respective contributions of urban form, socio-demographics and travel attitudes and to distinguish their direct as well as indirect effects. The results from this case study of Xiamen City demonstrate that, although the direct effects of factors on transportation GHG emissions are dominant, the majority of factors also show indirect effects, to different extents, through respective paths among factors, because of their interrelationships. Therefore, in mitigation planning and implementation for the transportation sector, decision makers should fully consider all the factors as well as their interrelationships, in order to make mitigation more efficient.

The present study reveals that the impact of urban form on residents' transportation GHG emissions is considerably greater than socio-demographics and travel attitudes. As demonstrated by the correlation analysis and path analysis, urban population density, land use mix, road connectivity and bus accessibility exhibit different degrees of impact on residents' transportation GHG emissions, with relatively high coefficients. However, only educational level in socio-demographics and willingness to ride the bus in travel attitudes, are found to have significant effects on residents' transportation GHG emissions, with relatively lower coefficients. This result is consistent with previous studies which conclude that urban form plays a more important role in travel behavior than do socio-demographics and residents' travel attitudes. Several case studies by [Salon, 2006](#) in New York City, [Zhou and Kockelman, 2008](#) in Austin, [Cao, 2010](#) in California, [Bhat et al., 2009](#) in San Francisco revealed that built environment—majorly urban form—accounted for 50% to 90% of total influence on travel behavior. It is well known that residents' transport GHG emissions vary with household socio-demographics, e.g. income, education, employment, age, however socio-demographic indicators that are statistically significant are different in previous empirical studies. Hence, we argue

that socio-demographics and residents' transport GHG emissions are not simply linearly correlated. Travel-attitude-based residential self-selection is receiving increasing attention, although its role on travel behavior and transport GHG emissions is still controversial. Many studies reviewed by [Cao et al., 2009](#) suggests that the built environment's effect on travel behaviors is influenced by residential self-selection, while works by [Chatman, 2009](#); [Ewing and Cervero, 2010](#); [Naess, 2014](#) show that residential self-selection seems not alter the effects of the built environment. Here we find that resident's travel attitudes exert a direct influence on transport GHG emissions with a relatively small effect compared to urban form and socio-demographics, which may contribute to explain this controversial issue.

Even though urban form is the dominant factor, socio-demographics and residents' travel attitudes also play roles in affecting transportation GHG emissions. On the one hand, as revealed by this study, enhancing household educational level and willingness to ride the bus can reduce residents' transportation GHG emissions, especially educational level, owing to its additional indirect effect through travel attitudes. On the other hand, urban form, socio-demographics and travel attitudes drivers of GHG emissions do not work in isolation; on the contrary, they become more effective when combined. Therefore, enabling and encouraging citizens and especially families—through education—to become more aware of possibilities for environmentally friendly transportation modes would help reduce carbon emissions.

It is worth paying extra attention to population density, since it is significant and large in both direct and indirect effects on residents' transportation GHG emissions. Previous literature about the relationship between urban density and transportation GHG emissions has also shown that urban density is significantly and negatively correlated with per capita transportation GHG emissions ([Brownstone and Golob, 2009](#); [Cervero and Murakami, 2010](#); [Clark, 2013](#)). Urban density directly affects GHG emissions in two main ways. On the one hand, high population density creates less average energy consumption of passengers in cars and buses than does low population density ([Lee and Lee, 2014](#)). On the other hand, higher population densities possess of high and concentrated public transportation demand that is necessary for the supply of diverse public transportation infrastructure, however transportation demand is relative low and dispersed, in built environment with lower densities, which hinders the switch over to less energy-intensive transportation modes such as public transportation, walking, and cycling ([Bunting et al., 2002](#); [Forsyth et al., 2007](#)). In addition, population density does not work in isolation, but affects road connectivity and bus accessibility, thereby posing indirect effects on transportation GHGs as well. Therefore, urban population density is the dominant driver of transportation GHG emissions when considering both direct and indirect effects. In addition to population density, land use mix, road connectivity and bus accessibility also impact transportation GHG emissions directly and indirectly. Mixed land use promotes diversity and integration of land uses at a given scale, and thus can reduce travel distances and facilitate walking and non-motorized modes of travel, thereby reducing aggregate amounts of vehicular movement and associated GHG emissions ([Kockelman, 1997](#); [Permana et al., 2008](#)). High connectivity means adequate and well-designed road intersections, which improve convenience of travel, thereby reducing VKT ([Ewing and Cervero, 2001](#); [Salon et al., 2012](#)). Moreover, high connectivity normally relates to easier access to bus stops, and high bus accessibility can promote the use of public transportation and therefore reduce GHG emissions.

##### 4.2. Implications

Over the past four decades, the overarching trend displays a persistent decline in population density of most Chinese cities like Xiamen. As shown in [Fig. 5-a](#), the built-up area of Xiamen City has been sprawling rapidly, leading to a decline in population density. Accompanied by this trend, however, is a substantial increase in per capita

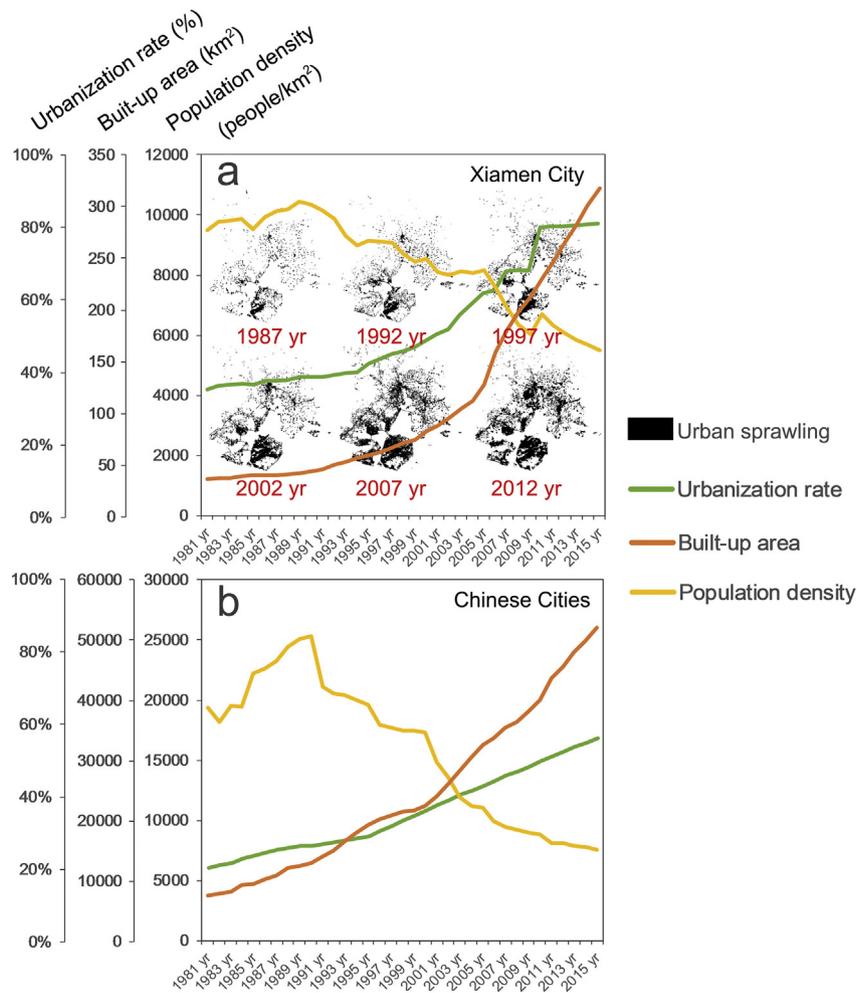


Fig. 5. Built-up area sprawl and population density declining trends in urban built environment of Xiamen City and other Chinese cities.

transportation GHG emissions. The average population density has also been declining due to urban sprawl, when looking at 661 Chinese cities (Fig. 5-b). According to the current urban planning of Xiamen City, population density will be lower than the current level by 2020. In addition, it is of highly probable that the average urban population density of Chinese cities will continue to drop owing to rapid lower-density urbanization (Bai et al., 2014). Therefore, it is foreseeable that great potential for GHG mitigation lies in the transportation sector for Xiamen and for other Chinese cities, if current urban sprawl and declining population density are not reversed.

As the vital components of global change, urbanization and climate change are tightly related. Cities already account for 70% of global greenhouse gas emissions and house more than half of humanity (Acuto, 2016). By 2050, 68% of the world population are projected to live in urban areas, and the rapid urbanization are projected to add 2.5 billion to the world's urban population, with majority of this growth happening in developing countries in Asia and Africa (United Nations, 2018). Consequently, transportation demand and vehicle kilometers traveled in the urbanizing area is about to increase massively over the next few decades, leading to severe challenges for carbon mitigation in transportation sector. Moreover, urban expansion and spatial form change, household socio-demographics transition and residents' travel attitudes change in the process of urbanization will also add huge uncertainties. Sustainable transportation is key to successful GHG reduction in transportation sector, since it is 'green' and has low impact on the environment, which is of multiple benefits in the senses of society, environment and climate change mitigation (Jeon and Amekudzi, 2005). Hence, measuring the relative roles of different influencing

factors and taking full account of their interrelationships in decision-making is vital and fundamental for planning, implementation and optimization of sustainable transportation.

#### 4.3. Limitations

While this study expands our understanding of the factors influencing urban residents' transportation GHG emissions, it also labors under several limitations that future research needs to address. First, residents' travel behavior recorded in this study only include local activities within city, and the resulting GHG emissions is direct emissions rather than life-cycle emissions due to data limitation. Second, more aspects of factors—beyond urban form, socio-demographics and travel attitudes—need to be expanded, for further understanding the driving forces of urban residents' transportation GHG emissions. Third, obtaining active data on transportation behavior via questionnaire normally results in subjective error from participants. Moreover, the biases may also occur as the result from survey design (e.g., time frame, recording destinations and distance estimation). Recently, urban residents' movement data recorded by mobile devices have been able to serve as an innovative data source that could be used in future studies.

#### 5. Conclusion

This study developed a path model and analyzed the direct and indirect effects of urban form, socio-demographics and travel attitudes on urban residents' transportation GHG emissions. As demonstrated by a case study of Xiamen City, several major conclusions can be drawn.

(1) The drivers of urban residents' transportation GHG emissions do not work in isolation. In addition to the direct effects, indirect effects also play a pivotal part owing to the interrelationships among factors. (2) Urban form, characterized by high population density, land use mix, road connectivity and bus accessibility; socio-demographics, characterized by high educational level; and travel attitudes, characterized by high willingness to ride the bus; are all applicable to carbon mitigation in the transportation sector. Urban form plays a leading role, in comparison to household socio-demographics and travel attitudes. (3) Population density is the dominant factor influencing urban residents' transportation GHG emissions, suggesting that urban sprawl is harmful to carbon mitigation.

The findings of this study have important policy implications. (1) Policy makers need to integrate broader factors and fully consider their interrelationships during decision-making. Pursuing one of them in isolation is insufficient for lowering emissions. (2) For rapid urbanization, urban planning—especially in developing countries—should focus on low-carbon-friendly urban forms, with more attention to urban density, land use mix, connectivity and accessibility, and, most importantly, avoiding urban sprawl.

### Acknowledgements

The authors gratefully acknowledge financial support from the National Key Research and Development Program of China (2017YFC0506603), and the National Natural Science Foundation of China (41371205).

### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2018.07.072>.

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