

Article

Measuring the Spatial Dimension of Automobile Ownership and Its Associations with Household Characteristics and Land Use Patterns: A Case Study in Three Counties, South Florida (USA)

Jie Song ^{1,2,*} and Ruoniu Wang ³

¹ Department of Urban and Regional Planning, College of Design, Construction, and Planning, University of Florida, P.O. Box 115706, Gainesville, FL 32611, USA

² The Shimberg Center for Housing Studies, College of Design, Construction, and Planning, P.O. Box 115703, Gainesville, FL 32611, USA

³ College of Architecture, Construction and Planning, The University of Texas at San Antonio, 501 W. César E. Chávez Blvd. Monterey Building, Office 1.140A, San Antonio, TX 78249, USA; ruoniu.wang@utsa.edu

* Correspondence: songjiescu@ufl.edu

Academic Editor: Mark Deakin

Received: 3 January 2017; Accepted: 30 March 2017; Published: 6 April 2017

Abstract: Motorization and increased levels of car ownership have partly contributed to traffic congestion and air pollution, which is a prime concern in the era of climate change. Therefore, vehicle ownership-related topics have been extensively explored by transportation scholars, economists, and planning researchers. However, relatively fewer scientists have investigated the spatial patterns and socioeconomic factors of car ownership simultaneously within a large geographic scale. Thus, the goal of this article is to illuminate how high levels of auto ownership may cluster spatially and what factors relate to such phenomena by developing an integrative framework and applying it in three counties in South Florida (US). Specifically, this study first evaluated whether vehicle ownership is spatially autocorrelated using Global and Local Moran's *I* statistics. It then justified significant factors associated with car ownership by employing Poisson and Corrected Poisson regression models. The findings, using raw data, show that there exist locally spatial clusters of the households with high levels of automobile ownership, while globally the patterns of auto ownership are statistically random. Furthermore, the results suggest that the number of drivers, the number of workers, household income level, housing tenure, the proximity to schools, and net house density significantly influence car ownership levels. The results can assist urban planners and local governments in developing planning schemes that aim at transit, cycling, walking, and other non-motorized travel modes, thereby furthering environmentally friendly communities.

Keywords: number of cars; autocorrelation; spatial distribution; regression; automobile; metropolitan region; elderly

1. Introduction

Both academic and non-academic worlds are increasingly concerned about the rising popularity of private cars, a known cause of exacerbated air pollution [1–3], greenhouse gas emissions [4], traffic congestion [5,6], and risks to public health [7,8]. Admittedly, a growing level of private-car dependence is beneficial to the auto industry and its deriving businesses [9]. The prosperity of the auto industry considerably benefits local governments and communities by boosting employment rates and overall economic conditions. It is evident that an excessive number of vehicles on roads results in enormous environmental and social issues such as traffic congestion [10] and air pollution [11].

The positive correlation between higher levels of auto ownership and aggravating traffic congestion has been justified by numerous studies [2,12–14]. For instance, based on the travel survey conducted in King County in the US, Frank et al. [15] (2006) found a significantly positive relationship between vehicles per household and environmental indicators, including traffic-related pollutants and volatile organic compounds.

Given the evident relationship between auto ownership and its detrimental impacts on the whole society, studies have focused on the understanding of key factors, including household attributes, built-environment characteristics, and life style indicators, on levels of automobile ownership. This line of inquiry corresponds to the lasting interest in the land use-transportation connection, which is “motivated by the possibility that design policies associated with the built environment can be used to control, manage, and shape individual traveler behavior and aggregate travel demand” [16].

Additionally, it is also crucial to understand the spatial layout, including global and local spatial clustering, of automobile ownership. The spatial patterns of car ownership are indispensable midpoints of the pathways to investigate the travel behaviors of a person or a group of individuals [17,18], city-level policies [19], regional-level travel demand [20], land use allocation [21], and many other interrelated research themes. As mentioned above, high levels of car ownership are negatively associated with societal well-being in terms of energy conservation, public health, and other social benefits, though it may be also beneficial in some aspects (for example, cancer screening and job accessibility) at the individual scale. Wang (2016) [22] stated that good access to private cars encouraged individuals to have a frequent checkup for potential cancer risks. The author further added that the travel preferences of a person may follow a similar pattern to that observed in his/her neighboring communities. Therefore, using aggregated data or indicators (car ownership) of geographical references is important to elucidate people’s travel behavior under a concrete context.

How car ownership may be spatially and globally aggregated facilitates planners and governments in the process of developing specific transportation policies and land use planning in response to various needs of practice and research. For instance, police makers may restrict the use of private cars when high car ownership is spatially correlated with decreasing trends of physical activity of citizens, increased road crashes, and higher levels of noise pollution [19]. By contrast, better access to cars, partly represented by high auto ownership, contributes to household-level benefits such as greater coverage of cancer screening uptake, necessitating that the parties with conflicting interests ought to seek a compromised policy on private vehicle usage [22]. Consequently, the spatial clustering of car ownership is a significant phenomenon in relation to policy making and the coordination of conflicting interests from a broader perspective, demanding additional research endeavors.

A growing body of the literature has highlighted the significance of employing spatial methods, particularly those excelling in detecting spatial heterogeneity at a local level, into analyzing vehicle count data [20,23]. Spatially explicit approaches have been increasingly advocated in recent years because of their effectiveness in addressing spatial dependence, which has been a common yet unavoidable issue in transportation research [24,25]. Ignorance of the spatial dimension may lead to imprecise and inefficient estimators of regression coefficients [23,26] and unreliable inferences. In addition, the delineation of local hot spots regarding high car ownership helps to better understand bicyclists’ preferences [17], job accessibility [27], social equity [28], and other behavioral, economic, and societal topics at a fine scale. In sum, it is equally consequential to pinpoint local spatial autocorrelation of car ownership on top of global measures.

Despite the literature’s stressing of the spatial impacts on transportation simulations [20], there is no rigorous attempt to incorporate spatial patterns as an explaining factor in addressing the causal mechanism in land use-transportation interaction. In an effort to bridge such gaps, this study explicitly incorporates spatial autocorrelation into the interpretation of spatial heterogeneity of automobile ownership. It develops an integrative framework that aims at understanding (1) whether or not automobile dependence is spatially clustered; (2) whether high levels of automobile ownership are locally correlated; and (3) how the spatial mechanism of automobile ownership is partly explained

by the factors associated with households, built-up environments, and the interacting terms of these two categories.

The remainder of this paper is organized as follows. The next section outlines findings of previous studies concerning the level of auto ownership and its driving factors. Following the literature review, Section 3 advances two primary hypotheses of this work. Section 4 introduces study areas, data sources, and approaches that were used to assess the hypotheses. Section 5 highlights several key findings of the analysis. Finally, Section 6 summarizes the whole study, discusses policy implications of current research, and directs future work.

2. Background

For years, the relationships between land use development and commuters' travel patterns have been under intensive debates [29–33]. Overall, the current literature focuses on two aspects; car ownership as a mediating variable and the exploration of various factors affecting vehicle dependence.

First, studies have primarily explored the connection between a range of variables and vehicle ownership, which is viewed as an intermediate link bridging different factors [34–38]. As early as the 1990s, for example, Golob (1990) [34] investigated a variety of interrelated factors, including vehicle ownership and weekly commuting times by private vehicle, transit, cycling, and walking. Using panel data, the author identified interconnected causal linkages between vehicle reliance and the remaining three variables. It was found that there existed a bidirectional casual effect between travel time by different modes and the number of cars per household. Furthermore, higher levels of car ownership were motivated by the propensity or willingness of households to lower their time expenditure as well as by people's cost-and-benefit considerations. It was also noted by the author that, in the short term, the shift to a more costly but less time-consuming mode would partly result in a rise in the number of cars. In the long run, the adjustments on car ownership may become a driving force behind the households' choices regarding residential locations [34]. Likewise, Raphael et al. (2002) [35] assessed whether car ownership substantively affects the employment characteristics of a household. Using employment status, work hours, and wages as dependent variables, the authors stated that the coefficients of auto ownership were significant and positive in all of three ordinary least squares regression models. Specifically, obtaining access to a car serves as a crucial factor in affecting labor market outcomes [35]. Nonetheless, these studies might chiefly concentrate on the interrelations between auto ownership and households' characteristics, possibly lacking a comprehensive account of the effects of built environment.

Second, recent studies have focused efforts on exploring the factors associated with car ownership, which is regarded as a dependent variable [39–44]. For instance, Cao et al. (2007) [43] evaluated the linkages between vehicle ownership and built environment using ordered probit and static-score models. They concluded that the number of vehicles of an examined family were prevalently determined by demographical and social factors; however, the effects of built environment were extremely limited. In the same year, Guo et al. (2007) [44] investigated the same issue, but a different definition of the built environment was introduced to their discrete choice models. A whole spectrum of measures, including land use types, urban forms, street networks, land use diversity index, and so on, were considered as built-up attributes [44]. Their findings are in accordance with Cao et al.'s findings [43]. Furthermore, not only do these attributes have impacts on the levels of car ownership but on households' decisions of residential choices as well. Unlike Cao et al. (2007), Guo et al. (2007) [44] maintained that both socio-demographics and built environment attributes were important determinants in car ownership decisions. However, a major limitation of these studies is that they might inadequately consider the potentially spatial signature of car ownership. Such spatially unobserved components may contain missing information from uncontrolled variables over space and time [26].

To address this limitation, further research has applied Graphically Weighted Regression (GWR) models that integrate the spatial autocorrelation of regression coefficients in analyzing the spatial distribution of car ownership. Several publications have studied the factors associated with car

ownership using the GWR approaches [41,45,46]. GWR technologies are promising in capturing local patterns. These approaches may be further enhanced if future efforts could attempt to improve GWR's generalizable power.

In this respect, this study contributes to the current literature by developing a modeling framework that targets the understanding of the spatial agglomeration of family's car ownership levels and the coupling effects of built environments and household attributes on the clustering phenomena. This work also sheds light on the literature by synthesizing different global and local techniques of spatial autocorrelation detection and corrected Poisson regression models. Such a synthesis is scarcely observed in previous studies. Moreover, it adds to transportation planning practices with additional insights by designing a straightforward procedure that planners find easy to implement for various policy purposes. Under this overarching framework, two research hypotheses were posited and will be specified in the next section.

3. Research Hypotheses

The goals of this article are to examine the following research hypotheses.

- (1) Households with three or more private cars are globally and locally clustered in a metropolitan region.
- (2) Household attributes, built-environment characteristics, life style factors, and several interacting terms collectively play a pivotal role in determining the level of a household's car ownership.

4. Data Description and Model Specifications

4.1. Data Sources and Descriptive Statistics

Three counties in southern Florida, US: Broward, Palm-Beach, and Miami-Dade, were identified as study areas in the empirical analysis because these counties are home to Miami, Fort Lauderdale, and other coastal megacities with enormous populations and exceptionally high levels of automobile reliance (Figure 1). Three data sources were used in this research. First, the National Household Travel Survey (NHTS) created by Federal Highway Administration represents a foundation of our data structures. There exist multiple versions of the NHTS [47]. This study opted to use the 2009 one, which is the most recent version with comprehensive information. The survey was conducted from March 2008 through May 2009 in the majority of the states in the USA. The NHTS provides such information as the travel patterns and socio-demographics of responding households. Specifically, NHTS's focus groups are the civilian and non-institutionalized populations, which denote households in this article. Second, the data concerning built environments stemmed from the parcel data downloaded from the Florida Department of Revenue [48] and were processed by the Institute of Transportation Engineers at the University of Florida. This data set primarily offered knowledge regarding land use types and transit accessibility. Third, the Tiger 2010 Census Tract Files collected from the Geospatial Data Gateway [49] were used to ameliorate the presentation quality. After data preprocessing and the mapping of the numerical data onto census tract maps, a sample comprising 3980 households was identified. The following section will discuss the main procedures for data processing and the model specifications in detail.

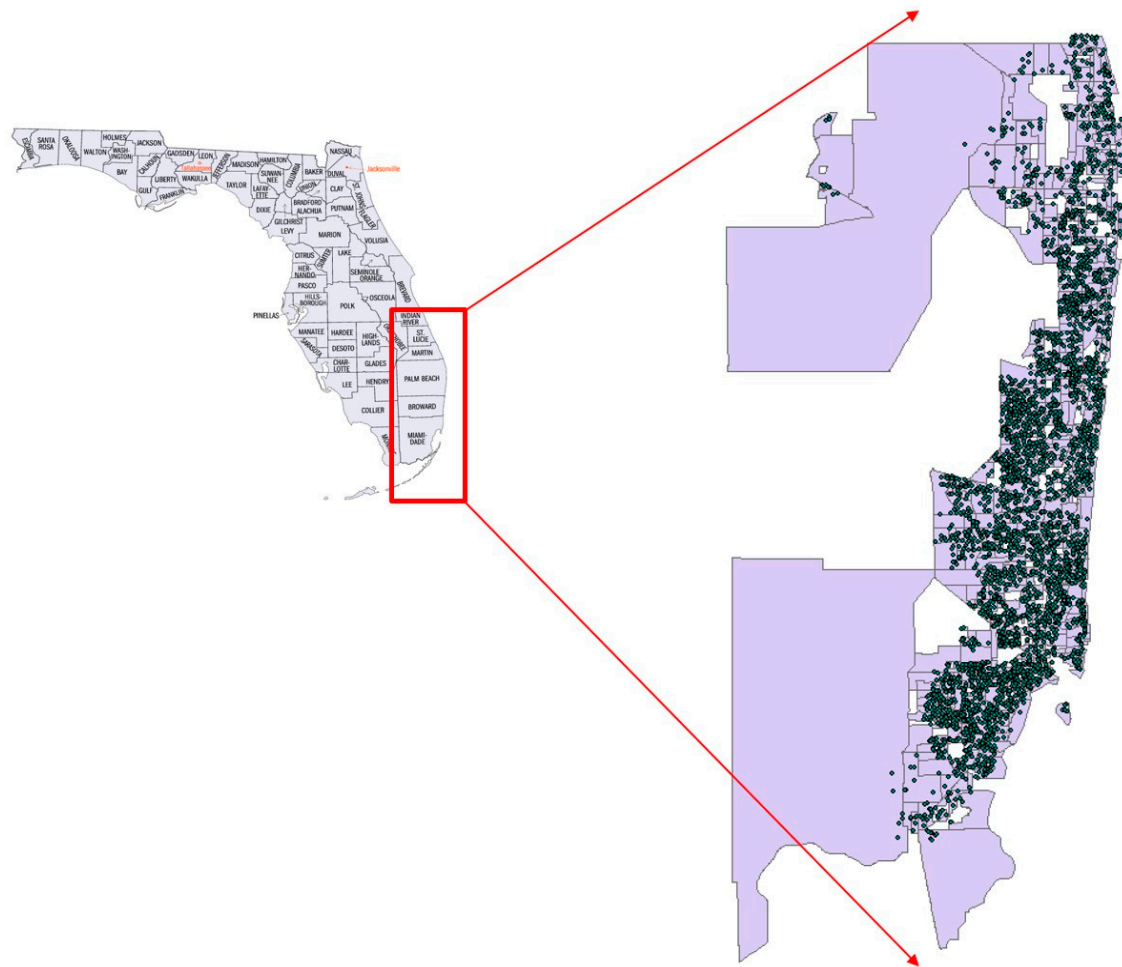


Figure 1. The case region for this work.

4.2. Model Specifications

Figure 2 exhibits an overall outline for this study. A quadrat count analysis was first conducted to examine whether or not the spatial pattern of households with high levels of car ownership (three or more cars) is non-random. Second, the Poisson regression accounting for spatial autocorrelation was used to recognize the factors influencing vehicle ownership. Poisson regression has been proved to be powerful in modeling count data [50]. Finally, the Global Moran's I statistics were used to validate the results of the quadrat count analysis regarding the point patterns of automobile ownership. We also employed the local version of the Moran's I to identify hot spots or cool zones. The model specifications are introduced in the next few sub sections.

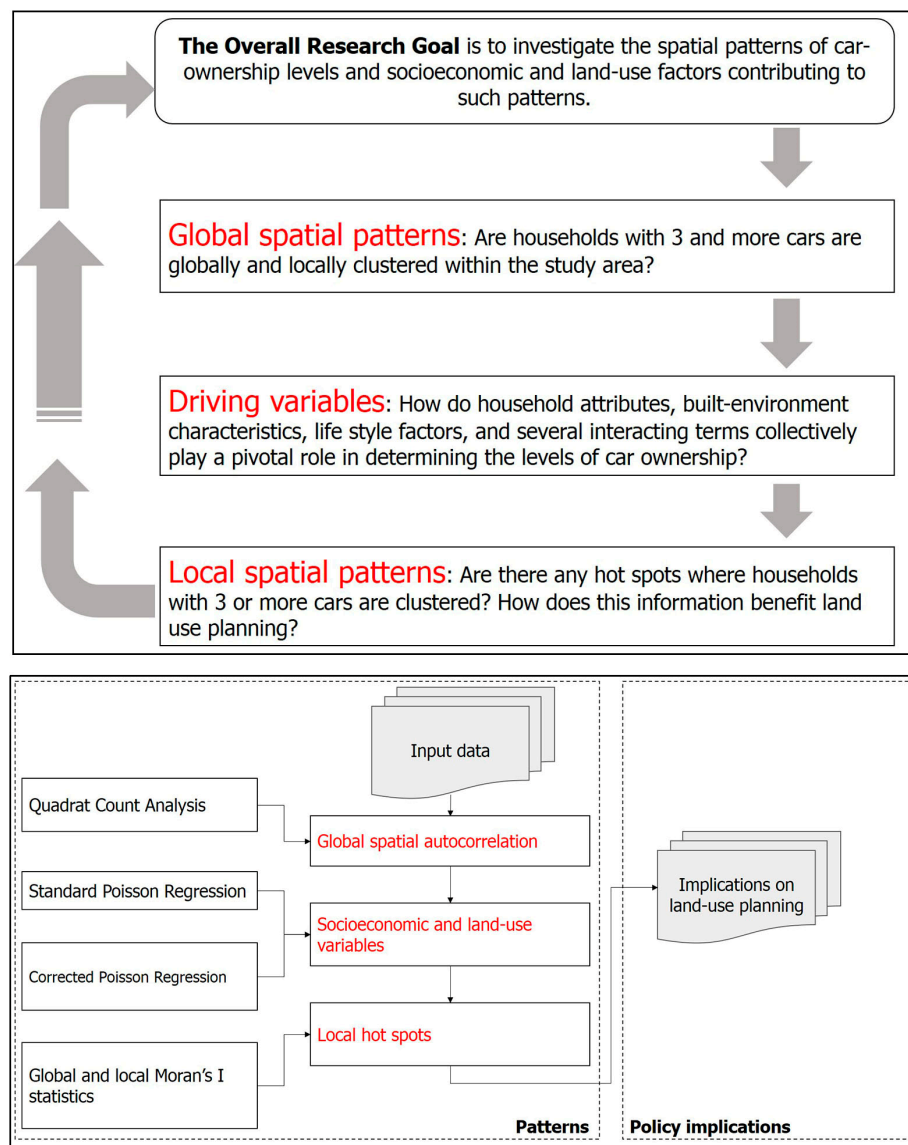


Figure 2. An overall research outline (top) and a technical roadmap (bottom).

4.2.1. Quadrat Count Analysis

The analysis was used to examine if spatial autocorrelation exists at a global level. First, the optimal quadrat size Q^* was determined by [51]:

$$Q^* = 2(A/N) \quad (1)$$

where A is the total area of the study region and N is the total number of events, namely households with three or more private vehicles.

Specifically, a total number of 661 households was first selected over a grid of 10,311 square kilometers, which was calculated according to the coordinates of the outermost households. Thus, the optimal quadrat size was approximately 34.89 square kilometers using Equation (1). Consequently, the suggested number of quadrats was $10,311/34.89$, namely, 295.5. After adjustments, the finalized quadrat number was 308 (Figure 3).

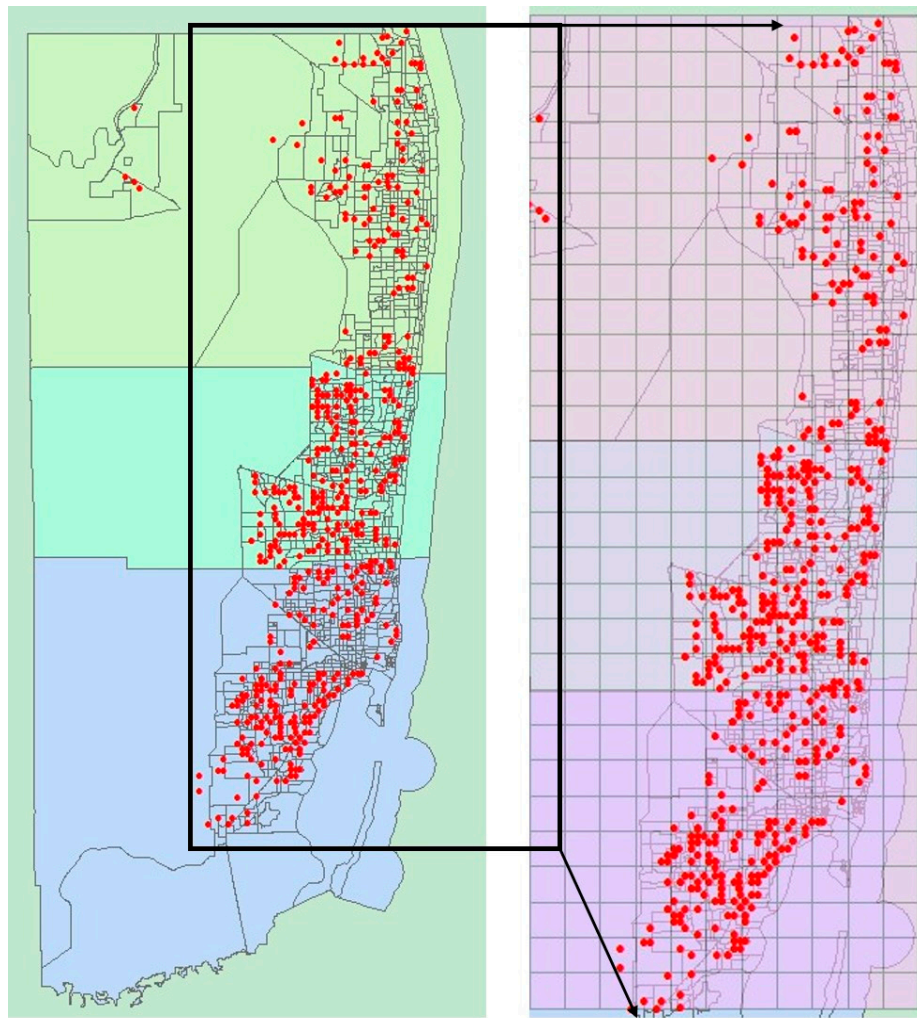


Figure 3. The study area (left) and overlaid quadrat grids (right).

Using the Geo-Spatial Modeling Environment Tool [52], this work next generated the frequency counts of quadrats that contained different numbers of events (e.g., 0, 1, 2, 3, etc.). Under the null hypothesis, the point pattern was random, complying with a Poisson distribution. Accordingly, the probability of observing X ($X = 0, 1, 2, 3$, and so on) events in a randomly selected quadrat was calculated by the following equation:

$$P(X = j|\lambda) = \frac{e^{-\lambda}(\lambda)^X}{X!} \quad (2)$$

where λ is the ratio of the sum of the events to the number of quadrats and denotes the average number of points in a given quadrat, namely 1.92 in this study, and $j = 0, 1, 2, \dots, 12$ and more, where the last category accounts for the possibility of 12 or more events in a given quadrat.

Therefore, the expected number of quadrats that included a given number of points, i.e., $X = 0, 1, 2, \dots, 12$ and more, was calculated by:

$$E_j = P(X = j|\lambda) * K \quad (3)$$

where K refers to the total number of quadrats.

Third, several tests were conducted to identify whether the observed probability distribution of households with three or more cars was significantly different from a benchmark distribution,

the Poisson distribution. Finally, the observed frequency of households with high levels of auto numbers were compared with their expected counterparts using the Chi-square test, described by:

$$\chi^2 = \frac{\sum_{j=0}^{12} (O_j - E_j)^2}{E_j} \quad (4)$$

where O_j is the observed number of quadrats with a given number j of the households with three or more vehicles and E_j denotes the expected number of quadrats with a given number j of the households.

4.2.2. Poisson Regression Analysis

Poisson regression was selected to justify the proposed variables that may explain the variation of the number of vehicles per household for the whole 3980 units of analysis. Specifically, it was utilized to model the associations between a wide range of explanatory variables and the count data. Based on the literature and data availability, the model calibrated three categories of factors, household characteristics, built environment, and life style, simultaneously taking into account the interactive effects between households and built environment [34,35] (Table 1). It has been justified that residential locations are associated with auto ownership levels [35,53], and the preferences of households' residential sites are argued to be partly reflected by an index describing the degree of land use mix [44]. Accordingly, this paper employed such an index as a potential explanatory variable. It adopted the paradigm of land use diversity designed by Guo (2007) [44], while minor modifications were made to accommodate the data structures of this empirical work. The modified measure of land use mix has a potential to be generalizable to similar studies that lack a rich and well-structured data source for the land use configurations. Specifically, it was defined by:

$$LUXs = 1 - \frac{|Rs - 0.25| + |Cs - 0.25| + |Is - 0.25| + |Os - 0.25|}{1.5} \quad (5)$$

where Rs , Cs , Is , and Os are the area percentages that correspond to residential, commercial, industrial, and other land use types surrounding a specific household in a 0.25-mile buffer area, respectively. According to Bhat and Guo (2004) [54], the indexes may range from 0 to 1, where 1 refers to an entirely diversified land use structure and 0 indicates zero land use mix.

Next, standard and corrected regression models were described by:

$$\ln(U_i) = \beta_0 + \beta_1 X_{i1} + \dots + \beta_k X_{ik} \quad (6)$$

where U_i is the number of vehicles of the i -th household, X_{i1}, \dots, X_{ik} represent k explanatory variables, and β_0, \dots, β_k denote the estimated coefficients corresponding to different independent variables.

Table 1. Description of possible explanatory variables for the Poisson Regression.

Variable Name and Description		Variable Type	Code Definition	Min.	Mean	Max.	Data Source
Household characteristics	HHFAMINCx (Derived total household income)	Category	1 = low income, 2 = medium income, and 3 = high income	-	-	-	NHTS [47]
	NUMADLT (Count of adult household members at least 18 years old)	Interval	-	1	1.88	10	
	HOMEOWN (Housing unit owned or rented)	Dummy	1 = rent and 0 = own	-	-	-	
	DRVRCNT (Number of drivers in household)	Interval	-	0	1.72	7	
	HHSIZE (Count of household members)	Interval	-	1	2.22	10	
	HH_RACEx (Race of household respondent)	Dummy	1 = white and 0 = other races	-	-	-	
	WORKER (Number of workers in household)	Interval	-	0	0.83	4	
Built environments	CLWORK (Close to work)	Dummy	1 = yes and 0 = no	-	-	-	FDOR [48] and UFIT
	DISTAC (Distance to nearest activity center in miles)	Continuous	-	0.69	11.24	42.51	
	DISTRES (Distance to nearest residential center in miles)	Continuous	-	0.60	9.21	47.10	
	MIX_25 (Land use mix index of a 0.25-mile buffer area of a household)	Continuous	-	0	0.43	0.93	
	BUS1MILE (Number of bus stops within one mile of a household)	Interval	-	0	36.01	259	FDOR [48] and UFIT
	DISTBS (Distance to the nearest bus stop in meters)	Continuous	-	2.89	1394.13	15,629	
	POPDENTRCT (Population density at census tract level (sq mile))	Continuous	-	0.03	5615.03	41,911.28	
	JOBDETRCT (Job density at census tract level (sq mile))	Continuous	-	2.54	2280.93	15,213.78	
Life style	HOSDETRCT (House density at census tract level (sq mile))	Continuous	-	0.01	3026.96	38,555.15	NHTS [47]
	URBAN (Category of Urban area)	Category	1 = city core, 2 = inner city, 3 = suburbs, and 4 = not in urban area	-	-	-	
	CLFRIEND (Close to friends)	Dummy	1 = yes and 0 = no	-	-	-	
	CLSCHOOL (Close to schools)	Dummy	1 = yes and 0 = no	-	-	-	
Interactions	CLRETAIL (Close to retail services)	Dummy	1 = yes and 0 = no	-	-	-	FDOR [48] and UFIT
	HHFAMINCx*BUS1MILE	-	-	-	-	-	
	HHFAMINCx*DISTBS	-	-	-	-	-	
	HHFAMINCx*MIX_5	-	-	-	-	-	
	HHFAMINCx*URBAN	-	-	-	-	-	
	HOMEOWN*BUS1MILE	-	-	-	-	-	
	HOMEOWN*DISTBS	-	-	-	-	-	

Note: NHTS: National Household Travel Survey; FDOR: Florida Department of Revenue; UFIT: Institute of Transportation Engineers, University of Florida.

4.2.3. Spatial Clustering Analysis

The third part of this work was to detect any local clusters of the households with a high level of automobile ownership. Census tracts overlaid with the counts of households with three or more cars served as basic units of analysis. Additionally, the study area was adjusted by excluding those census tracts such as national parks and beaches, which are not considered residential locations. A total of 661 points of interest were overlaid with 1214 polygons, using the Geospatial Modeling Environment software, an open-source platform built upon the R language [52]. We then assessed if there are any ‘hot spots’ or ‘cool zones’ using the Global and Local Moran’s I statistics, two crucial functions in GeoDa, a freeware widely used among geographers [55]. Specifically, the Global Moran’s I is represented as:

$$I = \left(\frac{n}{C} \right) \frac{\sum_{i=1}^n \sum_{j=1}^n c_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (7)$$

where X_i and X_j are the number of households with three or more cars in the i -th and j -th census tracts, respectively, and $C = \sum_{i=1}^n \sum_{j=1}^n c_{ij}$, and c_{ij} is a typical element from a pre-defined n -th order connectivity matrix, with C describing the connectivity between the i -th and j -th census tracts.

Additionally, the Local Moran’s I can be defined (for a given i -th census tract) as [56]:

$$I_i = \frac{n(y_i - \bar{y}) \sum_{j=1}^n w_{ij}(y_j - \bar{y})}{\sum_{j=1}^n (y_j - \bar{y})^2} \quad (8)$$

where y_i and y_j denote the number of households with three or more cars in the i -th and j -th census tract, respectively, and w_{ij} is an element of the spatial weight matrixes that correspond to distinct connectivity definitions; Rook’s, Queen’s, and k -th Nearest Neighbor measures. The application of three connectivity concepts helped the reliability of hypothesis testing. Another layer of the credibility was further secured by the utilization of both raw data and standardized data in the ratio of events to the population at risk.

5. Empirical Results

5.1. Quadrat Count Analysis

Table 2 indicates that at the 95% and 99% confidence levels, the observed spatial pattern of households with three or more vehicles is other than random, exhibiting a tendency of clustering. Accordingly, it is critical to explore whether the clustering of households with high rates of vehicle ownership can be explained by the demographic and life style characteristics of households as well as their surrounding built environments. The findings will be presented in the Section 5.2.

5.2. Poisson Regression Results

Table 3 displays the results of the standard Poisson procedure, and the lack of fit tests show that we fail to reject the null hypothesis that the model provides adequate model fit. In other words, at the 99% and 95% confident levels, this best-fit model sufficiently explains the variation of the number of cars per household. Nevertheless, the value of Dispersion Phi, 0.2865, implies an under-dispersion issue of this current model, which may affect the efficiency of independent variables. This issue may potentially relate to the distribution of the dependent variable and spatial autocorrelation of the error terms.

Table 2. Goodness of fit test for the Quadrat Count Analysis.

Number of Households with Three and More Vehicles per Quadrat	Observed Number of Quadrats	The Probability of Events under a Completely Random Poisson Distribution	Expected Number of Quadrats	Chi-Square Statistics
0	191	0.1468	45.2078	470.1711
1	15	0.2816	86.7460	59.3398
2	16	0.2702	83.2255	54.3015
...
...
10	5	0.0000	0.0084	2955.6760
11	3	0.0000	0.0015	6114.4168
12 and more	8	0.0000	0.0003	232,467.0013
Total	308	1	308	242,658.76 *
Lambda: point density		1.9188		

* significant at a 95% and 99% confidence level with a degree of freedom of 12.

Table 3. The results of standard Poisson regression.

Significant Explanatory Variables	Coefficients	Wald's Chi Square
DRVRCNT	0.35 **	129.38
HHFAMINCx	0.12 *	3.1
HOWNOWN	−0.19 **	5.06
HOSDENTRCT	−0.00 **	4.95
WORKER	0.06 **	10.03
Dispersion Phi	0.29	
Pseudo R Square	0.49	
Final log likelihood	−4357.11	
Intercept-only likelihood	−4833.37	
Lack-of-Fit Test	DF	Chi Square
Pearson	3300	945.45
G statistics	3300	990.58

$n = 3980$; DF = Degree of Freedom; ** significant at 95% confident level; * significant at 90% confident level.

To address the under-dispersion problem, we reran the regression using Dispersion Phi to correct standard errors. Table 4 displays the model results, indicating an enhancement of the significance of explanatory variables. Surprisingly, six variables are found to be significant at a 95% confidence level. Specifically, the number of licensed drivers, household income, and the number of workers have a significantly positive association with the household's vehicle ownership level. Such statistical inferences are intuitively reasonable since rich families have more purchasing power than poor ones and therefore are more eager to obtain driving licenses to fulfill their flexible travel needs. Further a household having more workers is more inclined to own more cars to commute to varying working sites than one with fewer workers. These findings are largely in accordance with similar research conducted in other metropolitan regions across the world [57,58].

Table 4. The results of the corrected Poisson regression.

Significant Explanatory Variables	Coefficients	Wald's Chi Square
CLSCHOOL	−0.16 **	5.88
DRVRCNT	0.35 **	451.60
HHFAMINCx	0.12 **	10.82
HOWNOWN	−0.19 **	17.67
HOSDENTRCT	−0.00 **	17.27
WORKER	0.06 **	35.02
Dispersion Phi	0.29	
Pseudo R ²	0.49	
Final log likelihood	−4357.11	
Intercept-only likelihood	−4833.37	
Lack-of-Fit Test	DF	Chi ²
Pearson	3300	945.45
G statistics	3300	990.58

n = 3980; DF = Degree of Freedom; ** significant at 95% confident level.

In addition, those households without properties have less cars than families living in their own houses or apartments, all else being equal, which was echoed by a similar study done by Li et al. (2010) [58]. Likewise, the variables of the distance to school and house density at the census tract level have similar impacts on car ownership. In other words, shrunken levels of automobile ownership are linked with higher densities of residential units and educational institutions, as also substantiated by a couple of studies (see, for example, [26,58,59]). However, only six out of twenty-seven variables add significantly explanatory powers in the current model. The majority of the measures of built environment are insignificant. Particularly, car ownership levels in three counties appear to be irrelevant to land use diversity, transit proximity, and job density; these variables have yet been argued to affect vehicle ownership [60]. Such inconsistency may be partially ascribed to three reasons. First, some other variables (such as housing densities) used in this work may already possess sufficient information regarding the land use characteristics, thereby rendering similar ones insignificant. Second, the interpretations are contingent upon concrete empirical locations. The USA has a long history of prioritizing auto oriented developments. Under such developmental strategies, therefore, her citizens may consider private cars favorably as a fundamental commuting alternative, even if recent years have witnessed a burgeoning advancement of transit-oriented development in this nation.

Third, the current model may inefficiently capture additional unobserved factors, such as spatial autocorrelation (Figure 4). Hence, the following sections will focus on exploring the spatial patterns of auto ownership.

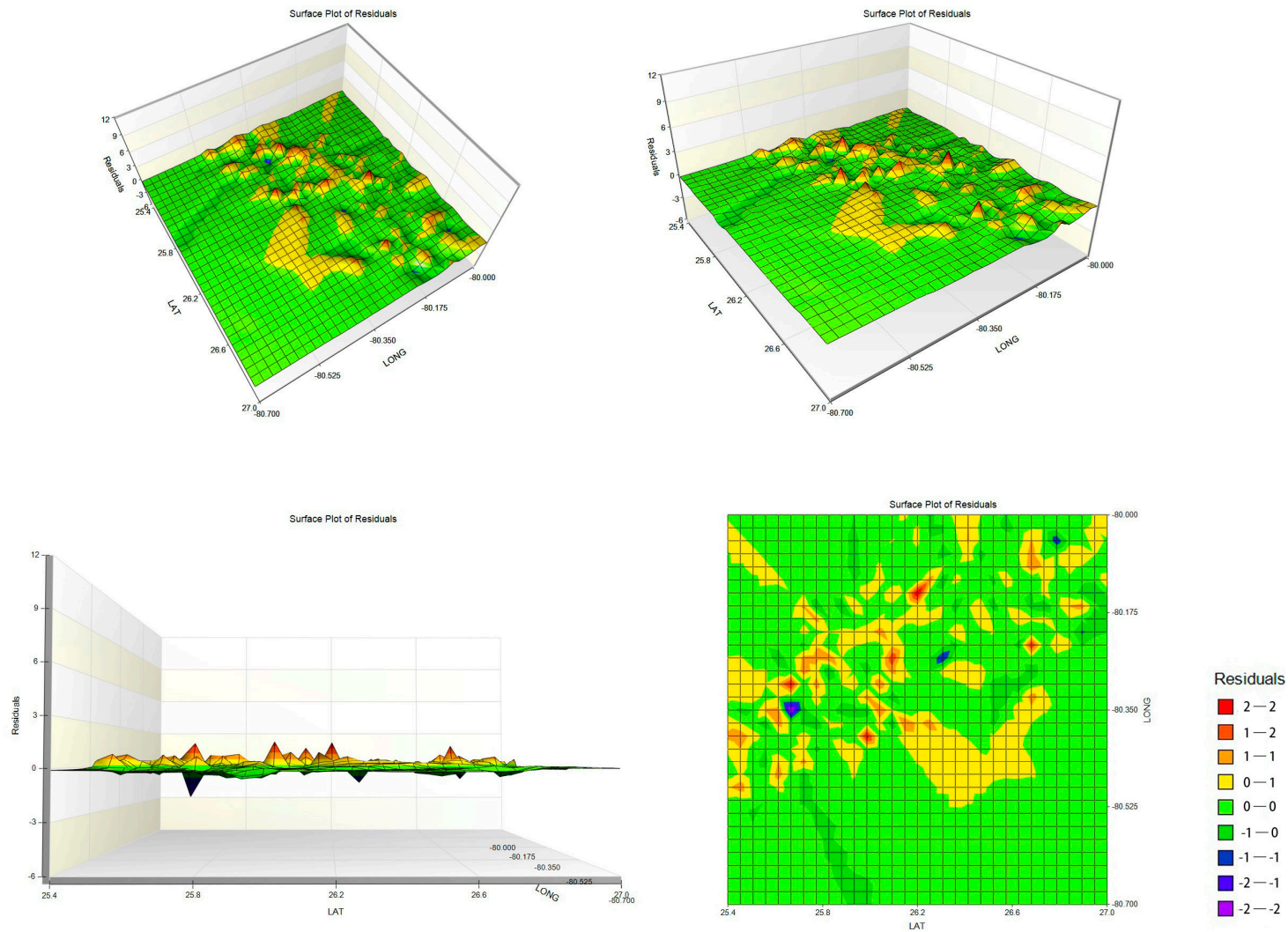


Figure 4. Spatial distribution of the residuals recovered by the corrected Poisson regression.

5.3. Spatial Clustering Results

5.3.1. 'Hot spot' Detection Using the Global/Local Moran I Statistics

Global Moran's I Statistics Based on Raw Data and Standardized Data

(1) Global Moran's I statistics with raw data

Using the GeoDa software developed by the Center for Spatially Integrated Social Science, we calculate the Global Moran's I statistics based on various orders of nearest neighbors (Table 5). The results show that, at the 95% confidence level, there exists globally spatial autocorrelation among raw data (cases) at the nearest neighbors of different degrees.

Table 5. Global Moran's I results for raw data at various scales of nearest neighbors (NN).

Moran's I Results	NN (2)	NN (3)	NN (4)	NN (5)	NN (6)
Moran's Index	0.1725	0.1784	0.1744	0.1721	0.1639
Pseudo p value (99 permutations)	0.01	0.01	0.01	0.01	0.01

(2) Global Moran's I statistics with standardized data

Next, raw data were standardized through dividing case data by population data, taking into account the different size of the population at each polygon. Figure 5 shows that outliers were eliminated after the standardization process.

Using the standardized data, the Global Moran's I statistics for k nearest neighbors was generated through GeoDa (Table 6). Interestingly, with 99 permutations of the Global Moran's I statistics, there is no evidence of global spatial autocorrelation even at a 90% confident level. In other words, the total population of each location heavily impacts the results of global autocorrelation. This result may also suggest that high auto ownership levels are correlated with population.

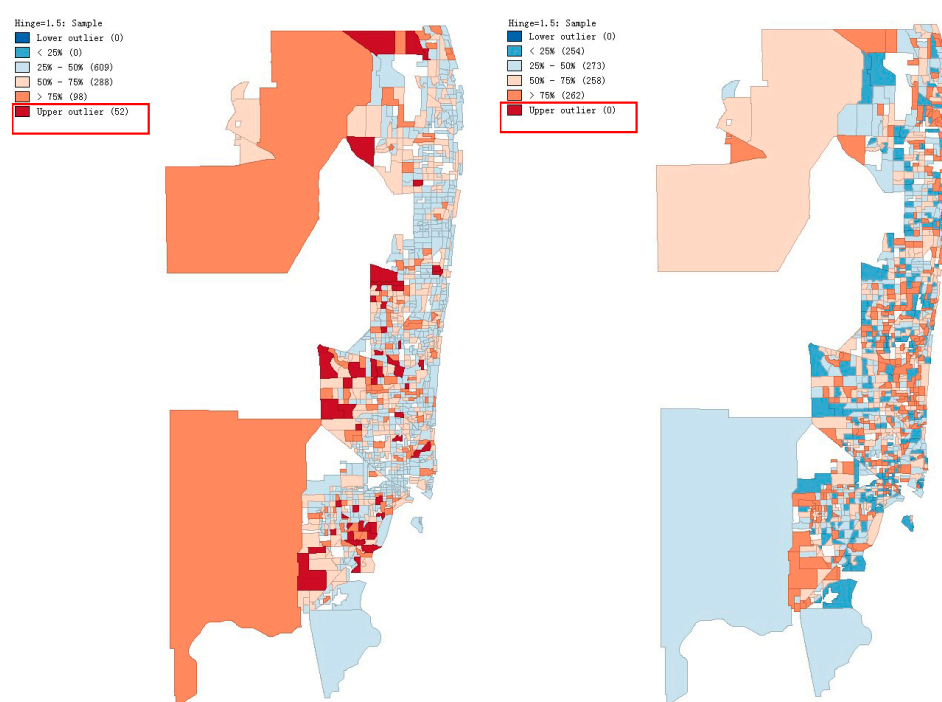


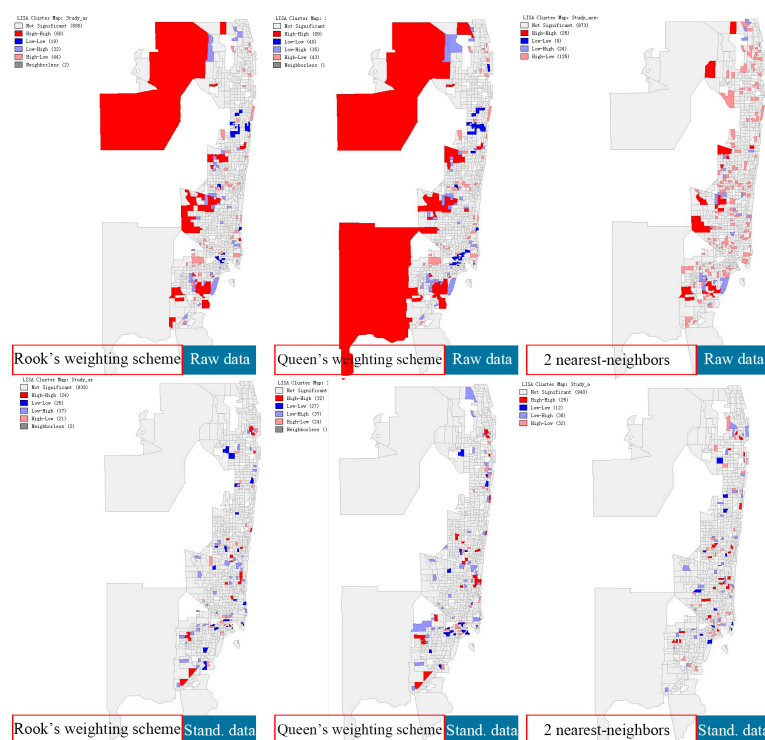
Figure 5. Box maps of raw data (left) versus standardized data (right).

Table 6. Global Moran's I results for standardized data at various scales of nearest neighbors.

Moran's I Results	NN (2)	NN (3)	NN (4)	NN (5)	NN (6)
Moran's Index	0.0355	0.0239	0.0026	-	-
Pseudo p value (99 permutations)	0.11 (around)	0.19 (around)	0.40 (around)	-	-
Pseudo p value (999 permutations)	0.10 (around)	0.14 (around)	0.40 (around)	-	-

Local Moran's I Statistics Based on Raw and Standardized Data

All tests were conducted in 999 permutations through GeoDa at the 0.05 significance level. Figure 6 indicates an obvious disparity of results between the raw and standardized data. As for the raw data, the largest census tract in the north-west study area exhibits a trend of hotspots both under Rook's and Queen's weighting schemes. However, this phenomenon is not intuitively reasonable in that this census tract is not a populated area. In other words, the results would be biased if the population at risk in each census tract is not considered. Furthermore, the results of the raw data are more similar to the outcomes of the standardized data under the 2nd Nearest Neighbor weighting scheme than they are under the other two. The results seem intuitively reasonable if the testing procedures take into consideration the households with high levels of car ownership in neighboring tracts. Consequently, there do exist several hot-spots and cool zones if the local test is based on raw data.

**Figure 6.** The comparison between raw data (**top**) and standardized data (**bottom**) regarding local hot spots (red) or cool zones (blue) of the levels of auto ownership.

With respect to standardized data, Figure 6 suggests a more consistent pattern than raw data concerning hotspots and cool zones; 'high-high' areas and 'low-low' regions. For instance, there appear only marginal differences of the sum and locations of the hotspots among three weighting schemes: Rook's (24), Queen's (32), and two Nearest Neighbors (25). When it comes to raw data, though, the number of hotspots ('high-high' areas) under boundary-based weighting schemes substantially differs from the number of hotspots under distance-based weighting schemes. Such discrepancies suggest that local hotspots and cool zones are randomly distributed over the study area. It seems that the three countries have an even distribution of high levels of auto ownership.

6. Discussion and Conclusions

The current paper illuminates the global and spatial patterns of vehicle ownership levels and explored the factors associated with households' vehicle counts. It develops a framework that can be used to visualize and explain the spatial heterogeneity of auto ownership at the county level. It validates this framework in Broward, Palm-Beach, and Miami-Dade Counties, southern Florida, USA. This research indicates that the global pattern of households with high rates of vehicle ownership is non-random if population at risk is not taken as a reference. Nevertheless, there is no statistical evidence that households with three or more cars were globally clustered based on standardized data. Moreover, this paper does not find robust evidence that those households with high levels of vehicle ownership were locally clustered if the conclusion is made based on standardized data. In addition, six variables are found to significantly affect car ownership, as shown by the regression results of the Standard and Corrected Poisson models. The most substantial factors are the number of drivers in households, housing tenure, and the number of workers in households. These findings are in accordance with earlier studies [35,45,53]. The contributions of this work to the literature are twofold. First, this paper establishes a refined index to characterize land use diversity based on the approach of Guo et al. [44], and the measure appears to be scientifically sound to address those data sets with limited information on land use. Second, the application of distinct connectivity models boosts the robustness of hypothesis testing.

This paper also adds additional insights into planning practice. Whilst the socio-demographics of households considerably impact their selection of travel modes, optimizing land use is beneficial to mitigate car dependency [61]. Compact urban forms and mixed land use structures may counteract households' propensity to own a car. However, transportation policies and the regulations of private vehicles should be tuned toward specific contexts. As stated in the introduction, regulators should make distinct car usage policies based on different needs. Figure 6 might indicate that a tendency of high car ownership is observed both in the downtown and rural regions, as represented by the red color. Imposing a strict tax on car use (such as road pricing) over the whole region may cause concerns about social inequity at the individual level. An elderly person with an apparent healthcare need may live in suburban areas, as suggested by previous studies regarding the transportation accessibility of people aged 65 or over [62,63]. These people residing in city peripheries may rely on private cars more heavily in order to make more frequent health checkups and cancer screenings than citizens in metropolitan regions. Thus, car ownership and its external consequences should be addressed in a way whereby flexible policies can accommodate the voices of different social groups. For example, when examining those areas of potentially high levels of car ownership, we need to be familiar with their demographic information and land use patterns before arbitrarily discouraging car dependence. For example, in downtown areas and central business districts, a variety of measures such as congestion pricing, the increase of parking fees, and restrictions on parking space can be deployed to deter people's desire to own a private car, thereby promoting mass transit, cycling, walking, and other environmentally friendly travel modes. Meanwhile, the elderly, disabled people, and those with frequent healthcare needs can be exempt from those regulations of car usage with free parking space and discounted congestion tolls [22]. The methods and outcomes of this work can be applied to formulate flexible transportation policies.

Several limitations of this study deserve further investigation. First, this study does not conduct a sensitivity analysis of the quadrat size, which may bias the results. Moreover, the quadrat analysis and the spatial autocorrelation tests fail to consider edge or boundary effects of the study area. This may hamper the testing statistics. Second, the study is based on sample data, limiting its ability to model or predict human behaviors, and the statistical implications are unbiased only when the population at risk is explicitly integrated in the correlation analysis. Third, the under-dispersion issue of the Poisson model requires further scrutiny.

This paper opens several promising avenues for follow up work and future research. First, prospective efforts can improve the techniques of the spatial autocorrelation of car ownership levels by

developing innovative ways for edge or boundary corrections. In addition, future studies may employ other types of generalized models, including spatial error, spatial lag, multilevel ordered-response, and system dynamics models, for better revealing the impacts of land use patterns on vehicle ownership. With the rapid development of hardware and computers' computational capacities, major auto manufacturers expand their investment in electric, hybrid-energy, and autonomous vehicles. Hence, the spatial patterns of the ownership levels of those vehicle types will be a fruitful direction in the near future.

Acknowledgments: The authors are grateful to Timothy Fik, who answered a multitude of questions and offered valuable suggestions regarding the overall development of research ideas and the whole analytical process. The authors highly appreciate Sivaramakrishnan Srinivasan, the U.S. Department of Transportation, the Florida Department of Revenue, and the Geospatial Data Gateway at the U.S. Department of Agriculture for offering the access to the data. We also thank Ruoying Xu for processing the data sets. The work is partly funded by the University of Florida Graduate School Dissertation Award, and it also received the support from National Natural Science Foundation of China award (No. 51408246). The publication of this article was funded in part by the University of Florida Open Access Publishing Fund.

Author Contributions: Jie Song and Ruoniu Wang made equal and substantive contributions to the research and writing. Specifically, Jie Song developed research ideas, collected relevant data sets, and initiated the writing of this paper. Ruoniu Wang helped with the modeling of spatial patterns of car ownership and wrote the section on research significance. Both authors made considerable efforts to improve the manuscript, and its final revisions were approved by both authors.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chen, X.J.; Zhao, J.H. Bidding to drive: Car license auction policy in shanghai and its public acceptance. *Transp. Policy* **2013**, *27*, 39–52. [\[CrossRef\]](#)
2. Whelan, G. Modelling car ownership in Great Britain. *Transp. Res. Part A Policy Pract.* **2007**, *41*, 205–219. [\[CrossRef\]](#)
3. Li, W.C.; Bai, H.T.; Yin, J.F.; Xu, H. Life cycle assessment of end-of-life vehicle recycling processes in China—take corolla taxis for example. *J. Clean. Prod.* **2016**, *117*, 176–187. [\[CrossRef\]](#)
4. Wu, T.; Zhao, H.M.; Ou, X.M. Vehicle ownership analysis based on GDP per capita in China: 1963–2050. *Sustainability* **2014**, *6*, 4877–4899. [\[CrossRef\]](#)
5. Woods, L.; Ferguson, N.S. The influence of urban form on car travel following residential relocation: A current and retrospective study in Scottish urban areas. *J. Transp. Land Use* **2014**, *7*, 95–104. [\[CrossRef\]](#)
6. Commins, N.; Nolan, A. Car ownership and mode of transport to work in Ireland. *Econ. Soc. Rev.* **2010**, *41*, 43–75.
7. Anowar, S.; Yasmin, S.; Eluru, N.; Miranda-Moreno, L.F. Analyzing car ownership in Quebec City: A comparison of traditional and latent class ordered and unordered models. *Transportation* **2014**, *41*, 1013–1039. [\[CrossRef\]](#)
8. Joh, K.; Chakrabarti, S.; Boarnet, M.G.; Woo, A. The Walking Renaissance: A Longitudinal Analysis of Walking Travel in the Greater Los Angeles Area, USA. *Sustainability* **2015**, *7*, 8985–9011. [\[CrossRef\]](#)
9. Zhu, C.; Zhu, Y.L.; Lu, R.Z.; He, R.; Xia, Z.L. Perceptions and aspirations for car ownership among Chinese students attending two universities in the Yangtze delta, China. *J. Transp. Geogr.* **2012**, *24*, 315–323. [\[CrossRef\]](#)
10. Belgiawan, P.F.; Schmocker, J.D.; Fujii, S. Understanding car ownership motivations among Indonesian students. *Int. J. Sustain. Transp.* **2016**, *10*, 295–307. [\[CrossRef\]](#)
11. Xu, B.; Lin, B.Q. Regional differences of pollution emissions in China: Contributing factors and mitigation strategies. *J. Clean. Prod.* **2016**, *112*, 1454–1463. [\[CrossRef\]](#)
12. Chin, A.; Smith, P. Automobile ownership and government policy: The economics of Singapore's vehicle quota scheme. *Transp. Res. Part A Policy. Pract.* **1997**, *31*, 129–140. [\[CrossRef\]](#)
13. Smith, P. Controlling traffic congestion by regulating car ownership: Singapore's recent experience. *J. Transp. Econ. Policy* **1992**, *26*, 89–95.
14. Li, J.P.; Walker, J.L.; Srinivasan, S.; Anderson, W.P. Modeling private car ownership in China investigation of urban form impact across megacities. *Transp. Res. Rec.* **2010**, *2193*, 76–84. [\[CrossRef\]](#)

15. Frank, L.D.; Sallis, J.F.; Conway, T.L.; Chapman, J.E.; Saelens, B.E.; Bachman, W. Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. *J. Am. Plan. Assoc.* **2006**, *72*, 75–87. [[CrossRef](#)]
16. Bhat, R.C.; Guo, Y.J. A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. *Transp. Res. Part B* **2007**, *41*, 506–526. [[CrossRef](#)]
17. Wang, C.-H.; Akar, G.; Guldman, J.-M. Do your neighbors affect your bicycling choice? A spatial probit model for bicycling to The Ohio State University. *J. Transp. Geogr.* **2015**, *42*, 122–130. [[CrossRef](#)]
18. Goetzke, F.; Rave, T. Bicycle Use in Germany: Explaining Differences between Municipalities with Social Network Effects. *Urban Stud.* **2011**, *48*, 427–437. [[CrossRef](#)] [[PubMed](#)]
19. Milne, E.M.G. A public health perspective on transport policy priorities. *J. Transp. Geogr.* **2012**, *21*, 62–69. [[CrossRef](#)]
20. Ding, C.; Wang, Y.; Yang, J.; Liu, C.; Lin, Y. Spatial heterogeneous impact of built environment on household auto ownership levels: Evidence from analysis at traffic analysis zone scales. *Transp. Lett.* **2016**, *8*, 26–34. [[CrossRef](#)]
21. Bhat, C.R.; Pulugurta, V. A comparison of two alternative behavioral choice mechanisms for household auto ownership decisions. *Transp. Res. Part B Methodol.* **1998**, *32*, 61–75. [[CrossRef](#)]
22. Wang, C. The impact of car ownership and public transport usage on cancer screening coverage: Empirical evidence using a spatial analysis in England. *J. Transp. Geogr.* **2016**, *56*, 15–22. [[CrossRef](#)] [[PubMed](#)]
23. Bhat, C.; Zhao, H. The spatial analysis of activity stop generation. *Transp. Res. Part B Methodol.* **2002**, *36*, 557–575. [[CrossRef](#)]
24. Chakir, R.; Parent, O. Determinants of land use changes: A spatial multinomial probit approach. *Pap. Reg. Sci.* **2009**, *88*, 327–344. [[CrossRef](#)]
25. Levine, N.; Kim, K.E.; Nitz, L.H. Spatial analysis of Honolulu motor vehicle crashes: I. Spatial patterns. *Accid. Anal. Prev.* **1995**, *27*, 663–674. [[CrossRef](#)]
26. Chen, T.D.; Wang, Y.Y.; Kockelman, K.M. Where are the electric vehicles? A spatial model for vehicle-choice count data. *J. Transp. Geogr.* **2015**, *43*, 181–188. [[CrossRef](#)]
27. Wang, C.H.; Chen, N. A GIS-based spatial statistical approach to modeling job accessibility by transportation mode: Case study of Columbus, Ohio. *J. Transp. Geogr.* **2015**, *45*, 1–11. [[CrossRef](#)]
28. Kaplan, S.; Popoks, D.; Prato, C.G.; Ceder, A. Using connectivity for measuring equity in transit provision. *J. Transp. Geogr.* **2014**, *37*, 82–92. [[CrossRef](#)]
29. Sarkar, P.P.; Chunchu, M. Quantification and analysis of land-use effects on travel behavior in smaller indian cities: Case study of agartala. *J. Urban Plan. Dev.* **2016**, *142*, 1–12. [[CrossRef](#)]
30. Stead, D. Relationships between land use, socioeconomic factors, and travel patterns in Britain. *Environ. Plan. B Plan. Des.* **2001**, *28*, 499–528. [[CrossRef](#)]
31. Milakis, D.; Vlastos, T.; Barbopoulos, N. Relationships between urban form and travel behaviour in Athens, Greece. A comparison with western European and North American results. *Eur. J. Transp. Infrastruct. Res.* **2008**, *8*, 201–215.
32. Moudon, A.; Kavage, S.; Mabry, J.; Sohn, D. A transportation-efficient land use mapping index. *Transp. Res. Rec. J. Transp. Res. Board.* **2005**, *1902*, 134–144. [[CrossRef](#)]
33. Zhang, M. The role of land use in travel mode choice—Evidence from Boston and Hong Kong. *J. Am. Plan. Assoc.* **2004**, *70*, 344–360. [[CrossRef](#)]
34. Golob, T.F. The dynamics of household travel time expenditures and car ownership decisions. *Transp. Res. Part A Gen.* **1990**, *24*, 443–463. [[CrossRef](#)]
35. Raphael, S.; Rice, L. Car ownership, employment, and earnings. *J. Urban Econ.* **2002**, *52*, 109–130. [[CrossRef](#)]
36. Koushki, P.A. Auto travel fuel elasticity in a rapidly developing urban area. *Transp. Res. Part A Policy Pract.* **1991**, *25*, 399–405. [[CrossRef](#)]
37. Pitombo, C.S.; Kawamoto, E.; Sousa, A.J. An exploratory analysis of relationships between socioeconomic, land use, activity participation variables and travel patterns. *Transp. Policy* **2011**, *18*, 347–357. [[CrossRef](#)]
38. Van Acker, V.; Witlox, F. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. *J. Transp. Geogr.* **2010**, *18*, 65–74. [[CrossRef](#)]
39. Caulfield, B. An examination of the factors that impact upon multiple vehicle ownership: The case of Dublin, Ireland. *Transp. Policy* **2012**, *19*, 132–138. [[CrossRef](#)]

40. Clark, S.D. Estimating local car ownership models. *J. Transp. Geogr.* **2007**, *15*, 184–197. [CrossRef]
41. Ogut, K.S. Modeling car ownership in turkey using fuzzy regression. *Transp. Plan. Technol.* **2006**, *29*, 233–248. [CrossRef]
42. Woldeamanuel, M.G.; Cyganski, R.; Schulz, A.; Justen, A. Variation of households' car ownership across time: Application of a panel data model. *Transportation* **2009**, *36*, 371–387. [CrossRef]
43. Cao, X.; Mokhtarian, P.L.; Handy, S.L. Cross-Sectional and Quasi-Panel explorations of the connection between the built environment and auto ownership. *Environ. Plan. A* **2007**, *39*, 830–847. [CrossRef]
44. Guo, J.Y.; Bhat, C.R. Operationalizing the concept of neighborhood: Application to residential location choice analysis. *J. Transp. Geogr.* **2007**, *15*, 31–45. [CrossRef]
45. Brunsdon, C.; Fotheringham, A.S.; Charlton, M.E. Geographically weighted regression: A method for exploring spatial nonstationarity. *Geogr. Anal.* **1996**, *28*, 281–298. [CrossRef]
46. Comber, A.J.; Brunsdon, C.; Radburn, R. A spatial analysis of variations in health access: Linking geography, socio-economic status and access perceptions. *Int. J. Health Geogr.* **2011**, *10*, 44. [CrossRef] [PubMed]
47. National Household Travel Survey. Available online: <http://nhts.ornl.gov/> (accessed on 8 August 2016).
48. Florida Department of Revenue Parcel Data. Available online: floridarevenue.com/dor/property/resources/data.html (accessed on 8 August 2016).
49. Geospatial Data Gateway. Available online: <https://datagateway.nrcs.usda.gov/> (accessed on 8 August 2016).
50. Cameron, A.C.; Trivedi, P.K. *Regression Analysis of Count Data*; Cambridge University Press: Cambridge, UK, 2013.
51. Diggle, P.J. *Statistical Analysis of Spatial and Spatio-Temporal Point Patterns*; CRC Press: Boca Raton, FL, USA, 2013.
52. Beyer, L.H. Geospatial Modeling Environment. Available online: <http://www.spatalecolology.com/gme/gmedownload.htm> (accessed on 8 August 2016).
53. Zhang, Y.; Wu, W.; Li, Y.; Liu, Q.X.; Li, C.Y. Does the built environment make a difference? An investigation of household vehicle use in Zhongshan metropolitan area, China. *Sustainability* **2014**, *6*, 4910–4930. [CrossRef]
54. Bhat, C.R.; Guo, J. A mixed spatially correlated logit model: Formulation and application to residential choice modeling. *Transp. Res. Part B Methodol.* **2004**, *38*, 147–168. [CrossRef]
55. Anselin, L.; Syabri, I.; Kho, Y. Geoda: An introduction to spatial data analysis. *Geogr. Anal.* **2006**, *38*, 5–22. [CrossRef]
56. Anselin, L. Local indicators of spatial association—Lisa. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
57. Bhat, C.R.; Koppelman, F.S. An endogenous switching simultaneous equation system of employment, income, and car ownership. *Transp. Res. Part A Policy. Pract.* **1993**, *27*, 447–459. [CrossRef]
58. Li, J.; Walker, J.; Srinivasan, S.; Anderson, W. Modeling private car ownership in China. *Transp. Res. Rec. J. Transp. Res. Board* **2010**, *2193*, 76–84. [CrossRef]
59. Zhao, Y.; Kockelman, K.M. Household vehicle ownership by vehicle type: Application of a multivariate negative binomial model. In Proceedings of the 81st Annual Meeting of the Transportation Research Board, Washington, DC, USA, 13–17 January 2002.
60. Khan, M.; Kockelman, K.; Xiong, X. Models for anticipating non-motorized travel choices, and the role of the built environment. *Transp. Policy* **2014**, *35*, 117–126. [CrossRef]
61. Pojani, D.; Stead, D. Sustainable urban transport in the developing world: Beyond megacities. *Sustainability* **2015**, *7*, 7784–7805. [CrossRef]
62. Rosenbloom, S. Transportation needs of the elderly population. *Clin. Geriatr. Med.* **1993**, *9*, 297–310. [PubMed]
63. Lord, S.; Luxembourg, N. The mobility of elderly residents living in suburban territories: Mobility experiences in Canada and France. *J. Hous. Elder.* **2007**, *20*, 103–121. [CrossRef]

