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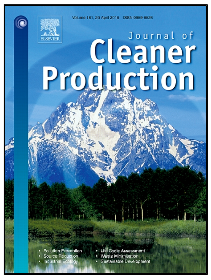

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Self-driving tourism induced carbon emission flows and its determinants in well-developed regions: A case study of Jiangsu Province, China

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Abstract:

Carbon emissions from the tourism industry are an important measure of the impact tourism has on the environment. Previous studies are predominantly focused on the static estimation of carbon emission from tourism transport. The effective estimation and analysis of carbon emission flows from self-driving tourism, and it's related determinants, has become increasingly important. Using expressway traffic flow data at the level of toll-gate across Jiangsu Province in China, 2014, this paper has estimated the carbon emission flows from self-driving tourism between counties, analyzed the spatial patterns of its inflow, outflow and net flows, and modelled the determinants of these flows globally and locally using the geographically weighted regression method. The spatial distribution of these flows show high concentration in the South, gradually decreasing to the North. The two geographically weighted regression models demonstrate that the determinants of both inflows (the per capita gross domestic product. and the scenic spot's score) and outflows (the per capita and total population of permanent residents) indicate spatial non-stationarity across Jiangsu province. The flow perspective and geographically weighted regression methods used in this paper have been proven to be effective in theoretical understanding and methodogical analysis of carbon emission trading. It is concluded that the spatial variation of these determinants has provided important evidence for carbon emission trading at county level. This suggests that local governments should take the variations of per capita gross domestic product, score of attractive spots and total population of permanent residents into the process of estimating carbon emission trading between counties.

Key words: Carbon emission; self-driving tourism; spatial pattern; determinants; geographically weighted regression; Jiangsu province

1 Introduction

The tourism industry is progressively becoming the largest and fastest-growing industrial sector in the world. Understanding carbon emissions from the tourism industry is a significant factor in the global emission reduction target (WTTC, 2009). The World Tourism Organization (UNWTO) and United Nations Environment Programme (UNEP) (2008) have concluded that a correlation exists between tourism and climatic change. In face of this global challenge, UNWTO has proposed a theoretical framework and practical measures to alleviate the influences of tourism on climate change and promote the development of low-carbon tourism (Jamal, Taillon, & Dredge, 2011; Cerutti, Beccaro, Bruun, Donno, Bonvegna, & Bounous, 2016). A policy report published by the Business & Climate Summit in 2009, states that greenhouse gas emissions from tourism industry should be massively reduced (Simpson, Gössling, Scott, Hall, & Gladin, 2008). Self-driving travel has recently experienced rapid growth, in line with improving standards of living, transport infrastructure and its associated facilities. Self-driving tourism is an organized and planned form of tourism with the self-driving car as the main means of transport (Becken, & Wilson, 2007). Self-driving tourism provides a flexible space for the tourists in the selection of objects, participation in the process and experience of freedom. Self-driving has become a dominant form of short-distance tourist travel as it enables to extend and expand the depth and breadth of tourist activities.

As the largest developing country in the world, China's private car production, sales and possession have been increasing steadily, as stimulated by its long-standing economic development. In contrast, the car manufacturing in developed countries relatively remains in the same speed. Therefore, in the future, China's government will be facing the challenges of emissions not only from existing cars but also from a huge number of newly purchased vehicles. It should be noted that the car sales in China are still dominated by the traditional fossil energy cars. The total volume of car sales in China was 23,491,900 in 2014, including the production and sales of only 74,800 new energy vehicles (including pure and hybrid electric cars) (China Automotive Industry Association, 2015). It is clear to see that the proportion of new energy cars is still very low, and subsequently, the vehicle carbon emission remains a serious issue and challenge. Admittedly, with the advancement of new technology in the future, the widespread promotion of new energy vehicles will help reduce or even solve the issues of carbon emissions from private cars. However, the situation of massive carbon emissions from private cars is still pressing for China at the current stage of development. Consequently, self-driving travel is contributing a large proportion of carbon emission in tourism industry (Katircioglu, Feridun, & Kilinc, 2014), particularly in China where tourism is developing rapidly.

Carbon emissions from the tourism industry have been extensively studied in the published literature across a wide range of themes. For example, recent studies include carbon footprints associated with tourism consumption (Munday, Turner, & Jones, 2013), CO2 emissions at hotels (Tsai, Lin, Hwang, & Huang, 2014) and from international tourism (Katircioglu, Feridun, & Kilinc, 2014), carbon footprint by transport (Filimonau, Dickinson, & Robbins, 2014) tourism investment (Cadarso, Gomez, Lopez, & Tobarra, 2016), and indirect carbon emission (Filimonau, Dickinson, Robbins, & Reddy, 2013). When categorised by modes of transport, it was revealed that the carbon emission from international aviation and private cars has occupied the majority of global tourism carbon emission (Howitt, Revol, Smith, & Rodger, 2013; Verbeek, & Mommaas, 2008; Gössling, Scott, & Hall, 2015). The estimate is that cuiseship contributes probably around 2% whereas aviation is now over 50% (Rutty, Gössling, Scott. & Hall, 2015; Scott, Hall, & Gössling, 2016; Scott, Gössling, Hall, & Peeters, 2016). Another case study in the Yangtze River Delta region found that the carbon dioxide emitted from planes and self-driving cars occupied 71.64% of the total carbon emissions from tourist transport (Tao, & Huang, 2014).

Among these studies, methods of estimating carbon emissions have been one of the main concerns in this area. Since the seminal paper by Gössling (2000), which proposed the first measurement of carbon emissions from the tourism industry, a variety of methods have been explored, integrated and applied on varied scales from global down to local (Ram, Nawijn, & Peeters, 2013; Coles, Dinan, & Warren, 2014). Including top-down (Tao & Huang, 2014; Jones, 2013; Filimonau, V., Dickinson, Robbins, & Huijbregts, 2011), bottom-up, and other methods (e.g. life cycle assessment; environmental satellite account) (Munday, Turner, & Jones, 2013; Sun, 2014; Huebner, 2012; Jones, 2015). For example, using a top-down as well as an extended tourism environmental satellite account method, Jones (2015) estimated the carbon emission from the Welsh tourism industry and revealed that approximately 77% of greenhouse gases had been produced from this industry within the country, 58.5% of which was directly emitted from tourism transport.

In recent years, there has been a wealth of literature detailing the influence of carbon emissions in the tourism industry and the relevant countermeasures against emission reduction (Scott, Gössling, Hall, & Peeters, 2016). The determinants in the published literature include energy structure and carbon emissions within the tourism industry (Gössling et al., 2007), carbon emission coefficient of all kinds of energy, scale of tourist flow, spatial behavior of tourists, consumption behavior of tourists and transportation means of tourism (Scott, Peeters, & Gössling, 2010; Lin, 2010). For instance, Gössling et al. (2007) argued that enterprises and governments should make use of renewable energy to optimize the energy structure and improve energy efficiency in the tourism industry. This led to call for changing the current unsustainable tourism development model (Ram, 2013). In addition, the environmental protection awareness of tourists has an important impact on the carbon emissions induced from tourism (Kachel, & Jennings, 2010).

In terms of emission reduction policies, tourism transport has been one of many concerns, with a focus on changing the consumption behavior and pattern of tourists (Peric, Jurdana, & Grdic, 2013), improving low carbon awareness and choosing low emission vehicles (Dickinson, Robbins, & Lumsdon, 2010). The development of a "slow travel" conceptual framework has a demonstrable effect on the practice of sustainable tourism (Lumsdon, & MeGrath, 2011). Environmentally sustainable modes of public transport should be promoted for tourist' use in comparison to traditionally unsustainable modes including tour buses, trains and air transportation (Gössling, 2000). It is argued that tourists should reduce the frequency of tourism by extending travel time, but increasing tourism travel distance is not conducive to the reduction of emission in tourism industry (Mckercher, Prideaux, Cheung, Law, Scott, & Becken, 2010; Ram, Nawijn, & Peeters, 2013). Carbon tax has been also recognized as one of the most important policies of emission reduction (Gössling, Scott, & Hall, 2015).

It is clear to see that many studies have focused on carbon emissions induced from tourism (particularly from tourism transport), among which the following two points should be highlighted:

Firstly, transport as a platform for tourism is key to carbon emission in the tourism industry. These previous studies have not made links to mobility, which is a fundamental function of transport. This has resulted in the focus of their analyses on static estimation of carbon emission. However, both energy production and consumption require an efficient energy transmission network (Kang, Zhou, & Chen, 2012). Consequently, there is a need to more accurately estimate the carbon emission based on the dynamic flows, which reflects the transport process of tourism (Jin, Cheng, & Xu, 2017). Secondly, the current analysis of carbon emissions from tourism transport aims to reduce carbon emissions through using a variety of methods. The analysis methods used in these studies have not explored the spatial heterogeneity in the pattern of carbon emission and corresponding socio-economic determinants, which are crucial for the carbon trading policy across a region. To summarize, there is a clear research gap in the published literature: the carbon emission induced by tourism transport should be measured by dynamic flows and account for spatial heterogeneity when making relevant policy for carbon trading in the tourism industry.

The carbon emissions from tourism transport should be represented as a dynamic flow (Huang, Cao, Jin, Yu, & Huang, 2017), similar to the flow of migrants in human geography (Cheng, Young, Zhang, & Owusu, 2014). Flow in this context is defined as the flow and transferal of carbon dioxide emitted from tourism-induced transportation system when tourists travel from their origin places to destination attractions. It can be split into two categories: inflow and outflow. The former refers to the carbon emission generated due to travelling to destination, while the latter referring to the carbon emission generated due to travelling away from origin places. The comparisons between inflow and outflow can effectively measure the regional balance between production and consumption of carbon emission from the whole tourism transport and thus provide quantitative evidence for investigating the regional tourism carbon trading (Becken, 2002; Sun, & Pratt, 2014).

The aim of this paper is to explore carbon emissions within self-driving tourism and its socio-economic determinants, discussing its geographical imbalance from the perspective of flow by using high-resolution traffic flow data collected at each toll-gate. Flow perspective, the focus of this paper, enables dynamic exploration of relationships between carbon emissions and tourist origins and destinations. The policy implication of the analysis results suggest that a shift from conventional static or areal analysis to flow-based modelling can reveal the spatial heterogeneity of carbon emission processes, which provides quantitative and exploratory evidence for carbon trading across a region. This paper has contributed a methodological development towards supporting policy making of carbon emission economy.

This paper is structured as follows. Following the introduction, section two introduces the case study area (Jiangsu Province, China), and the data sets and methods used. Section three presents the results obtained from measuring and analysing carbon emission flows induced by self-driving tourism. Section four presents a discussion of the results and summarizes the overall conclusions.

[Fig. 1 Location of the study area and its administrative units]

[Fig.2 Location of toll-gates and expressway across the study area]

2. Data and Methods

2.1 Study area and data sources

Jiangsu Province is located on China's eastern coast (Fig 1), covering an area of 102,600 km^2. Jiangsu is situated in the well-developed regions of China, but has a geographical development imbalance (Wei, 2010). With a total of 63 counties and cities, this province is usually divided into three regions; Northern (29 counties), Central (16 counties and its capita, Nanjing City), and Southern (18 counties). This is due to large variations in economic growth and social welfare between the regions. . The Southern region in particular, popularly called SuNan, has become a model of growth in China in international literature (Wei, 2010). In 2014, Jiangsu has achieved a gross domestic product (GDP) of up to 6.51 trillion yuan RMB (JPBS, 2015), which is now one of the fastest growing economies and most robust provinces in China.

It is estimated that there have been 2971 thousand foreign tourists travelling to Jiangsu and staying overnight, with the number of domestic tourists reaching figures of up to 570 million. The added-value of tourism industry has amounted to 363.39 billion yuan RMB, occupying 5.5% of Jiangsu's GDP (JPBS, 2015). Tourism is a key industry in Jiangsu and has played an increasingly important role in the overall national economic development. The high rate of car ownership in the South, which is above 200 cars per 1000 people, has stimulated the growth of self-driving tourism. This provides a good case study for carbon emission induced by tourism transport and for exploring spatial heterogeneity in the pattern and determinants of carbon emissions. Meanwhile, Jiangsu, a dominant province in energy consumption which depends heavily on fossil energy (JBS, 2016), poses a prominent contradiction in emission reduction. Therefore, Jiangsu Province will be an ideal case study area for this topic.

The main data source for this case study is Jiangsu Expressway Network Operation & Management Center, which provides the historical data of real-time traffic flow on expressways across the study area. As shown in Fig. 2, there are 334 toll-gates in total across the province, showing a high concentration in the South. The flows of transport between any pair of two toll-gates are recorded. Each record includes a serial number and time slot that each vehicle has arrived at and departed from a toll-gate. In total, 235 million records of high temporal resolution, were produced for 2014, based on which a two-dimensional OD flow matrix (334*334) between gates was created for further spatial analysis. As most statistical data of population and economy in China are reported at county level, a two-dimensional OD flow matrix (59*59) between counties was formed by spatial aggregation (note: in the total 63 counties, 4 counties have no toll-gates as shown in Figure 3a, as such only the rest 59 counties are selected for this study). Socio-economic statistical data on county scale were collected from *Jiangsu Statistical Yearbook* (JPBS, 2015). The tourism data (the number of domestic tourists, the revenue from domestic tourism and the scenic spot's score) is from the *Jiangsu Tourism Development Report* (Jiangsu Provincial Tourism Bureau, 2015). Socioeconomic data and tourism data are used to analyze the influencing factors of carbon emissions from self-driving tourism. The data are describes in Table 1.

[Table 1 Data Sources]

The ratio of self-driving vehicles to total flows is estimated through a process of sampling. The specific procedure is described below. There are 334 toll-gates in total across 63 counties, with an average number of 5.3 toll-gates per county. For each county, we randomly selected 1-2 expressway toll-gates and allocated 2~3 students at each toll-gate to count the percentage of self-driving tourism over the total. It is assumed that the ratio of self-driving tourism varies with season. The sampling was taking place during each season: 28 days from 1-7th March, 1-7th June, 1-7th September and 1-7th December, 2014. Specifically, the survey was conducted from 8 a.m. to 8 p.m. each day. The ratio of self-driving to the total traffic flow was calculated accordingly for each day, and then their average values within a week was recorded for each season. The final ratio was calculated by weighting the average values between the four seasons for the selected 59 counties, as shown in Figure 3b. It is estimated that this ratio ranges from 2-8% across China, though its spatial variation has been recognized (CATT, 2015).

[Fig. 3 Number of toll-gates (a) and ratios of self-driving to total traffic flows (b)]

2.2 Analytical methods

(1) Measurement of self-driving carbon emission

Using the well-recognized method of measuring carbon emission from tourism transport (Filimonau, Dickinson, & Robbins, 2011), the regional carbon emission from tourist travel, based on inter-county traffic flow, was calculated using the equations below (1-5):

$$S_{ij} = \alpha_j \times T_{ij} \quad (1)$$

$$C_{ij} = \beta \times P \times S_{ij} \times D_{ij} \quad (2)$$

$$C_{ini} = \sum_{j=1}^{n} C_{ji} \quad (3)$$

$$C_{outi} = \sum_{j=1}^{n} C_{ij} \quad (4)$$

$$NC_i = C_{ini} - C_{outi} \quad (5)$$

where C_{ij} denotes the carbon emission from self-driving tourism from County i to County j; P is the average number of self-driving tourists. S_{ij} denotes the self-driving vehicle flow; D_{ij} means the distance from County i to County j. β is the unit carbon emission coefficient from self-driving tourism. T_{ij} denotes the total amount of traffic flow from County i to County j. α_j denotes the ratio of self-driving vehicles to total flows in County j. C_{ini} and C_{outi} indicates the carbon inflow and outflow within county i. NC_i represents the net carbon emission. Carbon emissions from self-driving tourism is a directed flow network, in which different nodes on the network have varied roles and positions.

The value of β (the unit carbon emission coefficient from self-driving tourism) demonstrates a spatial variation, i.e. different country has a different standard and the β values in developed countries are generally higher than that in less developed countries (Chenoweth, 2009; Gössling, Scott, & Hall, 2015). Xiao, Zhang, Lu, Zhong, and Yin (2010) have made reasonable corrections and adjustments on the β value for China, and proposed that β should be set as 99 g/pkm, which will be used in this study, together with the P value of 2.97, determined through the survey.

(2) Geographically weighted regression (GWR) model

The most frequently used modelling framework to analyse social and economic data is regression analysis based on ordinary least squares. Regression analysis is the standard technique for formalising statistical associations between a dependent variable and a set of explanatory variables, and for estimating the best fit between the predicted and observed values of the dependent variable as illustrated in equation 6, where y is a dependent variable, the x_k are independent or explanatory variables, and β_k are the coefficients to be estimated from observed data; β_0 is an intercept term.

$$y = \beta_0 + \Sigma \beta_k x_k \tag{6}$$

Such a model is termed 'global' in that all the data are used to derive one set of parameter estimates which are assumed to be constant over space. In turn, this assumes the processes being examined are stationary over space. The application of models of economic processes between counties across a province is interesting because there may well be different economic and spatial processes operating either county. In addition, areas near the economic agglomeration zones often self-organize into a special region with some socio-economic activities within the zone, such as tourism and commuting. Global modelling that ignores spatial non-stationarity is not able to capture such complexities (Cheng, & Fotheringham, 2013); what is needed are more flexible spatial models. Geographically Weighted Regression (GWR) is a local modelling technique that is able to capture spatial variations in processes (Brunsdon, Fotheringham, & Charlton, 1998; Fotheringham, Brunsdon, & Charlton, 2002). The basic GWR relationship is shown in equation 7.

$$y_i = \beta_0 (u_i, v_i) + \Sigma \beta_k (u_i, v_i) x_k \tag{7}$$

where (u_i, v_i) denotes the coordinates of the ith point in space and $\beta_k (u_i, v_i)$ is a realisation of the continuous function $\beta_k (u, v)$ at point i. Equation 6 is a special case of equation 7 in which the parameters are assumed to be spatially invariant. The estimator for the local parameters in the GWR model is:

$$\boldsymbol{\beta}^{\wedge} (u_i, v_i) = (\mathbf{X}^T \mathbf{W}(u_i, v_i)\mathbf{X})^{-1} \mathbf{X}^T\mathbf{W}(u_i, v_i)\mathbf{y} \tag{8}$$

where the bold type denotes a matrix or vector; the vector $\boldsymbol{\beta}^{\wedge}$ represents an estimate of $\boldsymbol{\beta}$**;** and $\mathbf{W}(u_i, v_i)$ defines a spatial weight function determined usually by a Gausian kernel. One of the main outputs from GWR is a set of local parameter estimates (and associated diagnostics) that can be mapped to show a surface of relationships. Fotheringham, Brunsdon, and Charlton (2002) explore local multiscale issues caused by the change of bandwidth defined for running GWR. In this sense, GWR can function as a spatial microscope in which relationships at different spatial scales can be seen by altering the bandwidth in the model.

The development of GWR model aims to explore spatial heterogeneity in the process of carbon emissions induced by self-driving tourism transport by analyzing the socio-economic determinants locally, which can be split into two models focused on inflow and outflow of carbon emissions at county level respectively. The aggregation of carbon emission flows into county level enable the linkage of carbon emission flows with socio-economic factors, which can be collected at county level in China. The maps produced by GWR models can help interpret the spatial pattern of socio-economic processes shaping the patterns of carbon emission across a region.

3 Results

3.1 Spatial distributions of expressway traffic flows

The traffic flow matrix between pairs of counties in 2014 across Jiangsu Province was created through aggregating the traffic flow at toll-gate level. Using the centroid of county as a representative origin and destination site, these flows at county level are mapped in Fig. 4. High-density flows are clearly concentrated in southern Jiangsu, with low-density flows observed in the North. This pattern is attributed to the higher rate of car ownership in the south, which is above 200 cars per 1000 people (see Figure 7a as well). The following six economically well-developed counties dominate the spatial distribution of these flows: Suzhou, Nanjing, Wuxi, Changzhou, Nantong and Jiangyin, in which dense distribution of transport networks can be observed in Fig 2. In these counties, cities, towns and countryside areas display a high rate of car ownership. For example, in the period from 2008 to 2014, the car ownership in Suzhou municipality has increased from 15.1 to 66.9 per 100 households for city/town areas and from 12.78 to 58.5 per 100 households for countryside, respectively (BSS, 2015).

[Fig. 4 All (a) and self-driving (b) traffic flow on expressway network across Jiangsu]

3.2 Spatial distribution of self-driving traffic flows

Self-driving traffic flows in Jiangsu were then estimated using Eq (3), and with the resulting spatial distribution is shown in Fig. 4b. The self-driving tourist flow shows a similar pattern with that of total self-driving traffic flow in Fig 4a. The south outperforms the north in both self-driving flows and self-driving tourist flows. The disparity between both is indicated in its spatial scale. For example, only four counties: Nanjing, Suzhou, Wuxi and Changzhou, dominate the distribution of self-driving flows. This has clearly revealed that there are more people favoring self-driving tourism in the South than in the North. There is a substantial variation in GDP per capita across the province (see Figure 7c), where some southern counties have achieved above 0.1 million yuan RMB, contrasting with most Northern counties below 50,000 yuan RMB (JBS, 2015).

3.3 Carbon emission from self-driving tourism

The carbon emission flows from self-driving tourism were estimated using Eq. (2), and displayed in Fig.5. The highest concentration of these carbon emission flows is observed in Nanjing municipality. As the provincial capital of Jiangsu, the rapid development of its high-density road network and high-ranking attractive spots have contributed to this pattern. In Figure 7d, the attractive score of Nanjing is higher than 80, compared with most other counties less than 20. High flows of carbon emissions are also observed throughout Suzhou, from Suzhou to Wuxi, Changzhou to Nanjing, Suzhou to Nanjing, Wuxi to Nanjing, Kunshan to Suzhou, Wuxi to Suzhou and Nanjing to Wuxi. The carbon emission flows between the counties in the North have much lower density relative to those in the South, such as from Lianshui to Binhai, baoying to Xiangshui and Lianshui to Xiangshui. Two reasons may contribute to the disparity between the South and North. First, the abundant tourism resources and high-level attractions (e.g. natural landscape and art history) distributed in the south are the crucial pulling forces (see Figure 7d). In addition to this, residents in this region have a much higher level of income (See Figure 7c), so they can afford a car (see Figure 7a) and travel costs.

[Fig. 5 Distribution of carbon emission flows from self-driving tourism]

3.4 Spatial patterns of carbon emission inflows and outflows from self-driving tourism

Carbon emission inflows and outflows from self-driving tourism between all counties were calculated using Eq. (3) and (4) and are shown in Fig. 6 (a) and (b), respectively. Net carbon emission flows from self-driving tourism can be further calculated using Eq. (5), as shown in Fig. 6 (c).

[Fig. 6 Spatial patterns of carbon emission flows from self-driving tourism]

Carbon emission inflow within a county refers to the carbon emission produced by the tourists' self-driving tourism from other areas to this county due to its pulling forces, including tourism attractions. Carbon emission outflows within a county refers to the carbon emission produced by the tourists' self-driving tourism to other counties due to their tourism activities. Net carbon emission flow from self-driving tourism is defined as the difference between its inflow and outflow. A positive net carbon emission flow within a county indicates that the carbon emissions induced by the tourism attraction in this county exceeds carbon emissions generated by the local residents' tourism activities. By contrast, a negative net carbon emissions flow indicates that the carbon emissions induced by the tourism attraction in this county cannot offset the carbon emission generated by the local residents' tourism towards other regions. Comparatively, the counties in the South are characterized by positive carbon emissions, where those in the north display negative carbon emissions.

Fig 6 demonstrates that Nanjing is the highest across three flows, followed by the economically advanced cities: Suzhou, Wuxi and Changzhou in the South. This spatial pattern of net carbon emission provides evidence to support provincial policy development in relation to carbon emissions trading from self-driving tourism. Counties with positive carbon emission flows have gained substantial income from the development of the tourism industry. In comparison, those counties with negative carbon emission flows sustained huge environmental damages caused by carbon emissions. Therefore, it is reasonable to propose that the counties with positive carbon emissions state should transfer the corresponding economic income to those counties with negative carbon emissions state for the purpose of compensation for environmental pollution.

3.5 Modelling the determinants of carbon emission

In general, the spatial patterns of carbon emission inflows and outflows from self-driving tourism are closely associated with the spatial arrangements of social and economic activities across the study area. To understand the global and local influences of these activities, it is imperative to develop spatial and statistical models with consideration of spatial heterogeneity. To achieve this, geographically weighted regression has been applied to analyse the local spatial variation of statistically significant determinants.

This study has selected eight indices, namely permanent resident population, GDP, fixed-asset investment, total retail sales of consumer goods, car ownership, the number of domestic tourists, the revenue from domestic tourism and the scenic spot's score, as explanatory variables. The first five indices were sourced from *Jiangsu Statistical Yearbook in 2015,* and the latter three were sourced from *Jiangsu Tourism Development Report* (Jiangsu Provincial Tourism Bureau, 2015). After conducting an exploratory regression analysis, which filters explanatory variables by variance inflation factor value, four variables of VIF > 10 were chosen to develop two GWR models in order to reduce multicollinearity.

Comparatively the bandwidth of the first GWR model (inflow) is 91,817.55m, and its value of the second GWR model (outflow) is 94, 741.43m. As two bandwidth values are very close, it indicates that both GWR models have similar scaling effects.

[Fig. 7 Spatial distributions of independent variables (a: number of private cars; b: total population; c: per capita GDP and d: attraction value of scenic spots)]

3.5.1 Modelling the determinants of carbon emission inflow

In the case of carbon emissions inflow, only two explanatory variables (per capita GDP and score of attractive spots (SAS)) were selected as suitable for the construction of GWR model. The regression equation (Eq. 9) for County *i* can be written as:

$$C_{in}(i)= \beta_0(i)+ \beta_1(i) \text{ x pc}GDP(i)+ \beta_2(i) \text{ x } SAS(i)+ \varepsilon(i) \qquad (9)$$

where $C(i)$ denotes the carbon emissions inflow from self-driving tourism, pc$GDP(i)$ the per capita GDP and $SAS(i)$ the score of attractive spots in this county.

A global model of the carbon emission inflow is calibrated by ordinary least squares (OLS) as shown in equation 10:

$$C_{in}= 8.689e{-10} + 0.119 \text{ pc}GDP + 0.907\, SAS + \varepsilon \qquad (10)$$

T-value (2.606) (19.790)

Its adjusted R^2 and AICc are 0.8543 and 122.04 respectively. This means 85.43% of the variance in the carbon emissions inflow can be explained by the two explanatory variables: pcGDP and SAS. These two explanatory variables are statistically significant. A Moran I value of ε is 0.4139, indicating the presence of spatial autocorrelation in the error term of this OLS model.

In the resulting GWR model, its adjusted R^2 has been improved to 0.9625 with a declining AICc value of 6.5689. The difference of AICc value between two models is larger than 3, suggesting that GWR is superior to OLS in model performance (Akaike, 1974). A Moran I value of $\varepsilon(i)$ is 0.0472, indicating the reduced spatial autocorrelation in the error term of this GWR model. The calibrated co-efficient values $\beta 1$ (pcGDP) and $\beta 2$ (SAS) and their t-values are displayed in Figure 8.

The regression coefficient β_1 demonstrates a general trend (Fig 8) of higher values in the North but lower values in the South. At the 5% significance level, all the 49 counties show positive correlation between per capita GDP and the carbon emissions inflow, mostly ranging between 0 and 0.5. The pattern indicates that the economic impact on carbon emissions inflow is stronger in the North than in the South. The southern counties have an abundance of tourism resources, which stimulates rapid development of the tourism industry. In this context, economic effects on self-driving tourism are weaker. By contrast, the northern counties are economically backward, so any economic investment can promote the investment in tourism industry and attract more tourists, leading to the increase of carbon emission inflows from self-driving tourism.

The regression coefficient β_2 demonstrates an opposite trend (Fig 8) as $\beta 1$: higher values in the South but lower values in the South. All have shown positive correlation between the score of attractive spots and the carbon emissions inflow, with large spatial variation across the province. At the 5% significance level, all the 54 counties are statistically significant apart from few in the North. Comparatively, the impacts of attractive spots on the carbon emission inflows are stronger than that of per capita GDP. There is a clear pattern: gradual decrease from the South to the North. The highest values are located around Nanjing. This indicates that the increase of diverse and high-quality attractive spots in the surrounding counties would promote growth in self-driving tourism in the South.

[Fig. 8 GWR regression results of the carbon emission inflow from self-driving tourism]

3.5.2 Modelling the determinants of carbon emission outflow

In the case of carbon emissions outflow, only two explanatory variables (total population of permanent residents and GDP) were selected for the construction of the GWR model. The regression equation (Eq. 11) for County i can be written as:

$$C_{out}(i)= \beta_0(i)+ \beta_1(i) \text{ x pcGDP}(i)+ \beta_2(i) \text{ x POP}(i)+ \varepsilon (i) \qquad (11)$$

where $C(i)$ denotes the carbon emission outflow from self-driving tourism, $POP(i)$ denotes the total population of permanent resident in and pc$GDP(i)$ the per capita GDP of this county.

A global model of the carbon emissions outflow is calibrated by ordinary least squares (OLS) as shown in equation 12:

$$C_{out} = 9.923e{-10} + 0.145\, pcGDP + 0.908\, POP + \varepsilon \qquad (12)$$

T-value (3.432) (21.520)

Its adjusted R^2 and AICc are 0.8756 and 122.0451, respectively. This means that 87.56% of the variance in the carbon emission outflows can be explained by the two explanatory variables: pcGDP and POP. These two explanatory variables are statistically significant. The Moran I value of ε is 0.3823, indicating the presence of spatial autocorrelation in the error term of this OLS model.

In the resulting GWR model, the adjusted R^2 has been improved to 0.9709 with a declining AICc value of -22.5754. The difference of AICc values between the two models is larger than 3, suggesting that GWR is superior to OLS in model performance (Akaike, 1974). A Moran I value of ε(i) is 0.0659, indicating a reduced spatial autocorrelation in the error term of this GWR model. The calibrated co-efficient values β1 (pcGDP) and β2 (POP) and their t-values are displayed in Figure 9.

The regression coefficient β_1 demonstrates a general trend (Fig 9) of higher values in the central but lower values in the South. At the 5% significance level, all the 39 counties show positive correlation between per capita GDP and the carbon emissions outflow, largely less than 0.3. The pattern indicates that the economic impact on carbon emission outflows is stronger in the central than in the south.

The regression coefficient β_2 demonstrates a clear spatial pattern (Fig 9): gradual decrease from the South to the North. All have shown positive correlation between the total population of permanent residents and the carbon emission outflow. At the 5% significance level, all57 counties are statistically significant apart from two counties, located in the Northwest. This indicates that residents in the South have a higher level of desire for self-driving tourism due to economic wealth.

[Fig. 9 GWR regression results of the carbon emission outflow from self-driving tourism]

4. Discussion and conclusions

Carbon emissions caused by tourism transport is an important part of the analysis surrounding carbon emissions from tourism. Emission patterns are very much linked with the pattern of tourism related traffic flow. Self-driving tourism has become an important mode of tourism in China, so the empirical study of self-driving tourism facilitates further understanding of carbon emissions in the tourism industry.

Carbon emissions produced from self-driving tourism vehicles, which connect origin and destination tourist activities, make it necessary to analyse and model the resulting carbon emission flows. This approach enables accurate measurement and clear interpretation of carbon emissions produced from self-driving tourism. These analytical methods allow both an accurate depiction of spatial patterns and geographical disparity, alongside detecting socio-economic processes which shape these patterns. The spatial heterogeneity disclosed in this paper provides quantitative evidence for carbon emission trading between different spatial units, in this case at county level. Using the expressway traffic data recorded at toll-gates across Jiangsu province in 2014, the spatial patterns of carbon emission flows induced by self-driving tourism has been assessed. This has been carried out at two levels: toll-gate and county, which has led to the following conclusions.

The carbon emission net flows (inflows and outflows), from self-driving tourism demonstrate similar spatial patterns. High concentrations are mostly located in the South of the province. High economic income and a larger quantity of attractive spots contribute to the concentration of positive carbon emissions observed in the South. The spatial pattern of carbon emissions provides evidence to support the proposition of carbon emission trading policies at county level. That is to say, counties in the South should transfer economic benefits from their tourism revenue to those counties in the North, which have negative carbon emission flows. Compared with other studies on the reduction of carbon emissions (Munday, Turner, & Jones, 2013; Gössling, Scott, & Hall, 2015), this paper, which is focused on trading, has provided quantitative evidences from modeling the determinants of these flows in a local rather than global way.

The two GWR models, showing spatial non-stationarity, have revealed that the determinants of both inflows (the per capita GDP and the scenic spot’s score) and outflows (the per capita and total population of permanent residents) demonstrate spatial variations across the province. Carbon emissions from tourism travel is an important quantitative measure of the development quality of tourism industry. Effective controlling and reduction of tourism carbon emissions contributes to promoting the tourism industry, which has currently become a leading objective in the transformation and development of China’s tourism industry. Theoretically, this study on carbon emissions from tourism travel has extended the estimation of carbon emissions, to quantitative modelling of its determinants by considering spatial heterogeneity. In practice, the spatial variation of these determinants has provided important evidence for carbon emissions trading at county level.

These results indicate that local governments should take the determinants of per capita GDP, score of attractive spots and total population of permanent residents into the process of estimating carbon emission trading between counties. The effects of the tourism industry’s energy structure, energy intensity, consumption level and passenger flow on carbon emissions could be further studied in future from the perspectives of technology and the political system (e.g. Hergesell & Dickinger, 2013; Hanandeh, 2013; Higgins, 2013). Carbon emission reduction policies tested in different countries (Juvan, & Dolnicar, 2014; Tsai, Lin, Hwang, & Huang, 2014) should be explored for China as well. In terms of energy conservation and emission reduction, in-depth studies on the relationships between low-carbon technology and tourism system (e.g. Hall, et al., 2015; Cadarso, Gomez, Lopez, & Tobarra, 2016) can be examined as well.

Transport is a key part of the tourism system (Jin, Huang, Xu, & Gu, 2013), however also acts as a source of carbon emission. Currently, self-driving tourism, a popular mode of tourism, has produced a large amount of carbon emissions and demonstrated a high level of geographic imbalance, threatening the sustainable development of tourism system. The spatial heterogeneity of carbon emission patterns and its determinants provide quantitative evidence for distinguishing the carbon trade between regions. Meanwhile, tourists should be encouraged to use public transport for tourism related activities in order to considerably reduce the carbon emissions induced by tourism travel and to further promote the sustainable development of tourism (Hall, Le-Klähn, & Ram, 2017).

It is necessary to highlight that China's carbon emissions trading has been steadily progressing since its pilot project began in November 2011. China's first carbon emission trade platform was launched on June 18, 2013 (Zhen, 2014), China has recently begun constructing a unified national carbon emissions trade market in which the accounting, reporting and testing of historical carbon emissions will be incorporated into the tax of enterprise. Currently, China's carbon emissions trading is implemented on the basis of accounting the existing emission values, and the estimation, a kind of longitudinal accounting of itself, is done by comparing the actual emission value and the accounted emission value. Since November 2017, nearly 3,000 key emission enterprises have been selected into a pilot emission trading system. The total volume from these enterprises has reached 200 million tons of carbon dioxide that is worth about 4.6 billion yuan RMB (National Development and Reform Commission (NDRC), 2017). On the basis of the tested pilot system, China officially started the construction of a nationwide carbon emissions trading system on December 19, 2017. The first industry for the carbon emissions trading system is power generation industry, which will be extended to include more industries in the future. China's carbon emissions trading market will be composed of three major systems and four supporting systems. The former includes carbon emission monitoring, reporting and verification system, key emission enterprises quota management system and market transactions system. The latter has carbon emission data submission system, carbon emission rights registration system, carbon emission trading system and carbon emission trading settlement system (NDRC, 2017). The construction of such a trading market is a key task for China to cope with climate change and low-carbon development at present and in the future.

Tourism behavior is characterized by creating horizontal flows of carbon emission from human movement across space. The destinations of tourists benefit from the revenues of tourism but other areas along the way have paid the price of absorbing the carbon emissions. Thereby, the analytical framework developed in this paper provides a new method for potential trade accounting of carbon emission flows. Firstly, the revealed spatial heterogeneity in the patterns of carbon emission and corresponding socio-economic determinants will help formulate these targeted emission reduction measures. Secondly, it is evidential that these counties with positive carbon emission contribution should transfer a certain amount of corresponding economic (tourism) income to those counties with negative carbon emission contribution, for the purpose of compensation for environmental pollution. Thirdly, it is suggested to further explore transport carbon emissions from the perspective of mobility and formulate transport carbon emissions policies accordingly.

This paper is subject to limitations as a result of the inherent complexity in carbon emissions trading from self-driving tourism, particularly from data availability. Firstly, there is limited availability of actual self-driving tourism flows data in China. The percentage of self-driving tourism-purposed flows over the total flows of vehicles is only estimated through a sampling process. Secondly, there is no attribute data of each vehicle, such as size or weight, which enables a more accurate estimation of carbon emissions. Finally, from an urbanisation point of view, it would be insightful to explore the dynamics of carbon emission flows, if a time-series data set was made available. Future studies would benefit from exploring the potential deployment of sensor and tracking technology for collecting substantial data on carbon emission flows.

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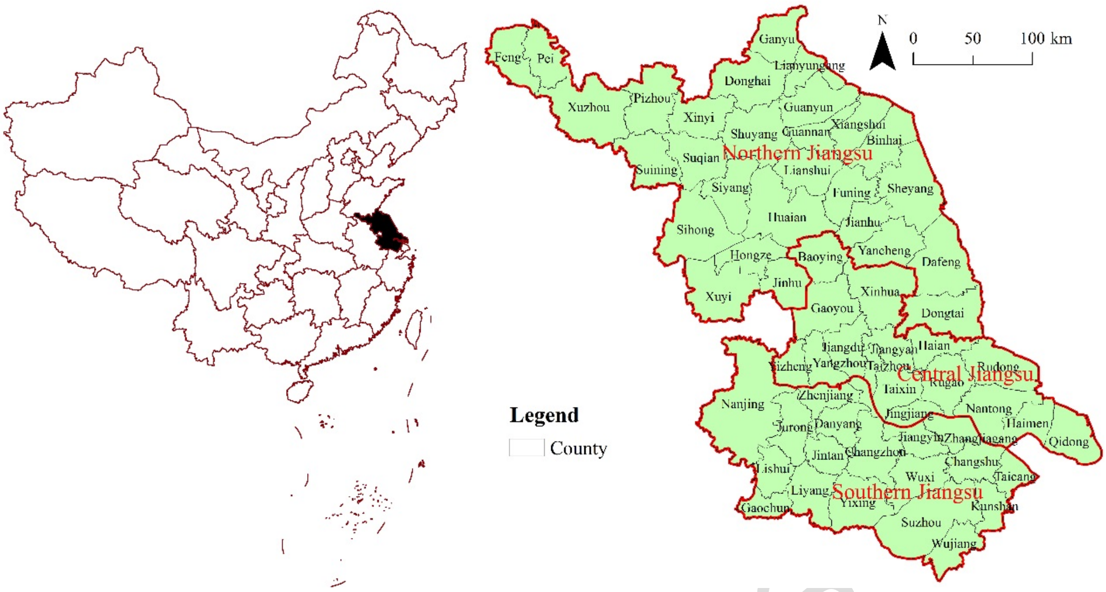


Fig. 1 Location of the study area and its administrative units

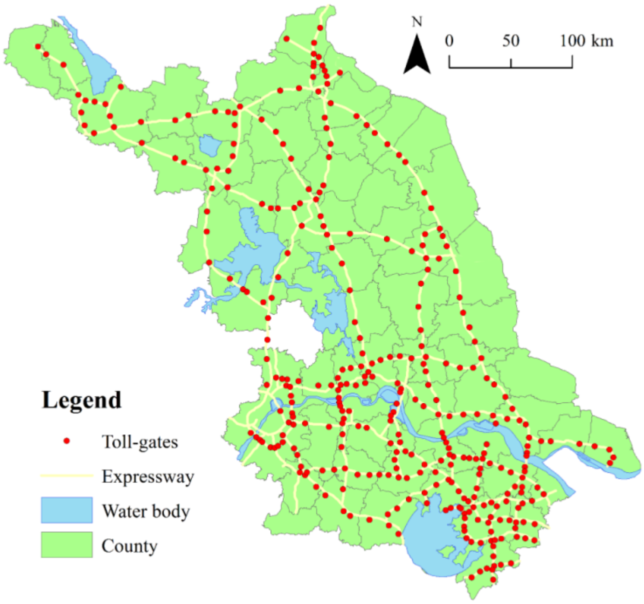


Fig.2 Location of toll-gates and expressway across the study area

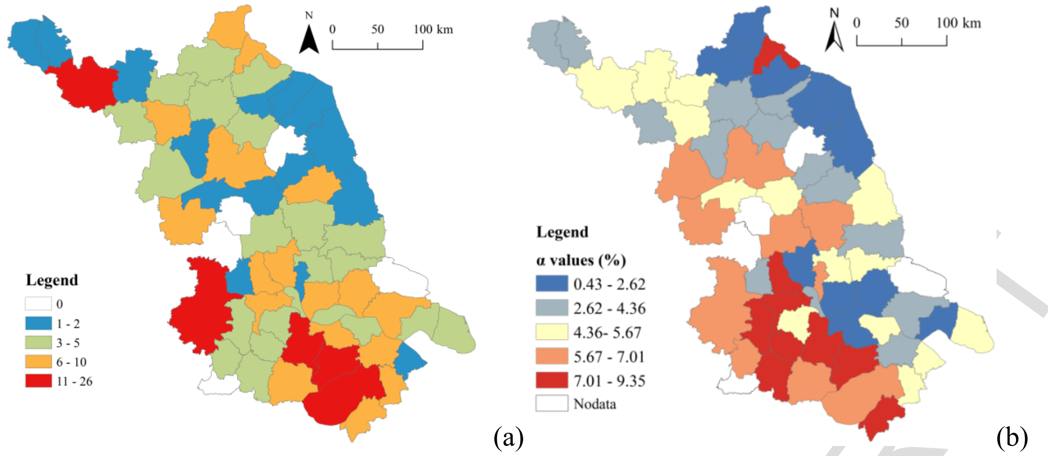


Fig. 3 Number of toll-gates (a) and ratios of self-driving to total traffic flows (b)

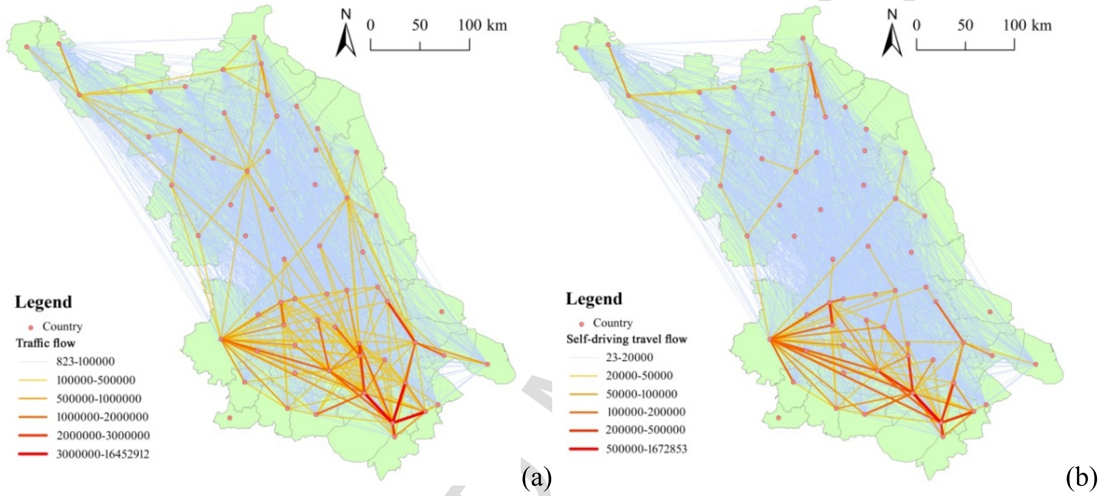


Fig. 4 All (a) and self-driving (b) traffic flow on expressway network across Jiangsu

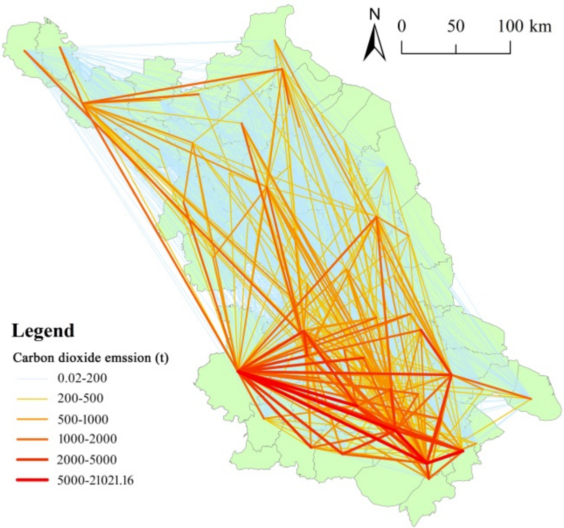
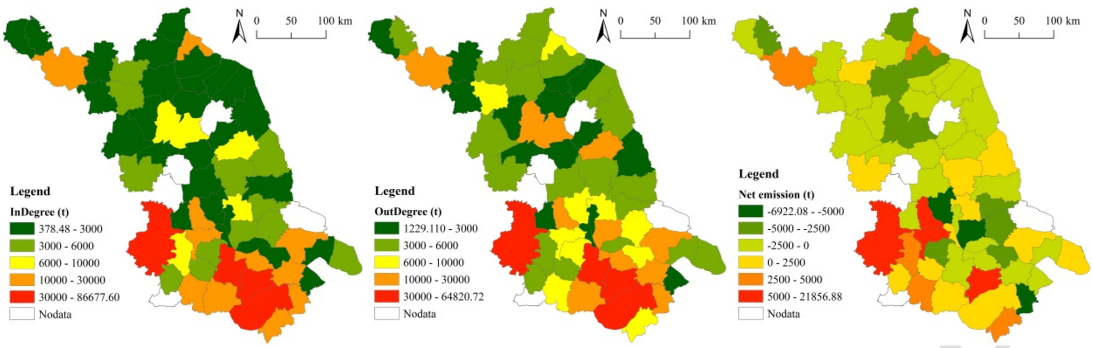


Fig. 5 Distribution of carbon emission flows from self-driving tourism



(a) carbon emission inflows (b) carbon emission outflows (c) net carbon emission flows

Fig. 6 Spatial patterns of carbon emission flows from self-driving tourism

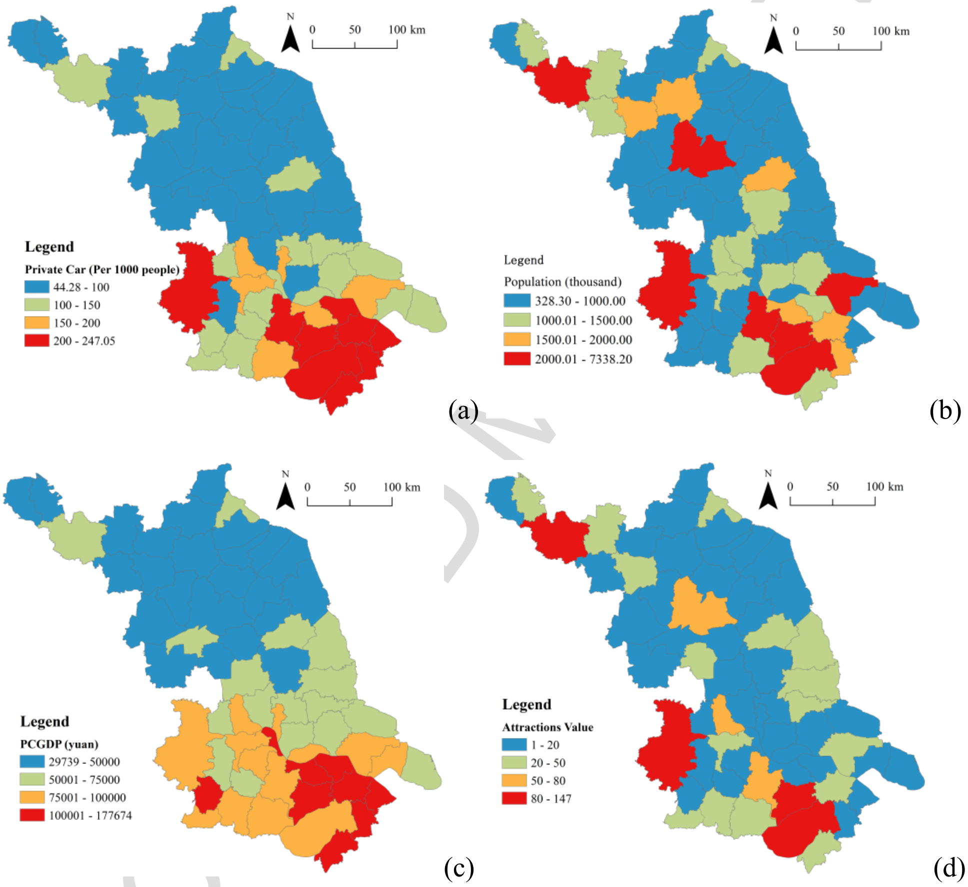


Fig. 7 Spatial distributions of independent variables (a: number of private cars; b: total population; c: per capita GDP and d: attraction value of scenic spots)

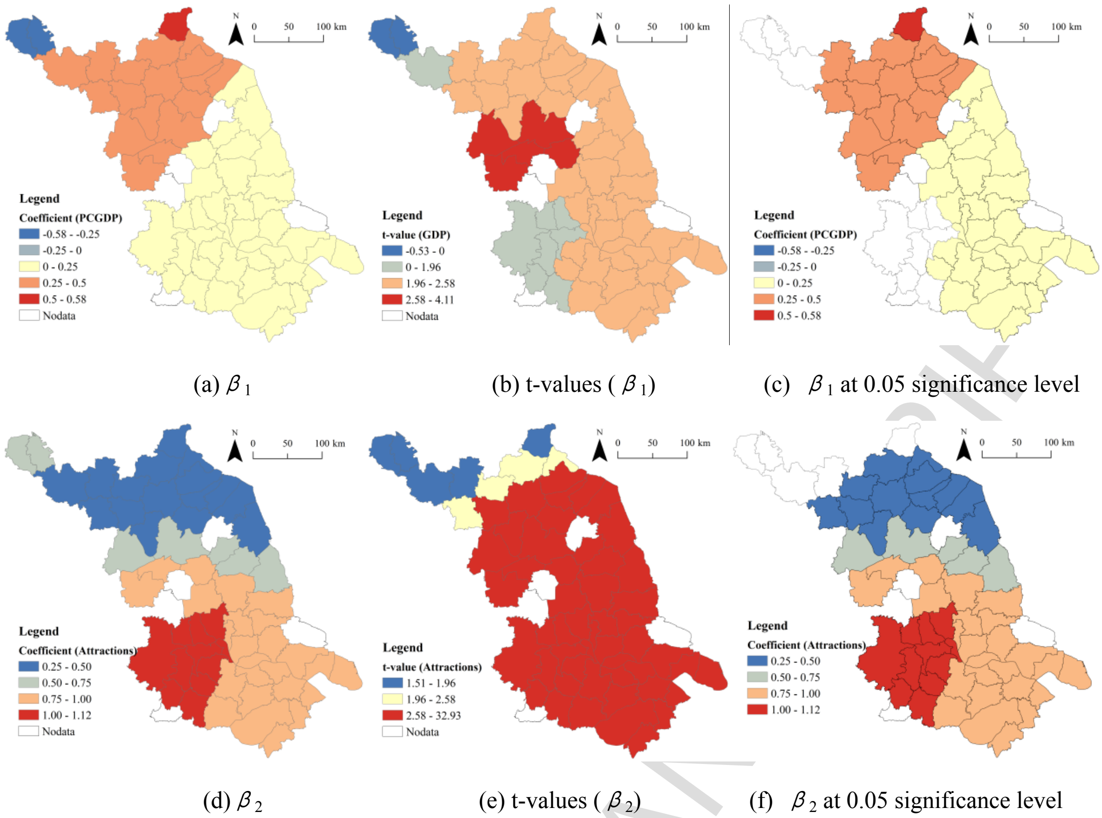


Fig. 8 GWR regression results of the carbon emission inflow from self-driving tourism

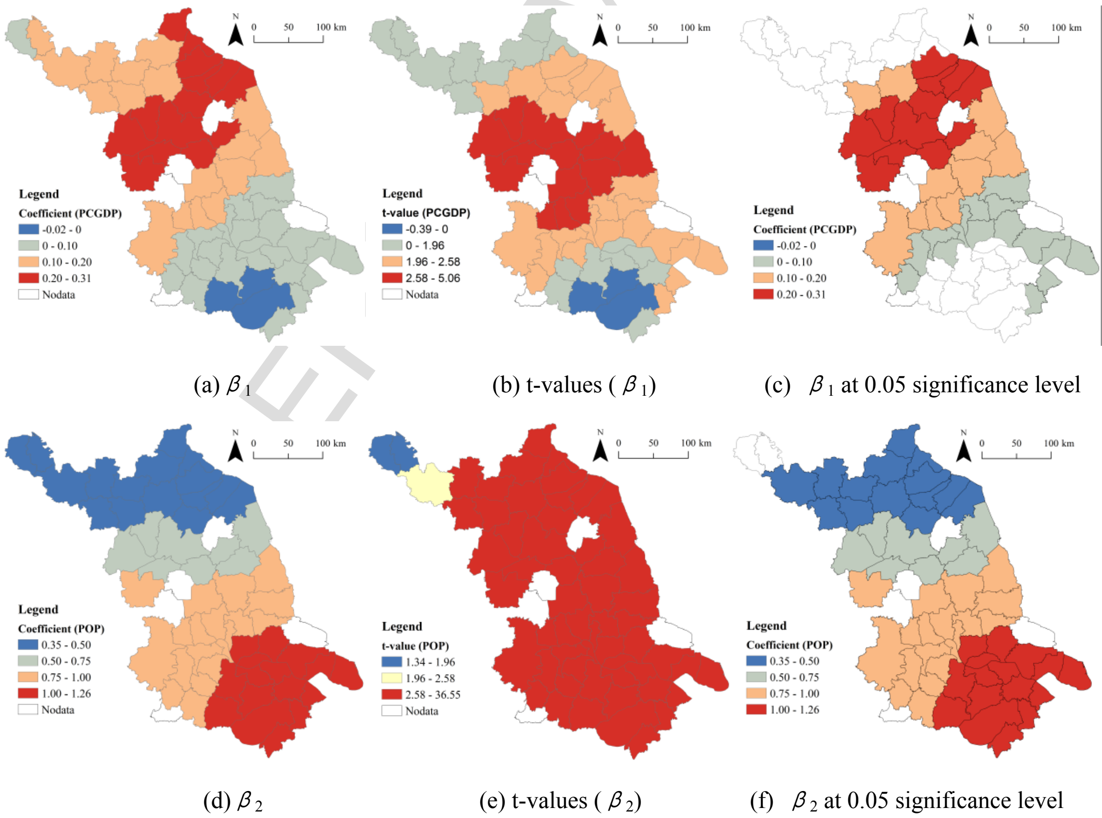


Fig. 9 GWR regression results of the carbon emission outflow from self-driving tourism

Highlight 1: We have estimated the carbon emission flows from self-driving tourism.

Highlight 2: We have modelled the determinants of these flows using GWR method.

Highlight 3: The spatial distribution of flows shows high concentration in the South.

Highlight 4: The determinants demonstrated spatial variations across the province.

Table 1 Data Sources

Data	Source	Description
Traffic flow data on expressway	Jiangsu Expressway Network Operation & Management Center	It is the key data for this study, mainly used for estimating flows of self-driving tourists.
GIS vector data (counties, expressway network, toll-gates location)	Jiangsu Provincial Bureau of Surveying Mapping and Geoinformation	Primarily used for the calculation of distance between gates as well as the spatial model (GWR) at the level of county.
Socioeconomic data（resident population, GDP, fixed-asset investment, total retail sales of consumer goods, and car ownership）	*Jiangsu Statistical Yearbook in 2015* (Jiangsu Bureau of Statistics, 2015)	Extensively used for creating a variety of variables into the GWR model.
Tourism related data （the number of domestic tourists, the revenue from domestic tourism and the scenic spot's score）	*Jiangsu Tourism Development Report* (Jiangsu Provincial Tourism Bureau, 2015)	Deployed to create relevant variables into the GWR model