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Infrastructure Impacts on Commercial Property Values Across El Paso in 2013

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THE UNIVERSITY OF TEXAS AT EL PASO

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UTEP Border Region Econometric Modeling Project

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INFRASTRUCTURE IMPACTS ON COMMERCIAL PROPERTY VALUES ACROSS EL PASO IN 2013*

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* A revised version of this study is forthcoming in ***Asia-Pacific Journal of Regional Science.***

ABSTRACT

Real estate property value analysis is used for municipal taxation and budgeting. Commercial properties make up a large percentage of the property tax base in many, if not most, taxing jurisdictions. Data constraints limit the number of analyses conducted on commercial property value patterns. This study employs a fairly extensive data set to address that problem in the context of El Paso in 2013. The sample contains data for 105,611 commercial real estate parcels. Empirical analysis is conducted using geographically weighted regression analysis. Results confirm that parameter estimation for the commercial property data in this sample should be conducted using methodologies that allow for spatial autocorrelation and heteroscedasticity.

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JEL Classification: R15, Regional Econometrics; R33, Nonresidential Real Estate Markets; R53, Public Infrastructure

Keywords: Transportation Accessibility; Geographically Weighted Regression; Commercial Property Values

INTRODUCTION

Investments in public infrastructure such as highways, airports, and mass transit facilities tend to improve productivity. Not surprisingly, these types of investments can increase adjacent property values, generating value premia for private developers and adjacent property owners. A portion of this value can be "captured" as public revenue via property taxes to assist financing such improvements. States and local governments generally attempt to anticipate and capture the economic value created by transportation accessibility as a means for funding capacity expansions. Value capture (VC) on real properties from investments in public infrastructure has historically been achieved via the tax mechanism.

In the United States, regional infrastructure expenditures are financed using three basic sources: (i) local government revenues (tax and non-tax), (ii) borrowing, and (iii) funding from higher levels of government. As more fuel efficient vehicles such as gasoline-electric hybrids enter public and private fleets, fuel tax revenues and the Federal Highway Trust Fund will continue to decline, reducing funding amounts provided to each state. Texas is no exception. Historically, Texas has been a “donor” state, a state that receives less revenue than what it pays to the Highway Trust Fund. Reduced funds are expected through 2050 (Hall, 2012). If the trends for declining fuel tax revenues, increasing transportation needs, and higher infrastructure costs continue, the funding required to address mobility needs is clearly beyond what traditional sources, like the dated fuel tax, can supply.

Because of the aforementioned revenue pressures, accurate valuation of taxable properties is important. Most of the non-roadway mechanisms for capturing value premia are used by local governments, with a few being employed by state departments of transportation (DOT). While VC represents an opportunity for regional agencies to recapture some transportation infrastructure costs, it is not clear how much value is added by infrastructure projects in a particular region.

This study applies geographically weighted regression (GWR) analysis to quantify the impacts of transportation infrastructure proximity and accessibility on commercial real property values in El Paso, Texas. The analysis takes advantage of a sample that contains data on 105,611 commercial property parcels in El Paso, Texas. It is an example of the types of data sets that are quickly becoming more prevalent in transportation and real estate settings (Sánchez-Martínez and Munizaga, 2016). The hypothesis tested is that transportation infrastructure proximity and accessibility impact commercial property values in El Paso. The next section provides a review of related literature. After that, a discussion of the data and methodology is presented. The fifth section reports empirical results. The paper concludes with key findings and suggestions for future research.

LITERATURE REVIEW

Real estate valuation questions have received substantial attention due to issues involving public finance and urban infrastructure (George 1920; Batt 2001; Peterson 2009; Levinson and Istrate 2011; Rybeck 2004; Vadali et al. 2009; Zhao et al. 2011). While many studies have examined residential property valuation issues, commercial properties have received comparatively less attention. Those that do analyze commercial property buildings generally document favorable effects of transportation facilities on such properties (Carey and Semmens 2003; Debrezion et al. 2007; Golub et al. 2012). Data scarcity is generally cited as the culprit behind the relative paucity of commercial property valuation studies (Montero-Lorenzo and Larraz-Iribas, 2012).

A small number of studies have examined property value issues for border metropolitan economies. For El Paso, Fullerton and Villalobos (2011) employ a hedonic pricing approach to analyze a random sample of 562 housing units and test the significance of 22 variables related to structural and locational features. Results indicate that housing prices are negatively impacted by distances from employment centers and international bridges. A similar effort for Ciudad Juarez, Mexico indicates that major avenues and accessibility do not always improve housing values (Fierro et al., 2009). One study examines the predictability of both commercial and industrial property cadastral values in El Paso (Arnold Cote et al., 2010). Results in that study indicate that structural econometric model forecasts compare well to other time series and random walk alternatives for predictive accuracy.

Spatial econometric techniques have proven useful in studies where spatial dependence is present (Dubin, 1988; Basu and Thibodeau, 1998). Such techniques allow modeling and testing spatial autocorrelation and spatial heterogeneity to assess spillover effects and dependence between observations that are in close geographic proximity such as real property parcels or tax jurisdictions (Paelinck and Klaassen 1979; Anselin 1988; Anselin 2010; and Elhorst 2010). By applying spatial econometric models, Zhang and Wang (2013) finds that housing prices in Beijing capitalize positive premia from distances to the nearest metro station. Concas (2013) applies a spatial autoregressive (SAR) estimator, and finds that houses near limited access roadways exhibit greater price resilience during and after market downturns. Several studies quantify accessibility using distance-based and drive-time variables (Chernobai et al. 2011; Diao and Ferreira, 2010; Shin et al. 2007; Vadali, 2008; and Srour et al. 2002). Results indicate that the premium diminishes as the distance increases. Siethoff and Kockelman (2002) analyzes parcel values along the U.S. 183 corridor in Austin, Texas using: (i) a total value model, (ii) an improvement value model, and (iii) a land value model. Freeway proximity, corner parcels, and timing of completion are found to significantly impact parcel values.

GWR allows for spatial heterogeneity by generating individual regression equations in subsamples of a geographic dataset. Unlike the average coefficients estimated by ordinary least squares OLS (i.e. global coefficients), GWR estimates location-dependent distributions for coefficients around a particular point or epicenter (i.e. local coefficients). GWR assumes that observations closer to the epicenter of each subset have greater weights in parameter estimation than more distant ones (Brunsdon et al. 1996; Brunsdon et al. 1998; Fotheringham et al. 2002;). Efthymiou et al. (2013) apply OLS, SAR, and GWR to determine the locations for transportation mobility centers. Results indicate that GWR modeling fits the data best and generates residuals that are random. Similar outcomes are reported in a variety of other studies that examine residential property and tax policy issues (Bujanda and Fullerton 2017; Du and Mulley 2007; Legg and Bowe 2009; Löchl and Axhausen 2010).

Spatial spillover effects and spatial dependence between observations also impact the marginal prices of structural housing characteristics (e.g. the price of an additional bedroom in two different neighborhoods) particularly within large metropolitan regions. GWR has proven useful in allowing for such spatial effects (Bitter et al. 2007; Wang et al. 2012; Páez et al. 2007, Yu et al. 2007, Farber and Yeates, 2006, and Kestens et al. 2006). One of the critiques of GWR is that multivariate parameter estimates might be intrinsically correlated, making the interpretation of map patterns for individual coefficients difficult. However, spatial dependence remains an issue even after including spatial independent variables in OLS (Löchl, 2007). Getis (2007) proposes several tests to check for spatial autocorrelation. Advantages provided include assessment of the strength of spatial effects on any variable; evaluation of spatial stationarity, spatial heterogeneity, and distance decay; and accommodation of spatial hypothesis testing. All of the latter potentially improve the efficiency and accuracy of cadastral value modeling, thus providing better quantification of municipal revenue gains associated with regional transportation and infrastructure investments.

METHODOLOGY AND DATA

The hypothesis tested is that transportation infrastructure proximity and accessibility impact real property values in El Paso, Texas. The procedure involves the application of hedonic price models using least squares regression analysis. Hedonic studies have been widely used to analyze the impact of transit on property values (Rosen, 1974). Prior empirical evidence indicates that the magnitude of the impacts on property values vary over space (Martinez and Viegas 2009; Anselin and Lozano-Gracia 2008; Lozano-Gracia and Anselin 2012). Tests for spatial autocorrelation and heterogeneity are used to assess spillover effects and dependence among close parcels.

GLOBAL AND LOCAL REGRESSION METHODS: OLS AND GWR

The methodology involves estimating three hedonic equations: (i) a total-value model, (ii) an improvement-value model, and (iii) a land-value model (Siethoff and Kockelman, 2002). GWR is used to test each specification using geographic information system (GIS) data. Data collected include 2013 certified cadastral parcel records for real property in El Paso County, with transportation accessibility and socioeconomic characteristics obtained using GIS and ESRI Business Analyst (Bujanda, 2014). The total-value model consists of all land-value and improvement-value variables and a constant as shown in Equation 1. The improvement-value model includes all attributes related to structural characteristics of improvements and buildings as shown in Equation 2. The land-value model employs characteristics exclusively related to land parcels as shown in Equation 3.

1. Total-value model:

$$TotValue_i = \beta_0 + \sum_i^n \beta_{i\,Impr} X_{i\,Impr} + \sum_j^n \beta_{j\,Land} X_{j\,Land} + \epsilon_i$$

where

$TotValue_i$ = dependent variable related to the total taxable value of a parcel (i.e. the taxable value for the land plus any improvements);
$X_{i,\,Impr}$ = vector of variables related to the characteristics of the improvements;
$X_{j,\,Land}$ = vector of variables related to the characteristics of the land; and
ϵ_i = random error term at point i.

2. Improvement-value model:

$$ImprValue_i = \beta_0 + \sum_i^n \beta_{i\,Impr} X_{i\,Impr} + \epsilon_i$$

where

$ImprValue_i$ = dependent variable related only to the value of improvements on parcel i; and
$X_{i,\,Impr}$ = vector of variables related to specific characteristics of the improvements.

3. Land-value model:

$$LandValue_i = \beta_0 + \sum_j^n \beta_{j\,Land} X_{j\,Land} + \epsilon_i$$

where

$ImprValue_i$ = dependent variable related only to the taxable value of the land corresponding to a parcel i; and
$X_{j\,Land}$ = vector of variables related to specific characteristics of that land.

GWR represents an enhanced version of the weighted least-squares approach of parameter estimation. It accounts for spatially varying relationships by generating individual regression functions for subsets of data at a specific location with coordinates (u_i, v_i). GWR incorporates a spatial weights matrix, which varies by location, and estimates a local regression for each observation in the dataset as shown in Equation 4 (Brunsdon et al. 1996). In Equation 4, observations located closer to the epicenter (u_i, v_i) of each subset are assigned greater weights in estimation than are more distant ones.

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) X_{ik} + \epsilon_i$$

where

y_i = dependent variable for a specific model (i.e. total values, improvement values, and land values);
(u_i, v_i) = spatial coordinates of a point i (i.e. geometric centroid of each parcel);
k = number of variables;
$\beta_k(u_i, v_i)$ = realization of function β_k (u,v) at point i; and
X_{ik} = value of explanatory variable k at point i.

The spatial weights matrix is determined including observations for the dependent and explanatory variables falling within a specific bandwidth around a given point (u_i, v_i). The bandwidth can be determined by distance, number of neighbors, or by a Gaussian kernel process. Kernel bandwidths can be fixed or adaptive depending on the density of observations at a particular location. The weights of the estimator used in each model are conditioned on the location coordinates (u_i, v_i):

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y_i$$

where

$\hat{\beta}(u_i, v_i)$ = vector of estimated parameters at location coordinates (u_i, v_i);
X^T = the transpose of matrix X containing explanatory variables;
$W(u_i, v_i)$ = n by n spatial weight matrix, which varies by location (u_i, v_i);
X = n by k matrix of covariates; and
Y = n by 1 vector of dependent values (across n observations).

Adaptive kernel bandwidths are typically preferred when some of the regression points are not uniformly distributed over space (i.e. the data are sparse). When the data are sparse, the spatial weight matrix is estimated using a small number of data points resulting in fairly large standard errors for the parameters. In order to minimize the standard errors, adaptive kernels adjust the bandwidth to include the same number of observations in a consistent manner regardless of their density variation across space. Kernel bandwidths are determined by minimizing a corrected Akaike Information Criterion (AICc) or a cross validation (CV) score, regardless of the type of kernel bandwidth selected (i.e. fixed or adaptive). The formula for the AICc, as applied in Hurvich et al. (1998) is:

$$AIC_c = 2n \log_c(\hat{\sigma}) + n \log_c(2\pi) + n \left[\frac{n + tr(S)}{n - 2 - tr(S)}\right]$$

where

AIC_c = information distance between the true and the fitted models;
n = number of data points;
$\hat{\sigma}$ = estimated standard deviation of the residuals; and
$tr(S)$ = trace of matrix S hat (also called the projection matrix, which maps the vector of observed values to the vector of fitted values); and
$S = X(X^T X^{-1})\, X^T$

The formula for the CV score, as applied in Fotheringham et al. (2002) is:

$$CV = \sum_{n=1}^{N_{obs}} \sum_{j=0}^{j} \left(I_{\neq n,j} - \hat{P}_{\neq n,j}(b)\right)^2$$

where

CV = cross-validation score minimized to find the optimal bandwidth value or number of nearest neighbors;
$I_{\neq n,j}$ = indicator variable for data points other than n, which equals 1, if parcel n is of land use type j, and 0 otherwise; and
$\hat{P}_{\neq n,j}$ = estimated probability for parcel n with land use type j.

The lower the AICc and the CV score, the closer the fitted model is to the true model. However, problems with local multicollinearity might prevent both the AICc and CV methods from calculating an optimal distance or number of neighbors. In such instances, the calculation must be completed manually using the following kernel estimator (Efthymiou et al. 2013):

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

where

$\hat{f}(x)$ = density;
n = number of data points;
h = bandwidth; and
K = kernel.

Finally, the Getis and Ord Gi test is used to check for spatial autocorrelation in the residuals as suggested by Getis (2007).

DATA COLLECTION AND STUDY AREA

El Paso County is a polycentric surface of 1,015 square miles with a population of 827,398 according to the 2012 Census estimate. El Paso Central Appraisal District (EPCAD) maintains parcel records and taxable values plus any exemptions. This paper focuses on parcels with a *Commercial* land use classification. *Commercial* includes land and improvements associated with businesses selling goods or services (e.g. office buildings, hotels, gas stations, retail stores, utilities, railroads, multi-family rentals, and vacant lots for sale still owned by developers). All personal property is excluded, including mobile homes and inventory. Non-taxable parcels (e.g. government properties, churches, etc.) are also excluded (Combs, 2013). The 2013 EPCAD certified cadastral roll included a total of 105,611 *Commercial* parcels (30.0% of the total parcel population), which occupy 62,423 acres of land within El Paso County. Although the Commercial land use classification does contain some multi-family rental properties, the majority of what are commonly considered as multi-family housing units are excluded from these data. That is because the State of Texas, and EPCAD, has a separate parcel category denominated as Multi-family in which most apartments, duplexes, and other multi-family units are included (Combs, 2013).

Proximity to transportation infrastructure for each parcel is determined as the distance from the front edge of each parcel to the centerline of the nearest interstate highway, freeway, and major arterial, respectively, measured in feet. Accessibility for each parcel is determined as the driving-time measured in minutes from the geometric centroid of each parcel to the nearest port-of-entry (POE) and shopping center, respectively. The driving times are estimated by calculating driving-time areas using the actual street network using GIS. El Paso County has 145 miles of interstates, 216 miles of freeways, and 482 miles of major arterials, as measured at the centerline of each link of a transportation facility. There are four international POEs in the County: 1) Bridge of the Americas, 2) Paso Del Norte Bridge, 3) Ysleta International Bridge, and 4) Stanton International Bridge. Table 1 provides descriptive statistics for the variables included in the sample. Figure 1 maps the transportation network, POEs, and shopping centers utilized in the analysis.

EMPIRICAL ANALYSIS

Three hedonic specifications are employed: (i) the total-value model, (ii) the improvement-value model, and (iii) the land-value model for Commercial. First, a statistically significant OLS model (i.e. a global model) is identified, and then its GWR version is developed (i.e. a local model). Results for each coefficient also include robust standard errors (Robust SE), t-statistics (Robust t), and probabilities (Robust Prob). Robust estimators are accurate even in the presence of nonstationarity or heteroscedasticity, and they are used to determine if an explanatory variable is significant (White, 1980).

Variables that do not render significant OLS coefficient estimates are excluded from the GWR specifications. A Koenker Bruesch-Pagan (BP) test is used to examine whether problems with nonstationarity or heteroscedasticity are present (Koenker, 1981). To counter local multicollinearity issues associated with insufficient variation of observations neighboring the epicenter (u_i, v_i), adaptive kernels are determined by setting the bandwidth to 1,000 neighbors as Wang et al. (2012). When the variance inflation factor (VIF) is larger than 7.5 for any variable, local multicollinearity is problematic and that variables is excluded from the GWR specification. Dummy variables and variables with spatial clustering of identical values

Table 1 | Descriptive Statistics for 2013 Commercial Data: 105,611 Parcels

Variable	Description	Min	Max	Median	Mean	SD
TotValuei	Total value	$0.00	$142,824,129	$174,617	$551,113	$2,184,180
ImprValuei	Improvement value	$0.00	$124,266,068	$95,187	$349,577	$1,708,898
LandValuei	Land value	$0.00	$24,924,930	$56,711	$203,814	$639,431
	Explanatory variables common in all models					
PopDens_CY	Population density per block	0.00	26,171	16	502	1,580
Renter_CY	Housing units occupied by renters	0.00	1,436	79	124	123
Vacant_CY	Number of improvements not occupied (empty buildings) per block	0.00	182	31	53	54
Unemp_CY	People 16/older unemployed per block	0.00	374	44	62	59
PCI_CY	Income per-capita per block	0.00	$54,598	$9,874	$11,424	$4,477
MP35003a_B	People with 3 or more air trips per yr.	0.00	509	38	70	54
DistInterst	Distance to nearest interstate (ft.)	28.2	121,166	46,302	48,249	24,451
DistFreeways	Distance to nearest freeway (ft.)	0.00	141,776	30,909	31,573	18,819
DistMajArter	Distance to nearest major artery (ft.)	0.00	60,597	10,944	15,809	13,715
POE_DriTime	Driving-time to nearest port-of-entry (minutes)	1.00	61	36	36	11
ShopC_DTime	Driving-time to nearest shopping centers (minutes)	1.00	53	33	31	11
	Land-only explanatory variables					
LandAcres	Lot size (acres)	0.00	914	0.27	0.59	4.59
	Improvement-only explanatory variables					
ImpSize	Improvement area (square ft.)	0.00	3,000,031	0	4,165	36,497
Stories	Number of stories	0.00	21	1	0.09	0.30
StoriesSqr	Number of stories squared	0.00	441	1	0.10	1.45
Baths	Number of bathrooms	0.00	8	0	0.00	0.11
BathSqr	Number of bathrooms squared	0.00	64	0	0.01	0.45
Beds	Number of bedrooms	0.00	7	0	0.00	0.07
BedSqr	Number of bedrooms squared	0.00	49	0	0.00	0.31
ImpAge	Age of improvement (years)	0.00	143	0	3.29	13.09
ImpAgeSqr	Age of improvement squared (years)	0.00	20,449	0	182	968
Depreciable	Depreciable life of improvement (%)	0.00	100	100	96	12.29
Vacant	Parcel without an improvement (DV)	0.00	1	1	0.91	0.29
Garage	Garage (DV)	0.00	0	0	0	0
Air	Air conditioning (DV)	0.00	1	0	0.05	0.22

Source: 2013 El Paso Central Appraisal District and 2013 Esri Demographic, Consumer, and Business Data.

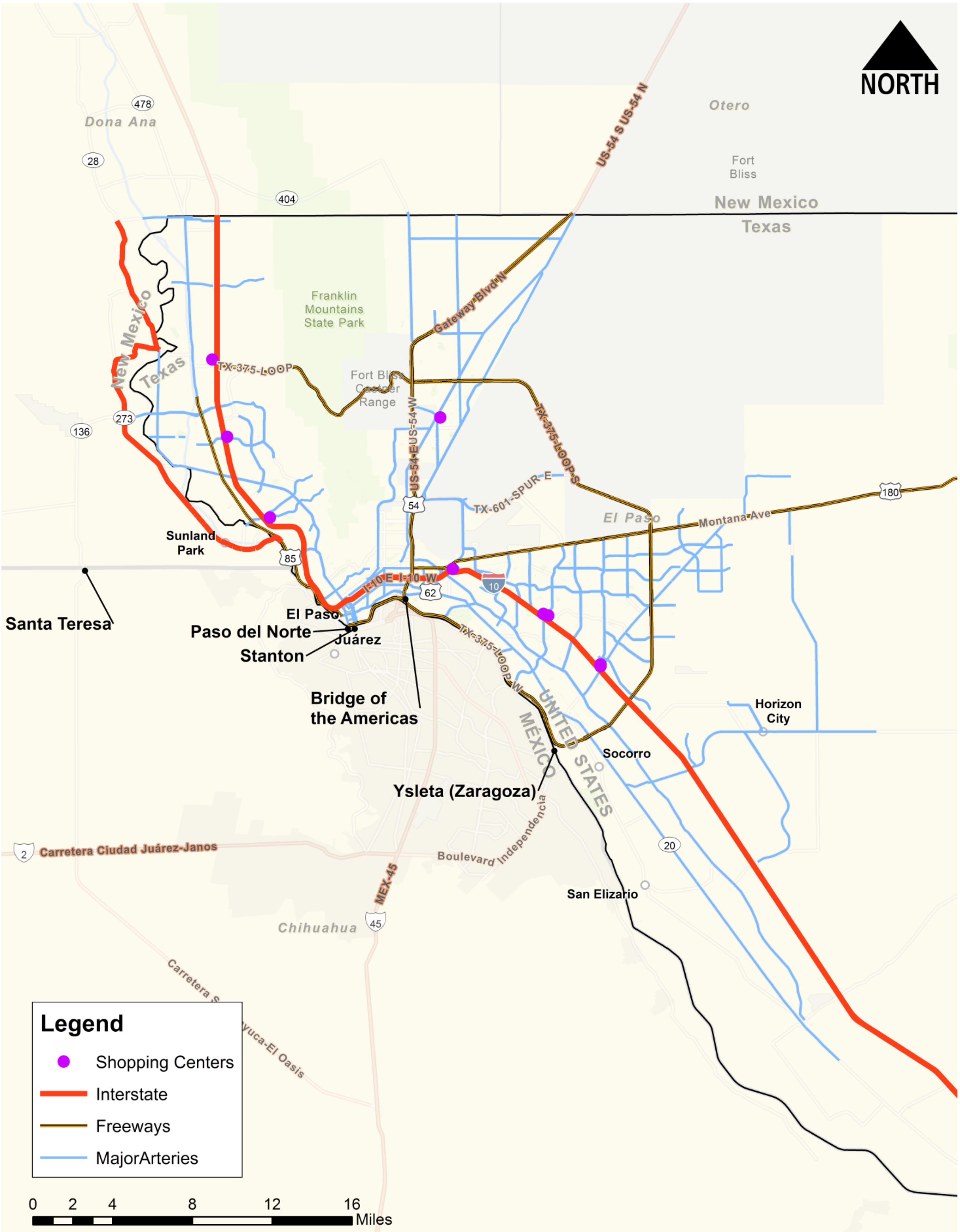

Figure 1 | Transportation Infrastructure System in El Paso County.

are also removed from the GWR equations. The GWR diagnostics include results from a baseline global model (i.e. residual squares, sigma, AdjR^2, AIC_c). Furthermore, a summary that defines the extent of the variability in the local coefficients and their standard errors (i.e. minimum, mean, and maximum). In GWR, it is necessary to visualize the local coefficients in maps to better interpret nonstationarity. Local coefficient maps are presented for each of the variables testing the hypothesis to better understand the local variation of the impacts on property values.

TOTAL VALUE MODELS

The total value sample for commercial properties includes 105,611 observations (30.0% of the total population). The dependent variable is $TotValue_i$. Table 2 reports the OLS estimation results for the 15 independent variables plus the intercept term, from which 9 parameters are statistically significant according to robust 95% confidence intervals. TotValue decreases $0.84 per foot as DistInterstate increases. DistFreeways and DistMajorArteries are not statistically significant at the 5% level. POE_DrivingTime indicates that TotValue decreases $2,058 for every minute it takes to drive from a commercial property to the nearest POE. ShopC_DrivingTime indicates that for every minute it takes to drive from a commercial property to its nearest shopping center, TotValue increases $1,755. The adjusted R2 indicates that the total value model explains 53.9% of the variation in TotValue. The significant Jarque-Bera statistic indicates that the residuals do not follow a normal distribution. The Koenker BP statistic is significant indicating that the residuals are nonstationary or heteroscedastic. The Joint Wald Statistic, however, indicates that the overall model is significant.

The GWR improvement value model yields 14,349 regression points with invertible matrices, equivalent to only 13.6% from the sample for commercial properties (Table 3). Wang et al. (2012) report a similar outcome where less than 10.0% of the sample yields invertible Hessians. The mean local GWR coefficients for DistInterstate and POE_DrivingTime have signs that are consistent with the OLS parameters, but with greater magnitudes. As shown by Figures 2 through 4, the impacts of transportation infrastructure in TotValue are highly sensitive to location. As DistInterstate increases, TotValue decreases $3.62 per foot according to the mean. DistInterstate ranges from a negative $394 to a positive $296 per foot, as shown in Figure 2. POE_DrivingTime indicates that for every additional driving minute to the nearest POE, the TotValue of a commercial property decreases by $22,500 on average. Coefficients from POE_DrivingTime range from a negative $588,108 to a positive $147,718 per minute, as shown in Figure 3.

For the impacts of driving time on commercial property total values in Table 3, ShopC_DrivingTime results indicate that TotValue decreases almost $9,937 per minute, on average. ShopC_DrivingTime ranges from a negative $602,337 to a positive $341,990 per minute, as shown in Figure 4. Results indicate that benefits from ShopC_DrivingTime are not capitalized by most commercial properties throughout the county, as shown in yellow in Figure 4. Some properties have negative coefficients, as shown by the parcels in blue and the darker tones in the image in Figure 4. This indicates that not all commercial parcels benefit from proximity to shopping centers, a result that is at odds with the positive sign of the OLS coefficient in Table 2.

As in other regions located near the border with Mexico, international commerce plays a prominent role in the economy of El Paso (Gibson et al., 2016). Properties with premia associated with POE_DrivingTime are

Table 2 | Total Value Model OLS Estimation Results

Variable	Coef.	Std. Error	t-Stats.	Prob.	Robust SE	Robust t	Robust Prob.	VIF
Intercept	-564784.98	32277.65	-17.50	0.00*	132987.38	-4.25	0.00*	----
ImpAge	839.79	265.40	3.16	0.00*	1078.38	0.78	0.44	4.55
Air	35897.51	11207.84	3.20	0.00*	29758.93	1.21	0.23	4.46
Depreciable	4195.10	271.59	15.45	0.00*	600.49	6.99	0.00*	4.20
LandAcres	-1244.54	363.34	-3.43	0.00*	3903.97	-0.32	0.75	1.05
ImpSize	15.56	0.05	314.76	0.00*	2.43	6.41	0.00*	1.23
Stories	165364.17	18434.53	8.97	0.00*	115085.77	1.44	0.15	12.00
Vacant	173080.29	22585.94	7.66	0.00*	121665.77	1.42	0.15	16.13
PopDens_CY	17.47	1.57	11.12	0.00*	6.26	2.79	0.01*	2.32
Unemp_CY	-175.99	42.99	-4.09	0.00*	65.62	-2.68	0.01*	2.49
PCI_CY	3.51	0.50	6.97	0.00*	1.76	2.00	0.05*	1.91
DistInterstate	-0.84	0.20	-4.12	0.00*	0.42	-1.97	0.05*	9.28
DistFreeways	-0.28	0.12	-2.25	0.02*	0.16	-1.81	0.07	2.07
DistMajorArteries	0.94	0.32	2.96	0.00*	0.58	1.63	0.10	7.19
POE_DrivingTime	-2058.95	553.99	-3.72	0.00*	1025.19	-2.01	0.04*	13.98
ShopC_DrivingTime	1755.97	420.24	4.18	0.00*	702.60	2.50	0.01*	8.65

Observations:	105611	AICc:	3083612
Multiple R-Squared:	0.539	Adjusted R-Squared:	0.539
Joint F-Statistic:	8226	Prob(>F), (21,198552) degrees of freedom:	0.00*
Joint Wald Statistic:	6335	Prob(>chi-squared), (21) degrees of freedom:	0.00*
Koenker (BP) Statistic:	10205	Prob(>chi-squared), (21) degrees of freedom:	0.00*
Jarque-Bera Statistic:	390970357898	Prob(>chi-squared), (2) degrees of freedom:	0.00*

*Statistically significant probabilities have an asterisk next to them.

located in the western, central, and eastern parts of the county. Parcels with premia are observed near the BOTA and Zaragoza POEs, but not near the downtown Paso Del Norte International Bridge. Many retail establishments in El Paso cater to Mexican shoppers by accepting pesos. Mexican shoppers and border commuters have to travel through the POEs. The further retailers are located away from the border, the less likely they are to accept pesos (Muñoz et al. 2011). In the total value model for commercial property, the a priori expectation is that parcels located closer to a POE will have a premium. Although parcels with a premium are observed near BOTA and Zaragoza, the highest premia are located distant from the POEs in Figure 3. Parcels located in downtown indicated no premia for POE_DrivingTime.

Further research is required to explore the underlying cause behind low or negative coefficients in the downtown area (e.g. exemptions, abatements, or similar agreements that reduce taxable values). A local newspaper cites the establishment of a Special Residential Revitalization District in the 1980s as the cause of a zoning issue in downtown with negative impacts on the property tax base (Mrkvicka, 2011). Property values within these special taxing districts sometimes fail to improve in the manners

Table 3 | Total Value Model GWR Summary Statistics

	Local coefficient estimates			Std. Error		
Variable	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Intercept	-203002	-4746110	1923541	987715	233372	9390194
Depreciable	3667	-7326	35524	5810	1454	84675
ImpSize	14.5	-9.09	52.5	27.2	0.216	640
PopDens_CY	33.4	-131	2676	1308	7.34	67255
PCI_CY	8.50	-69.0	114	37.8	3.96	929
DistInterstate	-3.62	-394	296	32.3	2.80	185
POE_DrivingTime	-22500	-588108	147718	53013	8081	292829
ShopC_DrivingTime	-9937	-602337	341990	46957	10272	290086
Residual Squares:	1001990355825183	Sigma:	977037	R^2:	0.853	
Effective Number:	29.3	AICc:	32844	AdjR^2:	0.849	

sought by local governments (Merriman et al., 2011). Alternatively, this could reflect a change in Mexican shopper preferences from older commercial areas in downtown to newer areas. For example, the Outlet Shoppes at El Paso (in the west side) and Las Palmas Marketplace (in the east side) are not located within walking distance of any POEs in Figure 3. Similar asymmetric impacts have been documented for other metropolitan economies in recent years (Álvarez-Ayuso et al., 2016; Shibayama and Ishikawa, 2016).

The GWR global diagnostics show improvement over OLS for the AICc which declines from 3,083,612 to 32,844. Similarly, the AdjR2 improves from 0.539 in the OLS model to 0.849 in the GWR baseline model. Figure 5 indicates that spatial autocorrelation is present among the residuals in the OLS model with hot spots predominantly clustered in the western and southeastern regions of the county, as shown in red. Cold spots dominate the outer western and eastern sides of the county, as shown in blue. Spatial autocorrelation is mostly absent from the GWR residuals, shown in yellow in Figure 6. However, a few cold spots remain on the east side of the county.

IMPROVEMENT VALUE MODELS

The improvement value sample for commercial properties contains 105,611 observations (30.0% of the total population). The dependent variable is ImpValuei. Table 4 reports OLS estimation results for the 17 independent variables plus the intercept term, 7 of which are statistically significant according to robust 95.0% confidence intervals. In this equation, Mp35003a_B, DistInterstate, DistFreeways, and DistMajorArteries do not satisfy the 5.0% significance criterion. POE_DrivingTime indicates that ImpValue decreases $2,260 for every additional minute it takes to drive from a commercial property to the nearest POE. The impact from accessibility to a POE for the ImpValue is very similar the impact found using the TotValue specification.

The coefficient for ShopC_DrivingTime in Table 4 indicates that for every minute it takes to drive from a commercial property to its nearest shopping center, ImpValue increases by $1,680. The impact from accessibility to a shopping center for the ImpValue is very similar to the impact estimated for TotValue. The adjusted R2

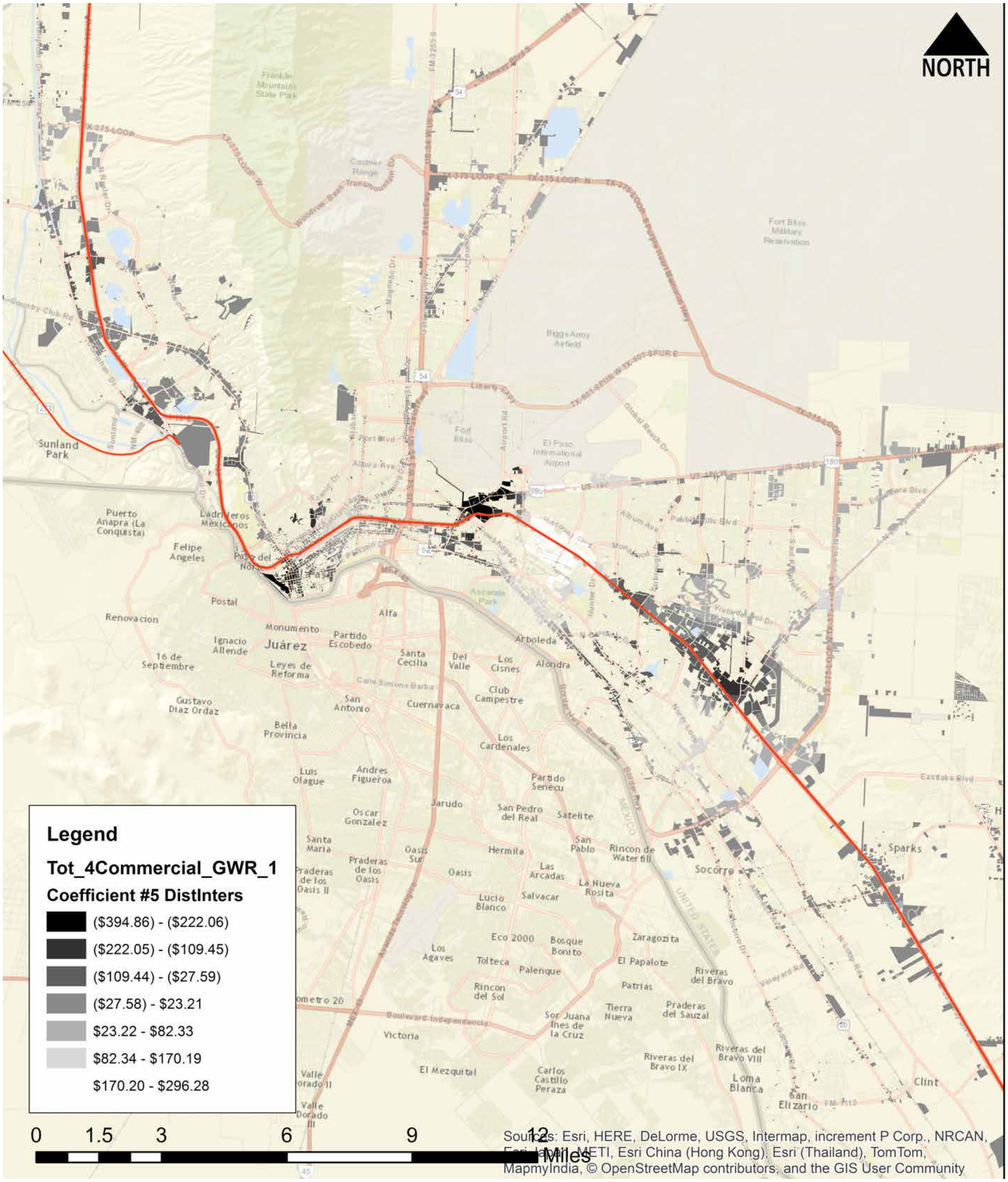

Figure 2 | Total Value GWR Model Coefficient Estimates for DistInterstate.

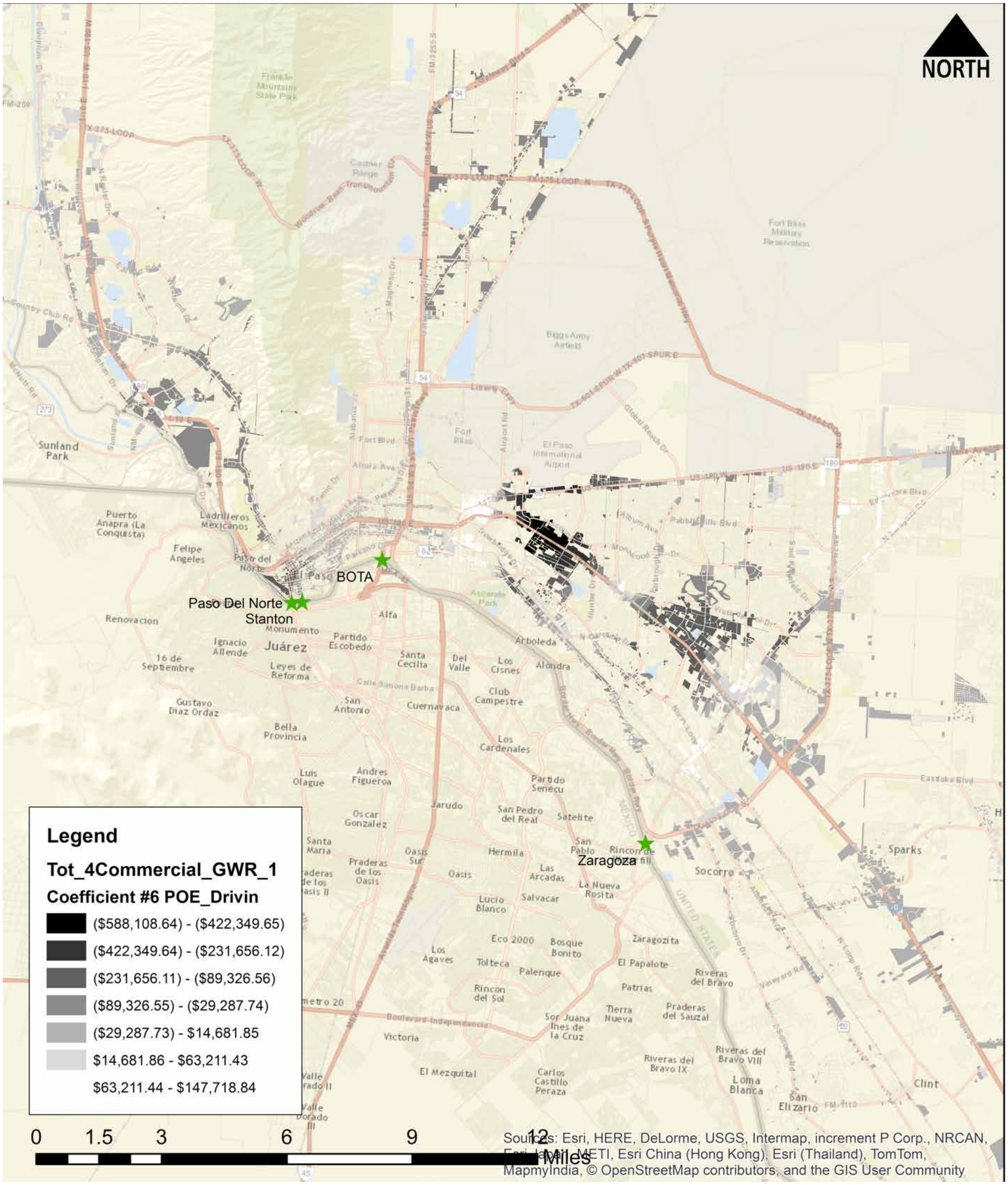

Figure 3 | Total Value GWR Model Coefficient Estimates for POE_DrivingTime.

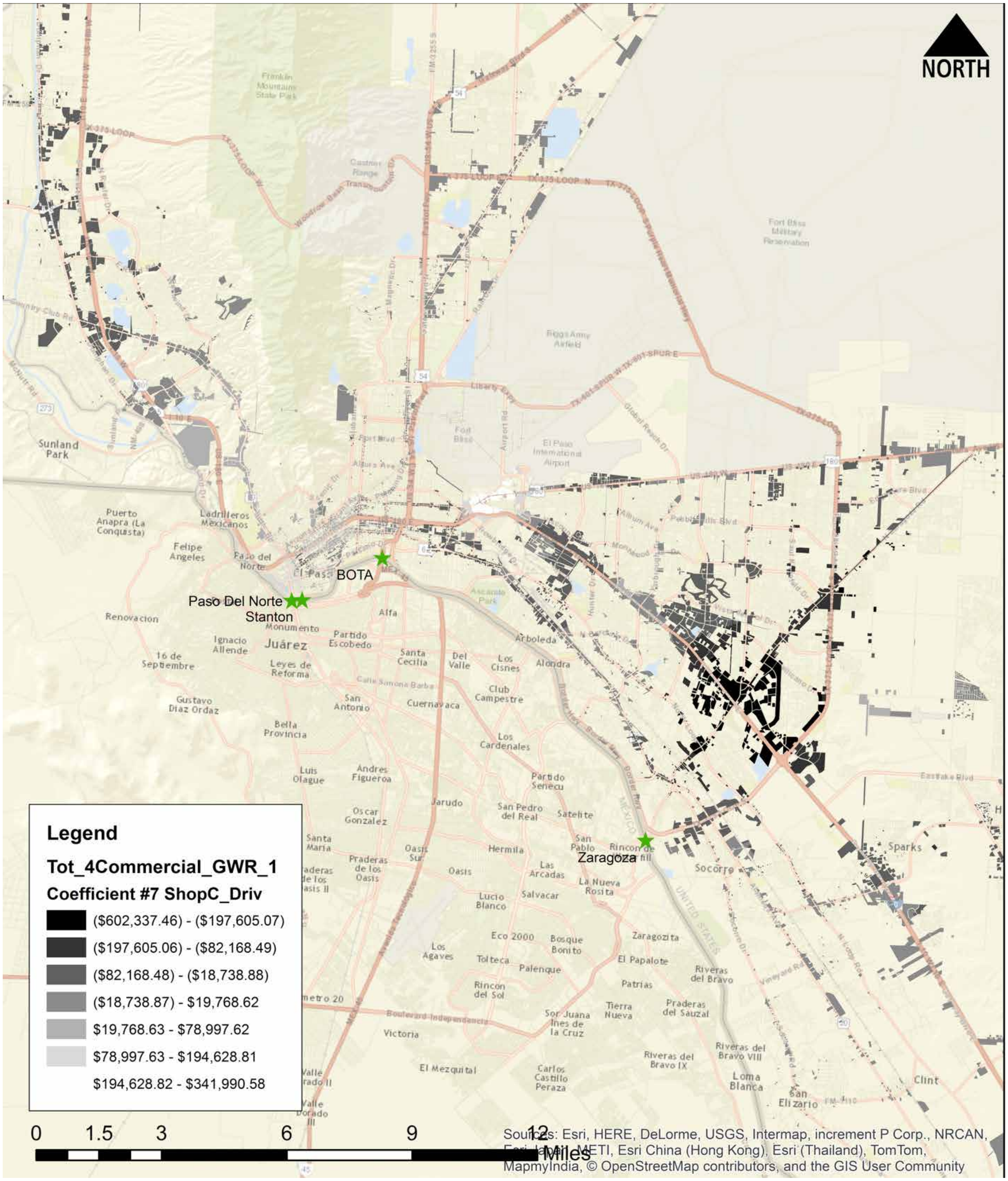

Figure 4 | Total Value GWR Model Coefficient Estimates for ShopC_DrivingTime.

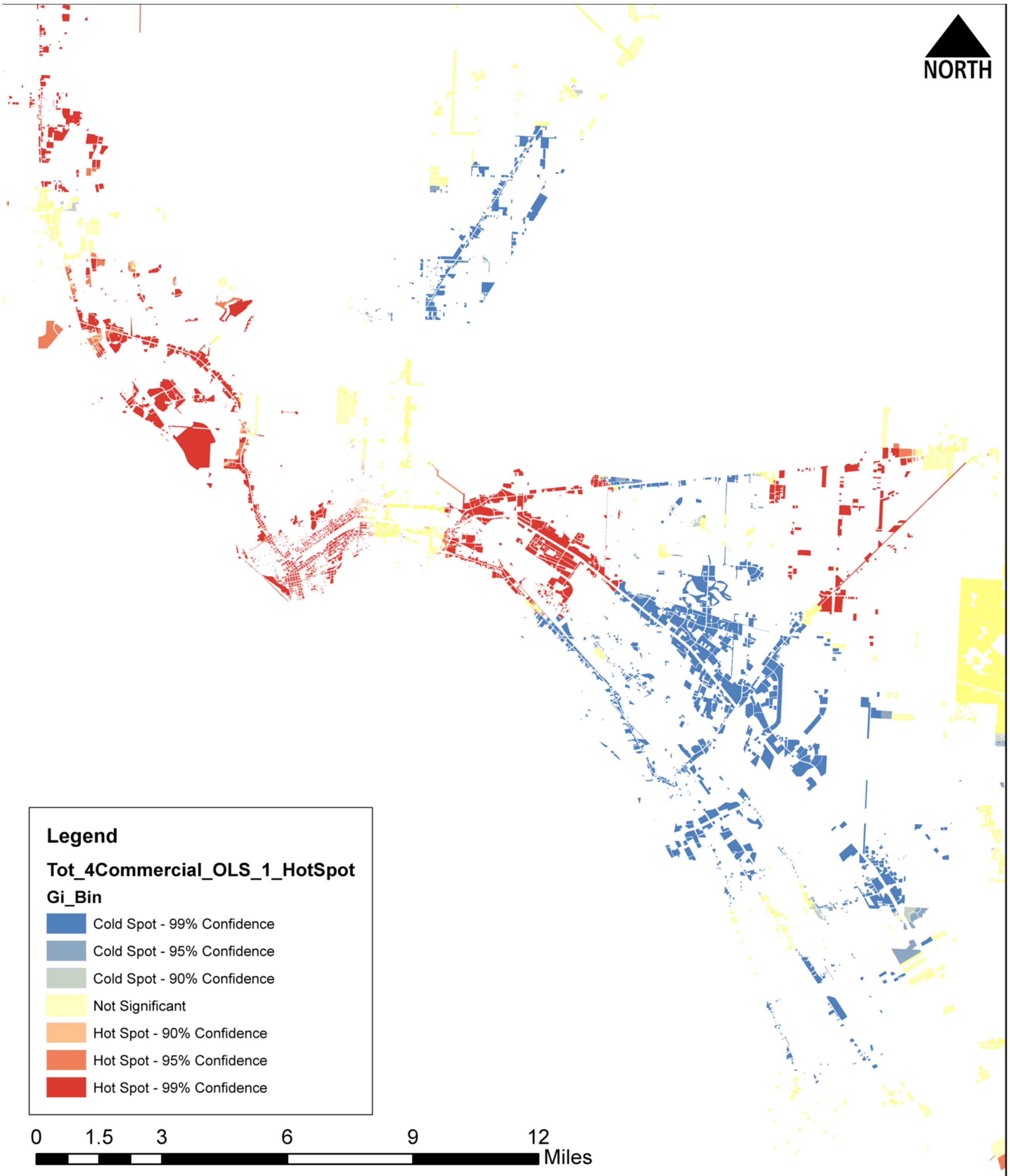

Figure 5 | Total Value Model Spatial Autocorrelation Test Results for OLS.

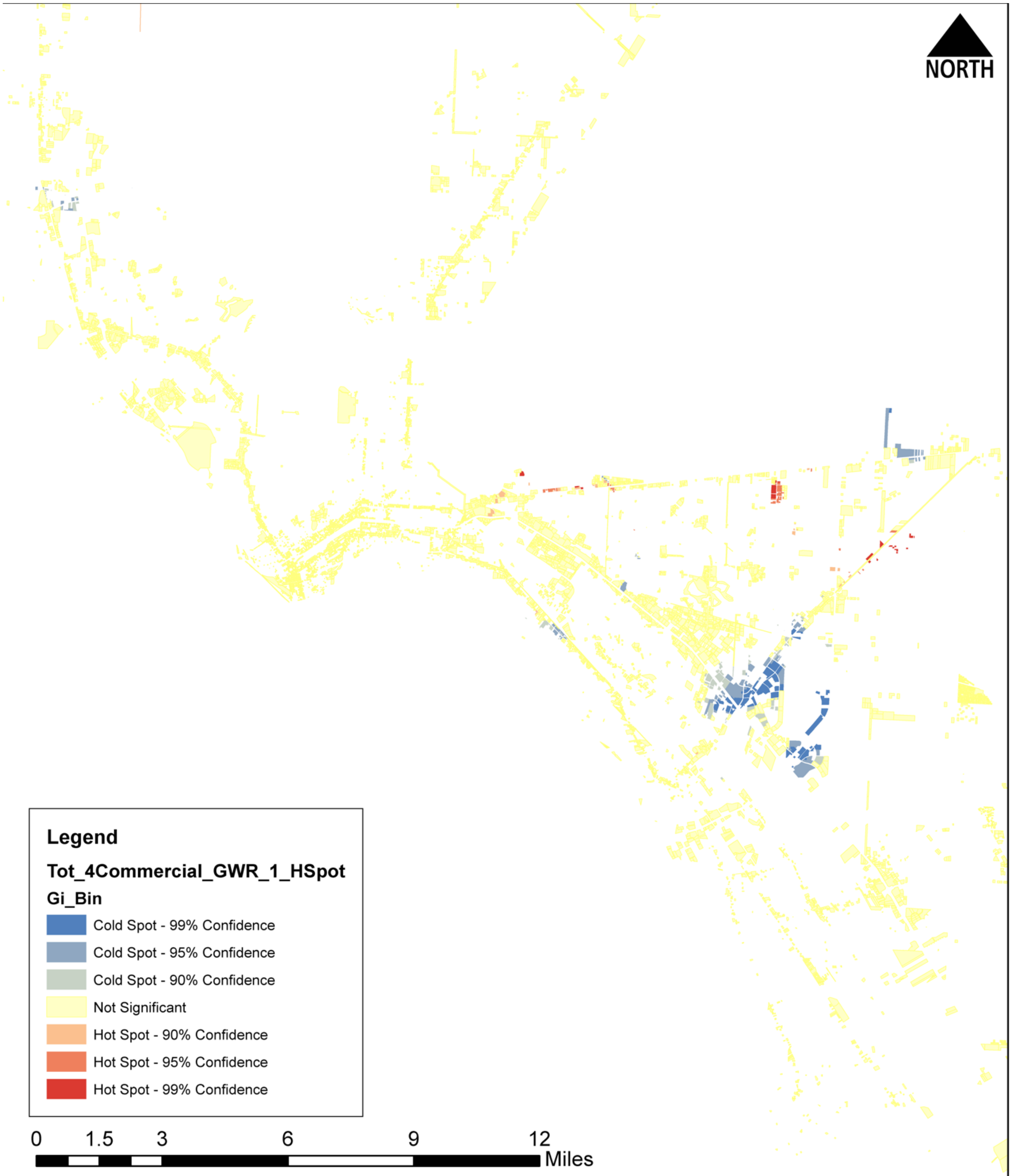

Figure 6 | Total Value Model Spatial Autocorrelation Test Results for GWR.

indicates that the improvement value model explains only 44.5% of the variation in ImpValue about its mean. The significant Jarque-Bera statistic indicates that residuals are not normal. The Koenker BP statistic is significant, indicating nonstationarity or heteroscedasticity is present in the residuals. The Joint Wald Statistic indicates that the overall model is significant.

The GWR improvement value model yields 16,232 regression points with invertible matrices, approximately 15.4% of the commercial sample data (see Table 5). The mean local coefficient for POE_DrivingTime has the same sign as that of the OLS counterpart and the magnitudes are very similar. The GWR mean estimated parameter value for ShopC_DrivingTime in Table 5 has a sign that is opposite that of the OLS estimate. Figures 7 and 8 reveal that improvements located in parcels near the downtown area have positive coefficients, in lighter shades. That pattern implies that benefits from proximity to a POE are capitalized mainly by the improvement rather than by commercial land parcels. That is contrary to what occurs for single-family in similar locations, where the land accrues higher premia than the improvements as estimated by Bujanda and Fullerton (2017).

The GWR POE_DrivingTime mean estimate in Table 5 indicates that ImpValue decreases almost $2,577 for every additional driving minute to the nearest POE. POE_DrivingTime ranges from negative $345,427 to positive $130,175 per minute depending on location, as shown in Figure 7. The parameter estimate mean for ShopC_DrivingTime indicates that ImpValue decreases by $3,177 per minute of additional drive time. The local coefficients for ShopC_DrivingTime range from negative $146,530 to positive $196,319 per minute, as shown in Table 5 and illustrated in Figure 8. Consistent with the findings in the total value model, a substantial number of improvements with high premia are located fairly distant from the POEs, on the western and eastern sides of the county. Parcels with positive ShopC_DrivingTime premia are near downtown and near the malls in the central area. The GWR global diagnostics show improvement over OLS for the AICc which drops from 3,049,392 to 217,096. AdjR2 improves from 0.445 for OLS to 0.652 in the GWR baseline model. Spatial autocorrelation is practically absent from the GWR residuals.

LAND VALUE MODELS

The land value sample for commercial properties consists of 105,611 observations (30.0% of the total population). The dependent variable is LandValuei. Table 6 reports OLS estimation results for 7 independent variables plus a constant term. All of the regression coefficients satisfy the 5% significance criterion. LandValue increases by $1.20 per foot as DistInterstate increases. Similarly, the DistFreeways parameter indicates an increase in LandValue of $4.84 per foot. DistMajorArteries is associated with an increase in LandValue of $5,110 per foot. POE_DrivingTime indicates that LandValue increases $1,885 for every additional minute a commercial property is located away from the nearest POE. The impact from accessibility to a POE for LandValue is contrary to the findings in TotValue and ImpValue. This reaffirms that, for commercial parcels, the benefits from accessibility to a POE are capitalized mostly by the improvement rather than the land.

In Table 6, ShopC_DrivingTime indicates that for every driving minute a commercial property is located away from its nearest shopping center, LandValue increases by $1,755. This is very similar to the findings in TotValue and ImpValue. The land value model explains 10.4% of the variation in the dependent variable about its mean. The residuals do not follow a Gaussian pattern. The Koenker BP statistic is significant

Table 4 | Improvement Value Model OLS Estimation Results

Variable	Coef.	Std. Error	t-Stats.	Prob.	Robust SE	Robust t	Robust Prob.	VIF
Intercept	-407101.72	25081.87	-16.23	0.00*	67941.03	-5.99	0.00*	-----
ImpAge	1106.54	228.84	4.84	0.00*	785.43	1.41	0.16	4.68
Air	1709.32	9376.45	0.18	0.86	27240.40	0.06	0.95	2.38
Depreciable	4316.60	227.22	19.00	0.00*	583.78	7.39	0.00*	4.06
LandAcres	-2835.19	308.95	-9.18	0.00*	2986.61	-0.95	0.34	1.05
ImpSize	11.16	0.04	265.47	0.00*	2.17	5.15	0.00*	1.23
Stories	47255.32	9941.65	4.75	0.00*	98657.03	0.48	0.63	4.83
PopDens_CY	10.26	1.36	7.53	0.00*	5.49	1.87	0.06	2.41
Renter_CY	22.55	20.71	1.09	0.28	57.19	0.39	0.69	3.38
Vacant_CY	958.33	83.66	11.46	0.00*	451.95	2.12	0.03*	10.97
Unemp_CY	-201.24	49.87	-4.04	0.00*	80.48	-2.50	0.01*	4.64
PCI_CY	-1.06	0.46	-2.32	0.02*	2.25	-0.47	0.64	2.19
Mp35003a_B	-669.22	66.95	-10.00	0.00*	359.56	-1.86	0.06	6.85
DistInterstate	-0.09	0.18	-0.47	0.64	0.44	-0.20	0.84	10.17
DistFreeways	0.56	0.12	4.80	0.00*	0.40	1.39	0.17	2.47
DistMajorArteries	0.48	0.28	1.73	0.08	0.43	1.12	0.26	7.63
POE_DrivingTime	-2263.33	512.75	-4.41	0.00*	809.37	-2.80	0.01*	16.56
ShopC_DrivingTime	1676.92	373.74	4.49	0.00*	634.62	2.64	0.01*	9.46

Observations:	105611	AICc:	3049392
Multiple R-Squared:	0.445	Adjusted R-Squared:	0.445
Joint F-Statistic:	4984	Prob(>F), (21,198552) degrees of freedom:	0.00*
Joint Wald Statistic:	3574	Prob(>chi-squared), (21) degrees of freedom:	0.00*
Koenker (BP) Statistic:	8533	Prob(>chi-squared), (21) degrees of freedom:	0.00*
Jarque-Bera Statistic:	584084025438	Prob(>chi-squared), (2) degrees of freedom:	0.00*

*Statistically significant probabilities have an asterisk next to them.

Table 5 | Improvement Value Model GWR Summary Statistics

	Local coefficient estimates			Std. Error		
Variable	Mean	Min	Max	Mean	Min	Max
Intercept	-223067	-3600630	1604137	1517231	226186	12284376
Depreciable	3024	-4858	31269	10653	1970	120744
ImpSize	11.1	-4.07	44.9	52.7	0.293	1845
Unemp_CY	449	-4884	7188	3283	744	233925
POE_DrivingTime	-2577	-345427	130175	72215	10230	401251
ShopC_DrivingTime	-3177	-146530	196319	59642	11284	398829
Residual Squares:	12085300606493702	Sigma:	1326669	R^2:	0.659	
Effective Number:	126	AICc:	217096	$AdjR^2$:	0.652	

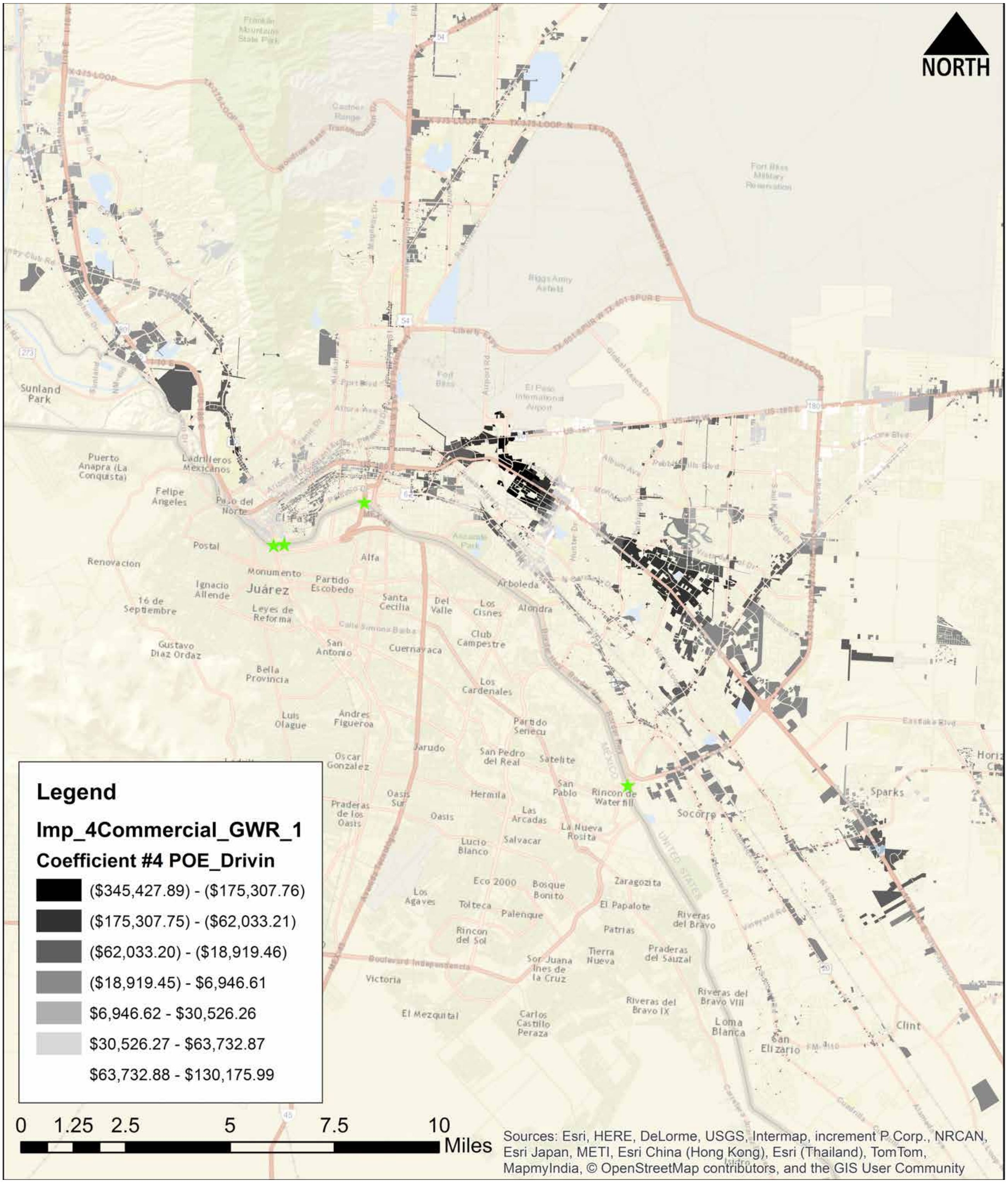

Figure 7 | Improvement Value GWR Model Coefficient Estimates for POE_DrivingTime.

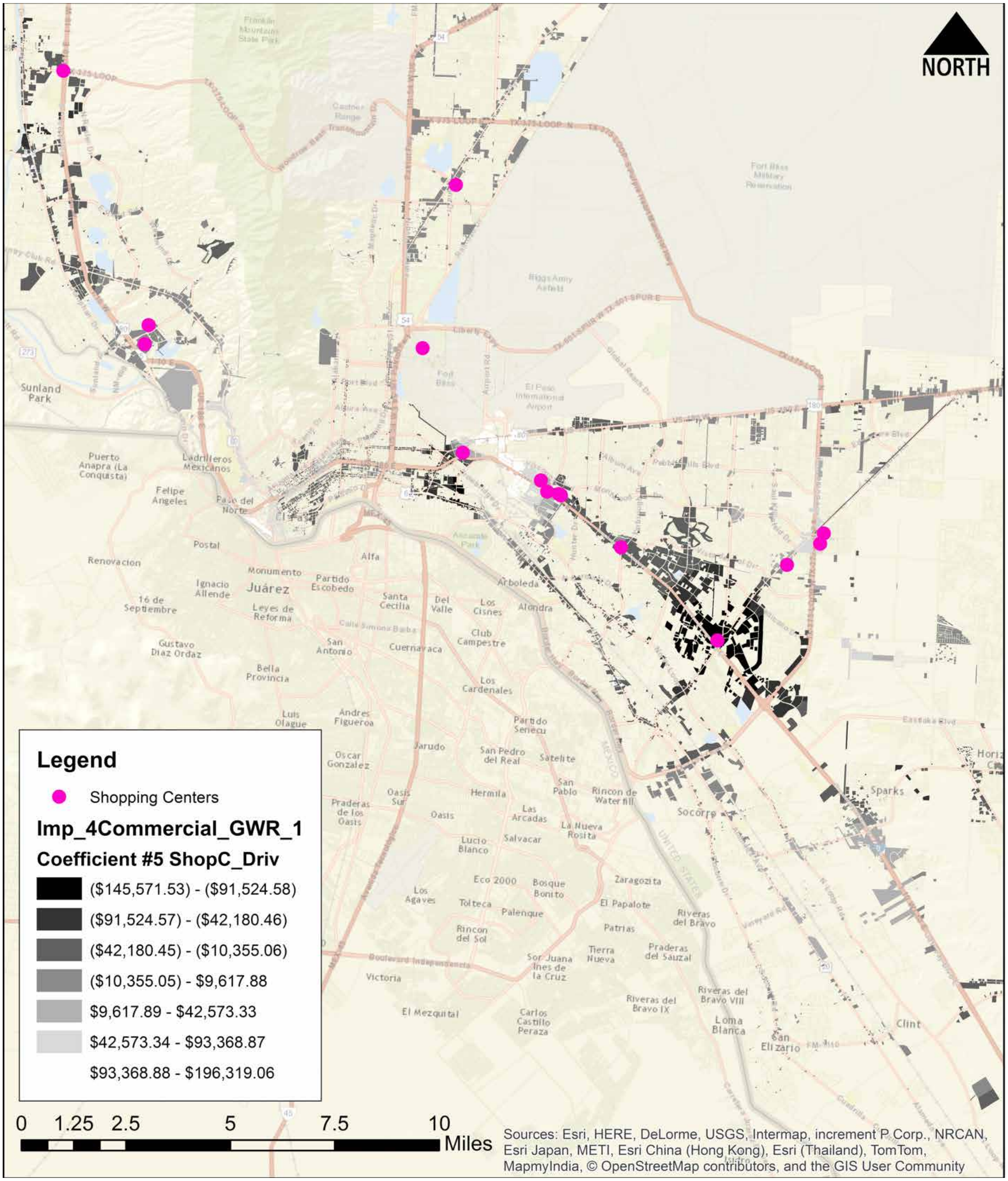

Figure 8 | Improvement Value GWR Model Coefficient Estimates for ShopC_DrivingTime.

suggesting nonstationarity or heteroscedasticity. The Joint Wald Statistic indicates, however, that the overall model is significant.

The GWR land value model yields 34,698 regression points with invertible matrices, 32.9% from the commercial sample (in Table 7). The mean values of all the local coefficients have signs that are opposite of the OLS parameters shown in Table 6. As illustrated using lighter shades of gray in Figure 9, DistInterstate is higher for the land located in the north and central parts of the county, and for a significant amount of parcels located in the eastern and southeastern parts of the county. As DistInterstate increases, LandValue decreases by $9.60 per foot according to the mean. Local coefficients for DistInterstate range from negative $182 to positive $93.60 per foot depending on location, as shown in Figure 9.

As DistFreeways increases, LandValue decreases by $2.70 per foot according to the mean. Local coefficients for DistFreeways range from negative $84.00 to positive $85.80 per foot, as shown in Figure 10.
The DistMajorArteries parameter mean indicates that LandValue decreases by $20.20 per foot. Coefficients for DistMajorArteries range from negative $334 to positive $126 per foot, as shown in Figure 11. Coefficients for POE_DrivingTime in Table 7 indicate that for every additional driving minute to the nearest POE, LandValue decreases by almost $3,021 on average. Parameters from POE_DrivingTime range from negative $129,986 to positive $149,563 per minute depending on location, as shown in Figure 12.

In general, positive premia for DistFreeways are visible throughout almost all commercial land. The POE_DrivingTime regression coefficients suggest that those premia are capitalized by the improvements rather than by the land parcels in the downtown area. In contrast, parcels along the interstate exhibit positive premia for accessibility to the nearest POE. The GWR global diagnostics compare favorably to those of the OLS results with the AICc declining from 2,897,570 to 198,541. The AdjR2 increases from 0.104 in Table 6 to 0.492 for the GWR baseline model summarized in Table 7.

CONCLUSION

Traditional hedonic models that are global in nature can yield potentially deceptive results as a consequence of examining the impacts of transportation infrastructure proximity and accessibility using all real property values. The sample used in this effort contains 105,611 commercial property data observations for El Paso, Texas. Koenker BP test outcomes above confirm that the data are characterized by spatial nonstationarity and heteroscedasticity. Significant values for the Jarque-Bera statistics for all of the OLS models also indicate non-normally distributed residuals. Information criteria estimates and coefficients of determination, adjusted for degrees of freedom, for the GWR equations are also superior than those for the OLS outcomes. The relationships for real property values and transportation infrastructure proximity and accessibility across El Paso County are highly localized and vary significantly over space. The presence of spatial nonstationarity and heterogeneity confirm that transportation infrastructure proximity and accessibility might generate premia for real property values, but that positive premia are not always present and are even negative in some areas.

Results obtained highlight the potential importance of allowing for spatial dependence and spatial heterogeneity in econometric models. GWR is a one alternative that allows visualizing the diverse spatial relationships between transportation infrastructure and real property values. GWR estimates indicate

Table 6. Land Value Model OLS Estimation Results

Variable	Coef.	Std. Error	t-Stats.	Prob.	Robust SE	Robust t	Robust Prob.	VIF
Intercept	292863.10	3767.08	77.74	0.00*	10536.15	27.80	0.00*	------
ImpAge2	8239.21	147.54	55.84	0.00*	3264.51	2.52	0.01*	1.01
LandAcres	1.34	0.07	17.92	0.00*	0.09	14.70	0.00*	7.31
DistInterstate	1.20	0.04	27.41	0.00*	0.05	25.99	0.00*	1.49
DistFreeways	4.84	0.11	43.59	0.00*	0.19	24.88	0.00*	5.09
DistMajorArteries	5110.57	168.00	30.42	0.00*	197.55	25.87	0.00*	7.48
POE_DrivingTime	1885.79	140.33	13.44	0.00*	147.90	12.75	0.00*	5.62
ShopC_DrivingTime	11.17	0.85	13.16	0.00*	1.38	8.10	0.00*	1.48

Observations:	105611	AICc:	2897570
Multiple R-Squared:	0.104	Adjusted R-Squared:	0.104
Joint F-Statistic:	1751	Prob(>F), (21,198552) degrees of freedom:	0.00*
Joint Wald Statistic:	1717	Prob(>chi-squared), (21) degrees of freedom:	0.00*
Koenker (BP) Statistic:	1561	Prob(>chi-squared), (21) degrees of freedom:	0.00*
Jarque-Bera Statistic:	72690700138	Prob(>chi-squared), (2) degrees of freedom:	0.00*

*Statistically significant probabilities have an asterisk next to them.

Table 7 | Land Value Model GWR Summary Statistics

	Local coefficient estimates			Std. Error		
Variable	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Intercept	132041	-1112420	2250256	1828481	78419	7641128
LandAcres	49707	-160	1088279	53121	614	220355
DistInterstate	-9.61	-182	93.6	41.3	2.20	343
DistFreeways	-2.70	-84.0	85.8	37.2	1.87	208
DistMajorArteries	-20.2	-334	126	54.3	3.59	310
POE_DrivingTime	-3021	-129986	149563	44153	6083	137962
Residual Squares:	1992943310671888	Sigma:	546548	R^2:	0.500	
Effective Number:	111	AICc:	198541	AdjR^2:	0.492	

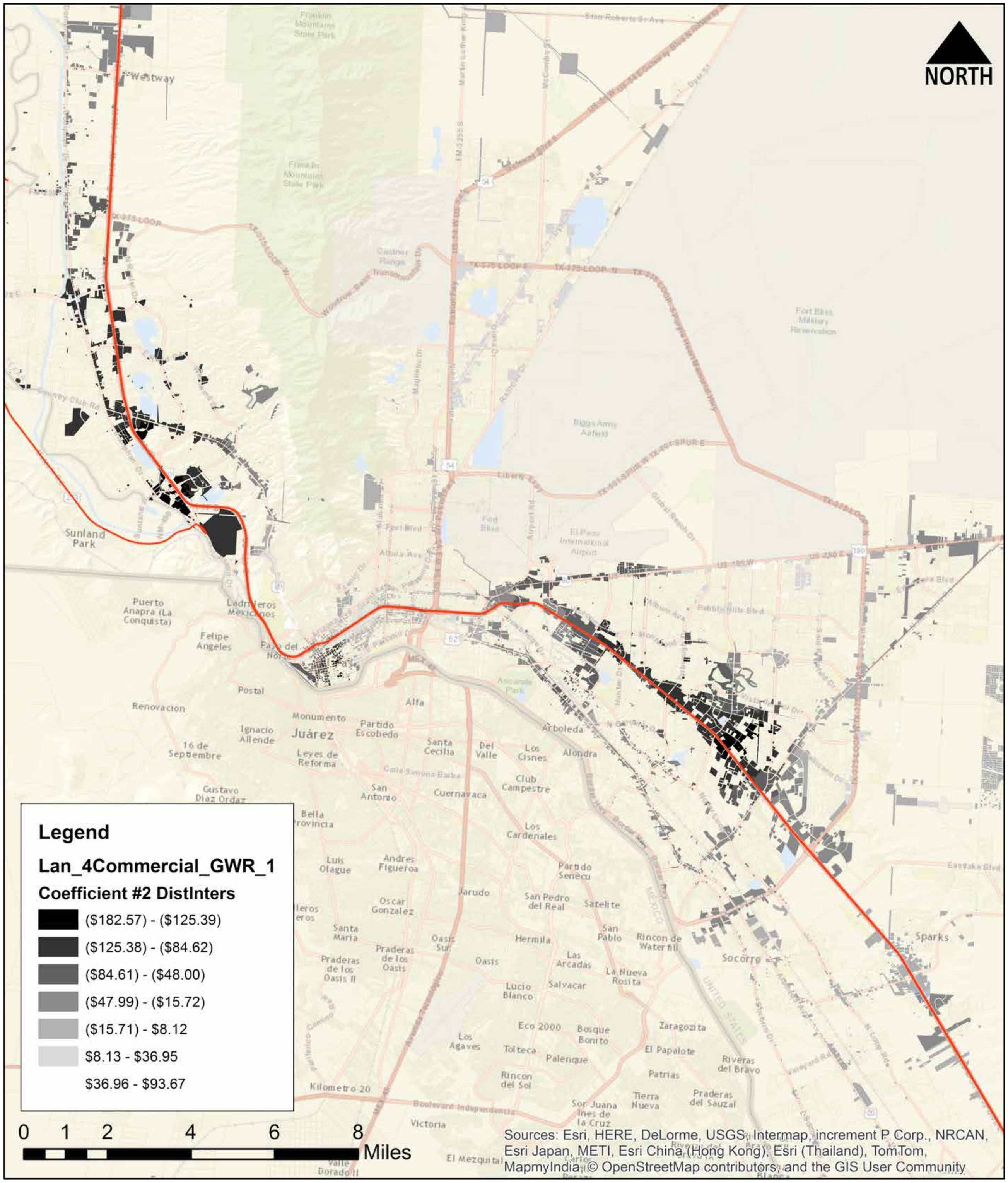

Figure 9 | Land Value GWR Model Coefficient Estimates for DistInterstate.

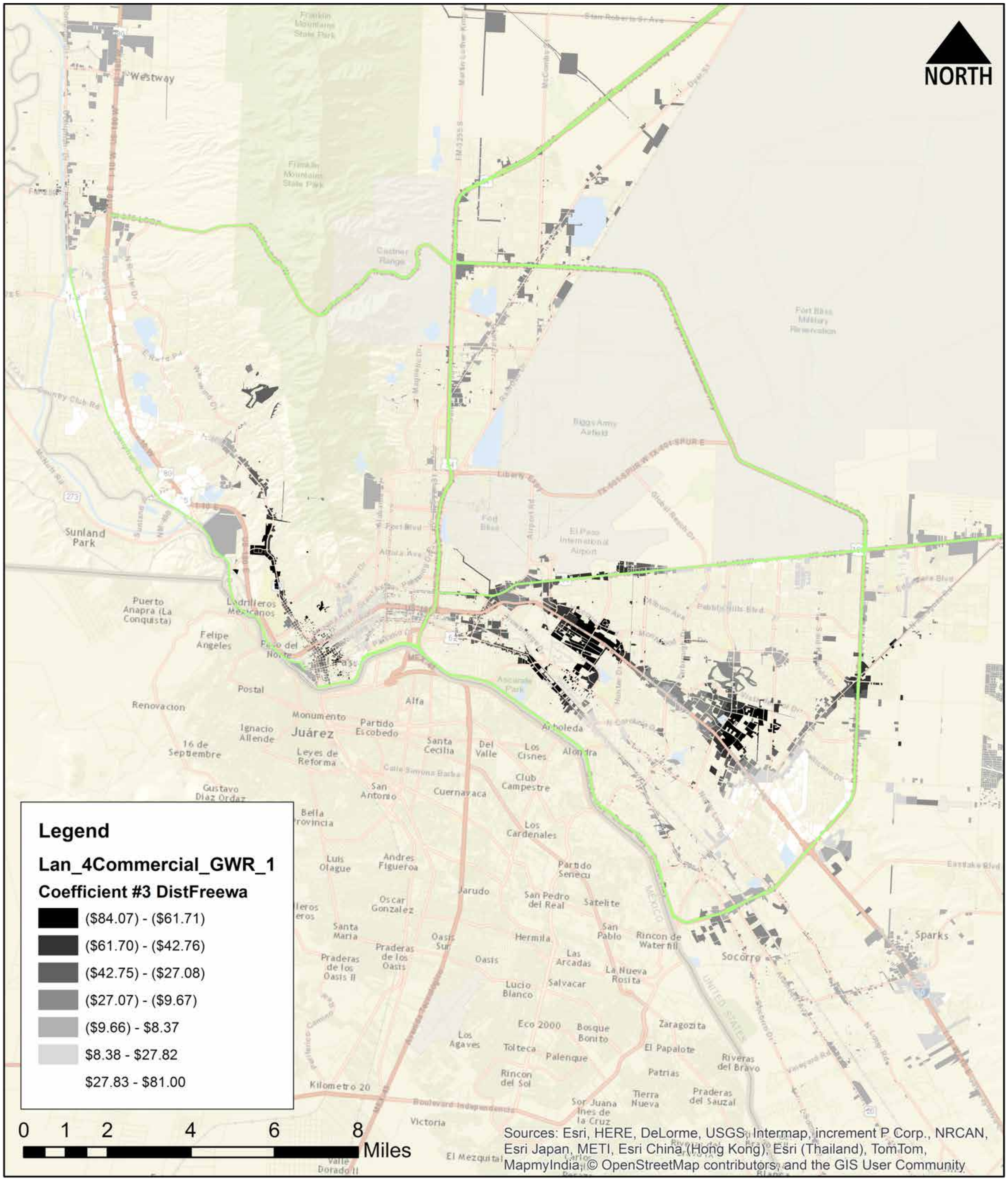

Figure 10 | Land Value GWR Model Coefficient Estimates for DistFreeways.

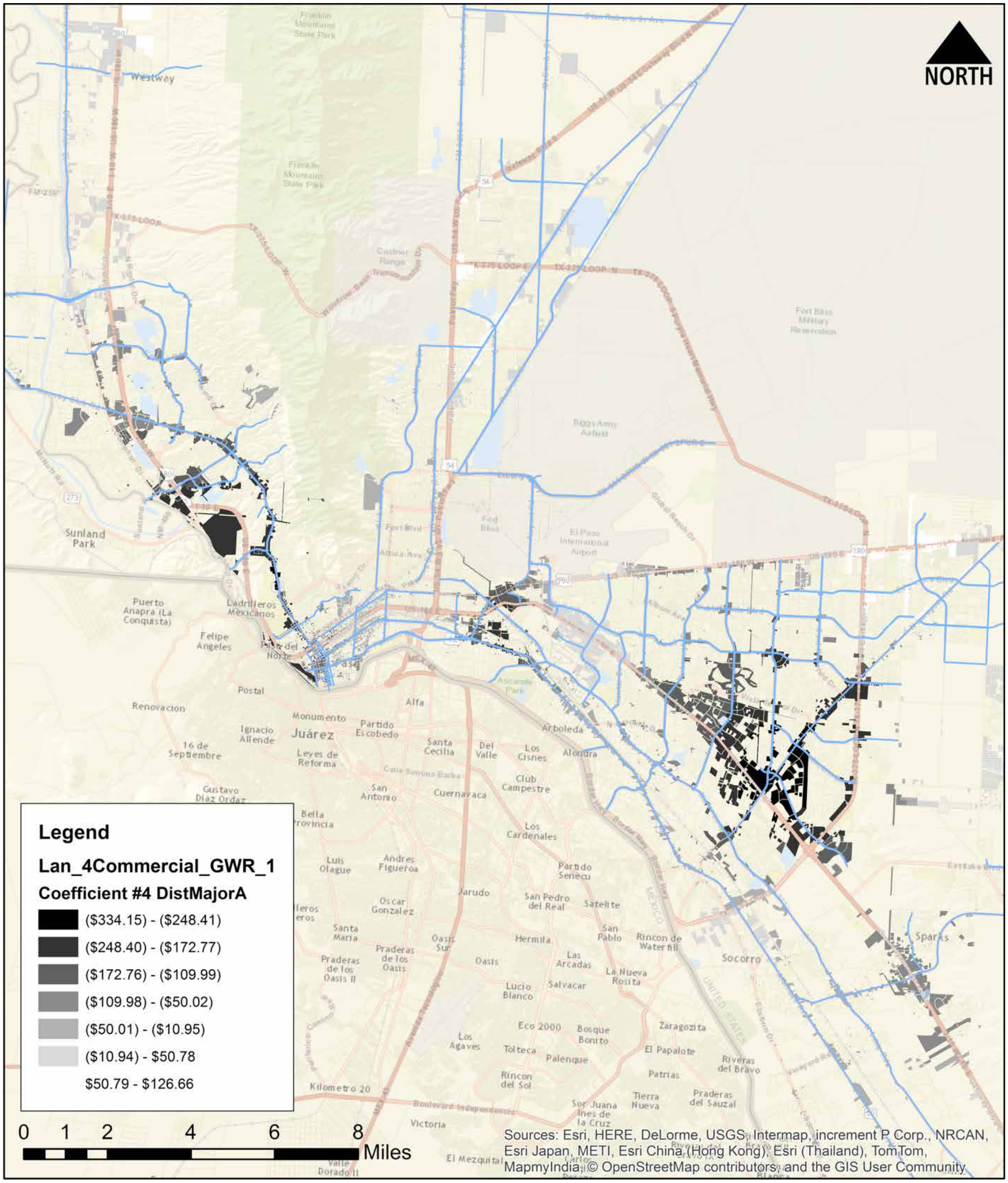

Figure 11 | Land Value GWR Model Coefficient Estimates for DistMajorArteries.

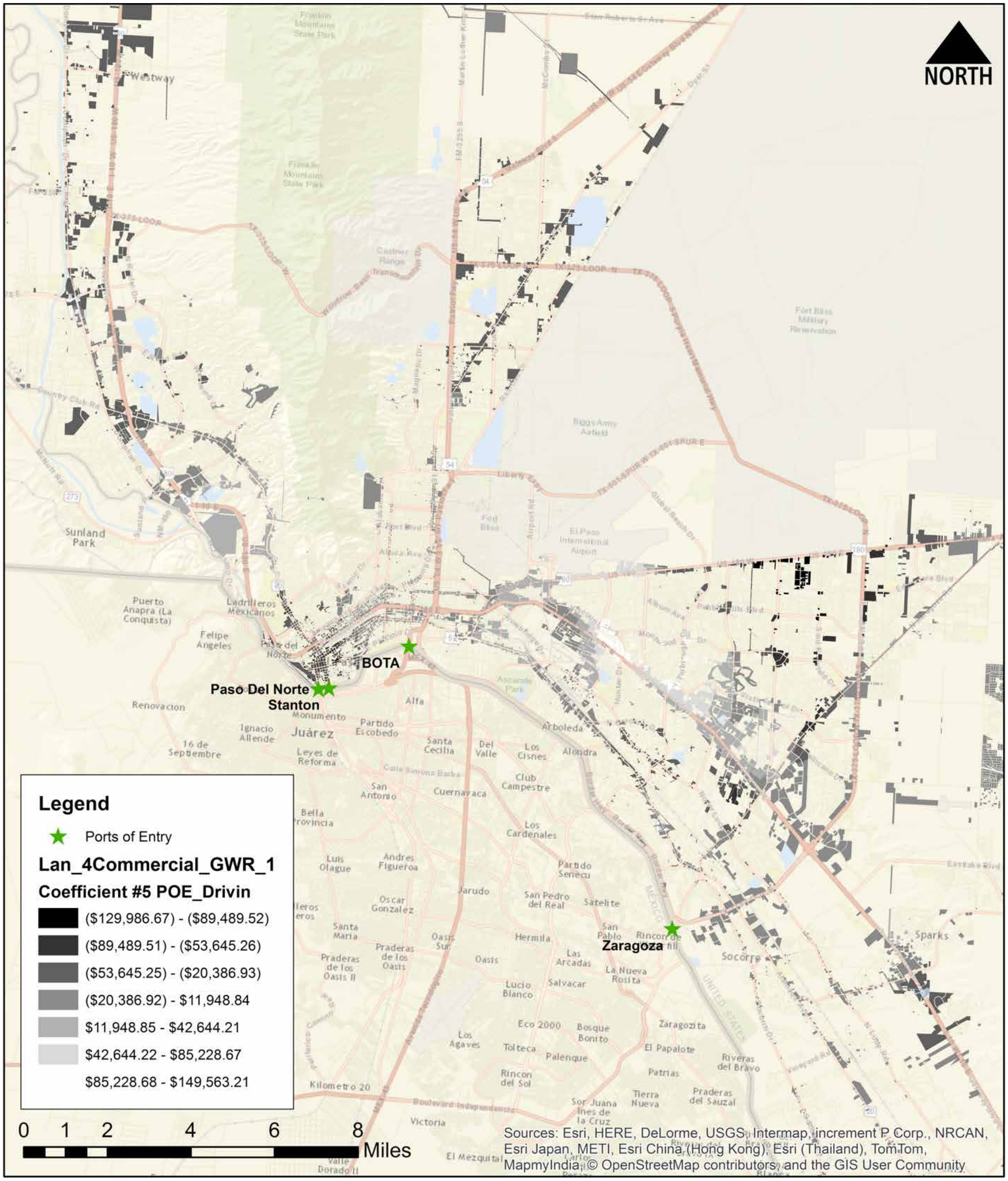

Figure 12 | Land Value GWR Model Coefficient Estimates for POE_DrivingTime.

that the different impacts from specific transportation facilities can swing from positive to negative regardless of proximity. Benefits from transportation infrastructure can be capitalized by parcels even if they are not located close to the facility. Furthermore, the local coefficients indicate, for this sample, that parcels that are adjacent to the facility do not necessarily obtain value premia.

This study employs a single cross-sectional dataset from 2013 to help quantify premia for property clusters and at the parcel level. However, it is not possible to explore how the relationship between property values and transportation infrastructure changes over time. When a transportation facility is built, the real estate market capitalizes such benefits, positive or negative, into new equilibrium prices and assessed values. Future research that incorporates data over time may yield additional insights. Spatial autoregressive approaches as in Anselin (1988) and spatial panel data methods similar to Baltagi (2013) emerge as natural candidates for such efforts. Adding a time dimension would potentially allow identifying both short-term and long-term impacts of transportation infrastructure on real property values.

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