Role of Travel Information in Supporting Travel Decision Adaption: Exploring Spatial Patterns

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Abstract:
How consumers acquire and use dynamic traveler information to adjust their travel behavior is a key component of Intelligent Transportation Systems (ITS). The association between information acquisition/adjustments and various socio-economic and contextual factors can be captured in traditional statistical models, known as global model which yields one overall set of coefficients as the estimate. However, the associations may vary across space, more specifically, people living in different spatial locations may have different information acquisition patterns and they may respond differently to dynamic information, which cannot be captured in global model. This study uses Geographically Weighted Regression (GWR) - a local model as an alternative, to answer: 1) which factors are associated with traveler information acquisition and decision adaption; 2) whether these associations are the same over the entire study region and 3) how these associations distribute spatially. A traditional logistic regression model referred to as the global model is also presented to compare. The results show locally-based model can capture spatial variance by producing a set of mapable parameter estimates and their significance levels (t-statistics), which continuously vary over space. It indicates that GWR provides a more complete picture of information acquisition/use by capturing how correlates vary over space. The implications of the results for ITS are discussed.

Keywords—geographically weighted regression, global model, local model, spatial deviation, travel decision, traveler information

INTRODUCTION

The rapid development of information technologies applications in transportation has provided customers with more diverse and dynamic information. Advanced traveler information systems (ATIS), part of intelligent transportation systems, are playing a key role in this regard. Nowadays, a variety of technologies, including the Internet, telephone services, television/radio broadcasts, dynamic message signs, and in-vehicle/on-board devices are available to provide pretrip and en-route information to help travelers make more informed decisions. Interests have increased in dynamic information provision, and understanding how information is used and whether travelers are willing to make travel decision changes based on the traveler information they receive [1-9].

Most of the current literature only concentrates on the non-spatial outcomes of activity-travel decisions as well as traveler information delivery mechanisms. Due to human, social or other environmental reasons, people may share attitudes or the same living styles when they are close, compared with people who live far away. This shapes some intangible or abstract patterns surrounding human activities in geographical space. Similarly, the role of travel information may show spatial patterns since how people respond to traveler information is likely to vary across space. For instance, people earning a certain and living in denser urban areas may have different information acquisition needs and they may respond differently than similar wage earners who live in suburban or rural areas. Furthermore, the association of various socio-economic and contextual factors may vary across space. For example, the need for dynamic travel information and its use may vary substantially across locales, depending on the types of services available. In such cases, averages for travel information acquisition and use in the entire region can only provide a sense of the overall need for information, but it may not indicate disparities in acquisition/use across localities in a region. It is desirable to ask: where are the parts of a region where people with higher/lower income or longer travel time are more sensitive to information acquisition and travel decision changes? Such questions cannot be fully answered directly by standard parameter estimation models — called a global regression model, since in these models, the estimated parameters are fixed and do not vary spatially. Although unrestricted models can be estimated for various spatial sub-classifications and compared with a global or pooled model, this is often cumbersome and rarely done-since the problem of fixed coefficient still exists within the sub-classifications and the definition of the boundary of those sub-classifications will influence the estimation of the coefficients, referred to as the (undesirable) "boundary effect"[10]. In this paper, Geographically Weighted Regression (GWR) is used to create coefficient surfaces for information acquisition and travel decision changes to explore spatial patterns. We answer the following research questions: Which factors are associated with acquisition of transportation information and travel decision changes? Whether these associations are the same over the entire study region? If not, what are the spatial patterns of these associations?

To answer these research questions, a comprehensive and recently collected behavioral survey from the Triangle area in North Carolina is used. Specifically, respondents were asked to answer questions about their acquisition and use of travel information as part of the 2006 Greater Triangle Household Travel Survey (N=5107). The content of travel information we discussed in this paper is those available to travelers in the area - the television, commercial radio, Internet, dynamic message signs, including both the en-route information available on freeways and pretrip information. Statistical analysis involves descriptive statistics and estimation of traditional logistic models and a set of more complicated local model using GWR (Geographically weighted regression) technique. All the coefficients and local T-statistic produced by GWR are mapped using GIS methods to show their spatial deviation.

LITERATURE REVIEW AND SYNTHESIS

Travel information acquisition and travel decision adaption

Existing evidence shows that individual characteristics are associated with travel information usage. Based on travel behavior data for users of a privately operated telephone traffic information system in the Bay Area, Kitamura et al. [11] found that as commute distance increased, respondents were prone to making more frequent calls. Furthermore, Fan and Khattak [12] found that daily travel distance and daily activity space (defined as the minimum convex polygon that contains all the daily activity locations) are both positively related to the usage of traffic information. Englisher et al. [13] found similar results among users of a publicly run service in the Boston area. Also in Seattle, the propensity to use information tends to increase with distance and duration of the trip [14]. And the decision to seek information does not seem to be strongly associated with traditional demographics such as gender or income, but is correlated with employment status, internet usage, and experience with congestion. Trip characteristics are another set of factors found by Peirce and Lappin [14] to influence travel decisions: travelers are prone to search information where (1) the trip is arrival-time sensitive and (2) substantial variability or uncertainty exists about travel times.

As for travel decisions changes, researchers have found multiple factors associated with travel decision changes. Khattak et al. [15] estimated a logistic model based on a behavioral survey and suggested that the likelihood of travel decision change (change route, time, mode, and cancel trip) has a significant positive association with the number of information sources and travel information use frequency. Wang et al. [16] estimated probit models with and without sample selection to capture the probability of travelers' propensity to change their travel decision conditional on their acquisition of traveler information. However, this paper did not consider the possibility of spatial variations. This current paper it is intended to explore the issue of spatial variability in behavioral patterns.

Although some of the models available in the literature have already considered spatial characteristics [12] by including categorical variables of landuse type in the correlates, such as land type, these models only explore association between the landuse and dependent variable. They do not typically answer questions such as: do socioeconomic or personal characteristics associated with dependent variables show spatial patterns? Furthermore, the geographical patterns for the socioeconomic or personal independent variables may not be consistent with the defined land units, e.g., traffic analysis zones. In this paper, a key issue is to explore spatial patterns of variation in correlates.

Capturing Spatial Pattern in transportation

Interest has increased in how to link spatial analysis, GIS technology and transportation [10, 17]. It's a timely issue to use spatial statistics and urban analysis techniques for urban transportation and land-use applications [18]. The general philosophy of capturing spatial patterns in transportation focuses on capturing spatial dependence and spatial heterogeneity.

Spatial dependence, referred as spatial autocorrelation problem, described the situation when association is the tendency of variables to display some degree of systematic spatial variation [18]. Extensive research already has been done to capture spatial dependence by including spatial factors in the error of the models [19, 20, and 21].

Spatial heterogeneity describes the situation when the mean, variance or covariance structure changes over space [18]. Geographically Weighted Regression (GWR) is a tool that can capture spatial heterogeneity by estimating model parameters locally instead of globally [22]. In GWR the estimated parameters that capture associations of variables (e.g., association of congestion or socioeconomic factors with information acquisition/use) can vary over space. It provides local parameter estimates for each variable in a spatial context. In doing so, more detailed local associations of variables are provided and the key assumption of global models, where "one size/model fits all" is relaxed. Furthermore, GWR is often interpreted as a smoother which can be used to approximate to a very high level of accuracy the observed variable surface, a feature that makes it very attractive for various aspects of urban analysis [18]. From a policy maker's angle, GWR can improve regional analysis and policy making since the subsequent policy inferences would be poorly suited to many local settings [23]. This is important since good traveler information, informed public policy, and private investment are critical to improving transportation network performance [24].

Application of GWR in transportation

Although GWR model has been used in other fields, for example, social science, environmental, investigation of industrialization, etc., studies of GWR applications in transportation are not so widely. Zhao [25] applied GWR to estimate AADT on non-expressway roads based on available AADT information on similar roads; the results indicated that the GWR models were able to better explain variations in data and to predict AADT with smaller errors than the OLS model. Chow [26] investigated the spatial variations by GWR model in the relationships between transit use and potential ridership predictors including demographics, socioeconomics, land use, accessibility, and transit supplies. Model testing indicates the GWR model improved accuracy in predicting transit use for HBW purposes over linear regression models. Du [27] looked at the relationship between transport accessibility and land value with the implication of a local model and GWR, which revealed that nonstationarity existed in the relationship between transport accessibility and land value. Clark [28] found the local model produced by GWR is more accurate in estimating the relationship between income and car ownership.

DATA USED

The study area is Triangle region of North Carolina including all portions of Chatham, Durham, Franklin, Granville, Johnston, Lee, Orange, Person, Wake, and Vance counties, the eastern portion of Harnett County, and the southern portion of Nash County. The data used in the paper is from the activity-based travel survey dataset in this region—the Greater Triangle Travel Study conducted in 2006. The Triangle regional travel survey utilized standard household travel survey methods, in which all the household members were asked to record all trips for a specified 24-hour period using a specially designed travel diary. The sampling plan included both geographic and demographic goals to ensure that the survey is representative of the region's population and activity-travel patterns. The detailed survey design and sample selection procedure can be found in the Greater Triangle Travel Study-Household Travel Survey Final Report [29].

The database contains three different levels of data: personal data, household data, and trip data. Most importantly, this database has all the households and trip origins and destinations geocoded while the coordinate is a basic requirement for running geographically weighted regression. The survey relied on the willingness of regional households to 1) provide demographic information about the household, its members and its vehicles; 2) have all household members record all travel-related details for a specific 24-hour period, including address information for all locations visited, trip purpose, mode, and travel time information; 3) provides household-level travel information usage data regarding information sources, as well as the acquisition frequencies and travel choice changes. The travel time used in the analysis is that reported by the head of the household.

Note that the content of travel information available to travelers in the area was mostly qualitative traffic reports of congestion/delays, and real-time details of traffic incidents. At the time of the survey travel information was available largely for the automobile mode, through the television, radio, Internet and variable message signs.

Descriptive Statistics

The descriptive statistics for the variables used in models are shown in Table 1. To capture various information sources used, the number of information sources accessed variable was created, by summing the number of sources used to seek travel information, where 0 = 0 electronic device used, 1 = 1 type of device used, etc, 5 = 5+ types used. The frequency of traffic information use was recoded as 0 = never, 1 = at least once a week, 3 = 2-4 times per week, and 5 = 5+ times per week. The average number of information sources accessed is 0.76.

The household income coded in the dataset is categorical; the categorical income in this paper is recoded with the average income of each category, where 0.75 = income<$15000, 2 = income is between $15000 and $24,999, 3 = income is between $25000 and $34999, 4= income is between $35000 and 49999, 6.25 = income is between $50000 and $74999, 8.75= income is between $75000 and $99999 and 10= income > $100000. There are 285 households who refused to answer this question. These data were replaced by the mean of household income which is $62,890.

The length lived at address is also categorical data, which was recoded as 0. 5 = <1 year, 1.5 =1 to 2 years, 3.5 = 2 to 5 years, and 7.5 = 5 to 10 years, 10 = longer than 10 years. The average length lived at their address is 6.68 years.

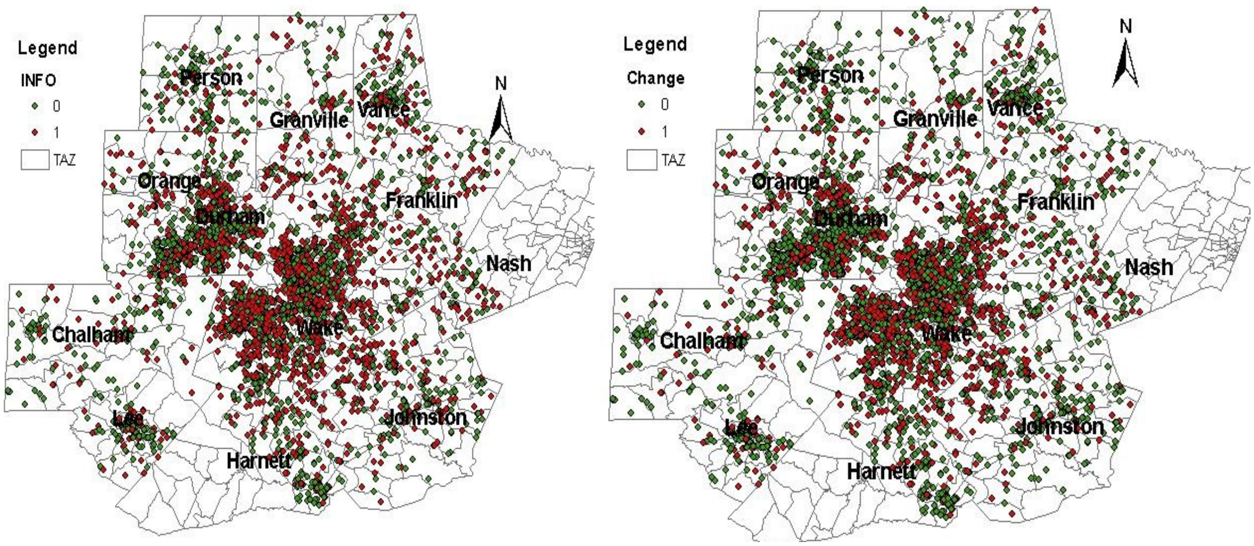
The variable 'INFO' and 'Change' are binary. The majority of respondents (51%) reported that they acquired travel information from electronic sources at least once a week, which means that 49% never seek regional travel information. About 40% of respondents reported that they changed travel plans based on information received. The spatial distributions of the variables 'INFO' and 'Change' are shown in Figure 1. From the graphs, they are slightly different, but generally, people who access traveler information and those who adjust their travel decision are distributed all around the study region—strong spatial clustering cannot be observed.

In terms of travel time, we define all trips with a "work" or "work related" purpose and all return trips from a work place to home as work-related travel. All the other trips are considered nonwork related trips. The average nonwork related travel time is longer than work related travel time (61 minutes vs. 26 minutes per day). Considering that differences in information usage/travel decision adaption may exist between travelers who traveled and those who did not make work or nonwork related trips, two dummy variables were created. Among them, 'Dummy_w' captures whether work related trips were reported; 'Dummy_nw' represents whether non work related trips were reported. Nearly 43% of respondents did not make work related trips on the survey day and 17% of the respondents did not make non work related trips on the survey day.

The average number of household vehicles is 2.0. Noting that there are some outliers with the variable age, 95 persons refused to answer this question, the average age of the remaining respondents is 51 years.

Table 1 Descriptive statistics for dependent and independent variables (n=5107)

Variable		Mean	S. D.	Min	Max
INFO	Acquisition of traveler information or not (1=yes, 0=no)	0.51	0.50	0	1
Change	Change travel plan or not (1=yes, 0=no)	0.40	0.49	0	1
NA	Number of information sources accessed	0.76	0.91	0	5
WORK	Work related travel time (minutes)	26.04	43.08	0	673
NWORK	Non-work related travel time (minutes)	60.74	62.24	0	750
Dummy_W	Travel for work related purposes (1=yes, 0=no)	0.43	0.50	0	1
Dummy_NW	Travel for nonwork related purposes (1=yes, 0=no)	0.17	0.28	0	1
FINFO	Frequency of info acquisition (weekly)	1.96	2.25	0	5
Live	Length lived at this address (year)	6.68	3.51	0.5	10
Income	Household income (categories)	6.29	3.09	0.75	10
Age	Age of respondent (household head, years)	51.2	15.1	18	98
HHVEH	Household vehicle number	2.01	1.02	0	8



a) **b)**

Figure 1 Spatial distribution for a) INFO b) Change

MODEL STRCUTURE AND RESULTS

Application of Geographically Weighted Regression (GWR)

Based on the spatial expansion method, GWR aims to show the spatial deviation of associations between dependent and independent variables by relaxing the assumption that coefficients hold globally. It allows associations to vary locally. In GWR the regression model is calibrated on data that lie around a (residential) location point within a certain distance (bandwidth) and these data are weighted by their distance from a regression point. That is for a given regression point, the weight of a data point is at a maximum when it shares the same location. This weight decreases continuously as the distance between the two points increases. In this way, a regression model is calibrated locally simply by moving the regression point across the region. For each location, the data will be weighted differently so that the results of any one calibration are unique to a particular location. By plotting the results of these local calibrations on a map, surfaces of parameter estimates, or any other display which is appropriate, can be generated. Therefore, when GWR is applied, key decisions must be made regarding 1) a weighting function (the shape of the kernel), and 2) the bandwidth of the kernel. The weighting function usually has a minimal effect on results, while bandwidth may affect results markedly [22,30]. Only if there is little variation in the local observations do the global observations provide reliable information on the local areas.

In its most basic form, GWR model takes the following form [22]:

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_k x_{ik} + \varepsilon_i$$

y_i = dependent variable at location i (i = 1, 2, . . . , n, where n is the number of observations);

β_{i0}=the constant variable at point i;

β_k= the coefficient at point i for variable x_{ik};

x_{ik} = independent variable of the kth parameter at location i,

ε_i = error term at location i,

p = number of parameters.

Logistic GWR:

$\mathrm{Prob}_i = \frac{e^{(Ci+\sum_k \beta_{ki} X_{ki}+\varepsilon_i)}}{1+e^{(Ci+\sum_k \beta_{ki} X_{ki}+\varepsilon_i)}}$

Ln (odds ratio of Prob_i)=$\ln(\frac{\mathrm{Probi}}{1-\mathrm{Probi}})$= $\mathrm{Ci} + \sum_k \beta_{ki} X_{ki}$

Note that for each location, the β parameter can be different. Monte Carlo significance tests for the parameter estimates can tell whether the parameters have significant spatial variability. AIC (Akaike Information Criterion) can be used to evaluate whether GWR provides a better fit than a global model [22, 30] as the smaller ACI indicates better result. In this study, Logistic GWR is calibrated using GWR 3 package and the calibration took 21 hours with more than 5000 samples, much longer than that of conventional logistic model.

MODEL RESULTS

Global Model

The global logistic model for information acquisition and behavior adaption are estimated by the maximum-likelihood algorithm and the results are presented in Table 2. The first model has traveler information acquisition as the dependent variable. The second model has change or no change as the dependent variable. Both of these models are statistically significant, overall. The directions of these coefficients are consistent with the probit models in a previous paper [16], but some marginal effects are different from the previous models owing to sample selection, which is not considered in this paper.

Table 2 Global logistic model results

Dependent	Info acquisition			Behavior change		
Variable	Coef.	T-stat.	Marg.	Coef.	T-stat.	Marg.
Intercept	-0.133	-0.948	-	-3.337	-13.739*	-
WORK	0.004	4.028*	0.001	0.000	0.112	0.000
Dummy_W	-0.221	-2.983*	-0.055	-0.224	-1.922	-0.047
NWORK	0.002	3.813*	0.001	0.001	1.259	0.000
Dummy_NW	-0.010	-0.116	-0.003	-0.106	-0.760	-0.022
NA	-	-	-	1.700	20.014*	0.361
Lived	0.003	0.295	0.001	0.054	3.571*	0.011
Income	0.053	4.932*	0.013	0.126	7.080*	0.027
HHVEH	0.112	3.441*	0.028	0.076	1.442	0.016
FINFO	-		-	0.532	20.701*	0.113
Age	-0.011	-4.614*	-0.003	-0.021	-5.543*	-0.004
Number of obs	5107			5107		
Log-likelihood	-3428.818			-1547.805		
AIC(Akaike Information Criterion)	6875.635			3117.609		

Note: * means significant at the 0.05 level.

From the information acquisition model, in line with our expectation, the possibility of information acquisition is higher when either the work-related or non work-related travel time is longer. More specifically, one hour increase in work related travel time or non work related travel time is associated with higher possibility of travel information acquisition by 6%. The negative coefficients of dummy variable of work related time indicates that if the work related travel time is not available, these households are less likely to use traveler information. Consistent with our earlier expectations, number of household vehicles, household income, and the age (young) of the respondent are positively correlated with information acquisition. One additional vehicle in household is associated with a 3% higher possibility of travel information usage. If the respondent is ten years younger, then information acquisition possibility increases by 3%. A ten thousand-dollar increase in household income would enhance the information usage possibility by 1.3%. The length of living at current address shows no significant association with information acquisition.

In the travel decision adaption model, in line with our earlier expectations, the changes are more likely if the household acquires travel information more frequently. One additional attempt to acquire travel information per week is associated with higher change probability by 11.3%. A respondent that is 10 years younger will have 4% higher likelihood of travel plan change. The length of living at the address, while showing no significant association with information acquisition, is significantly associated with the likelihood of travel plan change. Ten more years of living at the same address would be associated with higher likelihood of changes, by 1%. All coefficients of travel time variables, including work related and non work related travel time, are not statistically significant in predicting travel plan change, while most of them are significant in information acquisition models. Travel time is more closely associated with the acquisition of travel information rather than with changes of travel behavior for the Triangle area respondents.

The traditional logistic regression model explains the determinants of probability of travel information usage and travel decision changes from a global average point of view. But this association is fixed across the space and the potential spatial deviation of these coefficients still remains unknown. GWR is an appropriate technique for the detection of spatial non-stationarity, which allows the regression parameters to vary across space, and can therefore expose possible local spatial deviation of these variables.

The Local Model

The local estimation describes the situation at an individual location level. A distinct difference between global and local estimation is that the global estimation has a consistent model for all observations, while the local model estimates a set of parameter estimates of explanatory variables for each household location. Figure 2 demonstrates how different the coefficient income shows in global and local model. Note here income in global model produced a flat surface in space (β=0.126), but local model produces a continuously changing surface to show where the parameter of income is higher and where is lower (β changes between 0.05 and 0.16), whose average value equals to the global model result.

In addition, pseudo t-statistic for each parameter, which can be obtained by dividing a parameter estimate by its standard error [22] are also mapped to show the varied t-statistic in space. By comparing AIC for global model and local model, we found the local model has smaller AIC than global model (6722 vs. 6876 in the information acquisition model, 3105 vs. 3117 in the decision change model). As a general rule, improvements in the AIC that are less than 3 in value could easily arise as a result of sampling error [22], while here the difference between the global and local models are greater than 3, which shows the local models are statistically better than the global model.

Based on the local parameter estimates, a set of parameter surfaces as well as T-statistic surface are generated to reveal the spatial variations of these independent variables. An Inverse Distance Weighted (IDW) interpolation algorithm is used to assign values to unknown points based on the 5107 known household parameters, thus a continuous coefficient surface covering the whole region is created. IDW assumes that each measured point has a local influence that diminishes with distance. It weights the points closer to the prediction location greater than those farther away. Figures 3 and 4 present the generated parameter surfaces for key variables with cell size of 1 km by 1 km.

In contrast to the unified parameters across space in the global model, all parameters in the local model vary across the study area and they have different spatial distributions. This means that the association of each correlate varies differently cross the study area. Meanwhile from the t-statistic surface, the parameters of frequency of information acquisition and number of information resources accessed in the change model are highly significant over the entire study area, while all other parameters have certain parts in the study area where they are statistically non-significant (95% level). Some variables which were statistically insignificant in the global model are locally significant in certain areas. The spatial distributions of t-statistics are consistent with that of corresponding coefficients, that is, when the parameter estimate is large, the associated t-statistic and significance is high.

For the travel information acquisition model, although both work related and nonwork related travel times are significant in the global model, these associations are not necessarily significant throughout the region. For instance, the coefficient of work related travel time is only statistically significant in Person, and Granville counties; non work related travel time is statistically significant only in Orange, Durham and parts of Wake, Harnett, and Johnson counties. Moreover, the global model shows that the coefficient of work related travel time is 0.004, but in the local model the coefficient work related travel time varies from 0.005 to 0.013. This indicates that misspecification can exist in the global model since it represents a spatial average that may obscure information about spatial variations [22]. Household income is also associated differently with travel information acquisition. Income has greater parameter magnitude with information acquisition in the southeast portion of the region such as the Johnston county, and part of Nash and Harnett County. Compared with global model, the difference is significant since the coefficient of income is only 0.053 on average, while in these areas, it can reach 0.1.

For the decision change model, the coefficient of frequency of information acquisition decreases from southeast to northwest with largest value in Wake County, Harnett and Johnston Counties (Figure 4b). This indicates that in those areas with darker colors, additional one time of information acquisition is associated higher possibility of travel decision changes. The number of information sources accessed has larger associations with change probability in southwest and northeast corners than other areas (Figure 4c) that include urban areas of Durham and Wake County. It seems that one more traveler information resource is associated with greater propensity to change travel decisions for people residing in rural areas. Income has a larger positive association with travel behavior change in northern areas and is significant over the entire study area except a small area in southwestern Wake County (Figure 4a). This is interesting since the northern areas are not higher income compared with the areas south of Orange County and the areas between Durham and Wake, but the association between income and traveler decision changes is 1.2-2 times of those higher income areas.

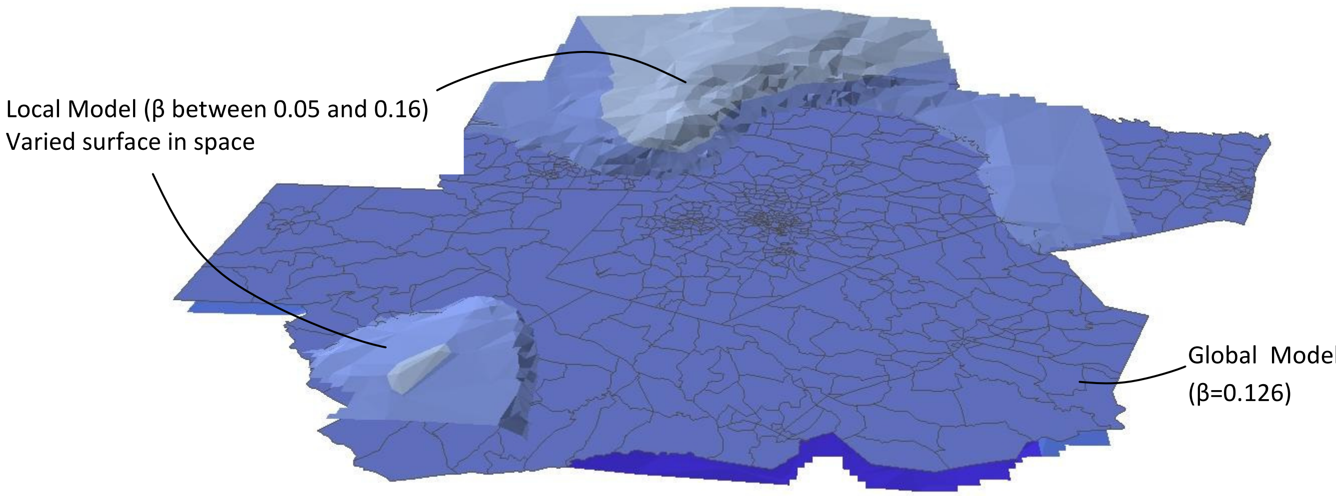
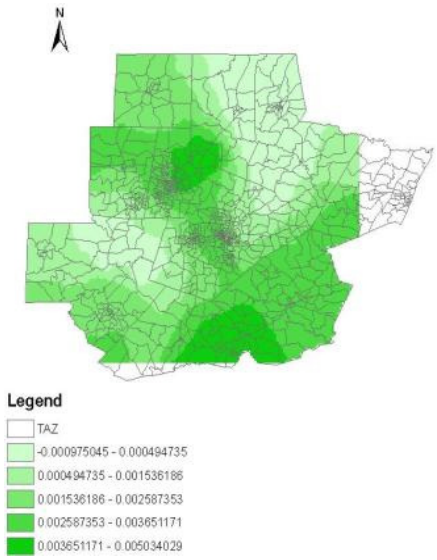
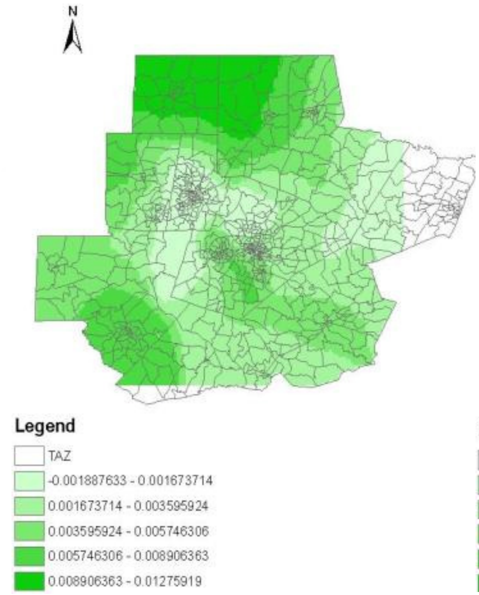


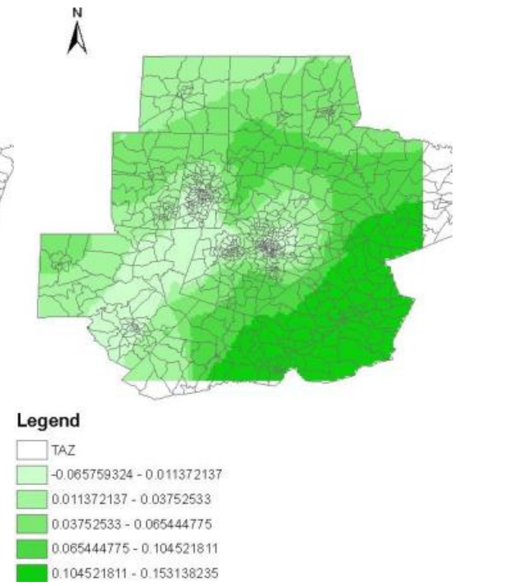
Figure 2 Global vs. local change model (variable: income)



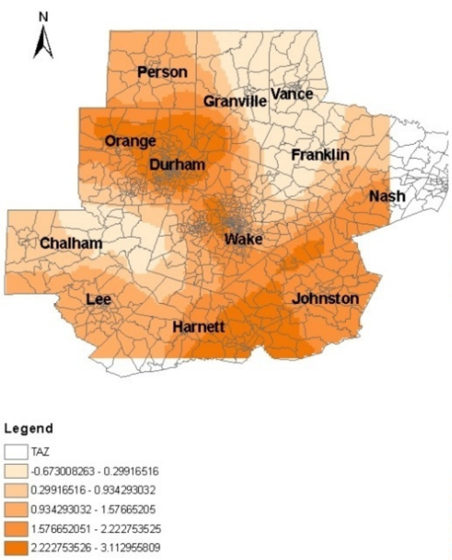
aa) NWORK coefficient



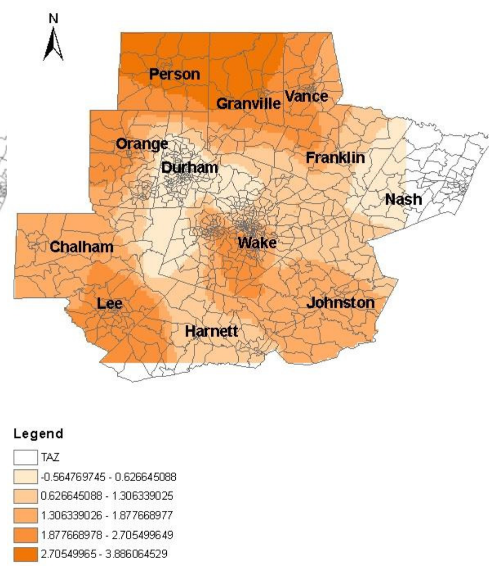
b) WORK coefficient



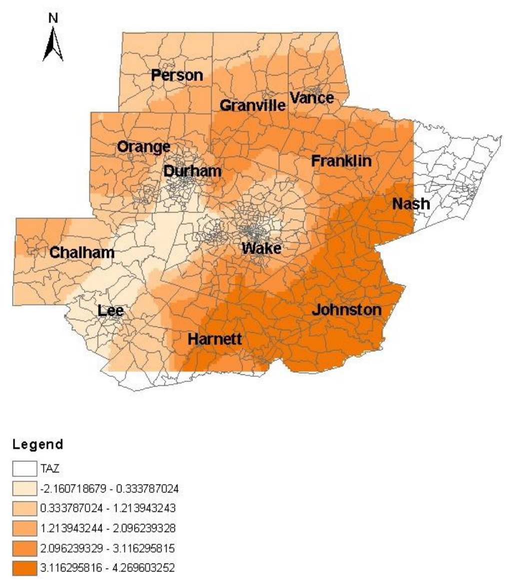
c) Income coefficient



d) NWORK t-statistic

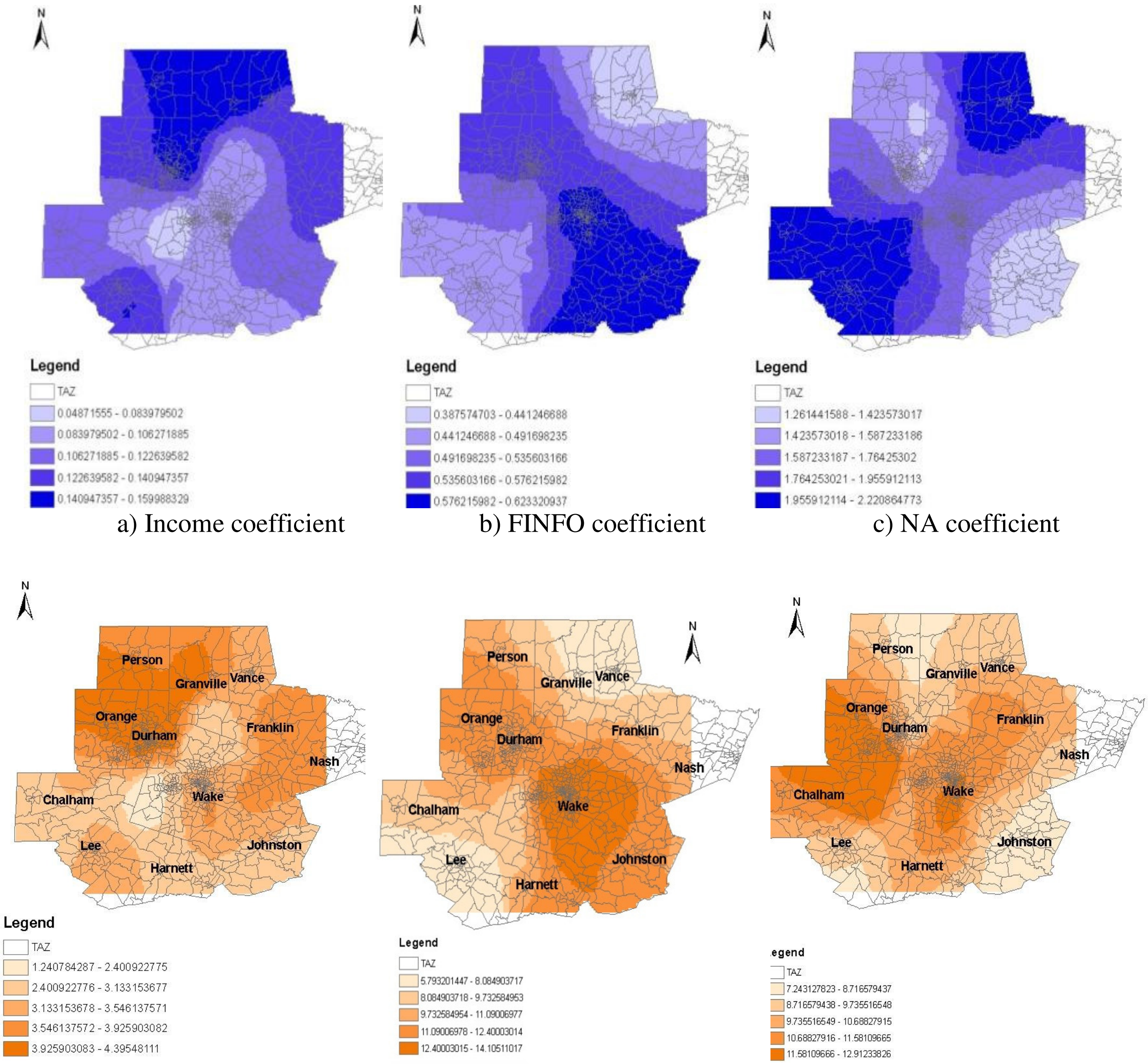


e) WORK t-statistic



f) Income t-statistic

Figure 3 Local model results and t-statistic for Info acquisition



a) Income coefficient b) FINFO coefficient c) NA coefficient

d) Income t-statistic e) FINFO t-statistic f) NA t-statistic

Figure 4 Local model result for Change or not

LIMITATIONS

A key issue is whether appropriate model specification was used. While important variables are captured in the GWR model specification, additional models were estimated with many other socioeconomic and traffic condition variables, for instance, driving density, household size and number of trips made by household head. However, variables that did not show significant local associations were not listed in this paper. Furthermore, not every regression coefficient in the model varies geographically. A mixed global-local model may allow some of the independent variables in the model to be global – that is, they do not vary over space while the remaining coefficients are local and vary geographically [22]. Further research is needed that can model variables that do and do not vary spatially.

The transferability of the findings from the Research Triangle area in North Carolina to other urban regions is somewhat limited [15, 16], partly because the regional characteristics—a rapidly growing area with a relatively highly educated (and higher income) population coupled with a less mature ATIS spatial deployment as compared with the rest of the country. Moreover, the spatial relationships that GWR captures is only valid for this region, which is to say, that any GWR model is based on the spatial characteristics of this particular region and cannot be transferred to any other region. Another limitation is that the behavior change model considers the whole sample in the spatial analysis and does not provide a framework for sample selection [16]. Future studies can incorporate sample selection into the logistic GWR model for investigating the conditional interactions between information usage and behavioral changes.

Only residential locations are used for weights calculation in GWR since most our socioeconomic factors are household characteristics. It will be interesting to compare local models estimated based on other relevant locations, such as job location.

CONCLUSIONS

This study contributes by examining spatial distributions of the factors associated with travelers' decisions to acquire information and change travel decisions. Such knowledge is critical to development and deployment of advanced traveler information systems. First, the study examines factors associated with travel information acquisition behavior and propensity to change travel plans in response to the acquired information. Consistent with earlier work [16], we found that travel information acquisition is positively related to longer travel times (both work and non-work related), higher household income, younger respondents, and those with more vehicles. Furthermore, the factors that are associated with a higher likelihood of travel decision changes are information acquisition frequency, information sources accessed, the length of time in the region, and age of the respondent. However, the magnitudes and deviations of coefficients for the global model assume no variation regionally, and it only shows spatially averaged associations between correlates. Most importantly, the study found that key associations are not the same over the entire study region for both information acquisition and behavioral change. Global logistic regression models mask the fact that for some portions of study area coefficients can have larger associations compared with other portions. The logistic GWR model provides deeper insights into the spatial variations by allowing the model parameters to vary across space. For instance, households with higher income in southeastern areas are more likely to use travel information but households with higher income in northern areas are more likely to change their travel decisions generally. Meanwhile, the variables which are statistically significant in the global model are not necessarily significant for all areas in the local models. And the global model may have misspecification by using a spatially averaged estimation. For instance, work related and non work related travel times are significant in the global travel information acquisition model but in the local model, they only show significant associations in certain study areas.

In general, the logistic GWR can significantly improve upon the global logistic regression. Statistical comparison shows that Logistic GWR has better performance in exploring the associations between variables than the global logistic model. The results presented in this paper support the application of GWR in this context as an appropriate tool for providing insights into the spatial distribution of parameter estimates.

Finally, it is interesting to map the coefficients in a continuous surface. It provides a unique way to visualize how people react to travel information provision in a spatial context: The map can show where the coefficient is higher and where the coefficient is lower, which produced an average coefficient represented by global model. People are more preferred to use information and where travelers are inclined to make decision adaptations. This provides a useful tool to help DOTs identify ATIS underserved areas and those areas which have lower chances of traveler decision adjustments; thus the populations in underserved areas can benefit from policy establishment that sets targets for higher access and use. Such populations may also have different information needs, e.g., greater needs for transit information, owing to higher use of transit. Furthermore, the approach can help private information service providers to accurately target their potential customers. Using the spatial distribution of ATIS access and use, the population can be segmented according to their demographics, attitudes and travel context.

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Reference

1. Toppen, A., S. Jung, V. Shah, and K. Wunderlich, *Toward a Strategy for Cost-Effective Deployment of Advanced Traveler Information Systems*, Transportation Research Record, Vol. 1899, 2004, pp. 27-34.
2. Shah, V.P., K. Wunderlich, A. Toppen, and J. Larkin, *Potential of Advanced Traveler Information System to Reduce Travel Disutility, Assessment in Washington,* D.C., Region, Transportation Research Record, Vol. 1826, 2003, pp. 7-15.

3. Toledo, T., R. Beinhaker, *Evaluation of the Potential Benefits of Advanced Traveler Information Systems*, Journal of Intelligent Transportation Systems Technology, Planning, and Operations, Vol.10, No. 4, 2006, pp. 173-183.
4. Walker, J. L., and M. E. Ben-Akiva, *Consumer Response To Traveler Information Systems: Laboratory Simulation Of Information Searches Using Multimedia Technology*, Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, 1547-2442, Vol. 3, No. 1, 1996, pp. 1- 20.
5. Goulias, K.G., T.G. Kim, and O. Pribyl, *A Longitudinal Analysis of Awareness and Use for Advanced Traveler Information Systems*, Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, Vol. 8, No. 1, 2004, pp. 3- 17.
6. Chorus, C.G., E.J.E. Molin, and B.V.Wee, Use and Effects of Advanced Traveler Information Services (ATIS): A Review of The Literature, Transport Reviews, Vol. 26, No. 2, 2006, pp. 127–149.
7. Lappin, J., and B. Bottom, *Understanding and Predicting Traveler Response to Information: A Literature Review*. 2001, [cited July 2009], Available from: http://www.itsdocs.fhwa.dot.gov/JPODOCS/REPTS_TE//13953.html.
8. Choo, S.H., and P.L. Mokhtarian, *Telecommunications and travel demand and supply: Aggregate structural equation models for the US,* Transportation Research Part A, Vol. 41, 2007, pp. 4-18.
9. Golob, T.F., and A.C. Regan., *Impacts of information technology on personal travel and commercial vehicle operations: research challenges and opportunities,* Transportation Research Part C, Vol. 9, 2001, pp. 87-121.
10. Miller, H.J., *Potential contributions of spatial analysis to geographic information systems for transportation (GIS-T),* Geographical Analysis, Vol. 31, 1999, pp. 373-399.
11. Kitamura, R., L. Laidet, and F. Mar, *The Evaluation Study of a Low-cost, Telephone-based Traveler Information System,* 1994, PATH Research Report.
12. Fan, Y and A.J. Khattak, *Urban form, individual spatial footprints, and travel: An examination of space-use behavior*. Transportation Research Record, Vol. 2082, 2008, pp. 98–106.
13. Englisher, L., R. Juster, S. Bregman, D. Koses, and A. Wilson, *User Perceptions of SmarTraveler Advanced Traveler Information System: Findings from Second-Year Evaluation,* Transportation Research Record, Vol. 1537, 1996, pp. 63-69.
14. Peirce, S., and J. Lappin, *Acquisition of Traveler Information and Its Effects on Travel Choices: Evidence from a Seattle-Area Travel Diary Survey,* 2003, [cited Nov. 2008; Available from: http://www.itsdocs.fhwa.dot.gov/JPODOCS/REPTS_TE/13813.html.

15. Khattak, A.J., X. Pan, B.Williams, N. Rouphail,Y. Fan, *Traveler Information Delivery Mechanisms: Impacts on Consumer Behavior,* Transportation Research Record Vol. 2069, 2009, pp. 77-84.
16. Wang, X., A.J. Khattak., and Fan, Y., *The Role of Dynamic Information in Supporting Travel Behavior Changes: A Two-stage Travel Decision Process,* Forthcoming in Transportation Research Record, 2009.
17. Buliung, R.N., and P.S. Kanaroglou, *Activity–Travel Behavior Research: Conceptual Issues, State of the Art, and Emerging Perspectives on Behavioral Analysis and Simulation Modeling*, Transport Reviews, 2007, Vol. 27, No.2: p.151–187.
18. Páez, A. and Scott, D. M., Spatial Statistics for Urban Analysis: A Review of Techniques with Examples, GeoJournal, Vol. 61, 2004, pp. 53–67.
19. Garrido, R. A. and H. S. Mahmassani (2000). "Forecasting freight transportation demand with the space-time multinomial probit model." Transportation Research Part B: Methodological 34(5): 403-418.
20. Bhat, C. R. and J. Guo (2004). "A mixed spatially correlated logit model: formulation and application to residential choice modeling." Transportation Research Part B: Methodological 38(2): 147-168.
21. Kwigizile, V. and H. Teng (2009). "Comparison of methods for defining geographical connectivity for variables of trip generation models." Journal Of Transportation Engineering 135(7): 454-466.
22. Fotheringham, A.S., Brunsdon, C. and Charlton, M., Geographically Weighted *Regression, the analysis of spatially varying relationships*. 2002, University of Newcastle, UK: John Wiley & Sons, Ltd.
23. Ali, K., M.D. Partridge, M.R. Olfert, *Can Geographically Weighted Regressions Improve Regional Analysis and Policy Making?* International Regional Science Review, Vol. 30, No. 3, 2007, p. 300-329.
24. Workshop on Identifying Traveler Information Research Needs to Achieve All Roads-All Modes-All the Time, 2009, Irvine, California, [cited July, 2009; Available from: http://www.trb.org/news/blurb_detail.asp?id=9253]
25. Zhao, F., and N. Park, *Using Geographically Weighted Regression Models to Estimate Annual Average Daily Traffic,* Transportation Research Record, 2004. 1879: p. 99-107.
26. Chow, L.F., *Transit Ridership Model Based on Geographically Weighted Regression,* Transportation Research Record, Vol. 1972, 2006, p. 105-114.
27. Du, H., and C. Mulley, *Relationship between Transport Accessibility and Land Value: Local Model Approach with Geographically Weighted Regression*, Transportation Research Record, Vol. 1977, 2006, pp. 197-205.
28. Clark, S.D., *Estimating local car ownership models, Journal of Transport Geography,* Vol. 15, 2007, pp. 184–197.

29. Greater Triangle Travel Study-Household Travel Survey Final Report. 2006, NUSTATS: AUSTIN, TEXAS.
30. Lloyd, C.L., *Local Models for Spatial Analysis,* 2007, Boca Raton, FL: CRC Press, Taylor & Francis Group.