Modeling the Spatial Effects on Demand Estimation of Americans with Disabilities Act Paratransit Services

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A reliable method for predicting paratransit ridership is important, especially for the efficiency of the services offered. The commonly used aggregate regression model is most accurate for forecasting the total demand for regional areas such as whole counties or cities; however, it is likely to be geographically inaccurate. This paper proposes a geographical weight regression (GWR) model for predicting the demand for the types of paratransit services required by the Americans with Disabilities Act. The GWR model reflects better the characteristic of each area having its own coefficient for predictors rather than the same value throughout. The results show that trip demand increased proportionately to (*a*) the population size, (*b*) the ratio of senior citizens, (*c*) the ratio of people below the poverty line, and (*d*) the ratio of African-American riders. These results suggest that the predictive performance of the GWR model is better than that of the ordinary least squares (OLS) regression model. The GWR model is of greater value than the OLS model to researchers and practitioners, because the predictor variables are readily available from census data; this availability of data allows researchers to use the model after calibration.

The Americans with Disabilities Act (ADA) requires providers to provide paratransit services, complementary to their fixed routes, for those who are eligible. Since the ADA was passed, demand for such services has increased steadily. Although paratransit services are designed to maximize loads by accommodating customers according to a share-ride model and various advanced operational and management methods have been adopted, overall service performance has decreased. The number of demand-response trips grew rapidly between 1996 and 2006, from 93 million trips to 126 million trips, an annual growth rate of 3.3%. However, productivity, measured as passenger trips per revenue hour, has gradually decreased by 1.6% annually (*1*).

Analyzing the geographic demand patterns of paratransit services is one of several ways providers can improve the service efficiency of their ADA paratransit services. When the demand number is the same, differing demand patterns during peak hours affect the number of vehicles to be used. According to trip patterns and service restrictions, operational patterns may be categorized as many-to-one, many-to-few, and many-to-many. Many-to-many operations are less productive than the other patterns because many-to-many operations involve more route deviations and intermediate stops. Another application of such an analysis is identification of the concentration levels of trip origins and destinations so that planners can allocate more available resources to timely collect and distribute patrons (such as drivers and vehicles) around the high-demand areas during peak hours. In addition, service providers can generate vehicle schedules and routes more easily by considering the spatial and time clustering effects. The ability to predict the demand locations of potential patrons is important to service providers.

A more accurate process for identifying and forecasting the times and locations of the clustering effect may mean passenger wait times and ride times can be reduced, improving service quality. In the long term, service providers could improve service quality by adding facilities or offering assistance in waiting areas in high-demand locations.

Two major methods are used for calculating the demand estimations for a given region: aggregate models and disaggregate models. Aggregate models such as regression models are estimated with single average values for variables distributed across an entire service area; there is no guarantee that the predicted effects will be the same over the entire area. This means, for example, that the population variable might be an important predictor of demand volumes in some locations of the study but perhaps a weak predictor in other locations.

Some researchers have used other methods to predict ADA paratransit demands. An example of applying a time series analysis was proposed by Menninger-Mayeda et al. (*2*). Time series analysis is useful for explaining changes in demand that depend on days of the week or seasons of the year. The model used by Menninger-Mayeda et al. included 15 predictor variables used to predict the ridership in Orange County, California. Denson used a survey questionnaire to investigate and examine the existing transportation patterns of people receiving dialysis treatments (*3*). This approach usually is expensive and cannot predict demand over time.

Koffman and Lewis used four tools consecutively to forecast the demand for ADA paratransit services: surveys, intuitive comparisons with other systems, cross-sectional econometric analyses, and time series econometric analyses (*4*). Their study showed denial rates to be an important predictor, along with fares and other factors. It was shown that existing research can predict the amount of demand over a certain period, but such research lacks the ability to capture or forecast geographic demand patterns within a given service area and over time. In similar research about building ordinary least squares (OLS) regression models to predict trips for paratransit services, LaMondia and Bhat mentioned that the impacts of some variables vary greatly depending on the spatial scale (*5*). Their research implied that the effects of the same factors may have both positive and negative influences on different census tracks. This conclusion justifies the notion that it is reasonable to use geographical weight regression (GWR) models in this type of research.

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To the authors' knowledge, no studies have thoroughly investigated the effects of spatial distributions on ADA demand forecasting. Moreover, the presented GWR model provides an excellent estimation of the trip demands in each zone base with simple but representative independent variables (population and percentage of senior citizens, African-Americans, and people below the poverty line). Service providers or agencies could use this model as a strategic tool for evaluating the growth trends of demand in each zone.

This paper models the geospatial patterns of ADA paratransit services. A GWR model is developed that has a superior ability to accommodate geospatial effects, as compared with OLS regression models. The paper is structured as follows. First, the data and methodology are introduced. Then, the results of application of the proposed methods are discussed. Finally, conclusions and possible topics for future research are provided.

DATA AND METHOD

This section summarizes the data used to model and predict travel demand. The steps in identifying trip patterns and in fitting models are outlined.

The trip data for the analysis were obtained from METROLift, the ADA paratransit service for Houston, Texas. The data contained information regarding 110,587 ADA paratransit trips occurring in 1 month, from June 1 to June 30, 2012. The data set included six variables or record columns: pickup addresses, dates, pickup times, user IDs, drop-off addresses, and triangulated distances between the pickup and drop-off addresses. The average numbers of trips made during weekdays and weekends were 4,522 and 1,737, respectively. The road shape file and the 2010 census data material were both downloaded from the Bureau of the Census website.

Before the generation model was fit, the demand was checked for a clustering effect over the service area. This cluster index gave the concentration degree of the demand pattern. Then exactly where the high demand areas were needed to be identified. As the results show, it was found that the clustering effects affected the predictive accuracy of the simple OLS model. These spatial interactions and variation effects on the OLS model were recognized by LaMondia and Bhat (*5*). Therefore, the GWR method was used; the performances of the OLS and GWR models are compared in the next section.

The method used can be separated into three steps: (*a*) check the data cluster index, (*b*) define hot spots for ADA trips, and (*c*) fit trip generation models—OLS and GWR. The formulations and characteristics of each step are presented in the following sections.

Average Nearest Neighbor

Average nearest neighbor (ANN) is a nearest neighbor index based on the average distance from each point to the nearest neighboring point. Equation 1 gives the calculation for the ANN:

$$\text{ANN} = \frac{\bar{d}}{\bar{\delta}} = \frac{\bar{d}}{0.5 \times \sqrt{\dfrac{A}{n}}} \tag{1}$$

where

$\bar{d}$ = average nearest neighbor distance,
$\bar{\delta}$ = average random distance,
A = area of the study region, and
n = number of points.

If the ANN is less than 1, the data contain clustered points. If the index is greater than 1, the data contain dispersive points. However, the ANN value can be interpreted only when the *Z*-value is significant. In other words, if the *Z*-value is not significant, the ANN value is meaningless.

Kernel Density and Spider Graph

Kernel density mapping is one of the most common methods used to define spatial hot spots for count data (such as the number of crimes or crashes), because kernel density mapping details both smooth and continuous probability targets within a given study area (*6*). The premise is to calculate the probability density of each trip end point instead of showing the actual value of each point. The density value is highest when the distance from the trip end point is zero; the density value decreases when the distance increases. Equation 2 gives the calculation of the quartic kernel density function used in ArcGIS; more details are available elsewhere (*7*).

$$K(u) = \sum_{d<\tau} \frac{3}{\pi\tau^2}\left(1 - \frac{d^2}{\tau^2}\right)^2 \tag{2}$$

where

$K(u)$ = kernel density value at location u,
d = distance from the trip end point, and
τ = bandwidth.

In addition to identifying spatial hot spots, a spider graph can identify temporal hot spots. Unlike a normal frequency figure that has time in the *x*-axis and frequency in the *y*-axis, a spider graph connects the beginning and the end times, and the time axis then acts as a circle. This circle makes examination of the complete time distribution much easier because there is no interruption. Readers of such a graph can easily answer the problem, "How long is a hot spot 'hot'?" (*8*, p. 114).

It is important that identification of hot spots considers the various time distributions of ADA trips, because the temporal distribution of ADA trips may relate to specific characteristics of passengers' daily activities. Concluding that the time distributions of ADA trips are the same for different hours of the day or different days of week would be simplistic and would result in no recordable temporal effects.

GWR and OLS Models

Most current models for generating and forecasting ADA paratransit trip demand are OLS models. Two assumptions are commonly made in the application of OLS models: (*a*) observations should be independent of one another and (*b*) error terms should be random noise. Such assumptions may be impractical for an ADA regression model; LaMondia and Bhat showed that spatial interactions exist in OLS models (*5*). The results of the present study support this finding, as discussed in the following section. If such interactions are neglected, the estimate of the parameters will be inefficient and biased, because the standard errors will be overestimated (*9*). This paper proposes use of the GWR model to fit the demand data if any spatial relationships among the adjusted areas are found. Equations 3 and 4 are the simplest forms of the OLS and GWR models. Details of GWR are available elsewhere (*10–12*). The main difference between these two models is that the parameters of the GWR model change from area to area, but the parameters of the OLS model are fixed for the entire study area. That is, in some areas the influence of independent variables may be much stronger than in other areas.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_m x_{mi} + \varepsilon_i \quad (3)$$

$$y_i(u) = \beta_{0i}(u) + \beta_{1i}(u)x_{1i} + \beta_{2i}(u)x_{2i} + \cdots + \beta_{mi}(u)x_{mi} \quad (4)$$

where

- y_i = ADA paratransit trips in census tract i;
- $x_{1i}, \ldots, x_{mi}$ = independent variables;
- $\beta_0, \ldots, \beta_m$ = parameters in OLS models, which are estimated with $\hat{\beta} = (X^TX)^{-1}X^Ty$;
- X^T = transpose of X, which is vector of x;
- $\beta_{0i}(u), \ldots, \beta_{mi}(u)$ = parameters in location u in GWR models $\hat{\beta}(u) = (X^TW(u)X)^{-1}X^TW(u)y$;
- $W(u)$ = weight matrix relative to location u, $W(u) = (1 - (d_i(u)/h)^2)^2$;
- $d_i(u)$ = distance between census tract i and location u;
- h = bandwidth; and
- ε_i = error term.

For model diagnostics in this study, two common indexes were used: the R^2 value and the Akaike information criterion (AIC). The R^2 value measures the ratio of the variation in the dependent variable, which was accounted for by the variation in the model and the possible values ranging from 0 to 1. When the R^2 value is closer to 1, the corresponding model has a better predictive performance. AIC is another common measure used to compare models having the same independent variable. Models with a lower AIC value are preferable to models with a higher AIC value. AIC combines a value for the model likelihood and a penalty for the number of model parameters. This penalty prevents overfitting.

RESULTS

The results described here are divided into three parts: (*a*) a cluster pattern index that uses the ANN index to examine the cluster patterns of ADA trips made during different periods, (*b*) kernel maps that show how the hot spots change over different periods, and (*c*) ADA trip generation models that use GWR and OLS models to fit the original ADA trips for each census tract area.

Cluster Pattern Index

The first step was to use the ANN index to define the cluster pattern for the ADA data. Table 1 shows the ANN value and the Z-value. The data were clustered when the ANN value was less than 1, and the Z-value was used to evaluate the ANN value's statistical significance. A comparison of peak hours in the morning and afternoon for weekdays and weekends revealed two significant conclusions: (*a*) during weekdays, the pickup and drop-off locations of the ADA trips were clustered, and the drop-off locations in the morning and the pickup locations in the afternoon (the attractions) were more concentrated than the pickup locations in the morning and the drop-off locations in the afternoon (the productions); (*b*) during weekends, the pickup and drop-off locations of the ADA trips were still clustered, but the pickups were more concentrated than the drop-offs.

Kernel Maps

For a better understanding of the spatial-temporal characteristics of the ADA paratransit trips in the Houston area, kernel density maps were created for the data covering five periods: midnight to 6:00 a.m., 6:00 to 9:00 a.m., 9:00 a.m. to 2:00 p.m., 2:00 to 5:00 p.m., and 5:00 p.m. to midnight. Figures 1 and 2 show the kernel density maps for the ADA paratransit trip data obtained from weekdays and weekends, respectively. The hot spots are easily identified by their colors. Warm colors (yellows, oranges, and browns) in the maps represent hot spots. The locations of these hot spots are quite different between weekdays and weekends.

The results showed that during weekdays, in the morning peak hours the origins of the ADA trips were spread out across the whole study area, but most destinations were concentrated around the central hospital area. The pickup and drop-off locations in the morning peak hours were inverse to those in the afternoon peak hours. Further analysis of the time and spatial patterns showed that many of the area's trips were round-trips. Although direct information about the characteristics of origins and destinations is lacking in the data, it has been found that nearly all patrons of paratransit services begin their trips from their homes (*3*). Thus, the ADA outgoing home trips generated were related to the characteristics of the local residents. Obtained from the census data, the characteristics of the local residents in each tract (income, age, population, race, education level) can be considered predictors.

On weekends, the distribution of pickup and drop-off locations looked different. In the early morning (midnight to 6:00 a.m.), the trend was similar to weekday trends. However, the patterns of hot spots changed in later hours: the pickup and drop-off locations in the morning peak hours were not exactly the inverse of the afternoon peak hours. Also, the drop-off hot spots were more spread out and were not only around the central medical area. This result was determined to be reasonable because most public medical centers, social worker institutes, and government offices are closed on weekends. In addition, the hot spots of drop-off trips were closer to pharmacies or community-based clinics (on Saturdays) and churches (on Sundays). Peak hours also changed on weekends. Peak hours for return trips shifted 1 or 2 h earlier. Figure 3 shows spider graphs of the number of trips per hour. For the distribution of ADA trips, Figure 3*a* is a spider graph of trip distributions sampled by time (hour) for weekdays, and Figure 3*b* is a spider graph of trip distributions sampled by time for weekends. On

TABLE 1 ANN Values of Pickup and Drop-Off Location Data

	Morning Peak (6:00–9:00 a.m.) (ANN, Z)		Afternoon Peak (2:00–5:00 p.m.) (ANN, Z)	
Pattern	Pickup	Drop-Off	Pickup	Drop-Off
Weekday	Cluster (0.07, −284)	Cluster (0.05, −282)	Cluster (0.06, −271)	Cluster (0.07, −272)
Weekend	Cluster (0.13, −109)	Cluster (0.15, −105)	Cluster (0.23, −70)	Cluster (0.24, −72)

FIGURE 1 Kernel density maps for ADA paratransit trip data on weekdays: (*a*) pickup and (*b*) drop-off.

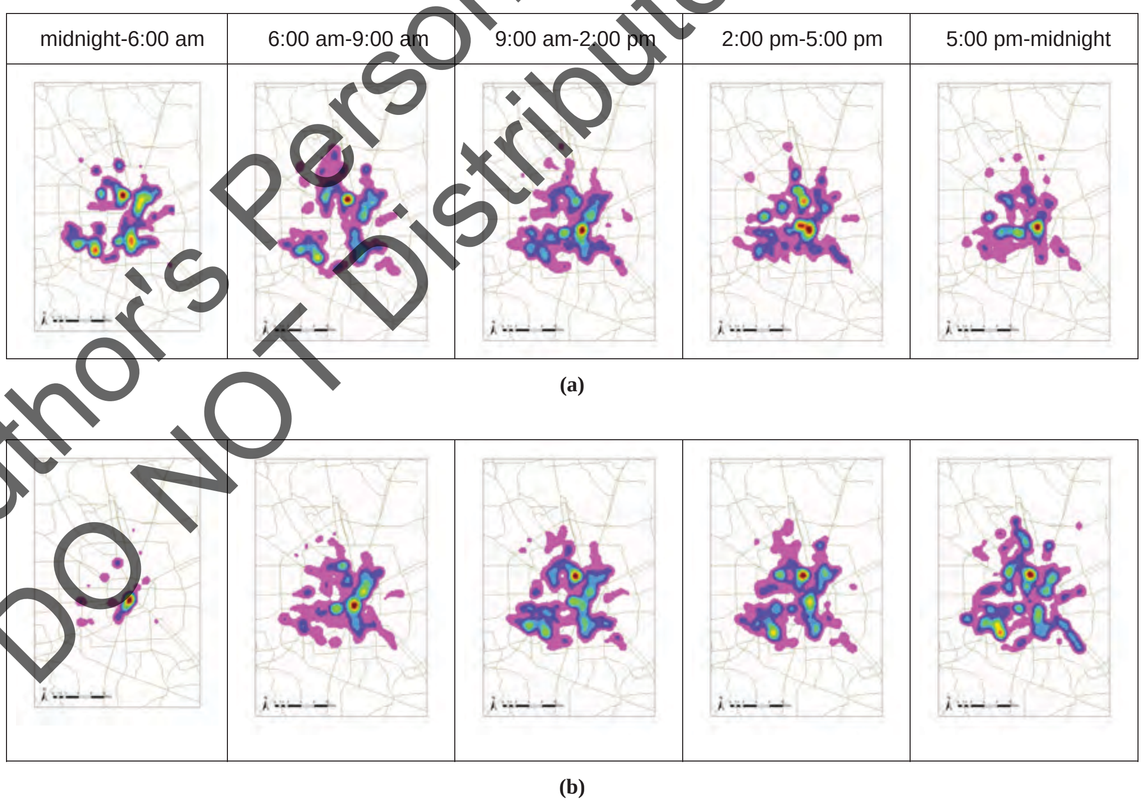


FIGURE 2 Kernel density maps for ADA paratransit trip data on weekends: (*a*) pickup and (*b*) drop-off.

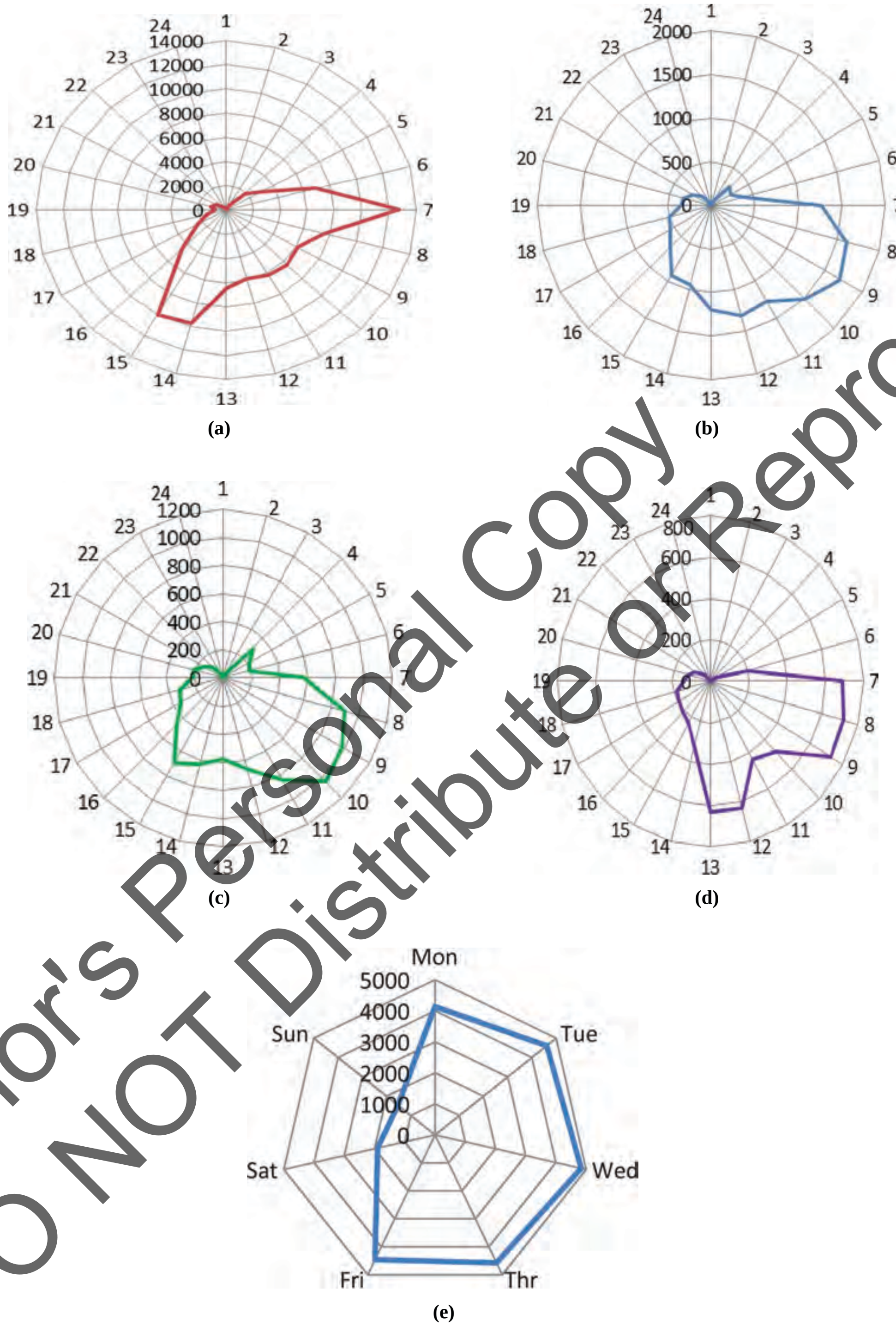


FIGURE 3 Spider graphs of trip numbers: (*a*) weekdays per hour, (*b*) weekends per hour, (*c*) Saturday per hour, (*d*) Sunday per hour, and (*e*) week per day.

weekdays, there was a morning peak period from 7:00 to 9:00 a.m. and an afternoon peak period between 2:00 and 4:00 p.m.; weekends had no afternoon peaks. When weekends were separated into Saturdays (Figure 3*c*) and Sundays (Figure 3*d*), Saturday showed no obvious peak period for return trips, and two peak periods were observed for Sunday (7:00 to 9:00 a.m. and noon to 1:00 p.m.). Figure 3*e* shows trip distribution by day. On weekdays, there were 4,000 to 5,000 ADA trips per day; the average numbers of trips on weekends were 1,500 to 2,000 per day.

The demand estimated from the models represented only the outgoing home-based ADA trips, and it is assumed that there would be an equal or similar demand for incoming home-based ADA trips (in the opposite direction). Future research could build on the ADA trip attraction demand model if researchers have information about the purposes of various trips.

ADA Trip Generation Models

The previous section showed that the production of ADA trips is related to the characteristics of local residents, and attractions are more closely related to locations of hospitals and specific medical institutions. Because of the availability of data and their easy application in future studies, the characteristics of local residents were chosen as the independent variable and the demand for ADA trip generations in each census tract was chosen as the dependent variable. For specific applications, the models can be modified and applied to other regions, because the census data sets are nationwide and are routinely updated and maintained. The census data used in this study were 2010 data, which can be downloaded for free from the Bureau of the Census website. OLS and GWR models were built and compared.

Researchers chose their potential variables according to suggestions made in previous studies (*5, 13*). The operational variables were not included in this paper because these variables (fare, denial rate, and fleet size) are commonly used to predict demands served rather than latent demands. Certain specific variables (such as a lower education level ratio and average household size) were avoided because of the higher ratios of missing data, unclear definitions, or redundancies among explanatory variables. Two types of trips were tested as dependent variables—all ADA trips and first outgoing trips from home—to fit the OLS models. There were 53,157 first outgoing trips from homes (about 48% of the total 110,587 trips); these trips were distributed through 597 census tracts. The results showed that use of all ADA trip data yields a very low R^2 value (.06), and use of outgoing trips from home yields a higher R^2 value (.38). This result is consistent with the assumption that trip generation is related to the characteristics of residents and that a removal of these ADA nonoutgoing home trips (trips made later in the same day) could increase the R^2 value of the appropriate model. The independent variables included population, ratio of seniors (older than 65), ratio of people below the poverty line, and ratio of African-American individuals. Their coefficients and *t*-values are listed in Table 2. Other variables were tested but determined not to be statistically significant: low education ratio, average household size, male ratio, and Hispanic ratio.

Although the R^2 value increased from .06 to .38, the residuals in the OLS models were clustered, not randomly distributed (Figure 4*a*). Figure 5*a* shows the residual values of each census tract area when an OLS model was used. The red areas are underestimated, and the blue areas are overestimated. The OLS models tend to underestimate around the central areas and overestimate in the outlying areas. Therefore, use of the GWR model to fit these trip data is

TABLE 2 OLS Model Specifications

Variable	Coefficient	*t*-Value	VIF[a]
Population	0.01	7.2	1.1
Ratio of seniors	3.86	5.4	1.2
Ratio of people below poverty line	100	6.3	1.3
Ratio of African-Americans	185.3	12.7	1.2
Intercept	–85.6	–5.9	na

NOTE: na = not applicable. R^2 = .38; AIC = 8,925.
[a]Variance inflation factor, which measures level of collinearity; a small number is better. If greater than 7.5, redundancy.

suggested because of its spatial relationship between the adjusted areas. The parameters of the GWR model changed from area to area, but the parameters of the OLS model were fixed for the entire study area. The R^2 value of the GWR model increased to .56, and the AIC value was reduced from 8,925 to 8,660. The GWR model better fit this study's trip model because of the higher R^2 value, lower AIC value, and more random noise (Figures 4*b* and 5*b*).

The characteristics of the coefficient estimates for the four variables used in the GWR model are summarized in Table 3. For the population variable, the mean of the estimated coefficient for the GWR model is 0.01 with a standard deviation of 0.01. The coefficients range from –0.004 to 0.056, and the model clearly has heterogeneity within the Houston area. Figure 6 shows the variations in the coefficient estimates of each census tract. Figure 6*a* shows that the impact of population on the model increases from rural areas to central areas. For example, if the population grows by the same amount in each census tract, the extra demand generated in central areas will be larger than in rural areas. In addition, the global coefficient from the OLS model and most of the coefficients (more than 97%) from the GWR model are positive, which means that a higher population generates more ADA paratransit trips, but few census tracts have negative coefficients. The situation is similar for the other variables (Figure 6, *b* and *c*), except for the ratio of African-American riders. Figure 6*d* shows that the impact of the ratio of AfricanAmerican riders in the model increases from downtown to the city's outskirts. (The direction is reversed for other variables.) The results show that a larger population, a higher percentage of senior citizens, a higher percentage of African-Americans, and a higher ratio of people below the poverty line all increase ADA trip demand. However, these variables may have different levels of influence (and may even be negative) in different census areas. Although LaMondia and Bhat used a different data set, the R^2 value for the linear regression of patron demand generation in their study was .494 (*5*). The results for the GWR method proposed in this paper show that a greater portion of the observed demand variance (an R^2 value of .56) can be identified with use of fewer variables.

Unlike the conclusions reached by the study presented in this paper, the research by Koffman et al. highlighted that high levels of poverty in a service area can significantly depress demand (*13*). The difference between these two conclusions can be explained in several ways. First, the demand data of the two studies are drawn from different scales. In this research, the model was based on the demand data from a single city; the model built by Koffman et al. was constructed from data obtained from several cities across the United States. This implies that in the regression model the poverty rate suggests opposite effects on demand within a single city and demand between several cities. In addition, the independent variables used to construct the regression

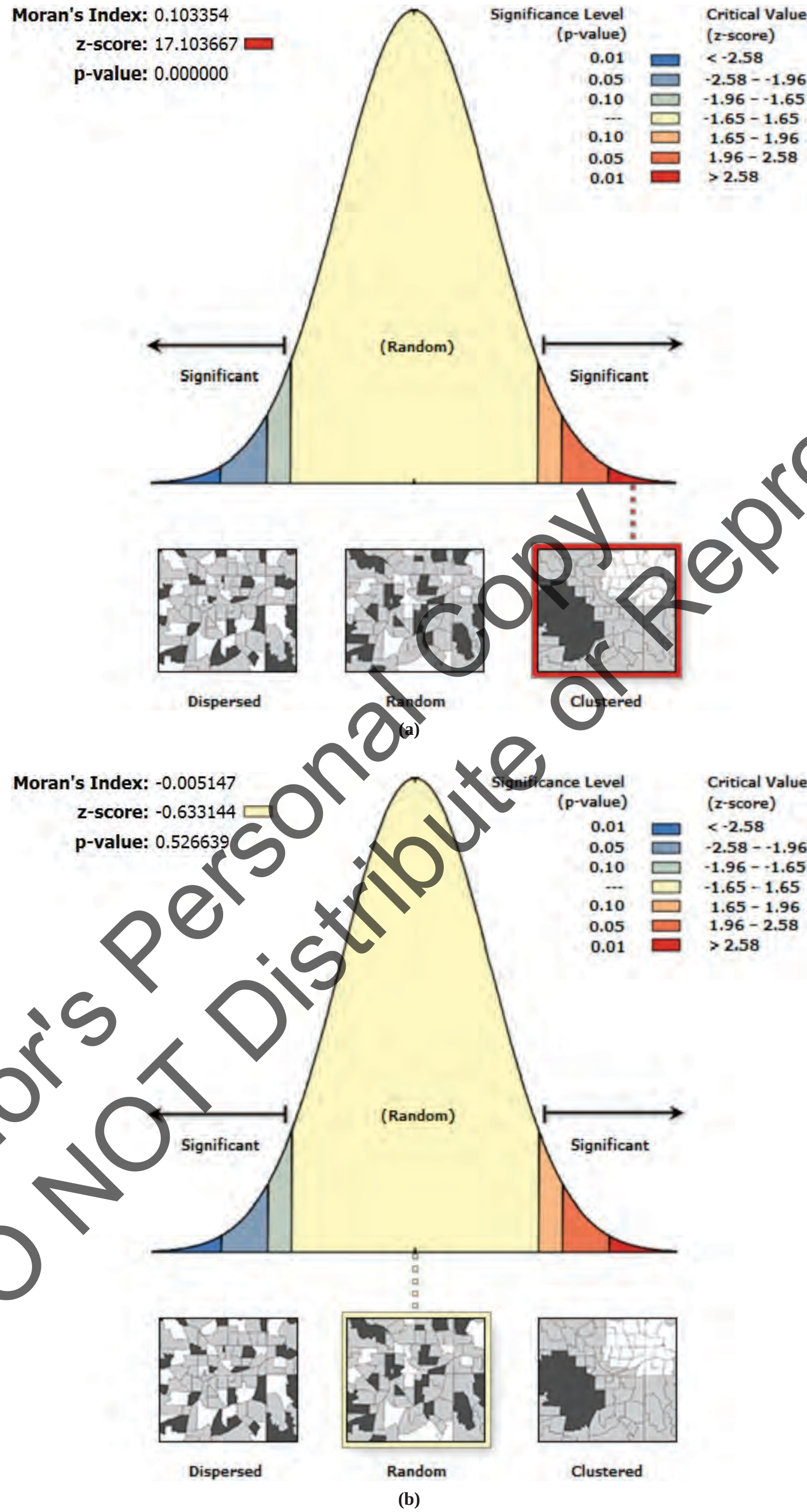
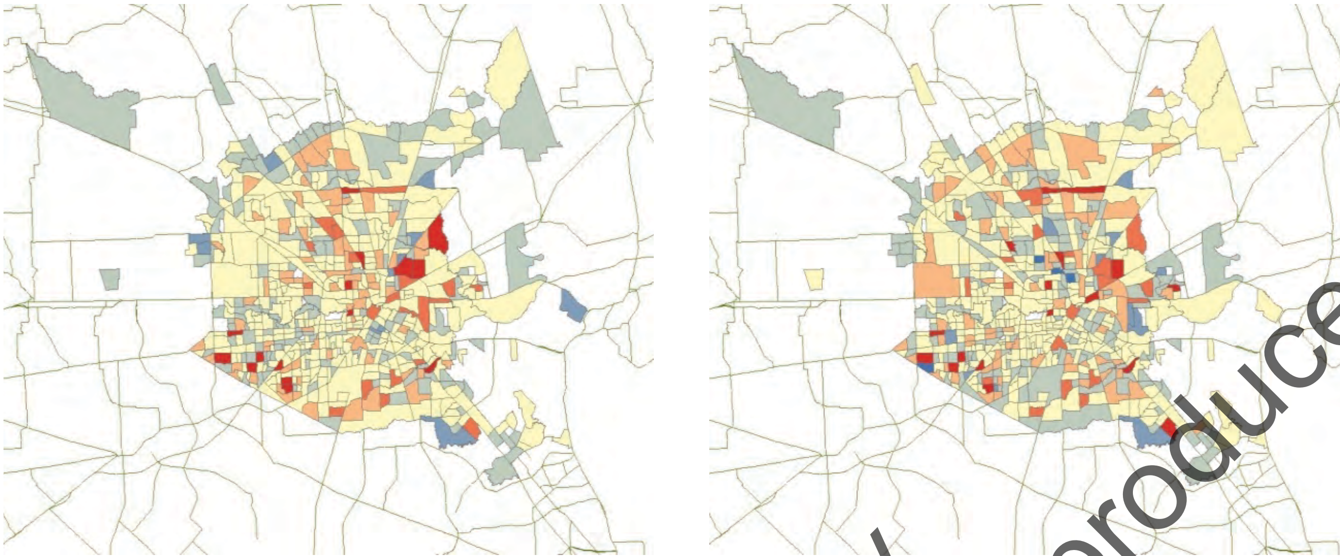


FIGURE 4 Spatial autocorrelation reports for (*a*) OLS model and (*b*) GWR model.



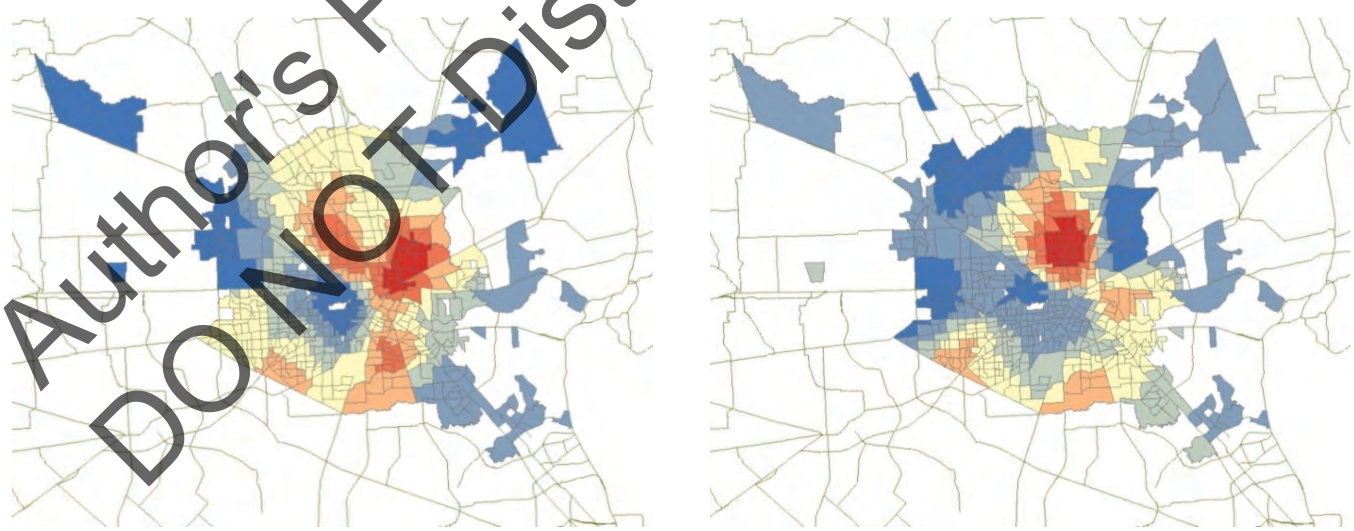
(a) (b)

FIGURE 5 Residual distributions for (*a*) OLS model and (*b*) GWR model.

TABLE 3 GWR Model Coefficient Estimates

Variable	Coefficient	Min.	Max.	Standard Deviation	Parameter Increase Direction
Population	0.01	–0.004	0.056	0.01	Rural to central
Ratio of seniors	3.86	–4.87	45.9	7.9	Rural to central
Ratio of people below poverty line	100	–104.7	589.1	105.8	Rural to central
Ratio of African Americans	185.3	–353.4	381.3	113.2	Central to rural

NOTE: min. = minimum; max. = maximum. R^2 = .56; AIC = 8,860.



(a) (b)

FIGURE 6 Coefficient estimates of each census tract for independent variables in GWR model: (*a*) population and (*b*) ratio of seniors.

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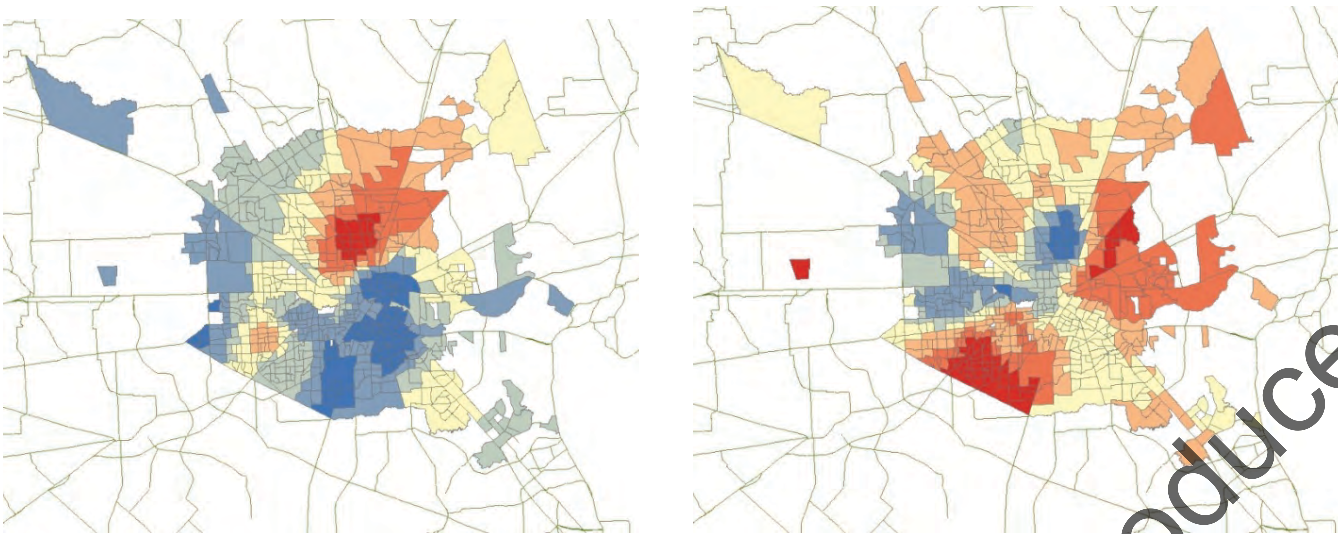

(c) (d)

FIGURE 6 *(continued)* **Coefficient estimates of each census tract for independent variables in GWR model: (*c*) ratio of people below poverty line and (*d*) ratio of African-Americans.**

models were not the same in the two studies. Other possible hidden factors, such as passenger characteristics, may be the true causal factors for demand prediction. General conclusions that would be applicable to all cases cannot be made, and further efforts are needed to investigate this issue.

CONCLUSION

The ADA paratransit service trip distributions used in this study showed both spatial and time concentration profiles. The GWR model successfully explained this spatial heterogeneity. The results of a comparison of the GWR and OLS models showed that the GWR model fit the study trip model better because of the higher R^2 value, the lower AIC value, and more random noise.

The presented regression model showed that a larger population, a higher percentage of senior citizens, a higher percentage of African-Americans, and a higher ratio of people below the poverty line all increased ADA trip demand. In comparisons with other studies, the model needed fewer variables but had better-fitting results. Also, the research presented here should be easy to apply to other study areas because census data are easily accessed. This study could be extended through combining the demand data with passenger characteristics (including age and sex) and trip characteristics (including trip purpose and distance). These extra key factors could be used to improve the model's accuracy and the overall explanation. In addition, the inclusion of the characteristics of temporal concentration in the regression models should be significant because the geographical concentration for ADA demand was identified as interactive with pickup times. These advanced models could help in the management of continuing increases in demand could be used to improve the overall performance of ADA paratransit services.

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