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Spatial Prediction of AADT in Unmeasured Locations by Universal Kriging and Microsimulation of Vehicle Holdings and Car-Market Pricing Dynamics

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Spatial Prediction of AADT in Unmeasured Locations by Universal Kriging and Microsimulation of Vehicle Holdings and Car-Market Pricing Dynamics

By

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Dedicated to

My parents, Fred and Maureen, and my siblings, Jen and Todd.

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Preface

This thesis is comprised of two parts. The first (Chapters 1 through 5) describes development and application of several spatial models to predict traffic counts across the state of Texas, using kriging and geographically weighted regression techniques. The second (Chapters 6 through 10) presents a 20-year microsimulation of automobile markets (and fleet holdings) using auction pricing for used vehicles.

ABSTRACT

Spatial Prediction of AADT in Unmeasured Locations by Universal Kriging and Microsimulation of Vehicle Holdings and Car-Market Pricing Dynamics

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The University of Texas at Austin, 2011

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Chapters 1 through 5 of this thesis explore the application of kriging and geographically weighted regression (GWR) methods for prediction of average daily traffic counts across the Texas network. Accurate measurements of traffic are essential for proper planning and management of pavements, roadway upgrades, congestion mitigation, and other aspects of ground-based transport. Results based on Euclidean distances are compared to those using network distances, and both allow for strategic spatial interpolation of count values while controlling for each location's roadway functional classification, lane count, speed limit, employment density, and population access. Both universal kriging and GWR are found to reduce errors (in practically and statistically significant ways) over non-spatial regression techniques, though errors remain quite high at some sites, particularly those with low counts and/or in less measurement-dense areas. Nearly all tests indicated that the predictive capabilities of kriging exceed those of GWR by average absolute errors of 3 to 8 percent. Interestingly, the estimation of kriging parameters by

network distances showed no enhanced performance over that with Euclidean distances, which require less data and are much more easily computed.

Chapters 6 through 10 explore vehicle purchase and use decisions, which can be central to estimates of crash outcomes, emissions, gas-tax revenues, and national energy security. An auction-style microsimulation of fluctuating vehicle prices is combined with a random-utility-maximizing choice model to produce a model for the evolution of personal-vehicle fleets, recognizing both used- and new-vehicle markets. All buyers and available vehicles are enter the auction process for vehicle selection, with demand, supply and price signals of used cars endogenous to the model. The thesis describes the modeling framework in detail, along with its implementation using Austin, Texas data (for behavioral parameters and a synthetic population). The fleet dynamics are simulated over a 20-year period, highlighting the model's flexibility and reasonable response to multiple inputs and contextual scenarios. A simulation of doubled gas prices showed a large increase (10%) in the share of the sub-compacts, with smaller decreases in pickup trucks, vans and large cars. A high scrappage rate, sometimes employed to increase turnover, resulted in used-vehicle sales falling by 12%, and new-vehicle sales growing by 3%.

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PART I. SPATIAL PREDICTION OF AADT IN UNMEASURED LOCATIONS

Chapter 1: Introduction

Traffic flow volumes represent key information for proper transportation engineering and planning decisions. Sampling, tracking, interpolating, and extrapolating annual average daily traffic (AADT) counts are fundamental to road construction and maintenance scheduling, as well as to demand modeling and validating estimates of network activity. However, assembly of accurate and robust traffic counts is not straightforward, due to difficulties in measurement and calculation. To obtain counts at a sample of specific sites across extensive road networks, departments of transportation (DOTs) tend to use a set of

permanently located automatic traffic recorders (ATRs) in league with portable traffic counters (PTCs), for short-term count samples. (FHWA 2005) While a U.S. state DOT may have 100 ATRs across its network, it is likely to sample at tens of thousands of short-period traffic count (SPTC) sites, for two or three days each, typically. Overall, spacing between count sites can easily average 5 miles or more, due to limited resources and competing interests (see, e.g., Wang and Kockelman [2009]).

The U.S. Federal Highway Administration's (FHWA's) standards state that interstates and other high-volume roads must be measured on a maximum three-year cycle, while other highways' count can be sampled up to every six years. Day-of-week averages are calculated for ATR sites each month. These are averaged over the months for each day's AADT and then all averaged to get a single AADT for that site. In the case of SPTC sites, data collection over at least 48 consecutive hours in a measurement cycle is recommended. Seasonal, day-of-week and month-of-year adjustments (to adjust SPTC values to AADT values) are calculated as ratios of ATR-site counts in the relevant time period to the year's count, based on average adjustments from groups of ATRs at similar/matched locations. (FHWA 2005)

The FHWA (2005) Highway Performance Monitoring System suggests that AADT estimates should lie within ± 10 percent of actual AADT values with a 90% confidence interval on urban arterials and 80% interval on all other roadway types. Using Minnesota and Florida ATR counts, Gadda et al. (2007) estimated that average errors in AADT

estimation using one- and two-days' counts produced estimates that, on average, fell within 10 to 20 percent of actual counts, when using own-site adjustment factors (i.e., best-case scenario). The 95% confidence interval notion would suggest an even wider range, generally, particularly as one relies on other sites for the adjustment factors. Of course, modelers must also anticipate counts at locations wholly unobserved by ATRs and PTCs, where average error rates can rise quickly to 100% or above. (Gadda et al. 2007)

Even with mobile measurement devices and the application of adjustment factors, a large portion of the network remains unmeasured. Limits on personnel and funds do not permit a solution involving large increases in the number of locations measured. More accurate prediction of traffic levels at uncounted sites would allow DOTs to improve information while possibly reducing resource expenditures. As discussed below, standard regression techniques and geostatistical methods have been used to estimate traffic counts at unmeasured locations across the U.S. This paper exploits information on local conditions that influence count values along with spatial relationships across the Texas network using the geostatistical techniques of universal kriging and geographic weighted regression (GWR).

Kriging essentially involves spatial interpolation, and universal kriging makes use of local information (such as lane count and population density) while also drawing on residuals in prediction from nearby sites. GWR uses similar concepts but a very different

method of harnessing the information. Aside from their distinct specifications and parameter sets, both universal kriging and GWR rely on the same inputs. Such methods cannot replace actual vehicle counts entirely, but they can reduce the need for extensive counting, if spatial interpolation errors are low. Furthermore, such methods are useful in other contexts, such as real-time count and speed predictions (to anticipate and avoid congestion via ITS techniques and variable-rate tolling, for example), as well as demographic prediction (e.g., population densities, annual household travel distances, and/or vehicle ownership levels throughout a region – based on a sample of sites or households). Familiarity with such methods can only help transportation engineers and planners, whose data normally comes from spatial contexts.

Kriging's origins lie in the prediction of mineral contents by mining engineer D.G. Krige in the early 1950s. Mathematician George Matheron outlined kriging for geostatistics, using a "semivariogram" variance function (for latent effects or prediction residuals) that depends on the distance between data points. In general, there are three types of kriging: simple kriging, ordinary kriging, and universal kriging. In simple kriging, the value of interest at a location is predicted directly from nearby values, based on the semivariogram and a known global mean value. Ordinary kriging is slightly more complicated, requiring the process to estimate an unknown mean as well as the semivariogram. Universal kriging is used when a global-mean assumption cannot be used, and combines the distance-based variance with a trend, such as a linear, parametric function, as pursued here (following Box-Cox transformation of the traffic count [AADT] response variable).

Proposed in 1998 by geographers Brunsdon, Fotheringham, and Charlton, GWR essentially is a spatially weighted regression over and over, across space, with each regression centered on a point in the data set. Weighted least squares (WLS) is the standard approach, with a "kernel" function which determines the spatial weights across data points. Instead of weighting the predicted covariance terms, the explanatory data's influence on the coefficient estimates is downweighted as distances increase. These distances can be measured in whatever unit makes the most sense – including travel time, network distance, or social linkages. In addition to its prediction capabilities, GWR produces a suite of parameter estimates over space (one set for each centering data point). In this way, the effects of covariates vary over space, and become a continuously varying surface.

Chapter 2: Literature Review

A variety of techniques have been implemented to estimate traffic counts. Each method takes known counts and uses additional information (e.g., local land use data, time-steps, road attributes, and nearby sites' residuals in count prediction) to make a prediction. These can be divided into future-year (or future-period) prediction and same-year prediction methods. Future-year prediction uses current and past data from measured locations to estimate counts at the same locations at future dates. This is important for many applications, including planning maintenance or capacity increases on roadways, as well as real-time transportation systems management decisions (like signal timing, ramp metering, and variable tolling). In contrast, current-year prediction methods estimate counts at locations whose traffic flow have not been measured, using data from nearby locations during the same time period. This paper's applications center on current-year prediction only, but there is insight to be gained from both streams of work.

2.1 Future Year Prediction

The yearly movements in AADT are typically positive and non-linear (Castro-Neto et al. 2009). For example, Sliupas (2006) tested three techniques to predict future AADT in Lithuania. The first was an annual growth rate (location-specific) calculated using this simple equation with two known year's counts:

$$g = \sqrt[k]{AADT_1/AADT_2} - 1$$

where k is the number of years between the known counts 1 and 2

This method is used by Idaho's Department of Transportation (DOT). Sliupas (2006) also tried an exponential growth factor function that is used by the Montana DOT:

$$ln(E_t) = a + b \cdot e^{-t/10}$$

His last approach to modeling Lithuania's traffic counts was a standard least-squares regression ($Count_i = y_i = x_i\beta + \varepsilon$) controlling for gross national product (GNP), population and number of vehicles . He found the first method, from Idaho, to perform best with the Lithuanian data, in terms of moderating both maximum and average errors.

Tang et al. (2003) tested and compared the Box-Jenkins, neural network (NN), nonparametric regression (NPR), and Gaussian maximum likelihood (GML) methods for short-term (less than one year into the future) prediction with data from densely urban Hong Kong. Their Box-Jenkins used autoregressive integrated moving average (ARIMA) specifications, which require an evenly-spaced time series data set. Their NNs iteratively adjusted a network of weighted sigmoidal equations using past-year traffic counts. Their NPR approach predicted counts by calculating similarity indices between the current state and prior states with known counts. Finally, their GML method used both flows and flow increments. They found the Box-Jenkins and NN methods to require considerably more calibration work, while producing higher errors. The GML and NPR techniques were easier to implement and performed better for their data sets.

Recently, Castro-Neto et al. (2009) implemented a "support vector regression with data-dependent parameters" for Tennessee's highway counts. This approach has similarities

to standard least-squares regression techniques as well as NN methods. Its objective is to keep all residuals below a certain value, rather than minimizing the global sum of squared errors. This is useful when a modeler desires a certain level of accuracy for all points rather than maximum overall accuracy. They compared it to "Holt exponential smoothing" and found it superior for longer prediction time steps and seasonal data.

Jiang et al. (2006) used a growth factor in conjunction with satellite images to enhance future year predictions. Satellite photos were reviewed for visible vehicles and adjusted by factors for time and season. The image-based estimates were then averaged with estimates from growth factor methods (using weights based on estimated variances of the two methods). Results suggested a great improvement in accuracy. Use of satellite imagery, however, was not attempted in any other study reviewed here.

2.2 Current Year Prediction

Zhao and Chung (2001) used local employment and population attributes along with roadway details for current-year predictions across Broward County, Florida by ordinary least squares (OLS) regression. They compared several models and found that number of lanes, functional classification, regional access to employment, employment in an adjacent buffer zone (ranging from 0.25 to 3 miles on either side of the highway, based on road type), and direct access to expressways (via an indicator variable) worked best in predicting their data set's AADT values (with n = 816). 66 to 83 percent of the variability was explained by these variables, particularly the number of lanes and

functional class. On their top performing model, they saw a mean squared error (MSE) of 50,000 vehicles per day and a bias of +0.25%, where MSE is defined as follows:

$$MSE = {}^{1}/_{n_{unknown}} \sum_{i=1}^{n_{unknown}} \left(\hat{Y}_i - Y_i\right)^2$$

Zhao and Park (2004) pursued a similar study, using geographically weighted regression (GWR) in place of OLS. This regression calculates local parameters using a distance-based weighting function (with a separate regression around each data point, essentially). The expectation is that variables have effects that may differ by location. Table 2.1 shows the variables included in their model. The GWR specification was clearly better in terms of MSE, maximum error in prediction (136%), and error distributions, over the OLS method for the same data, suggesting a strong spatial aspect to traffic counts.

Zhao and Park (2004)	***Eom et al. (2006)***
Lanes	Lanes
Direct access to expressway (binary)	Suburban (indicator)
Employment in buffer zone	Urban (indicator)
Population in buffer zone	Median income (Census block level)
Job accessibility index (by travel time)	Functional class (indicators)

Table 2.1: Explanatory variables used in two previous studies

Wang and Kockelman (2006) used ordinary kriging functions built into ESRI's ArcGIS to estimate AADT counts, thus offering the advantage of being easily replicated by anyone with this popular software package. However, ordinary kriging does not allow the analyst to control for point-specific characteristics, like the number of lanes and class of roadway. Their findings suggested that given limited information, ordinary kriging can provide estimates of counts of unmeasured sites throughout a network, though errors

can be significant. Their median (non-absolute) error was 33%, meaning that half of all predictions were more than 33% *over* the actual value. They also found ArcGIS to be very limiting.

Eom et al. (2006) used universal kriging to predict Box-Cox transformed AADT counts (as discussed below) on non-freeway facilities in Wake County, North Carolina. They tested three semivariogram models (Gaussian, exponential, and spherical) and four estimation methods (OLS, weighted least squares, maximum likelihood, and restricted maximum likelihood (REML)). Their results suggest that universal kriging improved prediction overall, particularly in urban locations. REML and WLS performed well in terms of errors, with REML slightly ahead. Improvements over non-spatial methods were more pronounced in the urban areas, where denser placement of measurement locations provides more nearby data points. Since they calculated the errors of transformed traffic counts, the results are not so interpretable for comparison with results of other studies.

This thesis expands on the work of Wang and Kockelman (2006), Eom et al. (2006), and Zhao and Park (2004) by modeling AADT counts in Texas via universal kriging (and GWR) while reflecting network distances (rather than just Euclidean distances) .

Chapter 3: Data and Model Specifications

All traffic counts and highway data used here come from the year 2005 in Texas, the U.S.'s second largest state (in population and area). Texas contains a number of major metropolitan areas, including Houston and Dallas-Fort Worth, as well as large swaths of sparsely populated land. AADT values vary tremendously across the state DOT's geocoded 79,000+ centerline-mile network. The sampled counts come from all types of roads, from local roads to interstates freeways, in both highly urban and very rural settings. Figure 3.1 shows where SPTCs are concentrated, with an average of 111 count sites per county (or one count site every 10 square miles, or every 3 miles of highway centerline, on average) in this particular data set (with a standard deviation of 70.8 sites per county).

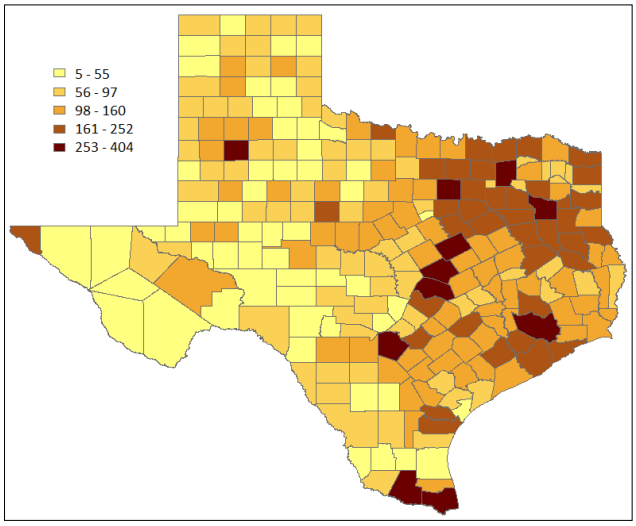

Figure 3.1: Number of annual count locations in each county

3.1 Data Sources

Traffic counts were obtained (and transformed into AADT estimates) for 2005 reporting requirements by the Texas Department of Transportation (TxDOT) using approximately 200 ATR sites and 28,000 short counts sites. Road information, (including number of lanes, functional class, and speed limits) was given in a GIS file of roads, represented as lines, with associated data from the TxDOT Roadway-Highway Inventory (RHiNo) database. Employment data from the Department of Labor Statistics and 5-year population data from the Bureau of the Census' American Community Survey (ACS) were collected and then geocoded into a GIS map of county- and tract-level polygons, respectively.

All data were spatially merged using ESRI's ArcGIS. Points with very low (possibly erroneously low) traffic counts (less than 200 vehicles per day) were removed. This resulted in 25,183 data point locations for obtained traffic counts across the 79,000+ centerline-mile network. These were divided into smaller regional data sets, to reduce computational demands on a standard PC (and recognizing that points hundreds of miles away should have no discernable relation to a local count). A subset of 3,145 points from 24 counties around the southeastern, Houston or Gulf Coast area of Texas, referred to here as the Houston Region[1] were evaluated in one set of models, followed by another set of 667 points for the 5-county Austin Region. Both sets were selected by hand, with boundaries guided by areas of sparse point coverage, and both included all functional

[1] The Houston Region subset of points is relatively sparse, with just 0.162 counts per square mile and an average distance of 3.06 miles to each count site's three nearest neighbors.

classes of roads. Additionally, regressions were performed on point subsets with interstate highways only (*n*=1,053), urban-classification only[2] (*n*=6,256), minor roads only (*n*=3,532), and the Houston Region only with interstates removed (*n*=3,017).

The resulting count concentrations (0.16 counts per square mile for the Houston region and 0.21 for the Austin region) are noticeably lower than those enjoyed by Eom et al. (2006) and Zhao and Park (2004) (at 1.35 and 0.65 counts per square mile, respectively). The more closely located data points are, the lower the resulting errors are likely to be, following spatial interpolation, ceteris paribus. Nevertheless, intelligent application of kriging remains a key tool of interest, particularly as data become costly and, typically, more sparse.

3.2 Variables in Model

The speed limit, number of lanes and functional class were taken from the road segment associated with the count location using the overlay function in ArcGIS. The high values for median and average speed limit (55 and 56 mph, respectively, as shown in Table 3.1) hint at the fact that relatively few count sites lie on the smaller roads in towns and cities. The employment densities were derived for the county in which each count was taken. This is a very coarse measure of local density, of course, but does help reflect some of the longer distance travel that many drivers regularly take (e.g., the NHTS 2005 data suggest

[2] The Urban subset of sites is spread across the state (such that a density measure [in count sites per square mile] is not very meaningful here), but the average distance to each site's three nearest neighbors is relatively low, at 2.32 miles.

that the average one-way commute trip in the U.S. is 12 miles long, while the average "radius" of a Texas county is 18 miles [if one were to form circles with the area of land present in Texas' 254 counties]).

Several population accessibility indices were created for each U.S. Census tract in Texas, from the Census's population and GIS files. These reflect the ease of accessing population in nearby tracts. Euclidean distances between all Texas tract centroids were used (since actual travel times and costs were not available). Intra-tract distances were assumed to be 0.1 miles (which is effectively the smallest distance between any adjacent tracts). The index was determined for each of the 4,388 tract and associated with all traffic count locations (roughly 28,000, across the State of Texas) within that tract. Three types of indices were constructed and tested in the count models: distance to a given population, population within a given distance, and inverse-distance-weighted population within a given distance. These accessibility indices do not account for population and jobs across the state boundaries, so the border site values will be biased low somewhat (in the case of the population-count and inverse-distance-weighted measures) and high in the distance-to-population measure. Areas along the Texas state borders have low population access regardless of context, so the bias should not prove a problem. The international border, on the other hand will introduce passenger and freight traffic which is not controlled for because the neither the model or dataset extend into Mexico. The could affect some of the points in the Urban dataset.

The distance-to-population measure was constructed for populations of 20, 50, 100 and 250 thousand. For each tract, all tracts were sorted by their distance from the tract in question. The population was cumulatively summed until the threshold value was reached. The distance of the point at which the threshold was reached was recorded as the index. The population at a given distance was calculated in the same way except that the thresholds were distances 1, 2, 5, 10, 25, and 50 miles. The following values were computed for the data set of 4,388 Texas tracts:

	Population			
	20,000	50,000	100,000	250,000
Average	5.1 mi.	8.5 mi.	11.9 mi.	21.1 mi.
Median	1.8	3.1	4.9	10.1
Min	0	1	2	3
Max	102	130	179	189
Std Dev.	7.8	11.5	15.0	22.0

Table 3.1: Summary statistics of accessibility indices, across tracts: Distance (miles) to reach a given population (in thousands)

	Limiting Distance (miles)					
	1	2	5	10	25	50
Average	10,871 persons	29,904	136,293	419,711	1,413,655	2,462,461
Median	9,442	24,648	103,270	247,100	992,985	1,768,050
Min	146	224	460	854	2,034	4,990
Max	52,376	122,480	548,170	1,487,200	4,031,400	5,113,700
Std Dev.	6,603	23,820	124,258	410,662	1,350,768	1,997,467

Table 3.2: Summary statistics of accessibility indices, across tracts: Population within a given distance (in network miles)

Preliminary tests showed slightly better prediction of traffic counts when using the population indices (within given distance values). Therefore, this style of accessibility

index was then extended to allow for more sophisticated controls for this notion of access. The first approach simply controlled for both a short-distance and a longer-distance index, such as 2 and 10 miles or 5 and 25 miles, simultaneously (as separate covariates) in the kriging and GWR regression models. The second used a gravity-based access measure, with a distance cut-off, as shown in the following equation:

$$AI_i = \sum_j pop_j / d_{ij}^{\alpha} \quad \forall\, j, d_{ij} \leq d_{target} \qquad (1)$$

where α is a user specified parameter, pop_j is the population in tract j and d_{target} is the index's (maximum) band distance.

The choice of accessibility index and parameter value, in the weighted case, was made by performance testing in the kriging models for traffic counts, as discussed in the Results section (Chapter 4). Optimal prediction was found with an α value of 0.1 and a distance limit of 25 miles and with two indices of unweighted sums of population at 5 and 25 miles (after testing all 35 indices).

All variables' summary statistics, for the data points included in the count subsets, are given in Table 3.3.

	Mean	Std. Dev.	Min	Max
AADT 2005 (vehs/day)	17,843	33,601	210	341,940
Speed Limit (mph)	53.6	10.4	20	80
Lanes (number)	3.18	1.48	1	12
Accessibility				
Weighted (d=25,α=0.1)	231,036	457,313	1,493	3,118,896
To 5 mi	23,093	47,436	460	498,860
To 25 mi	298,162	592,482	2,034	4,031,400
Jobs / Sq Mile	0.576	0.962	1.04E-3	4.22
Rural Interstate (indicator)	0.049	-	0	1
Rural Major Road	0.188	-	0	1
Urban Interstate	0.047	-	0	1
Urban Principal Arterial	0.058	-	0	1
Local & Collector Roads*	0.658	-	0	1
Number of data points = 10,978 * Used as base case in regression				

Table 3.3: Summary statistics of model variables of data in all subsets

Fourteen functional classes of highway exist in Texas (as designated by TxDOT), with seven being rural in designation and seven urban. As shown later (and noted in Table 3.4), these were combined into six categories, based on regression results that indicated a lack of statistical distinction on coefficients for certain classes.

Not considered here is the measurement-type (ATR or PTC) for the counts. The data set provided has no such distinction, so it was not an option in these analyses. In other data contexts, weighting by measurement type could be used to give more consideration to counts from permanent counters (ATRs), due to their added reliability as known traffic count values.

Rural		***Urban***	
Functional Type	***Frequency***	***Functional Type***	***Frequency***
Interstate	533	Interstate	520
Principal Arterial[1]	315	Principal Arterial (Freeway/Expressway)[2]	630
Minor Arterial[1]	491	Principal Arterial (Other)[3]	2889
Major Collector[1]	1250	Minor Arterial[3]	1768
Minor Collector[3]	2108	Collector[3]	438
Local[3]	25	Local[3]	11
[1] Rural Major Road, [2] Urban Principal Arterial, [3] Minor Road			

Table 3.4: Frequency of traffic counts by functional class for data used in all subsets

3.1.2 Distance Measures

In previous applications of kriging for AADT count estimation (e.g., Eom et al. [2006] and Wang and Kockelman [2006]), only Euclidean distances have been used (to estimate covariances via the semivariogram). Many experts would expect actual travel distance or impedance (time plus cost) to be a better indicator of count relationships; however, computing the hundreds of thousands of inter-point distances is challenging (if not impossible) for software like ArcGIS. Here, TransCAD travel modeling software was used to obtain shortest-path distances. (This activity required 7 hours to produce almost 800 million distance calculations across the Texas network.) Euclidean distances were calculated using the Vincenty formula for great circle distance (Thomas and Featherstone 2005). All estimates and model performances are described below.

Initially only distances under 25 miles were considered for estimation of the kriging model. The reason was primarily computational: sparse matrix computation could be

applied (thereby saving space) and faraway points could be easily ignored without concern for loss of accuracy. This is theoretically acceptable, since the spatial element of universal kriging captures only local influences and does not require a minimum number of points. However, when the GWR model was created, the distance cutoff in the input data became problematic. Though technically speaking GWR does not have a strict requirement of minimum points (beyond basic identification), the cutoff could arbitrarily affect some of the kernels discussed later. Additionally, it would introduce unnecessary complications to the program.

Consequently, the kriging model had two distance sets with which to estimate, the complete set (to match the inputs used in the GWR model) and the limited set (which had been originally used). These were tested against each other to see the effect on performance of such cutoffs.

3.2 Model Specification

For both the universal kriging and GWR models, the dependent variable used was a power-transformed traffic count. The Box-Cox transformation is a likelihood-maximizing power transform that gives skewed data a more normal distribution, thereby stabilizing variation (Collins 1991). It is performed by maximizing the likelihood function over a power variable, λ. The transformation equation is as follows (Collins 1991):

$$Z = \begin{cases} \left(Y^{\lambda} - 1\right)/\lambda & \lambda \neq 0 \\ \ln Y & \lambda = 0 \end{cases} \tag{2}$$

Here, λ's estimation was performed during the data set's pre-processing, using an in-built STATA software command (that maximized the likelihood of the transformed distribution), resulting in a value of 0.15.

3.2.1 Kriging

The following kriging theory and implementation details derive from content in Schabenberger and Gotway (2005) and Cressie (1993). Weighted Least Squares (WLS) was chosen over restricted maximum likelihood (ReML) techniques for relative ease of implementation, as well as comparable performance seen in Eom et el.'s (2006) work. Moreover, WLS does not require an assumption of the error terms' distribution. The general equation for universal kriging is as follows:

$$z_i = \mu(x_i) + \varepsilon_i \tag{3}$$

where $\mu(x_i)$ typically is a linear function of explanatory variables at location i, ε_i is a spatially dependent error term, z_i is the dependent variable, and $i=\{1,2,\ldots,N\}$.

WLS can be applied to this with the matrix notation:

$$Z = X\beta + \varepsilon \tag{4}$$

where Z is the vector of response outcomes (e.g., Box-Cox-transformed AADT values), and X is an N by (K+1) data matrix with K explanatory variables, interacted with the linear parameters (β).

The variances of the N error terms (ε) are assumed to follow a semivariogram relation, $\gamma(h_{ij})$, as a function of distances (h_{ij}) between the locations of data points i and j. Here, such distances were calculated both using Euclidean distances (the standard approach) and network distances, to see whether the latter enhances prediction. The semivariogram's parameters can be estimated with mean or trend removed using WLS – or simultaneously with mean parameters when using REML. Three types of theoretical semivariogram functions, each with parameter set $\theta = \{c_0, c_e, a_s\}$, were tested, to ascertain the best performance (Cressie 1993):

Gaussian $$\gamma(h_{ij}; c_0, c_e, a_e) = c_0 + c_e\left(1 - e^{-h_{ij}/{a_s}^2}\right) \quad (5)$$

Spherical $$\gamma(h_{ij}; c_0, c_e, a_s) = c_0 + c_e\left(1.5\, h_{ij}/a_s - \left(.5\, h_{ij}/a_s\right)^3\right) \quad (6)$$

Exponential $$\gamma(h_{ij}; c_0, c_e, a_e) = c_0 + c_e\left(1 - e^{-h_{ij}/a_s}\right) \quad (7)$$

Feasible generalized least squares (FGLS) regression was used to recognize heteroskedasticity in error terms (but neglecting spatial autocorrelation across pairs of points), and enhanced estimates of AADT residuals. After performing the two-step FGLS estimation process, the squares of differences in all residuals were used in the Cressie-Hawkins robust estimator. This estimator divides the distances between points into a series of bins, from 0 miles to some maximum distance, and creates an empirical semivariogram using the following equation (Schabenberger and Gotway's [2005] Eq. 4.26):

$$\tilde{\gamma}(H) = {}^{1}/_{2}\left({}^{1}/_{|N(H)|}\Sigma_{N(H)}|e_i - e_j|\right)^4 \Big/ \left(0.457 + {}^{0.494}/_{|N(H)|}\right) \quad (8)$$

where H is the distance bin, $N(H)$ is the number of ij pairs in that bin and e_i is the FGLS residual from point i. The number of bins is a user-specified parameter; 15 to 25 bins were used here to allow for some resolution in distance and while ensuring more than one residual in most bins.

An iterative least-squares approach converges on the values for c_0, c_e, and a_s that minimize the sum of squared residuals (between empirical and theoretical semivariogram values). In equation form, the objective was $\min\left(\tilde{\gamma}(H) - \gamma(H; c_0, c_e, a_s)\right)^2$ with respect to c_0, c_e, and a_s. This optimization was performed using MATLAB's built-in function *lsqnonlin*.

The covariance matrix for kriging, C_{dd}, is then estimated from the theoretical semivariogram and the FGLS error-term variance, σ^2. Additionally, a vector of covariances, c_{d0}, for error terms across all known-response locations and all target (predicted) locations can be estimated. Each value in these two matrices is given by the following equation:

$$C_{dd,ij} = C(h_{ij}) = C(0) - \gamma(h_{ij}; c_0, c_e, a_s) = \sigma^2_{FGLS} - \gamma(h_{ij}; c_0, c_e, a_s) \quad (9)$$

With the inverse of the covariance matrix, C_{dd}, as the weight matrix, the β values can be re-estimated using a full-matrix-weighted least-squares regression, and response predictions (of Z) can be derived at all "new" locations x_0 as follows (Schabenberger and Gotway 2005):

$$\hat{\beta} = \left(X^T {C_{dd}}^{-1} X\right)^{-1} X^T {C_{dd}}^{-1} Z$$

$$\hat{Z}_0 = \left(X_0 - c_{d0}^T {C_{dd}}^{-1} X\right)\hat{\beta} + c_{d0}^T {C_{dd}}^{-1} Z \tag{9}$$

where X_0 is the data matrix for the predicted (new) locations and $\hat{Z}_0$ is their predicted Box-Cox transformed value.

3.2.2 GWR

GWR is mathematically simpler than kriging, as shown in the following equations from Fotheringham et al. (2003). Its form and estimation are the same as that of a repeated WLS regression, with a spatially varying coefficients:

$$Z = X\beta(s) + \varepsilon \tag{11}$$

(Strictly speaking, Z, X and ε are also spatial since they correspond to data points at specific locations, so they can also be represented as $Z(s)$, $X(s)$ and $\varepsilon(s)$.)

The β is estimated using the WLS equation at any (known or unknown) location, i:

$$\hat{\beta}_i = (X^T W_i^{-1} X)^{-1} X^T W_i^{-1} Z \tag{12}$$

where W_i is an nxn diagonal matrix of spatial weights:

$$W_i = \begin{bmatrix} w_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{nn} \end{bmatrix}$$

As this implies, there are values of β can be estimated for any location of interest and one set will be estimated for each unknown location. These values vary based on the weight matrix, W_i, which varies by location. The weights are based on the distance between

point *i* and other locations, 1 through *n*. Location *i* need not be included in the calibration set, X, allowing the β's to be estimated at the unmeasured locations. This matrix can be calculated in several different ways. For example, the weight matrix can function as a moving window by giving a weight of 1 to all locations within a certain distance or order of adjacency and 0 to any outside that. This setup can result in boundary conditions where one data point included fully, while another of nearly identical proximity goes neglected. This can be solved using weight functions that fall smoothly to 0 over distance or adjacency order. This approach is also consistent with the idea that each nearby site's influence will decrease with distance. Two such functions given by Fotheringham et al. (2003) are the Gaussian and bi-squared functions, respectively, shown below and in Figure 3.2:

$$w_{jj} = exp\left[-0.5\left(d_{ij}/b\right)^2\right] \tag{13}$$

$$w_{jj} = \begin{cases} \left[1 - \left(d_{ij}/b\right)^2\right]^2 & d_{ij} \leq b \\ 0 & otherwise \end{cases} \tag{14}$$

where *b* is the distance bandwidth and d_{ij} is the distance between points *i* (the point of interest) and *j*.

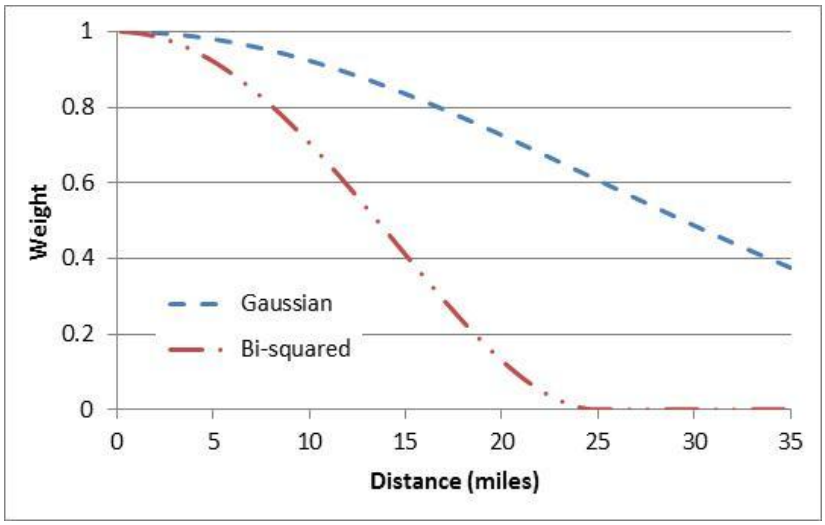

Figure 3.2: Gaussian vs. bi-squared weighting functions, *b=25*

These equations require a bandwidth, provided directly or indirectly by the modeler. In the direct case, called "fixed spatial kernels" by Fotheringham et al. (2003), the modeler selects a maximum neighborhood distance based on the density of points and some conception of relevant neighborhood size. In some data sets with fairly regularly spaced points, this is a viable method. In Texas' AADT data sets, the point locations are very non-uniform, varying from small cities with many count sites to large counties with just 5 counts. Thus, an indirect method for neighborhood determination that does not depend on a directly applied, constant bandwidth or distance, called "adaptive spatial kernels", is necessary here. Under this indirect technique, the modeler selects a number of closest points on which the estimation is to be based, so the bandwidth distance varies from point to point, effectively equaling the distance of the furthest point in each estimation. Therefore the ratio of distance to bandwidth, seen in the Gaussian and bi-squared equations, is:

$$d_{ij}/b = d_{ij}/d_{in} \leq 1 \quad for\ j\ \forall\ R_{ij} = \{1,2,\dots,n_b\} \tag{15}$$

where n_b is the number of points to be included, R_{ij} is the rank of closeness of point j to point i, and points j are the correspond to the n locations closest to i.

Another alternative tested here is to use a weight function of proximity ranking. This takes the n_b closest points and ranks them, but does not use their distances explicitly in the function. The weights falls as the points get further away (i.e., their rank value rises), but the values depend on the locations of all the other points, rather than just the furthest one as in equation (15). It is therefore susceptible to variations in spatial distributions: the uneven distribution of locations will allow sharp decreases in weight at dense distance bands and very gradual decreases over long stretches in sparse distance bands. This seems less intuitively consistent with the traffic behaviors at play in count data sets, because it is so dependent on the DOT's selection of locations. Nevertheless, a comparison of its performance (relative to that of the two distance functions) was pursued here. Weight is calculated by using the following equation, referred to here as a "rank-exponential" function:

$$w_{ij} = \begin{cases} exp\left[-\left(R_{ij}/n_b\right)^2\right] & R_{ij} \leq n_b \\ 0 & otherwise \end{cases} \tag{16}$$

where R_{ij} is the rank of closeness of point j to point i.

Possible drawbacks of GWR are its computational burden and interpretation issues. As stated above, a unique set of coefficients (β) is calculated for each data point, and then interpolated for each new location of interest (e.g., intermediate traffic sites). The steps for this include: finding the closest n_b points (to each data point in the sample), calculating the weight matrix, and performing the regression. In this work, regression run times were short, thanks to use of standard WLS. The initial calculation of distances between all starting points is the most arduous feature of the work, and generally only needs to be done once.

3.2.3 Comparison of Results

The model parameters were estimated using a randomly selected collection of the data points from each regional sample analyzed. The remaining 10 to 20 percent of count sites, from each subset, were used for model validation. The prediction errors were measured using MSE and averages of absolute percentage errors. Since the model uses Box-Cox transformed AADT values, the reverse transformation was used here, in order to work directly with AADT estimates, $\hat{Z}_i$, before generating the MSE and percentage errors shared here. Reversing the transform is provides measures of error and fit that can be interpreted directly. Of course, the predictions of the Box-Cox transformed values are random variables, so the reverse non-linear transformation can introduce bias. The coefficient estimates were therefore simulated using the (asymptotic) multivariate normal assumption for the models' parameter estimates, and the biases were found to be in the positive direction, but small in magnitude. (On average there was less than 0.5%

difference between the direct reversal and the mean value of simulation. Indeed, the results of the traffic count prediction did not produce any persistent bias. Collins addressed this in his paper stating, "deterministic point prediction is not generally unbiased, [but] nevertheless, a deterministic approach may be reasonable if point prediction bias is not too severe" (1991, pg 8).

$$MSE = {}^{1}/_{n_{unknown}} \sum_{i=1}^{n_{unknown}} \left(\hat{Y}_i - Y_i\right)^2 \tag{17}$$

$$Percentage\ Error = 100 \cdot {}^{\left(\hat{Y}_i - Y_i\right)}/_{Y_i} \tag{18}$$

In both equations there is a known value for each traffic count, $Y(s_i)$, from the data and an estimated count from the model, $\hat{Y}(s_i)$. Results are summarized by reporting the median percentage error (MPE) and average absolute percentage error (AAPE), for each data set under each specification.

$$MPE = median\left\{100 \cdot {}^{\left(\hat{Y}_i - Y_i\right)}/_{Y_i}\right\}_{i=1}^{n_{unknown}} \tag{19}$$

$$AAPE = {}^{100}/_{n_{unknown}} \cdot \sum_i {}^{\left|\hat{Y}_i - Y_i\right|}/_{Y_i} \tag{20}$$

As noted earlier, both shortest-path network distances and Euclidean distances were used in the semivariogram and GWR kernel methods (though the accessibility index, as an explanatory variable, was based only on Euclidean distances). Their prediction errors were compared to determine the value, if any, of using network distance. In each case three semivariogram equations – gaussian, spherical, and exponential – and three kernel equations – Gaussian, bi-squared and rank-exponential – were tried. As a point of

comparison, error statistics were calculated for an aspatial FGLS approach (reflecting heteroskedasticity in count volume residuals but ignoring spatial relationships and correlation in error terms across count sites).

The error measurements were also considered for choice of optimal program settings for several items: (1) the GWR nearest-neighbors specifications, (2) the distance inputs to kriging (i.e., the full set versus the set limited to 25 miles, as discussed in section 3.1.3), and (3) choice of accessibility index parameters. Each combination of settings for each model was run to isolate the individual effects, and then select the best specifications (by minimizing error/maximizing fit statistics).

3.3 Software

The following software packages were used in the processing of the data: TransCAD, ArcGIS, MATLAB and Stata. TransCAD's multiple paths function calculated all network distances and Euclidean distances were calculated by great circle distance equation in MATLAB. Analysis and overlaying of spatial data was done in ArcGIS and TransCAD. The model was coded in MATLAB's m language and run on the MATLAB platform. All these equations were coded into MATLAB software, and the run times were 2 minutes for kriging and 9 seconds for GWR for the largest data subset described here (i.e. the urban set, with 4,979 known-count locations and 1,281 prediction locations).

MATLAB provides an environment in which models can be coded quickly with the help of built-in functions. There is a cost associated with this, in terms of computing overhead and a convenient, but generic memory management. Additionally, the nonlinear optimization tool available in the standard package was found to have convergence problems when estimating the semivariogram parameters, θ. This issue was oddly inconsistent, as cases cropped up of models which did not have convergence while nearly-identical models – with slightly varied accessibility parameters – would complete the estimation. Failures in convergence resulted in absurd (absolute percentage) errors – anywhere from twice the normal values to many orders of magnitude higher. Limiting the upper bounds of the θ parameters enabled the optimizer to work properly for kriging, giving values similar to those of related models.

The MATLAB program for the kriging model had the following structure:

batchmain – Runs a loop of *main*, inputting each subset of data and model parameters.

main – Runs the kriging model, calling *BCtrans, calcVarMat, CressieHawks, fitvario, invBCtrans,* and *variogram.*

calcVarMat – Calculates the differences in variances for the empirical semivariogram.

CressieHawks – Uses the Cressie-Hawks equation to estimate the empirical semivariogram.

fitvario – estimates optimal parameters for the theoretical semivariogram.

variogram – Calculates the semivariogram for a set of distances between points.

mainGWR – Runs the GWR model, calling *BCtrans, invBCtrans,* and *makeWind*.

makeWind – Calculates the weight matrix by the specified kernel for a set of distances between points.

batchGWR – Runs a loop of *mainGWR*, inputting each subset of data and model parameters.

BCtrans – Transforms AADT using the Box-Cox method.

invBCtrans – Reverses the Box-Cox transform back to AADT.

Proprocessing was executed in the following functions:

preProcDist - Prepares .mat file of network distance data from a subset for the kriging or GWR program.

preProcDistEuc - Prepares .mat file of Euclidean distance data from a subset for the kriging or GWR program.

preProcData – Prepares .mat file of explanatory data from a subset for the kriging or GWR program.

Preprocbatch – Runs of *preProcData* and/or *preProcDist* for all subsets.

countNeighbors – Collects statistics for number of nearby neighbors at each location.

These programs include all the work described in this section. They were run repeatedly for a large set of inputs. Their results are shown and discussed in the following chapter.

Chapter 4: Results

Testing all combinations of parameters showed some trends in the model's performance. These trends held true in most of the data subsets. In some cases the results varied little across the semivariogram, kernel, or accessibility index choice. This chapter presents the parameter estimates and prediction errors for the tests. In addition to discussing the primary objectives of comparing GWR to kriging predictions, and the value of network distances versus Euclidean distances, the model compositions are broken down and analyzed.

4.1 Kriging

The kriging model uses a single regression for all the locations in a data set. The estimation is done iteratively with the semivariogram, such that the β's are estimated with the correlation of errors by spatial function considered. Table 4.1 shows the values estimated for the β coefficients applicable to each data subset. Values are missing for cases in which road types were not used in the data subset. Overall, the variables of road type, speed limit, and number of lanes were most important to the prediction of AADT values (based on their relatively high elasticities).

	Constant		Rural Interstate		Rural Major Road		Urban Interstate		Urban Principal Arterial	
Data Subset	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Houston No IS	6.06	13.56	-		2.08	13.18	-		3.56	9.48
Houston	6.35	14.28	7.3	18.49	2.08	13.13	4.86	9.99	3.7	10.17
Austin	0.97	0.85	3.1	2.70	0.31	0.96	4.66	9.45	2.94	6.44
Interstates	33.33	24.68	-1.14	-5.71	-		-		-	
Minor Roads	7.27	14.77	-		-		-		-	
Urban Roads	13.31	50.96	-		-		5.83	31.23	3.79	21.09

	Speed Limit (mph)		Lanes (number)		Jobs / Sq Mile		Population Accessibility	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Houston No IS	0.0297	4.32	1.63	27.16	1.09E-3	0.89	6.23E-06	29.04
Houston	0.0285	4.13	1.52	26.10	3.15E-4	0.28	6.22E-06	29.58
Austin	0.0372	2.56	1.73	12.42	1.01E-2	0.66	2.78E-05	12.29
Interstates	-0.1753	-9.31	0.56	10.57	6.07E-4	0.33	5.48E-06	21.89
Minor Roads	-0.0054	-0.66	1.65	20.37	2.85E-2	3.83	5.29E-06	21.07
Urban Roads	0.0068	1.45	1.16	29.64	-1.05E-3	-0.90	4.12E-06	31.34

Table 4.1: β values and t-stats for kriging model

Removing the Interstates from the Houston subset did very little to change prediction performance. In this case, the Interstate variables were removed, and the impacts of others rose or fell. The traffic prediction became more sensitive to the population accessibility variable, as well as to the number of lanes and speed limit. While the Interstates may have had high flow volumes regardless of population accessibility and speed limit, leaving them out lets the model pick up more of the effects on varied, lower-flow roads, whose traffic counts are more location dependent.

Interestingly, the Urban Interstate indicator in the Houston region data set has a lower coefficient than the the Rural Interstate term, perhaps due to greater night-time use of

rural interstates. This ordering of coefficients is not evident in the other models, which include both Interstates, the Interstates subset, and the Austin region's count stations. Higher population accessibility, employment density and numbers of lanes in urban contexts offset the lower coefficient value, resulting in higher overall count predictions for urban locations, on average. The other coefficients on road types are more intuitive, with urban principal arterials having higher count predictions than rural major roads, ceteris paribus, but both types ranking lower than either Interstate class.

The counts were increasing with speed limit except in Interstates and minor roads. The elasticities for the regional sets, in table 4.2, show the counts (transformed) vary substantially with speed limit. The higher speed roads in the Austin region, Houston region and urban subsets would be expected to have higher volumes because this would pick up the larger roads in the cities. The opposite is true for minor roads and Interstates. Interstates vary little in speed and allow the highest speeds in long stretches with fewer exits, not in dense areas. The elasticity for this set is, as a result of the small variation, deceptively high. This small variation results in an absolute value that is, at 0.175, much higher than that for the other subsets. Minor roads vary in speed, but it is those in the most open areas with low traffic, that allow higher speeds. Speed limits have less impact on the counts in the urban and minor sets.

	Speed	Lanes	Employ-ment Density	Access-ibility	Rural Interstate	Rural Major Road	Urban Interstate	Urban Principal Arterial
Houston No IS	9.36%	25.43%	0.11%	1.15%	-	6.73%		0.98%
Houston	8.78%	24.11%	0.03%	1.25%	0.52%	6.30%	0.69%	0.95%
Austin	9.78%	27.82%	0.42%	7.78%	0.12%	0.80%	1.32%	1.03%
Interstates	-44.17%	10.60%	0.06%	1.60%	-2.13%	-	-	-
Minor Roads	-1.77%	28.59%	1.35%	1.15%	-	-	-	-
Urban Roads	1.60%	20.65%	-0.10%	1.37%	-	-	2.29%	1.79%

Table 4.2: β elasticities for kriging model (% change in **transformed** counts / % change in variable)

The number of lanes has a positive coefficient indicating that the traffic count should be greater on roads with more lanes, ceterus paribus. Adding a lane makes a big difference in the traffic counts across all data sets. This clearly a strong and very important indicator for the model. The lower, though still high, elasticity for the interstate subset is a product of its higher average number of lanes as well as their lower marginal impact.

Minor roads is the only subset for which the β on employment density does not fail the t-test. (reject null hypothesis that $\beta_{Minor,emp}=0$) This is likely a result of the coarseness of the density – measured by county. For the minor roads, it indicates proximity to a city or job center, or lack thereof. The other data sets or mostly limited or oriented around the urban areas, such that this density provides less additional information. It was kept as a variable in all the models for consistency and comparison.

The population accessibility had an impact on the traffic counts and the accuracy of the predictions for each dataset. Because of the range of the index value, the elasticities even

understate the effect it can have on the prediction. It is the Austin dataset, that stands out which a much higher coefficient the than others. Despite being a much smaller area than the Houston dataset, the variance of the indices was higher for the Austin data. This suggests that the traffic is uniquely centered in population clusters in this area.

4.3 GWR

The GWR model produces a set of beta vectors with length equal to the number of predicted locations. The distribution of these coefficients reveal the spatial variations in the covariates' impacts on traffic counts. The GWR model produced predictions which were similar to, but consistently less accurate than those from kriging. These coefficients are expected to be similar to those from kriging, but differences will arise as a product of the methods' objectives. Firstly, drawing out a distribution of estimates at different points weights each point equally while weighted least squares will give higher weight to data points with higher residuals, i.e., outliers.

Table 4.3 shows a typical distribution of all the β's estimated for the unknown locations in the Houston area. For between a quarter and a half of the locations the speed limit has a negative coefficient applied to it. The value in the kriging model, 0.0285, falls above the median and mean values. Number of lanes, a strong indicator in the other model, is strictly positive here and fairly consistent in the region. The employment density's low average and median β suggests that for this model, also, it does not contribute a great deal to this regression.

	Speed	# Lanes	Employment density	Population at 5mi	Population at 25mi
Mean	0.0102	2.01	-0.035	5.15E-05	3.64E-05
Max	0.2085	4.89	2.489	3.31E-04	6.01E-04
75th percentile	0.0470	2.66	0.032	6.35E-05	9.86E-05
Median	0.0088	1.84	-0.005	1.76E-05	2.09E-05
25th percentile	-0.0297	1.26	-0.097	3.38E-06	-8.59E-06
Min	-0.2058	0.57	-4.347	-2.13E-04	-1.04E-03

	Constant	Rural Interstate	Rural Major Roads	Urban Interstate	Urban Principle Arterial
Mean	9.68	6.80	1.14	5.99	3.40
Max	21.17	12.31	6.10	13.25	9.07
75th percentile	13.93	8.90	2.50	7.48	4.77
Median	10.06	6.63	1.05	5.91	3.32
25th percentile	6.07	5.30	-0.30	5.03	2.10
Min	-2.39	-1.27	-3.11	-10.62	-6.13

Table 4.3: Distribution of GWR β estimates – Houston subset

For GWR it was found that two separate sum-to-distance population accessibility indices produced better results than a single gravity index. Having more than one allows complicated spatial relationships of population to play out. There may be rings of influence – highly positive at a certain distance, more negative nearer or further away. The meaning of the 5 mile index coefficient in the GWR model is different from that of a single index. This gives the additional impact of the population, that has already been counted within 25 miles, being within 5 miles. In this data set, the two were positive a majority of the time and the 25 mile index had a generally higher impact on the traffic, based on the coefficients and distribution of variable values. Roughly speaking the impact on the (transformed) traffic counts of people within 5 miles is around double that of someone who lives within 25 miles but not 5 miles. The indicator variables will

usually have positive coefficients as the base case contains all the smallest of road classifications.

In the Interstate set, the values were more consistent across space, despite being distributed all around the state. The trends, in table 4.4 are more clear and agree more closely with those seen in the kriging model. Its speed's coefficient was once again negative reflecting the idea that interstates have reduced speed limits mostly for high flow areas, which tend to be in cities. The number of lanes was again important to the model as was the rural designation.

	Constant	Rural Interstate	Speed	# Lanes	Employment density	Population at 5mi	Population at 25mi
Mean	34.65	-1.03	-0.18	0.58	-0.0003	7.27E-06	4.13E-06
Max	66.97	1.35	0.17	1.31	0.0489	2.50E-05	3.56E-05
75th percentile	40.12	-0.67	-0.09	0.84	0.0055	1.07E-05	7.02E-06
Median	34.90	-1.00	-0.16	0.70	-0.0001	3.94E-06	2.89E-06
25th percentile	27.80	-1.39	-0.25	0.38	-0.0089	3.19E-06	8.92E-07
Min	13.38	-2.69	-0.63	-0.38	-0.0677	-1.04E-06	-1.21E-05

Table 4.4: Distribution of GWR β estimates – Interstate subset

The following sections provide in depth analysis of the model inputs and predictive capabilities of the GWR and kriging models. The specifications used here were determined by cross validation comparisons which are to be discussed.

4.3 Kriging versus GWR

Table 4.5 shows the top performing kriging and GWR models for each of the subsets and distance types. It is immediately clear that kriging is significantly better at prediction in

terms of percentage error in most cases. Only the Austin region had a lower AAPE from GWR. However, for both Houston subsets and Austin data points, GWR achieved the lowest MSE. While percentage errors are normalized by the traffic count for each given point, MSE has an absolute value that is being averaged. This means that overestimating by 2,000 cars at a location with 6,000 cars is weighted the same as doing so at locations with 400 cars by MSE. AAPE would give the former an error of 33% and the latter, 500%. This discrepancy in performance measures suggests that the GWR model is sometimes better at predicting higher values of AADT and kriging is better at lower values.

			Houston Region, No IS	Houston Region	Austin Region	Interstates	Minor Roads	Urban Roads
Kriging	Euclidean	AAPE	63.1%	62.0%	55.8%	13.7%	59.0%	61.0%
		MPE	2.9%	3.9%	-6.5%	-1.1%	0.6%	-2.8%
		MSE	1.4E+11	2.0E+11	4.0E+10	1.7E+10	3.6E+10	5.1E+11
		Semivario.	Spherical	Exponential	Exponential	Exponential*	Exponential	Exponential
	Network	AAPE	62.4%	61.1%	55.9%	14.5%	59.6%	60.5%
		MPE	2.9%	4.1%	-0.3%	0.5%	2.1%	-2.1%
		MSE	1.4E+11	2.0E+11	4.0E+10	1.6E+10	3.3E+10	4.8E+11
		Semivario.	Exponential	Exponential	Exponential	Exponential*	Exponential	Exponential
GWR	Euclidean	AAPE	70.2%	68.6%	51.8%	23.1%	83.5%	65.0%
		MPE	7.8%	7.4%	1.1%	-6.7%	5.0%	0.0%
		MSE	1.0E+11	1.5E+11	2.8E+10	5.4E+10	4.8E+10	4.9E+11
		Kernel	Bi-squared	Bi-squared	Bi-squared	Bi-squared	Bi-squared	Bi-squared
	Network	AAPE	70.1%	68.1%	60.1%	21.4%	75.7%	63.5%
		MPE	8.6%	8.2%	2.4%	-5.2%	5.6%	0.8%
		MSE	1.2E+11	1.6E+11	2.6E+10	4.1E+10	4.5E+10	4.9E+11
		Kernel	Bi-squared	Bi-squared	Bi-squared	Bi-squared	Bi-squared	Bi-squared
FGLS (aspatial)		AAPE	103.6%	103.0%	115.3%	38.4%	114.0%	80.6%
		MPE	8.5%	9.1%	-8.6%	-10.9%	6.8%	-3.4%
		MSE	4.91E+11	4.63E+11	3.59E+11	7.62E+11	1.48E+11	3.25E+12

Table 4.5: Results comparing kriging and GWR preferred models using each distance method to each other and non-spatial regression

* Notes: The interstate (IS) subset is the only set shown that uses a full distance matrix for kriging MSE, MPE, and AAPE are shown in Eqns. 16, 18 and 19, respectively.

Models for prediction of interstate flow values performed relatively well, perhaps as a result of the nearby count locations being on the same route and due to greater homogeneity (of high volume settings) for this special class or highway. With the lowest number of nearby count locations and a steep semivariogram function, the interstate count estimates were influenced in kriging by counts of only the nearest 7 (on average)

count sites (compared to roughly 30 or more nearby sites for other data sets analyzed here).

Both GWR and kriging produce some bias, as shown in the MPE. While GWR equations tend to underestimate the high traffic volumes found on interstate highways, they tend to overestimate those of smaller roads, as found in the other data subsets. Kriging does not exhibit a consistent bias in terms of over- or underestimation of traffic counts, but maintains lower bias with only one case above 4.1% among the six data sets. GWR on the other hand, has several MPE values over 5%.

While each model's percentage errors in prediction on the hold-out samples are significant, they offer a dramatic improvement over the non-spatial FGLS technique, averaging between 20 and 63 percentage points lower AAPE. The greatest improvement from kriging application was seen in the Austin data set, as well as those with lower traffic counts in general (e.g., minor roads). Figure 4.1 shows that the cumulative distributions of absolute percentage errors for the models follow the same overall trend. For the Houston region, kriging has fewer data points (i.e., a slightly lower density of hold-out-sample locations) with absolute percentage errors above 100%, while GWR has a small tail that extends further. Kriging with the network distances is the nominal leader, but the four stay close together throughout. Half of the predicted locations have errors of at least 55%.

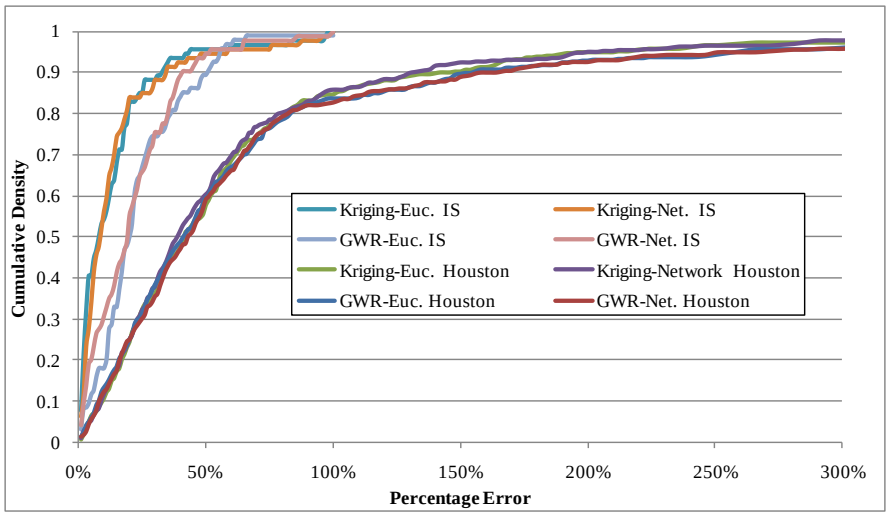

Figure 4.1: Cumulative distribution of absolute percentage errors for Houston and Interstate (IS) subsets

Compared to Houston and others, the Interstate subset had a much lower distribution of AAPE, that varied more between GWR and kriging. Over 90% of the interstate locations enjoy absolute percentage errors under 35% when using the kriging model; that number is under 80% when using GWR methods. Outcomes of the other subsets, however, resembled Houston's results, rather than the steep CDF of the interstates. The difference between the Euclidean and network distance types was not very significant in any of these cases, suggesting that Euclidean distances, which are far easier to compute, can be recommended for data situations of the type analyzed here (i.e, traffic counts with average spacing of several miles).

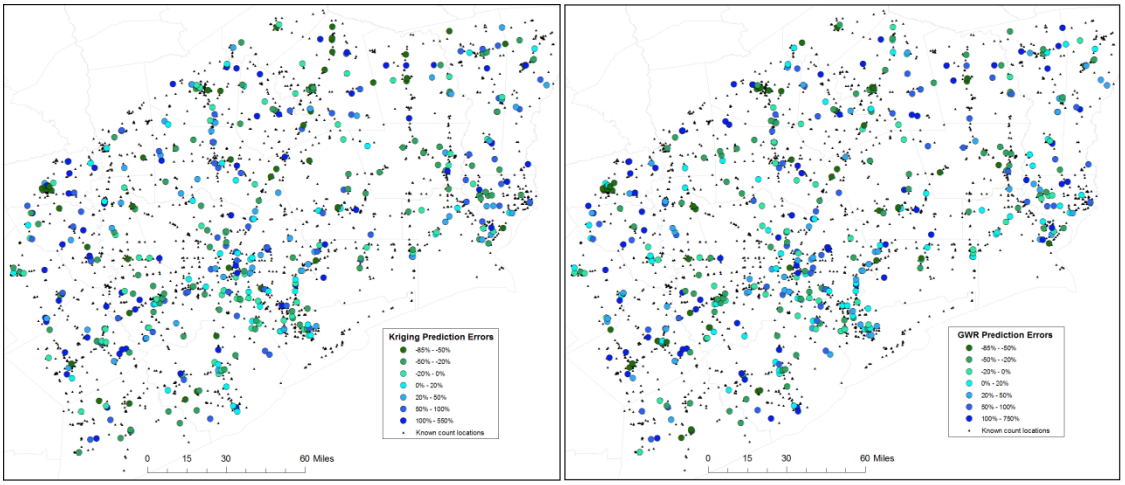

Figure 4.2: Maps of errors in Houston region from kriging and GWR

In general, the results reveal only small differences in the predictions. Figure 4.3 further emphasizes the similarities between the two models despite being based on different mathematical formulations. The three graphs are identically scaled and feature the same count locations, all with AADT under 50,000 vehicles per day. There is significant scatter in both graphs of actual versus predicted counts; however, the third graph, which compares the predicted values to each other, has less scatter. This suggests that GWR and kriging are more correlated in their estimates than with the original data. This makes sense when considering that the data and primary/core regression equations used were identical under both settings.

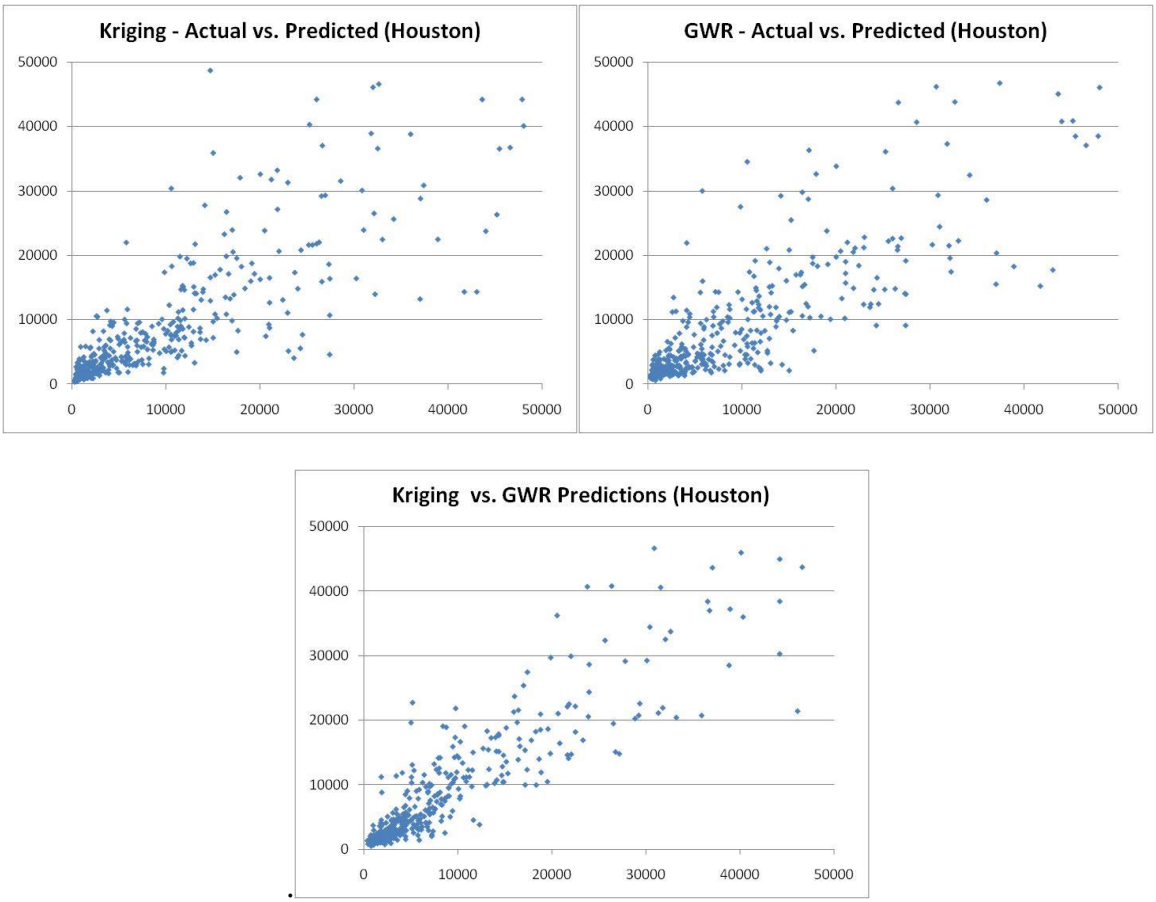

Figure 4.3: Comparing predictions from GWR and kriging against the actual values

It was also expected that locations with fewer close neighbors, or longer distances in the kernel, will have higher errors. Because kriging and GWR use information from their neighborhood, it should follow that having information from fewer neighbors will reduce their accuracy. On the other hand, the points with fewer measured neighbors tend to lie in areas with lower population and road densities, so the relevant influence may be more far flung. The estimated semivariograms, which depict the covariance trends as a function of distance, are shown later in this chapter, in Figure 4.5.

Figure 4.4 shows the average (absolute percentage) errors by distance band, suggesting a vague trend of higher errors for sparser areas. It is more pronounced in the GWR case.

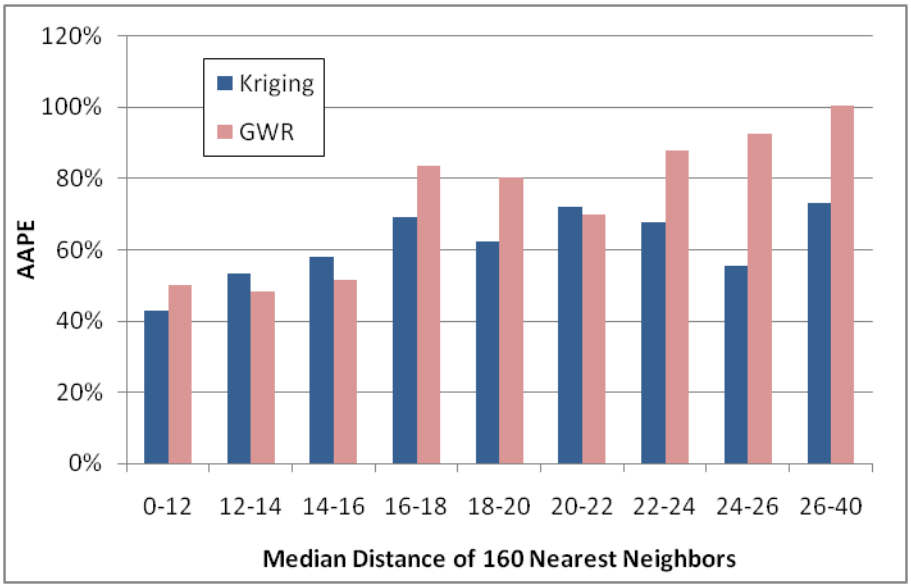

Figure 4.4: Average errors by nearest neighbor median distance band (Houston Region)

4.4 Use of Network Distances Versus Euclidean Distances

As described above, the results illuminate no clear or pronounced distinctions between the use of network and Euclidean distances in the spatial models' specifications. Table 4.6's more in-depth illustration of their relative performances in kriging again suggests no noticeable trend. It can be said that the results within each subset are consistent, in the sense that either network or Euclidean distances produced lower error for all semivariograms. And the differences are not large enough to make any strong conclusions.

			Houston Region, No IS	Houston Region	Austin Region	Interstates	Minor Roads	Urban Roads
Spherical	Euclidean	AAPE	64%	62%	56%	24%	60%	62%
		MPE	5%	5%	-7%	-9%	0%	-2%
		MSE	1.9E+11	2.4E+11	4.0E+10	4.0E+10	4.0E+10	5.0E+11
	Network	AAPE	63%	62%	57%	24%	62%	62%
		MPE	3%	2%	-1%	-9%	2%	-2%
		MSE	2.0E+11	2.4E+11	4.0E+10	4.1E+10	3.7E+10	4.7E+11
Exponential	Euclidean	AAPE	63%	62%	55%	14%	59%	61%
		MPE	3%	4%	-1%	-1%	1%	-3%
		MSE	1.4E+11	2.0E+11	3.9E+10	1.7E+10	3.6E+10	5.1E+11
	Network	AAPE	62%	61%	56%	15%	60%	61%
		MPE	3%	4%	0%	0%	2%	-2%
		MSE	1.4E+11	2.0E+11	4.0E+10	1.6E+10	3.3E+10	4.8E+11
Gaussian	Euclidean	AAPE	64%	63%	56%	-	61%	64%
		MPE	1%	2%	-1%	-	1%	-2%
		MSE	2.0E+11	2.5E+11	4.1E+10	-	4.2E+10	5.0E+11
	Network	AAPE	64%	62%	57%	-	63%	63%
		MPE	2%	4%	-1%	-	3%	-2%
		MSE	1.9E+11	2.5E+11	4.0E+10	-	3.8E+10	4.9E+11

Table 4.6: Network and Euclidean results for all semivariograms (kriging model)

Comparisons of the two distance metrics in the GWR setting have similarly ambiguous outcomes, as shown in table 4.7. In fact, there is no pattern which associates better error values with network or Euclidean distances. That is, finding a lower error using network distances with the exponential semivariogram for Houston, does not suggest that network distances will be best for the other semivariograms or subsets. At first glance, there is one data subset in which one distance type stands out: the minor roads subset. For this set, the AAPE is 6 to 7% lower for Euclidean distance use, and the MPE is similar to MPE values for other models shown. The MSE, however, tells the opposite story, with each model having lower squared errors in network distance. Therefore, the errors, location-by-location are generally lower when using the Euclidean distances, but there are enough

dramatically positive errors that amplify the overall sum of squared errors. Consequently, the final choice of distance metric appears to rest with the modeler's preference and prediction needs – as well as data context, since other settings may offer different results. It should be noted that the tests for the minor roads showed an uncommon dependence on the choice of accessibility index. (Full analysis and discussion of accessibility indices can be found at the end of this chapter.)

			Houston Region, No IS	Houston Region	Austin Region	Interstates	Minor Roads	Urban Roads
Gaussian	Euclidean	AAPE	74%	72%	59%	26%	78%	67%
		MPE	6%	6%	-4%	-6%	6%	-2%
		MSE	8.0E+10	1.7E+11	3.5E+10	6.9E+10	5.3E+10	4.7E+11
	Network	AAPE	75%	74%	59%	26%	85%	65%
		MPE	7%	7%	-1%	-5%	7%	-1%
		MSE	9.4E+10	1.8E+11	3.2E+10	5.3E+10	5.0E+10	4.5E+11
Bi-squared	Euclidean	AAPE	70%	69%	52%	23%	73%	65%
		MPE	8%	7%	1%	-7%	2%	0%
		MSE	1.0E+11	1.5E+11	2.8E+10	5.4E+10	4.6E+10	4.9E+11
	Network	AAPE	72%	70%	52%	22%	79%	63%
		MPE	9%	8%	2%	-5%	6%	1%
		MSE	1.2E+11	1.6E+11	2.6E+10	4.1E+10	4.5E+10	4.9E+11
Rank-exponential	Euclidean	AAPE	76%	74%	63%	27%	79%	67%
		MPE	9%	9%	-1%	-7%	6%	-2%
		MSE	7.7E+10	1.8E+11	3.6E+10	7.8E+10	5.7E+10	4.7E+11
	Network	AAPE	77%	75%	64%	26%	86%	66%
		MPE	8%	8%	-1%	-7%	5%	-1%
		MSE	8.8E+10	1.9E+11	3.3E+10	5.9E+10	5.2E+10	4.6E+11

Table 4.7: Network and Euclidean results for all kernels (GWR model)

4.5 Performance of Semivariogram Types

The theoretical semivariogram is a smooth function to which the estimated covariances are fit as closely as possible. The choice of which to apply in the kriging model can be based on a modeler's preference and/or empirical results, but the function choice itself

may not always be crucial. Table 4.8 shows the estimation results for all three models using both distance measures. The nugget, sill and range parameters play similar roles in each of the equations, but it is important to remember that they cannot be compared directly. Though the improvements are small, it is clear that the exponential function performed best and the Gaussian worst, in terms of MSE and AAPE. This also holds true for Table 4.8's error results, including for the data subsets not listed.

		Semivariogram function	Parameters			Performance of model using these specifications	
			Nugget, c_0	Sill, c_e	Range, a_s	MSE	AAPE
Houston Region	Network Distance	Spherical	4.51	4.64	11.73	2.0E+11	63.5%
		Exponential	3.83	5.57	4.88	1.4E+11	62.4%
		Gaussian	5.19	3.98	5.77	1.9E+11	63.9%
	Euclidean Distance	Spherical	4.19	4.73	12.05	1.9E+11	63.5%
		Exponential	3.49	5.67	4.93	1.4E+11	63.1%
		Gaussian	4.85	4.06	5.89	2.0E+11	64.0%
Minor Roads	Network Distance	Spherical	5.34	5.79	16.67	3.7E+10	61.7%
		Exponential	4.47	7.12	7.00	3.3E+10	59.6%
		Gaussian	6.05	5.05	7.87	3.8E+10	62.6%
	Euclidean Distance	Spherical	5.09	6.10	17.33	4.0E+10	60.0%
		Exponential	4.05	7.56	6.91	3.6E+10	59.0%
		Gaussian	5.80	5.34	8.03	4.2E+10	61.0%

Table 4.8: Semivariogram parameter estimates for Houston region and minor roads data subsets (with limited distance set)

The upper portion of Figure 4.4 shows how the estimated, parameterized semivariogram functions compare to each other across the two distance metrics used, in the Houston data subset. The functions flatten at different points relative to their ranges, a_s, such that they follow a similar curve (despite a factor-of-two difference in their range estimates). Though the semivariograms from the exponential and Gaussian specifications are close,

the exponential consistently outperformed the Gaussian in terms of average error values. Figure 4.5's upper graphs show great variety in the semivariograms of different subsets. The interstates' semivariograms, when using all inter-site distances, vary the least and exhibit the lowest rise in variance over distance. The urban-data subset was closest to this pattern, while minor roads was furthest, with all the regional sets falling somewhere in between. Removing the interstate highways from the Houston data set had little effect here.

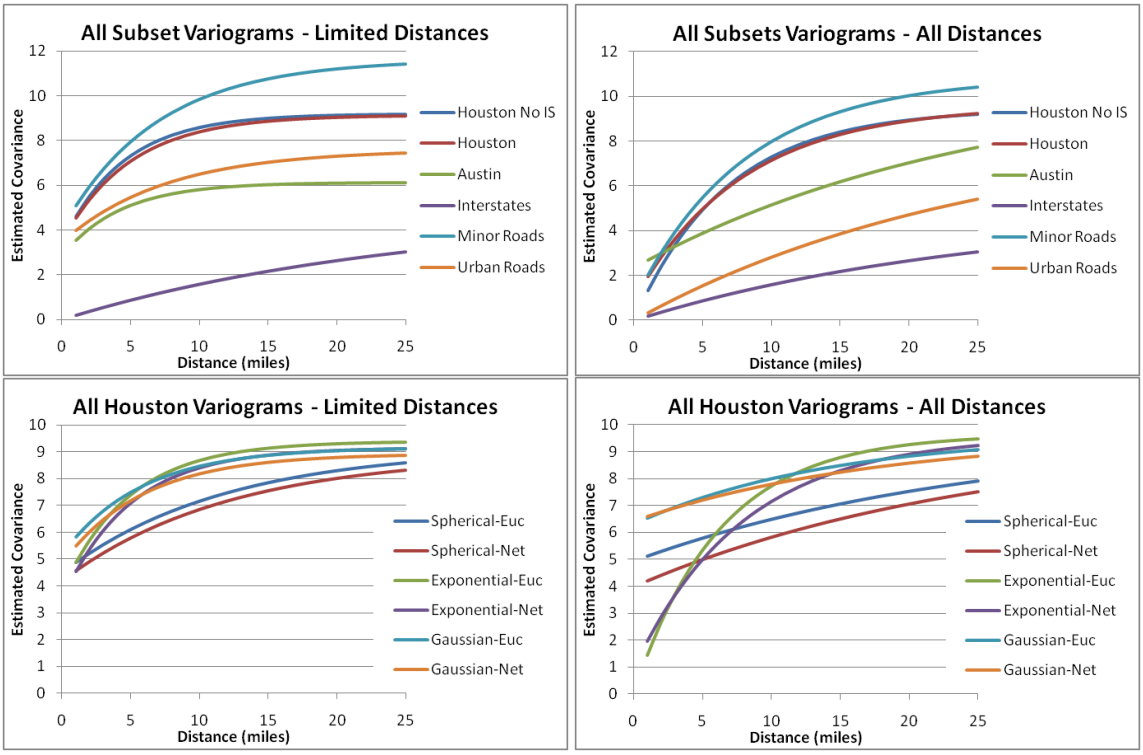

Figure 4.5: Estimated semivariogram functions for all data subsets (top) and Houston models (bottom), with a limited set of distances (left) and a full set of distances (right)

4.6 Using Cutoff Distance in Kriging

Cutting off the distances at 25 miles was initially done to reduce computing times when creating the distance matrices in preprocessing and to reduce the memory load. 25 miles was chosen because it was thought to be long enough to include all relevant associations and correlations in unobserved factors. The full distance set was reintroduced to ensure a fair comparison to GWR results, which required more than 25 miles of neighboring points to have enough data for local regressions. Not surprisingly, the interstate set, which had the longest distances between points, significantly benefited from the full-distance set. Across the other sets, there were only slight improvements or, in a few cases, a worsening of prediction accuracy. And the MATLAB program had difficulty optimizing the Gaussian semivariogram with the full distance set.

4.7 Performance of Kernel Types in GWR Models

As discussed earlier, adaptive-bandwidth kernels, which rely on a specified number of neighbors, were used here in the GWR models. Testing was performed to find the preferred weighting function and number of nearest neighbors. Initially, 150 through 300 neighbors were considered in intervals of 5. It quickly became apparent that smaller neighbor groups performed better. The minimum, however, was increased to 160 because a few locations' regressions were becoming unstabledue to loss of identity. Essentially, at around 130 to 140 points, most of the data subsets reached minima in AAPE, but some locations exhibited very high errors, so the 160-point cutoff was used. Table 4.9's values give one a sense of the differences.

		Kernel function	160 Neighbors		255 Neighbors		350 Neighbors	
			AAPE	MSE	AAPE	MSE	AAPE	MSE
Houston Region	Network Distance	Gaussian	72%	1.7E+11	73%	1.7E+11	75%	1.7E+11
		Bi-squared	68%	1.5E+11	70%	1.5E+11	73%	1.6E+11
		Rank-exp.	72%	1.8E+11	74%	1.7E+11	77%	1.8E+11
	Euclidean Distance	Gaussian	69%	1.7E+11	72%	1.7E+11	74%	1.8E+11
		Bi-squared	66%	1.5E+11	69%	1.5E+11	71%	1.6E+11
		Rank-exp.	70%	1.8E+11	73%	1.7E+11	75%	1.9E+11
Minor Roads	Network Distance	Gaussian	80%	5.4E+10	82%	6.0E+10	86%	6.2E+10
		Bi-squared	76%	4.6E+10	79%	5.1E+10	80%	5.5E+10
		Rank-exp.	82%	5.8E+10	83%	6.5E+10	87%	6.5E+10
	Euclidean Distance	Gaussian	78%	5.3E+10	80%	6.0E+10	84%	6.3E+10
		Bi-squared	73%	4.6E+10	76%	5.1E+10	79%	5.4E+10
		Rank-exp.	79%	5.6E+10	81%	6.4E+10	86%	6.6E+10

Table 4.9: Results of different kernels and numbers of neighbors for Houston region and minor roads data sets (Highlighted are the bottom two in terms of errors for each subset.)

In all tests, the bi-squared equations produced the best results, offering an edge of 3% or more in AAPE and at least marginally lower MSE. Table 4.9 also shows only, but this bi-squared superiority trend was seen in every subset. In all cases shown here and most others, use of the best kernel specification was more important than choice of the distance metric used. As evident in Table 4.9, for each specification tested the lowest two values were from the bi-squared kernel. The bi-squared curve falls much more sharply over distance than the Gaussian curve. This suggests that the data points just half the bandwidth away from the prediction location will have half the influence of those very close. The optimal number of neighbors was equally clear and only bounded by regression limitations. The lowest practical value was chosen: 160. Except when otherwise specified, the GWR results described below are those from a bi-squared kernel with 160 nearest neighbors.

The neighborhoods of the GWR regressions are a function of the number of points (160 in this case), the location of the focal data point, and the data subset. Table 4.10 contains the average of the mean, median and maximum distances between each prediction location and its 160 nearest neighbors. The interstate subset has by far the largest neighborhoods with points well over 100 miles away used in the local regressions. The regional subsets saw the lowest distances, since all of their points were concentrated in one place.

	Network			***Euclidean***		
	Mean	Median	Max	Mean	Median	Max
Houston No IS	17 mi	18	27	13	14	21
Houston	16	17	26	13	14	21
Austin	15	16	24	13	13	19
Interstates	88	88	150	76	77	127
Minor	22	24	35	18	20	29
Urban	31	30	55	26	26	48

Table 4.10: Average distance values (in miles) to nearest 160 locations

4.8 Selection of an Accessibility Index

Initial tests indicated that population within a given distance serves as a better predictor of traffic counts than distance to a given population. Thus, only population within a given distance was controlled for in the various count models (both GWR and kriging specifications). In addition to single sums of population, a distance-weighted sum of population and combinations of two population indices were tried. This resulted in 30 potential accessibility indices plus another 5 combinations of such indices.

Across the kriging model contexts, the AAPE varied by less than 5% when controlling for each of various index types, in any given model context. No specific index performed best for all data sets, but those which included jobs and/or population at further distances tended to provide better predictions. Two accessibility indices were ultimately chosen: one for use with the kriging distances cutoff at 25 miles and another for use with the full kriging distances. The index for the former was a weighted sum with bandwidth of 50 miles and $\alpha = 0.5$. The latter had a bandwidth of 25 miles and $\alpha = 0.1$.

The GWR model results depended more heavily on the choice of accessibility index. Table 4.11 shows the validation of 27 or the 35 indices for the minor roads subset using network distances. (Full results for all model specifications can be found in the appendix 2) This subset had a much higher range than usual for errors across indices. Clearly, in this case, the mid-range index-limiting distances offered better predictive capabilities than the low and high distances. The combination of populations indices within 5 and 25 miles was chosen for all network distance GWR models due to these indices' strong performance.

To Dist	*AAPE*	*MSE*
1 mi.	90%	5.42E+10
2	86%	5.23E+10
5	80%	4.82E+10
10	77%	4.87E+10
25	90%	4.72E+10
50	88%	5.02E+10
2 & 10	75%	5.00E+10
2 & 25	84%	4.86E+10
5 & 10	76%	4.60E+10
5 & 25	**79%**	**4.46E+10**
5 & 50	78%	4.64E+10

dist,a	*AAPE*	*MSE*	*dist,a*	*AAPE*	*MSE*
5 mi, 1	90%	4.97E+10	25, 1	89%	4.96E+10
5, 0.5	84%	4.83E+10	25, 0.5	84%	4.75E+10
5, 0.25	81%	4.81E+10	25, 0.25	88%	4.70E+10
5, 0.1	80%	4.81E+10	25, 0.1	90%	4.72E+10
10, 1	89%	4.91E+10	50, 1	89%	4.96E+10
10, 0.5	79%	4.84E+10	50, 0.5	86%	4.98E+10
10, 0.25	77%	4.84E+10	50, 0.25	89%	4.99E+10
10, 0.1	77%	4.86E+10	50, 0.1	89%	4.99E+10
Distance-Weighted: $AI_i = \sum_j p_j \cdot dist_{ij}^{-\alpha}$					

Table 4.11: Comparison of accessibility indices for minor roads subset in the GWR model using network distances

Note: The chosen model chosen is shown in bold.

4.9 Issues with Non-Euclidean Distances in Kriging

One final issue deserving attention relates to the covariance matrices used here. When non-Euclidean distances are used in kriging, the covariance matrix may not be positive semi-definite (PSD), a condition necessary for mode validity (Curriero, 2006). To test for PSD, eigenvalues were calculated for each estimate covariance matrix. Within the same subset, semivariogram and distance type, there were, in some cases, a mix of PSD and non-PSD covariance matrices. For example, the Austin subset in a model with Gaussian semivariogram and network distances had a PSD estimated covariance matrix when certain accessibility indices were used. These small changes affected the optimization of the semivariogram parameters. It is unclear what is an effect of errors in optimization and what is the effect of being non-PSD is. Since the Euclidean-distance methods used here perform nearly as well as their network-distance counterparts (and are far easier to estimate in practice), it seems wise to simply use Euclidean distances.

Chapter 5: Conclusions

The first part of this two-part thesis has shown that universal kriging and GWR methods can provide more accurate traffic count estimates than aspatial regression techniques, across a variety of road types and data contexts in Texas. Moreover, the simpler, Euclidean-distance-based relationships proved just as predictive as the network-based metrics in both the kriging and GWR cases, suggesting that the latter's complexity is not warranted in such applications.

Universal kriging methods reduce count-prediction error by controlling for local attributes and recognizing distance-based correlation structures that exploit information found in nearby residuals. In contrast, GWR techniques limit observation windows to the area around each data point's location. Harnessing the spatial structure with GWR and kriging resulted in average absolute error reductions between 16% and 63% and at least 50% reductions in MSE over aspatial (FGLS) regression, depending on the data set and model specification used. Both the spatial and aspatial methods examined here offered lower misprediction in the Austin and Interstate data sets. Errors tended to be lower at locations with higher counts (i.e., higher traffic flows) and more nearby count locations, though the urban set, which was above average for both, offered substantial count variation and thus was among the highest in overall errors.

It is interesting to find that network distances offer little improvement to the various models' predictive performance over controls for Euclidean distances. This was the case

for every subset of data tested in both kriging and GWR settings. The only exception came in the Austin subset with GWR, in which Euclidean distances performed much better. It is possible that using either of these modeling approaches with a more densely located set of count sites the model would benefit more from network distance information (especially when sites are upstream and downstream of the site in question, on the same road facility). Results may be context specific. Given the number of links and sites of interest in large networks, like the ones used here, calculation of shortest-path distances appears unwarranted (especially since it can be very computationally intensive and requires additional information on network structures).

Though each model has its strengths and limitations, in terms of performance, kriging clearly offered better overall predictions of AADT than did GWR methods. On average the AAPE were 7 points lower. Though in some cases the MSE of each were close, suggesting a few high values in kriging; in other cases kriging's MSE was clearly lower. It seems the traffic counts follow a global regression trend with spatially correlated errors more so than local spatially weighted regression trends. This result follows the idea that more calibration information, even from locations across Texas, is useful for prediction. Nearby data has additional importance, but should not be relied on exclusively.

Limitations with kriging involve the optimization of the semivariogram, particularly in MATLAB, and the need for a PSD covariance matrix. Additionally, the dataset must be limited in size due to matrix inversion issues. GWR avoids these issues because it only

requires basic WLS estimation and inherently limits the matrix size to the chosen number of nearest neighbors. In fact, the entire dataset could have been used in a GWR setting, without being broken into localized subsets. The two biggest computational limitations of GWR are that a regression must be done for each location and spatial fluctuations in regression coefficients can result in unreasonable trends. Though GWR is a viable option, kriging is preferred, when feasible.

The issue with non-PSD covariance matrices makes network distances even less compelling. To combat or work around this problem, some solutions have been suggested, including spatial moving averages (Ver Hoef et al., 2006) and low-rank thin-plate splines (Wang and Ranalli, 2007). Cressie and Johannesson's (2008) "fixed rank kriging" scheme uses scales of spatial dependence to create the covariance matrix, which they show is always positive semi-definite.

As a way of exploiting spatial information (while capitalizing on local attributes), universal kriging is worthy of application in a variety of transportation and other contexts and offers some predictive advantage over GWR in this work. Opportunities to improve upon universal kriging, to better reflect heteroskedasticity in response variability, would be useful. Though the implementation here included the Cressie-Hawkins method and FGLS (as opposed to only OLS), estimation of the covariance matrix, C_{dd}, still requires a constant-variance assumption. Spatial processes and data sets abound in the real world, and more specifications (and data contexts) should be evaluated.

Chapter 6: Introduction

Automobiles dominate the U.S. transportation landscape. Much effort is put into the design of vehicles and the infrastructure they use, directly and peripherally. To understand and anticipate travel patterns, along with emissions, air quality, energy use, and gas-tax revenues, transportation engineers and planners model vehicle ownership and use decisions. This section of the thesis tackles the simulation of vehicle purchase and re-sale decisions via an auction process among individual households in the market for vehicles (new and used).

An appreciation of the near- and long-term effects of demographic, economic and policy changes on vehicle fleet composition allows for better decision making. For example, the adoption of plug-in electric vehicles (PEVs) is expected to result in reduced petroleum consumption, an increase in electric-power consumption, and a decline in gas tax revenues. Vehicle purchase rebates and scrappage subsidies can induce a more rapid fleet turnover, toward more efficient and less emitting vehicles. This thesis evaluates such scenarios.

The most direct way to model ownership is by microsimulating the actions of individual agents. If analysts can identify measurable attributes of consumers and producers that propel the buying, selling, scrappage, and use of cars and trucks, they can predict the choices made at an aggregate or disaggregate level. Several researchers have attempted to do this for personal vehicles via models of varying complexity and scope (e.g., Musti

and Kockelman, 2009, Mohammadian and Miller, 2003, and Berkovec, 1985). This work focuses on the choices made when households are offered the option to buy new or used personal vehicles, and the market clearing achieved by auction-driven price fluctuations. Previous works have either overlooked the used-vehicle market completely or have depended on some exogenously-provided function for price changes due to vehicle aging. This paper makes explicit the role of user preferences in vehicle price fluctuations through a market auction process, without strong assumptions about supply and demand. The model framework is applied with 5,000 U.S. households to illuminate inputs needed and predictive results for simulation of household-fleet evolution.

Chapter 7: Literature Review

A number of researchers have sought to model automobile markets. The frameworks depend on analyst purpose as well as available data and computing power. At the core of most model specifications is a utility maximization function to simulate consumer transactions. This can be a standard logit choice function which stochastically chooses an alternative based on a set of probabilities. Alternatively, it can be triggered by random benefits exceed a burden: Mohammadian and Miller (2003, p. 99) sum up their transaction model: "from a utility-maximizing perspective, when the household's net utility gain from transacting exceeds a threshold, a transaction is triggered". The following sections of this chapter describe the previous market simulations of this tradition, as well as auction simulations, vehicle depreciation and consumer vehicle preferences, in the context of the models to be applied in this thesis.

7.1 Vehicle Market Simulations

Earlier work by Berkovec (1985) allowed an oligopoly of manufacturers to sell to consumers and consumers to sell to each other or to scrappers. Notably, this included a random repair cost function and a market-clearing requirement in each one-year period. Berkovec and Rust (1985) focused on each household's choice to keep or release a vehicle based on holding duration. These are much simpler than later models but provided useful groundwork, while identifying some important issues in model specification. Berkovec's (1985) model achieved market clearing conditions when the supply from manufacturers and current stock matched the demand by consumers and

scrappers. To achieve this, he used a simple supply-demand function that adjusted price for each of 13 vehicle types, with demand was summed over all consumers. This is the only model found which established market prices. He included devaluation in a vehicle's "expected capital cost", as a function of its current price and the previous model year's current price without consideration of usage or other heterogeneous trends. In Berkovec and Rust (1985) the depreciation is a simple constant (20% per annum), regardless of year or vehicle type.

Musti and Kockelman (2009), Paul et al. (2011), and Mohammadian and Miller (2003) are the best examples of robust, recent models of vehicle ownership and use choices. Musti and Kockelman simulated households in the Austin, Texas region, with demographic and residential attributes evolving over time. There were many levels to their model, including population evolution, vehicle ownership and transaction decisions, and vehicle choice and use decisions. (A final sub-model also projected greenhouse gas emissions, but was not part of their market simulation.) Each year every household had to acquire a (new) vehicle, retire a vehicle, or do nothing. The yearly transaction period ended when this behavioral adjustment process was completed. No market clearing price mechanisms were simulated; exogenous prices were given based on current manufacturer suggested retail prices (MSRPs).

Musti and Kockelman's (2009) transaction model quantified the utility of vehicles owned by each household and available new from manufacturers. Vehicle choice relied on a

multinomial logit (MNL) model initially calibrated using stated-preference survey results, and then adjusted (via the alternative-specific constants), to match the household's actual relatively-new-vehicle acquisitions. The households were heterogeneous in their attributes (socio-economic and geographic) as well as their evolution. While their models simulated vehicle use (among the various fleet-evolution and market-focused models described here), they did not consider devaluation and maintenance at all. Conspicuously missing from their models was the buying and selling of *used* vehicles. Paul et al.'s (2011) fleet-evolution model for the entire U.S. relied on very similar survey questions and methods, but allowed for households to both buy and release (i.e., "replace") a vehicle in any given year (rather than waiting a year to replace a released vehicle). Paul et al. also tested the fleet effects of many more scenarios (for gas price and vehicle price variations, feebate policies, and the like).

Mohammadian and Miller (2003) undertook a similar, MNL-driven simulation with fewer sub-models, but included an option to both release and acquire a vehicle. Used-vehicles released by households in their model essentially vanished, and buyers could choose any model year they wanted, with prices given by exogenous market averages. To account for changes in utility as a result of evolving household attributes, the transaction model controlled for up/down changes in household size and number of workers (as opposed to these attributes' absolute numbers), but lacked home-neighborhood, age and gender information. Mohammadian and Miller's choice model strongly depended on previous vehicle types and transaction decisions. Interestingly,

they found that unobserved preference heterogeneity was not statistically significant after controlling for previous behaviors. This suggests that differences across decision makers may not be practically useful, if information about their current and past vehicle holdings is known.

Mueller and de Haan (2009) constructed a bi-level choice model for new vehicles, randomly presenting consumers a subset of choice alternatives. Notably, it contained a Markov process to carry prior-vehicle-owned attributes (by household) over to new-vehicle choice. Esteban (2007) created a model to investigate the fleet effects of scrappage subsidies. She focused on transaction decisions and found that "a subsidy can induce scrappage even if it pays less for a used car than its without-subsidy price" (2007, p. 26). Since her work focused on national market dynamics, it provides little insight for household-level microsimulation. Emons and Sheldon (2002) gave a very different perspective in their implementation of a "lemons model", focusing only on vehicle attributes, rather than owner attributes. They predicted inspection failures, representative of car quality, based on duration of ownership. No studies in the literature appear to integrate this information with microsimulation of consumer choices.

Berry et al. (1995) presented a method for combined empirical analysis of preference functions, cost functions, aggregate consumer attributes, and product characteristics to derive price estimates, quantities, profits, and consumer welfare. They found their model accurately reproduced actual US markets when changing one parameter at a time,

everything else constant. Though they only used aggregate inputs and output, their approach could be used to feed information to a microsimulation model, like those previously mentioned.

7.2 Auction-Model Microsimulation

Though none of the market models for vehicle choice have used an auction method, such methods have advantages for pricing and vehicle selection. Products are auctioned, as suggested by Cassady (1967), if they have no standard value, such as antiques. Zhou and Kockelman (2011) used auctions to model real estate markets with various agents. If a property received no bids, the price fell by a certain (small) amount; with multiple bids, the price rose (by a similar amount). The bidding ended when each property hit its (pre-set) minimum price, received a single bid, or hit its (pre-set) maximum price (with a winning buyer randomly selected). Properties in high demand from buyers experience price increases and those with little demand see prices fall. At or below a minimum threshold price, sellers can be assumed to keep their property. This may be described as a type of alternating double auction market. (See Sadrieh [1998] and Gibbons [1992] for more on these markets.) Unlike Berkovec's (1985) approach, Zhou and Kockelman's auction did not require aggregate supply and demand equations.

7.3 Vehicle Depreciation, Lifespan, and Holding

Greenspan and Cohen (1999) described an upward trend in vehicle lifespan, with the median age of US personal vehicles just 10 years for 1960 models, and nearly 13 years for 1980 models. DesRosiers (2008) describes heterogeneity in longevity (in Canada)

with over 50% of large pickup trucks from 1989 still registered 19 years later, while only 8.2% of subcompacts remain. He shows that the median age for all Canadian personal vehicle types is at least 14 years, with most over 16 years. The 2001 (US) National Household Travel Survey indicates that the average age of vehicles is 8.2 years. National Highway Traffic Safety Administration (Lu 2006) analysis showed that a typical passenger car would travel a lifetime mileage of 152,137 miles, while light trucks would travel 179,954 miles. In terms of holding durations, Emon and Sheldon (2002) found new US vehicles to be held by a household an average period of four to six years.

7.4 Consumer Preferences and Decision Making

Three-quarters of respondents in Musti and Kockelman's (2009) survey placed fuel economy in their top three criteria for vehicle selection. However, fuel costs were not statistically significant in their model of vehicle choice. Espey and Nair (2005) found the opposite: consumers do accurately value the savings from lower fuel cost. Bhat et al. (2008) suggested that people value fuel cost less than vehicle purchase cost, but with marginal statistical and practical significance. And Greene's (2010) recent survey of the literature reports a continuing lack of consensus on the importance of fuel economy in vehicle choice decisions.

Sallee et al. (2010) examined the prices of cars at wholesale used car auction. This gave them the advantage of having a huge data set with actual price of sale, reliable odometer reading, and make, model and specifications of each car. The caveat is that these prices

reflect dealers' willingness to pay, with the expectation that a consumer could be found to buy the vehicle at a higher price. In place of age, odometer readings were used as the proxy for wear. The prediction price was considered as estimate of value minus maintenance and fuel cost. Assumptions were made to simulate future fuel costs and estimate a discount rate of valuation of future costs or benefits. They concluded that the wholesale prices reflected most or all estimated future fuel costs.

Bhat et al. (2008) undertook one of the most comprehensive vehicle-preference studies based on travel surveys in the San Francisco region. They estimated how vehicle type, size, age and use relate to each owner's socio-economic attributes, as well as neighborhood attributes and the home's general location within the region. Specifically:

- Older people were more likely to have older vehicles, and younger people were more likely to have newer vehicles;
- Households with higher incomes and/or more workers tended to own fewer older vehicles and used less non-motorized transportation;
- Households in higher density, mixed use and urban areas held fewer trucks and vans;
- Households in neighborhoods with bike lanes used more non-motorized transportation;
- Race and gender affected vehicle holdings and use; and

- In general, less expensive, bigger (by luggage and seating capacities), more powerful, and lower emission vehicles were preferred, ceteris paribus.

Mohammadian and Miller (2003) predicted the “do nothing” transaction with much higher likelihood – and accuracy than any other choice. They found that each option related to different variables in the model. For example, an increase in the number of household workers seemed to induce a purchase or trade but not reduce the chance of a disposal. However, an increase or decrease in household size improved the chances of trading and disposing, respectively, while not affecting the chances of a purchase.

This work builds on these market and discrete choice concepts to provide a new method for simulation of an automobile market. It draws on several specifications from Musti and Kockelman’s (2009) fleet simulations, incorporating certain beneficial features of Storchmann's (2004) and Kooreman and Haan's (2006) work. It adds an auction strategy for pricing of used cars not yet available in the literature.

Chapter 8: Model Specification

The model used here includes MNL models to predict each household's vehicle fleet from year to year. The upper level model is a once-a-year market entrance model to simulate a household's decision to modify or maintain its "fleet" of personal vehicles. This level's MNL model evaluates the probability that a household will choose to retire a vehicle, acquire a vehicle, or do nothing. The lower-level MNL predicts which vehicle the purchasing/acquiring households will want, among available new and used vehicles. This vehicle choice model runs many times each year, within an auction model, to re-evaluate choices under different price conditions until equilibrium is reached. To improve the simulation, a hazard function was later added which would allow loss of vehicle which was not selected for sale. (e.g. accident, mechanical failure, etc.). This new simulation is referred to here as the "Modified" model with the previous call "Initial".

The objective of this work was to explore the features of such a framework, demonstrate auction-model feasibility, and examine the results of different context assumptions. The simulation described here was not calibrated as a whole (to match used U.S. vehicle prices, for example) but, rather, constructed from previously estimated models and empirical equations. The following sections describe the behavioral choice and pricing models, along with simulation details.

8.1 Market Entrance and Vehicle Choice Models

The utility model parameters for the market entrance model are based on those from Musti and Kockelman's (2009) transaction model, as given in Table 8.1. The choices are

“acquire”, “dispose” or “do nothing” (which serves as the base case). Because these choice models were calibrated in a different context, a “trade”/swap choice was not available and some parameter values required adjustment (as discussed in the Conclusions and Results sections).

Variable	**Coefficient**	**T-Stat**
Acquire	-1.8314	-7.33
Dispose	-3.7824	-8.96
Number of vehicles in the household x Dispose	0.4077	2.44
Number of workers in a house x Acquire	0.2510	2.31
Female indicator x (Acquire, Dispose)	-0.3303	-1.79
Maximum age of vehicle in household x (Acquire, Dispose)	-0.0955	-4.63
Income of household x Do nothing	-2.25E-06	-1.33
(Number of workers – number of vehicles) xAcquire*	1.5	-
Log Likelihood at Constants	-505.37	
Log Likelihood at Convergence	-448.65	
Pseudo R^2	0.3679	
Number of households	640	

*Variable added to Musti and Kockelman’s model. Not present in “Initial” model.

Table 8.1: MNL parameter estimates for annual vehicle transactions (Source: Musti and Kockelman, 2009)

Musti and Kockelman’s transaction model, in its original form, was not directly adaptable to this new and used vehicle simulation. Because it was not set up to remove vehicles by scrapping within the market, it underperformed in this task. As a result, a hazard function was established, which could remove vehicles from a household without that household choosing to dispose in the transaction model. It was necessary to curb the excessive lifespan of vehicles held by owners who had little chance of choosing the dispose option. With vehicles being retired at reasonable times, the transaction model’s initial specification failed to replace them fast enough, resulting in some zero car households.

The final change was made, at last resort, to add a variable which would greatly increase a household's chances of acquiring a vehicle if there were more workers than vehicles. This reflects the correlation between the number of vehicles and workers. The new model is the "Modified" model.

The hazard function helps to account for accidents or mechanical failure which total the vehicle as well as any other loss of a vehicle. A robust transaction model with data collection crafted for the purpose could account for all cases of vehicle retirement, but the hazard function can also be a reasonable option. The hazard function removes a vehicle with the probability given by the following equation:

$$P_{remove} = 1 - \alpha \cdot exp(0.295 \cdot age - 9.25) \tag{21}$$

where α is a scaling parameter and age is the vehicle's age.

This curve is based on the reported vehicle crash rates observed by the Texas DOT (TxDOT, 2009). When the age is zero, the exponential matches the fatal accidents per year per car – a very small number, $exp(-9.25)$. This increases over time to approach the rate of total crashes reported at 25 years, recognizing that older, less valued vehicles will be totaled with less severe problems. This curve was compared to the vehicle lifespan data in DesRosiers (2008) and NHTSA's (Lu, 2006) reports. The scaling factor was used to make the function more aggressively remove vehicles, particularly those which are around 25 years old and are not expected to stay on the road. Figure 8.1 shows the comparison of the hazard function to the empirical survival curves. The survival rate

in the simulation is a result of a combination of the hazard function and the scrappage in the market.

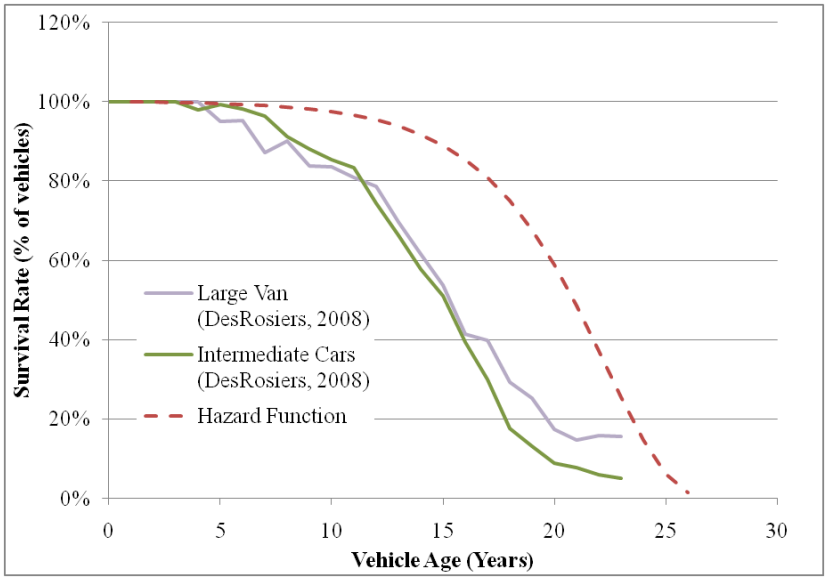

Figure 8.1: The survival rate of the hazard function in the simulation with the empirical survival rates of intermediate cars and large vans give for example comparison

The lower-level MNL vehicle choice model estimates the systematic utility of each vehicle available in the market for each household. The model used here offers nine vehicle choices with distinct body types, fuel costs and prices, representing the range of the most popular vehicles available in the US . Each of these nine vehicle types were offered as new (with set prices and unlimited supply) and competed with any used vehicle put up by sellers. Vehicle and household attributes serve as covariates in the utility expression (Table 8.2).

Variables not related specifically to used vehicles were taken from Musti and Kockelman's (2009) vehicle choice model, as shown in Table 8.2. In addition to these,

four used-vehicle variables were added. Musti and Kockelman's (2009) model did not contain such variables, so these were derived based on other sources (Kooremand and Haan (2006) and Storcheman (2004)), as discussed below.

Variable	**Coefficient**	**t-stat**
Fuel cost	-8.514	-2.83
Purchase price (current) x 10^{-5}	-5.57	-3.94
Age of respondent less than 30 yrs indicator x Midsize car	0.3627	2.28
HHsize greater than 4 indicator x SUV	0.8756	3.41
HHsize x Van	0.2895	4.66
Crossover utility vehicle (CUV)	-0.4148	-2.43
Luxury car	-1.121	-3.51
Suburban x SUV	0.2632	1.32
Urban x Midsize car	0.1864	1.21
Used indicator x (Income class - 3)*	-0.3333	-
Price new x 10^{-5} x Used indicator*	5.57	-
Price new x 10^{-5} x exp(age $\times$ δ)*	-5.23	-
Over 100k miles indicator x Purchase price (current) x 10^{-5}*	-0.2785	-

Note: * denotes variables added to the model of Musti and Kockelman (2009).

Table 8.2: Vehicle choice model parameters

The *Used* indicator x *Income class* level has a coefficient that makes the lowest income groups more likely and the highest income groups very unlikely to choose a used car. The income groups were given from one to twelve with one being the lowest (under $5,000) and twelve being the highest (above $250,000). At the lower income levels this has a value in the utility equation close to the difference between two similar body types, making it slightly more probable that a buyer would switch from his/her optimal body type, to a similar one, if a reasonable used one is available. This was done by design on a purely intuitive basis. At high income levels, a used car would decrease the utility at a value close to that expected between dissimilar body types, making a used car a very unlikely choice for a household making $200,000 or more each year.

The next two variables are based on the price when new (*Price new*) and correspond to loss of vehicle value/utility with vehicle age. This is assumed to be universal to all buyers in the market. The values are based on Storcheman's (2004) price depreciation equation, as discussed later. Thus, the negative utility from vehicle aging should generally match the utility difference that comes with paying the initial auction price versus the new price. They will not exactly cancel, however, because different income groups are assumed to value used vehicles differently, and the market model allows prices to vary, as explained in the next section.

Table 8.2's last variable interacts a 100,000-mile (odometer reading) indicator with current price, to reflect the nonlinear drop in vehicle value associated with this significant usage milestone. The coefficient is such that the loss of utility will be that of 5% of its monetary value, as suggested by Kooreman and Haan (2006).

8.2 Auctioning and Market Pricing

In lieu of neglecting prices or referring to exogenous price functions, the model developed here uses an alternating double auction-based market pricing simulation, similar to that in Zhou and Kockelman (2011) and Sadrieh (1998), for used vehicles' prices. Unlike the transaction and vehicle choice models, the auction structure is not a direct simulation of the actions of buyers or sellers in the automobile market. Clearly, the sale of used vehicles directly or through dealers does not have such a bidding process.

Here, an auction methodology is used to simulate prices and outcomes, based on the preferences of individual buyers and offerings of actual sellers.

The market entrance model selects the (mutually exclusive) buyers and sellers participating in the market each year. The vehicles consist of new vehicles (in unlimited supply, with fixed prices) and those to be sold by households making a sell transaction. The buyers are the households making a buy transaction. The rules are such that all buyers must buy an automobile, and all used vehicles (from sellers) must be bought, returned to the selling household, or scrapped.

The auction cycle alternates between seller bids and buyer bids. Initially, sellers offer their vehicles at an opening bid set at prices (P_0) described below. Buyers bid at that price on vehicles chosen by the vehicle choice model (i.e., those offering maximum net utility, after reflecting initial offer prices). Buyers act independently, and may only bid on a single (new or used) vehicle at each stage. There is no limit on number of bids a vehicle can receive. At the beginning of the second cycle, sellers make price adjustments based on the buyers' bids. The sellers will decrease and increase prices of all used vehicles in zero- and two-plus (buyer-) bidder situations, respectively, by a small increment (assumed to be 1% of the vehicle model's price new – or $200 for a $20,000 MSRP vehicle), while single bid vehicles keep their current price. The vehicle choice model then runs again, and all remaining buyers put in new bids on those vehicles

offering them the greatest (random) utility gain. These cycles continue until all buy decisions have been executed.

If a vehicle's price falls below the scrappage price, it is immediately taken off the market and cannot return. If a vehicle's price reaches its maximum allowed price with more than one bidder, it is given, at that maximum price, to a randomly chosen bidder. A vehicle at maximum price is no longer evaluated by other bidders, but the winning bidder may choose to switch to a different vehicle as prices change. The minimum and maximum prices are set by an arbitrary $[P_0 - 0.15P_0, P_0 + 0.15P_0]$.

For the bidding to end, two conditions must be met: no vehicle may have more than one bidder and no vehicle may have zero bidders if it is at a price greater than its (exogenously set) minimum price. Similar to Zhou and Kockelman's (2011) removal of low-bid dwelling units and commercial space from their land use model, if a vehicle reaches its minimum price without bidders, it is returned to its owner.

The opening auction prices (P_0) of used vehicles are set using the logarithmic depreciation function recommended by Storchmann (2004), where $P_t = P_{new}\, e^{\alpha + \delta t}$. Here, P_t is price at year t, P_{new} is new price, and α and δ are depreciation parameters. There is also an additional 5% drop for vehicles past 100,000 miles, as implied by Kooreman and Haan (2006), and the minimum P_0 is the scrappage price. Though Storchmann's study included regressions which were model- (and nation-) specific, a single number is used

here for all models, for simplicity and because he did not include vehicles representing all body types. Only U.S. coefficient values are applied here, as shown in Table 8.3. Table 8.4's vehicle models were chosen by Kooreman and Haan because they are very common in the US's used-car market. Here, these values were assumed to be $\alpha = -0.05$ and $\delta = -0.175$. It should be noted that the Civic and Accord are considered to have some of the lowest depreciation rates among all makes and models (Lienert 2005, Consumer Reports 2010). Prices of new vehicles are set exogenously, based on MSRPs used in Musti and Kockelman (2009).

Vehicle Make & Model	α	δ
GM Cadillac Seville	-0.14	-0.163
Toyota Camry	-0.01	-0.168
Honda Accord	0.14	-0.191
Honda Civic	-0.15	-0.172

Table 8.3: Parameter values for price depreciation from Storchmann (2004), $P_t = P_{new} e^{\alpha+\delta t}$

8.3 The Simulation Program

A simulation program was written in MATLAB's m-language, to mimic Austin households making new- and used-vehicle choices over 20 years The program has a main layer to track households and vehicles over time, and a market–level layer that determines prices and vehicle selection in a given year, mimicking the layers of the logit models. The main layer initializes households and vehicles, and is called the "market entrance model". This main layer selects vehicles and buyers for the market, and updates ownership and other information. The market layer uses the vehicle choice model to determine purchases and runs until market clearance is achieved.

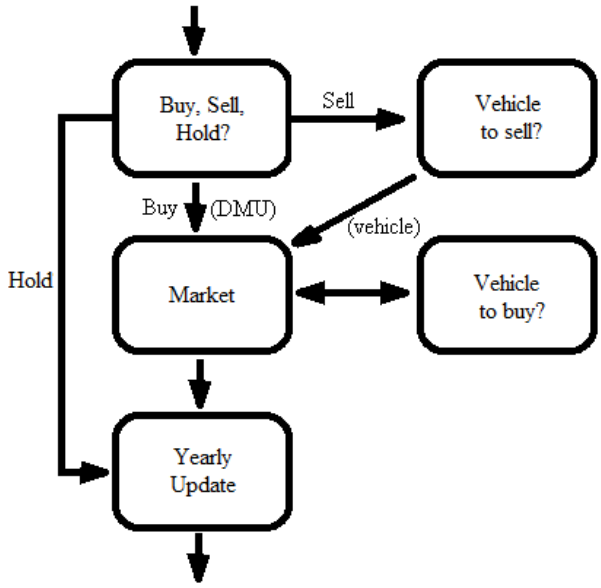

Figure 8.2: Schematic of the simulation

Figure 8.2 shows the basic flow in one year of the simulation. In the market entrance model, households choose to bypass the market (do nothing), sell a vehicle in the market, or enter it as a buyer. The vehicle choice model selects a vehicle in the household fleet to sell, and this vehicle is put into the market. In the market, vehicles and households are run through the vehicle choice model to determine which automobiles households wish to buy. After the market clears, the yearly update module places vehicles into their new (or old, if unsold) households and updates mileage and vehicle age information. The mileage added on a vehicle in any given year varies by its current owner, who has an associated usage per year which is given in input data. The yearly mileages are based on averages from the household data and are held constant through the simulation.

The model was run for 20 year-long iterations on a fixed set of households. These households' attributes were not updated over time (to reflect aging individuals and the like), and no households were added or removed (to allow for more straightforward simulation). Such updating is, of course, feasible and useful in the context of real-world applications but beyond the focus of this work. The data used for simulation included 5,000 simulated households generated by duplicating the 637 households (not including those with incomplete data) from Musti and Kockelman's (2009) survey data. Table 8.4 provides a summary of these households' attributes (and the set of respondents on the Musti and Kockelman survey).

	Average	**Minimum**	**Maximum**	**Std. Dev.**
Household Size	2.21	0	7	1.25
Number of Vehicles	1.61	0	5	0.87
Age (years)	36.8	20	70	15.0
Income ($/year)	86,271	5,000	250,000	67,048
Female Indicator	0.36	0	1	0.48
Number of Workers	1.46	0	5	0.85
Miles per Year per Vehicle	10,568	750	42,000	4,687

Table 8.4: Summary of simulated households' attributes

Chapter 9: Simulation Results

The simulation successfully ran through 20 years of market decisions among the 5,000 households in 25 to 40 minutes, with each year taking between 20 seconds and 10 minutes. The bidding loops generally took between 20 and 500 iterations, but occasionally required more than 1000. This volatility can be greatly reduced by limiting repeated, similar-price steps, but was allowed here for simplicity.

While having more than 5,000 households involved in the auction process would produce smoother market outcomes, it would entail longer equilibrium search times and may not reflect the limited knowledge of market participants and the evolution of market participants over each year. (Few households are probably in the market for more than six months, with many averaging a month or less, and largely confining their search to a single region.)

This section includes the results from two models: an Initial model in section 9.1, which uses only the market to move vehicles into, out of and around the market, and a Modified model in section 9.2, which includes a hazard function to remove or destroy/"total" vehicles based on a stochastic function of vehicle age. The latter model was devised to alleviate issues in the former that had allowed vehicles to stay on the road beyond a reasonable period. Both models were run through some of the same scenarios.

9.1 Results from Initial model

Several tests were undertaken to examine the effects of changes in model parameters. One important adjustment was required in Musti and Kockelman's (2009) market entrance model: The value of the coefficient on maximum age of a vehicle in the household's fleet for the buy and sell options was negative (-0.0955), making it less likely that a household would get rid of a vehicle or buy a new one as its oldest vehicle aged. With no other time-varying inputs to increase the chance of a buy or sell, most households ended up locked into their initial fleets. Households could have a 30+ year-old vehicle and less than 1% chance of selling. To address this unrealistic result, the coefficient was made positive (+0.01), and the alternative specific constants were decreased slightly (to -3 for acquire and -4 for dispose) to keep the general probabilities close to normal. This adjustment was used for all the results presented here and produced reasonable results for the smaller data sets, but seemed to cause the fleet to grow too large with the full 5,000-household set. One of the options for removing old vehicles, scrapping according to a hazard function's prediction, is implemented in the section 9.2.

9.1.1 Increasing Fuel Cost

Increasing fuel costs can affect vehicle purchase decisions and thereby the vehicle fleet. Table 9.1 shows how the model predicts vehicle holdings (by type) will change over 20 years. For the base case, compact cars, pickups, luxury cars and SUVs dropped dramatically, while sales of large cars, subcompacts and vans increased. CUV was the only type whose share changed little. Doubling the price of fuel, from $2.50 to $5 per

gallon, affected the type of vehicle held by making larger, less fuel efficient vehicles less desirable. The effects of the simulations were similar to each other, however, when compared to the initial (empirical) holdings. Therefore, it is the comparison of different model specifications that there is a clear trend towards subcompacts, and away from vans, pickups and SUVs, but compacts only saw a modest rise. The increase in fuel price did not have any effect on other aspects of the fleet (e.g. scrappage, new cars sales), as fuel prices were only important in terms of which vehicle type to choose. Further discussion can be found in section 9.2.2.

	Initial (from data)	**Base Case Shares ($2.50/gallon) Year 20**	**High-Fuel Cost Scenario ($5/gallon) Year 20**
Subcompact	12.7%	26.6%	36.6%
Compact	23.8%	10.2%	11.1%
Midsize	16.2%	14.5%	14.3%
Large	3.7%	7.1%	7.3%
Luxury	4.6%	1.0%	1.0%
CUV	6.2%	7.5%	6.8%
SUV	15.7%	6.3%	4.3%
Pickup	11.6%	8.8%	5.4%
Van	5.6%	18.0%	13.2%

Table 9.1: Vehicle holdings by type after 20 years (Initial Model)

9.1.2 Adjusting Auction Price Variability

Table 9.1 summarizes results from a simulation for the base case with an arbitrarily set $500 scrappage price and all parameters specified as previously noted. These suggest a percentage of households choosing to buy or sell vehicles similar to that in Musti and Kockelman (2009) and Mohammadian and Miller (2003). The number of vehicles

scrapped is quite low considering most of the automobiles were held at the beginning of the simulation. This, as well as the high average vehicle age, shows an obvious bias towards older used vehicles and, more importantly, a bias against putting them on the market. Increasing the simulation duration (to 30 and 40 years, for example) allowed increases in average vehicle age, but these were less than the number of simulated years. Despite this, an average of 11 vehicles that went into each auction (i.e., 4% of those, not including scrapped vehicles) were returned to their previous owners as unsold.

	Base Case		***25% Price Variability***	
	Per Year	*Total*	*Per Year*	*Total*
Buyers in Auction	413	8258	415	8301
Vehicles in Auction	264	5,270	257	5,141
Auction Rounds	229	4,573	722	14,447
Vehicles Unsold	11	219	9.5	189
Total Vehicles	12,294		12,534	
New Vehicles Purchased	4,255		4,495	
Vehicles Scrapped	1,048		1,146	
Average Veh Age in Year 20	20.9 yrs		20.6 yrs	

Table 9.2: Base case (15% price variability) and 25% price variability simulation results (Initial Model)

The left side of Table 9.1 show results when price was allowed to vary by up to 15% above or below initial auction price. When this was increased to 25%, as seen on the right side, 9% more of the used vehicles fell below the scrappage price and were removed from the market. This resulted in 6% more new vehicles being purchased and fewer used vehicles being returned from auction to their previous owners. However, the wider allowance on market price range did not encourage more convergence on a market price with the current parameters. For the base case, only 7.0% of vehicles that went into an auction were sold at a market price, the rest were either returned to owners, sold at

maximum price, or scrapped. With the higher price deviations, this number fell to only 6.5%. (Excluding scrapped vehicles, 8.7% and 8.3% were sold at market price with the base and higher variability models, respectively.) Adding price variability does increase the number of auction rounds if left unchecked. Changing the variability to 25% from 15% increased the range of prices by 66%. The number of auction rounds increased, as a result, by over 200%.

9.1.3 Subsidized Scrappage

Since governments sometimes choose to induce car turnover (thereby improving fleet emissions or safety) by offering scrappage subsidies (e.g., the Obama Administration's "Cash for Clunkers" program or those described in Esteban [2007]), scrappage value is a variable parameter of interest. A simulation was done in which the scrappage incentive (per qualifying vehicle) was increased from $500 to $2500 (for all vehicles). Table 9.3's results show several changes from results of the $500 base case, as described earlier. Scrappage rates increased by over 85%, while about 20% more new cars were sold. 65% fewer vehicles went unsold, most likely being taken out of the market for scrappage reasons. The average vehicle age and the number of buyers and vehicles in the auctions were very close to the base scenario's outcomes – suggesting that the incentives did little to encourage people to drive newer cars.

	Base Case		***$2500 Scrappage***	
	Per Year	*Total*	*Per Year*	*Total*
Buyers in Auction	413	8258	410	8,201
Vehicles in Auction	264	5,270	257	5,130
Auction Rounds	229	4,573	334	6,674
Vehicles Unsold	11	219	3.9	77
Total Vehicles	12,294		13,137	
New Vehicles Purchased	4,255		5,098	
Vehicles Scrapped	1,048		1,950	
Average Veh Age in Year 20	20.9 yrs		19.7 yrs	

Table 9.3: Average simulation results with $2500-per-vehicle scrappage incentive (Initial Model)

These simulation runs exhibit a trend of an increasing number of used vehicles in the market over time. The only reason the likelihood of the dispose choice can increase over time comes via increases in the maximum vehicle age (in the household's fleet), since there is no mileage or person-age (or other) factor to consider here, and no other attributes are changing over time. When the disposal choice is made, however, the oldest vehicle in a household's possession might not be chosen to be put on the market.Comparing the average age of all vehicles to those in the (yearly, used) market shows how younger vehicles were being selected for disposal, since they bring in more money when sold used. Therefore, simulated households appear to be undervaluing new-ness in their vehicles, in exchange for the added value from sale of newer cars.

9.2 Results from Modified Model

To address the issues of unreasonable vehicle holding durations and lifespans, a hazard function was added to remove vehicles from households without selling them – allowing the model to account for stolen and destroyed vehicles (e.g., via collision or major mechanical failures). While more detailed survey data may capture such effects, this

exogenous function can fill in the gaps. The duration parameters are based on crashes reported in Texas (TxDOT, 2008), and results were compared with the U.S. fleet make up (by age of vehicle), as described in NHTSA's report (Lu, 2006).

Initial tests of the hazard function showed that, while it was eliminating vehicles, mostly older ones, their owners were not buying new ones. Instead, purchasing rates remained similar to simulations without the hazard function. The average vehicle age plummeted as well as the number of vehicles in the total fleet. The transaction model was not, in its previous form, well suited to such adjustments. The number of workers in each household, but not the number of vehicles, was present in the utility equation for the acquire alternative. To keep the number of vehicles held by each household at a reasonable level, a covariate was added for the number workers minus number of vehicles in each household. The results below reflect this addition.

9.2.1 Modified Model's Base Case Results

Differences between results of the new Modified Model, with the hazard function for vehicle removal , and the Initial Model, discussed previously, can be seen in Table 9.4. The new model has many more vehicles – total and purchased new – being involved in the fleet over the 20 years. More buyers were entering the market each year – 34% more on average than in the Initial Model –seeking a new or used vehicle to replace the vehicles they no longer had. The sharp drop in number of vehicles scrapped over the 20-year simulation suggests that the hazard function removals may have competed with

scrappage for removal of used vehicles. On the other hand, the totals show that many more were removed by hazard than would have otherwise been sold for scrap. The hazard function and scrappage compliment each other, as they should, however it does seem that the hazard function had more of an impact in its current form. Differences in the number of auction rounds and vehicles unsold are probably the result of having fewer used vehicles for sale and more potential used-vehicle buyers (adding pressure for the markets to clear quickly).

	Modified Model		***Initial Model***	
	Per Year	*Total*	*Per Year*	*Total*
Buyers in Auction	557	11146	413	8258
Vehicles in Auction	201	4023	264	5270
Auction Rounds	346	6914	229	4573
Vehicles Unsold	2	47	11	219
Total Vehicles	15294		12,534	
New Vehicles Purchased	7,255		4,495	
Used Vehicles Purchased	3,891		4,003	
Vehicles Scrapped	85		1,146	
Vehicles removed by hazard	8,250		0	
Average Veh Age in Year 20	7.81 yrs		20.6 yrs	

Table 9.4: Results of the Modified and Initial Model Specifications' Base Case Simulations

The biggest change evident was a lowering of the average age of vehicles down to a reasonable level (from 20.6 years to 7.81 years), as sought by the model modification. This matches the actual average age, 7.86 years, of registered vehicles in the US according to NHTSA. (Lu 2006). Removing the old vehicles from households, without modifying the market achieved this over 60-percent drop in average age. Among these new results only the number of used purchases stayed relatively constant, despite there being fewer used cars available. It could be that the desire for used vehicles in the

revised models exceeds the supply, or that the vehicles that would not be desired by used-vehicle buyers are being removed before they enter the market.

As with the Initial Model, three test scenarios were run with the Modified Model, to examine the effects of greater price variability allowance in auction, higher fuel costs, a higher scrappage subsidy – relative to the base case results. The results are presented below in the same format.

9.2.2 Increasing Fuel Cost

The effect of fuel cost increase on vehicle shares was very similar in both the Initial and Modified Models. Table 9.6 compares the fleet mix in the high-price and base-price scenarios after 20 years, and in year 0 of the simulate, using the Modified Model. The increased gas prices (at $5, rather than $2.50, per gallon) result in share reductions for large cars and all light trucks (CUVs, SUVs, Pickups, and Vans). Small share increases were observed in compact and midsized cars, with the majority of the shift going to subcompact class – the most fuel efficient type modeled.

	Base Case Shares ($2.50/gallon) Year 20	***High-Fuel Cost Scenario ($5/gallon) Year 20***
Subcompact	25.9%	35.0%
Compact	11.0%	11.8%
Midsize	14.6%	14.9%
Large	8.1%	6.8%
Luxury	1.1%	1.2%
CUV	7.0%	6.4%
SUV	6.5%	4.9%
Pickup	8.2%	5.8%
Van	17.4%	13.1%

Table 9.5: Vehicle holdings by type after 20 years (Modified Model)

The changes in compact and midsize cars were small, but only subcompacts were rated substantially above average for fuel economy. Figure 9.1 plots the fuel economy of the nine vehicle classes along with the share shifts under the doubled-price scenario. Interestingly, the 20-year share shifts at $5 per gallon (versus $2.50 per gallon) nearly match the fuel economy values. Relative to the other types, the market shares of SUVs and pickups were less dependent on fuel cost. The shares changed little for vehicles around 18-19 mpg. Compared to these, the subcompacts gained over 1% for each mpg over that baseline and vans fell at about the same rate.

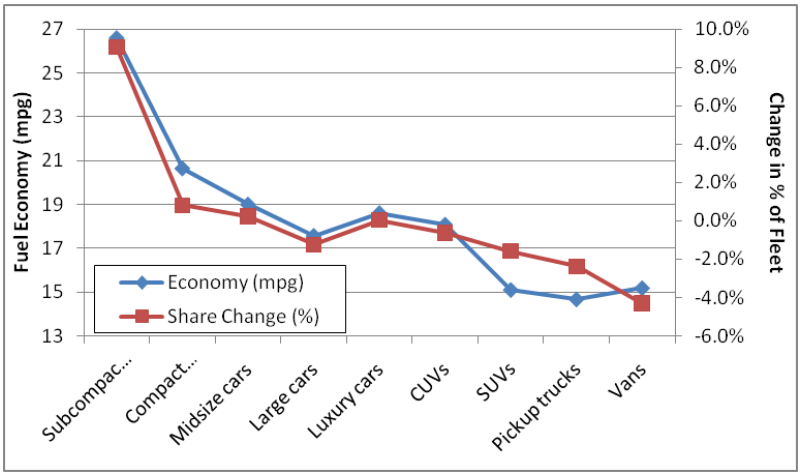

Figure 9.1: Fuel economy by vehicle type and fleet composition change following doubled fuel prices

9.2.3 Adjusting Auction Price Variability

As before, the model parameter for price variability was increased from 15% to 25% to examine the effects on model performance of sellers decreasing the minimum price and buyers increasing the maximum price. The number of unsold vehicles fell as expected. However, because so few were unsold in the base case, the number could not fall by a substantial amount. Additionally, any desire for more used vehicles, which could now be sold at lower prices, would not be captured, because they were in short supply. The differences between the two were mostly limited to the operation of the simulation (i.e., a reduced number of auction rounds), rather than the results vehicle fleet's make-up (e.g., age and new vehicles purchased).

	Base Case (15% PV)		***25% Price Variability***	
	Per Year	*Total*	*Per Year*	*Total*
Buyers in Auction	557	11,146	554	11,086
Vehicles in Auction	201	4,023	198	3,952
Auction Rounds	346	6,914	960	19,194
Vehicles Unsold	2	47	2	31
Total Vehicles	15,294		15,293	
New Vehicles Purchased	7,255		7,254	
Used Vehicle Purchased	3,891		3,832	
Vehicles Scrapped	85		88	
Vehicles Removed by Hazard	8,250		8,250	
Average Veh Age in Year 20	7.81 yrs		7.80 yrs	

Table 9.6: Results of increasing price variability (Modified Model)

With the higher variability, there were more price steps that could be taken for each vehicle during auction: 50 steps, rather than the base case's 30. This caused the number of auction rounds to increase by an average factor of nearly three. For any given number of buyers and vehicles in the market, computing time increases with number of rounds, though not quite proportionally. Because some vehicles and buyers drop out when maximum prices are reached, there are not as much computations per round in later rounds.

9.2.3 Subsidized Scrappage

The increase in scrappage value scenario described earlier (when discussing scenarios under the Initial Model specification, in Section 9.1.3) encouraged an expected rise in vehicles sold for scrap and a drop in the number removed via the hazard function. The shifts are close and opposing between the base and subsidy cases, as seen in Table 9.7.

The introduction of the hazard function in the Modified Model, and its removal of vehicles, greatly affects the availability of vehicles for scrappage, so these results differ rather significantly from those found in the Initial Model. Three changes occurred in the auctions, between the Initial and Modified Model contexts. First, the average number of auction rounds fell by more than 50%, with vehicles exiting for scrappage more quickly. Second, only one vehicle went unsold every two auctions, on average, when the subsidy was offered. Third, used-car sales went down 12% (by about 475 vehicles), while new car sales were up 3% (by 225 vehicles). Counter-intuitively, there were more total vehicles in the 20 years of simulation with the higher scrappage rate offered, but fewer purchases made. This may be the result of the removal of low-value cars which had been sold multiple times in the base case, but scrapped early on in with the higher subsidy. The ending vehicle age did not change substantially between the cases.

	Base Case *($500 Scrappage)*		***Subsidy*** *($2500 Scrappage)*	
	Per Year	*Total*	*Per Year*	*Total*
Buyers in Auction	557	11,146	545	10,897
Vehicles in Auction	201	4,023	203	4,053
Auction Rounds	346	6,914	154	3,081
Vehicles Unsold	2	47	1	10
Total Vehicles	15,294		15,517	
New Vehicles Purchased	7,255		7,478	
Used Vehicles Purchased	3,891		3,419	
Vehicles Scrapped	85		624	
Vehicles removed by hazard	8,250		7,808	
Average Veh Age in Year 20	7.81 yrs		7.95 yrs	

Table 9.7: Average simulation results with $2500-per-vehicle scrappage incentive (Modified Model)

9.2.4 Age Composition of Vehicle Fleet

Along with information on vehicle types owned and their characteristics, vehicle age is of strong interest to planners and policymakers (due to, for example, emissions equipment and safety regulations evolving over time). In addition to the data from the original surveys, there is national data on vehicle ages from NHTSA (Lu, 2006). Figure 9.2 gives distributions of vehicle age at several years in the simulation, for direct comparison with the NHTSA curves for cars and light trucks. It appears that, over the 20-year period, the program is reshaping the synthetic distribution of 5,000 households' vehicles into a smoother function. The rough peaks of the original data are removed by the 20th year, as those vehicles are all retired and replaced by a regular flow of new cars. Given that the fleet takes about 20 years to turn over, the nation's age distribution is only clearly emerging at the end of the 20-year simulation (of this limited household sample).

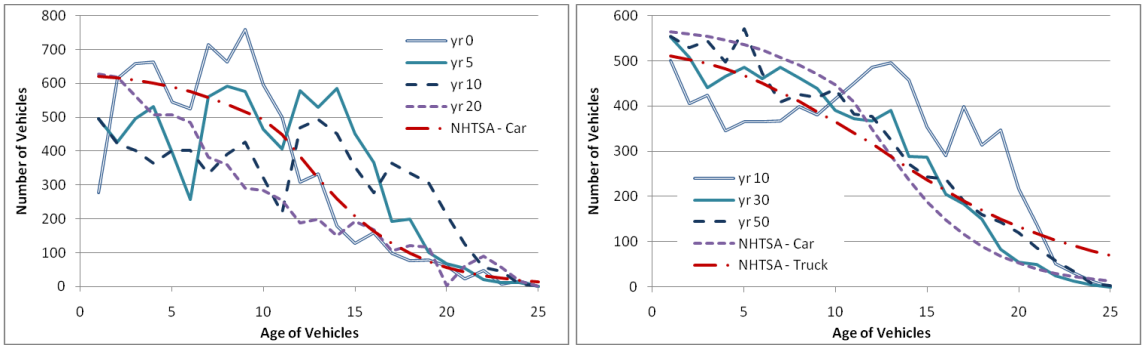

Figure 9.2: Vehicle-age distributions for 20-year and 50-year simulations (the NHTSA light truck curve is omitted on the left for viewability)

Important concerns when running a simulation over a long period of time are the system's equilibrium, encroachment on boundary conditions, and/or cyclical patterns that the program may enter . The target length for this simulation is 20 years into the future. Longer runs were performed with a length of 50 years to examine the program's trajectory. Figure 9.2's right side shows age distributions moving towards a function that is more linear than, but not still similar to NHTSA's empirical curves. The curve progression shows that the shape becomes established as the initial set of vehicles are leaving the fleet. This suggests that the model has some

These various simulations illustrate the framework's flexibility, with results shown here highlighting just a few of the comparisons that can be pursued. Not only can fuel costs, scrappage incentives, vehicle attributes, and household inputs be changed, but modules can be added without recalibration to incorporate more behavioral sophistication, including household evolution and greenhouse gas emissions estimation.

Chapter 10: Conclusions

This work's results suggest significant potential of auction-style microsimulation for used- and new-car market modeling, while indicating areas for model enhancements. The general modeling approach offers analysts the opportunity to anticipate market prices without requiring explicit supply and demand functions. It also sets all prices and purchase choices simultaneously, for the entire set of market actors (i.e., buyers and sellers). This type of model is designed to mimic disaggregate decisions for market-wide supply and demand, with microsimulation permitting nearly limitless complexity in behavioral processes. With a fluid market and representative groups of buyers and vehicles, the prices and choices may tend toward an optimal set. Increasing gas prices and wider availability of alternative fuel vehicles are changing the behavior of American consumers. To better implement energy and environmental policy or better plan manufacturing and pricing of automobiles, more flexible and accurate models are needed. To more effectively serve travelers, transportation engineers and planners will use these models to understand the state of the vehicle fleet populating the networks.

The approach taken to include used cars extended previous works which either excluded them completely (e.g. Musti and Kockelman, 2010) or assumed an external supply (e.g. Mohammadian and Miller, 2003). In this thesis, available used vehicles were compared directly to new vehicles by prospective buyers. This is a departure from Mohammadian and Miller's (2003) tiered selection process, in which the consumer chooses a body type, then chooses a model year. By comparing sale vehicle options directly, the model allows

individual vehicles to have unique characteristics and avoids the assumption that every model year of a vehicle is for sale in a market. The auction structure sets prices based on the availability of (used) vehicles and the individual preferences of people in the market. This allows prices and decisions to react to market conditions such as changes in gas prices. With doubled gas prices, the model showed subcompact's share jumping by 10% and the shares of all light-duty-truck types falling by 1% to 5%.

This simulation also suggests some opportunities for model enhancement. For example, the market entrance model populates the used-vehicle market with vehicles and buyers based on existing household and fleet attributes, while recognition of actual vehicle prices and availability in the new and used vehicle markets should prove more realistic. Robust data collection would encompass the current holdings and future plans of households, as well as the supply and pricing of vehicles. A shift in the conditions of the new and used markets will induce some buyers or sellers to join the market and discourage others, changing market makeup. Households should also be allowed to sell and buy vehicles in the same year, and consider budgetary constraints that many may be under when selecting a vehicle to pursue (and making an offer on that vehicle).

The model used here also provides a history of prices, trades and other information as outputs but does not use such information itself. A more sophisticated approach could incorporate it into subsequent years' market entrance decisions and pricing schemes. Previous information can provide a starting point for the current year. This would give

some measure of continuity, a realistic assumption, from year to year. In the examples he scope of the evolution was limited to age progression and constant mileage addition based on household. Further expansion should include realistic vehicle and household evolution with temporally-varying, vehicle-type- and household-dependent yearly use (VMT), changing household size and income, and updated new-vehicle pricing.

As seen in the final (Modified Model) results, scrappage prices affected market and vehicle holdings, with 3% more new cars sold and 12% fewer used vehicles purchased under a higher scrappage incentive. This model uses only a price floor to scrap vehicles. It does not scrap vehicles which are not being sold, which is problematic in this case due to the issues with the market entrance model. To counter this, a hazard function was used to randomly remove vehicles as they age. This method sought to permit early or owner-unexpected exits of vehicle due to a serious crash or other form of vehicle loss. However, it was based on age only, not vehicle type, mileage, or owner demographics. Of course, ideally, this loss should be better integrated with other market decisions (like vehicle use and age) or removed in favor of a more robust market calibration which more clearly models used-car behaviors. Predicting the price accurately depends some on starting at the right point and a great deal on properly calibrating and quantifying the valuation of wear on a vehicle.

One final note on the future of vehicle market modeling: fundamental changes in vehicle technologies and offerings, such as the introduction of electric vehicles, change the

landscape. For example, the preference for electric vehicles and/or lifespan of their batteries may result in very different utility functions than those enjoyed by conventional vehicles. Such behaviors are challenging to anticipate, since there is no data with which to calibrate the associated preferences just yet. However, such technologies and preferences are critical in projecting fleet shares decades into the future.

Including market pricing and used automobiles is a complicated but presumably central part of modeling a population's evolving vehicle fleet. This work provides a framework for doing so while requiring relatively few parameters for simulation.

APPENDIX 1: MATLAB Code for Part 1's AADT Prediction

batchmain.m

```
%function batchmain
k=1;
Errs=zeros(12,4);
scores=zeros(71, 6*3);
access=[(1:30)' zeros(30,1); 26 28; 26 29; 27 28; 27 29; 27 30];
beta = [];
for i=2%1:5
    switch i
        case 1
            cols=[4;5;6;7;9;11];
            path='data\houstonNoIS\';
            name='houstonNoIS2';
        case 2
            cols=[4;5;6;7;8;9;10;11];
            name='houston';
            path='data\houston\';
        case 3
            cols=[4;5;6;7;8;9;10;11];
            name='austin';
            path='data\austin\';
        case 4
            cols=[4;5;6;7;8];
            name='IS';
            path='data\OnlyIS\';
        case 5
            cols=[4;5;6;7];
            name='minorL';
            path='data\minorL\';
        case 6
            cols=[4;5;6;7;10;11];
            name='urban';
            path='data\urban\';
    end

    zPredOut = []; eigens=[]; %beta = [];
    out = [];
%     model=2;
    for model=2%1:3
    for accInd=22%1:35 %22 for lim, 20 for all
        for network=0:1
            t =clock;
            id=i*100+model*10+network;
            disp([t(4:6) id]);
            [zPredOut1, out1, beta1, eigens1, score] =
main(path,name,model,network,cols,access(accInd,:));
            zPredOut = [zPredOut
[id*ones(1,size(zPredOut1,2));zPredOut1;]];
            out = [out [id; out1]];
```

```
            if size(beta1,1)<size(beta,1)-1
                beta1(size(beta,1)-1,:)=0;
            elseif size(beta1,1)>size(beta,1)-1 && size(beta,1)>0
                beta(size(beta1,1)+1,:)=0;
            end
            beta = [beta [id id id id;beta1]];
            eigens = [eigens [id; eigens1]];

            col=(model-1)*6+i;              %col for every subset
            row=1+35*network+accInd;        % 24 rows per network
            score(1);
            scores1(row,col) = score(1); scores1(1,col) = id; %mean abs
% err
            scores2(row,col) = score(2); scores2(1,col) = id; %SSR
            scores3(row,col) = score(3); scores3(1,col) = id; %median %
err
        end
    end
    end

    t =clock; disp(t(4:6));

%     name2 = [name 'Acc5-new'];
% %     xlswrite([path name2 '.xls'],{''});
% %     xlswrite([path name2 '.xls'], beta,'beta');
% %     xlswrite([path name2 '.xls'], out,'vario');
% %     xlswrite([path name2 '.xls'], zPredOut, 'pred');
% %     xlswrite([path name2 '.xls'], eigens, 'eigens');
%     csvwrite([path name2 'beta.csv'], beta);
%     csvwrite([path name2 'vario.csv'], out);
%     csvwrite([path name2 'pred.csv'], zPredOut);
%     csvwrite([path name2 'eigens.csv'], eigens);
end
```

main.m

```
function [zPred, out, beta, eigens, meanErr] = main(path,
name,model,network,cols, accInd)

% data, dist later
%kMat: [ind ID count speed lanes jobs pop RurIS RurMaj UrbIS UrbPrinArt
Minor...
%pMat: [ind ID count speed lanes jobs pop RurIS RurMaj UrbIS UrbPrinArt
Minor...
%distdata: [dataIDi dataIDj dist] this has a redundant rows
%distpredict: [predictID dataID dist]
% data2 (houston only on 7/26) has datamat3's cty popden

global m
m = model;
lam=.15;
% lam=0;
```

```
% bins = 15; %always used 15
bins = 25; %final is 25
distfilenum= '3';
% distfilenum= 'all';

load([path 'data5']);
[n dwidth] = size(kMat);  n2 = size(pMat,1);
Y = BCtrans(kMat(:,3), lam);
X = [ones(n,1) zeros(n,size(cols,1))];
for i=1:size(cols,1)
    X(:,i+1) = kMat(:,cols(i));
end
Wp = [ones(n2,1) zeros(n2,size(cols,1))];
for i=1:size(cols,1)
    Wp(:,i+1) = pMat(:,cols(i));
end
clear kMat pMat

%Accessibility index test
load([path 'access5']);
X(:,5) = kAcc(:,accInd(1)+1);
Wp(:,5) = pAcc(:,accInd(1)+1);
if accInd(2)~=0 %use if more than once accessibility
    X(:,size(X,2)+1) = kAcc(:,accInd(2)+1);
    Wp(:,size(Wp,2)+1) = pAcc(:,accInd(2)+1);
end
clear kAcc pAcc


% do OLS
betaOLS = (X'*X)\X'*Y;

% get resids
resid = Y - X*betaOLS;

% do FGLS
gamma = (X'*X)\X'*log(abs(resid));
clear resid
W=diag(exp(X*gamma).^(-2));
betaFGLS = (X'*W*X)\X'*W*Y;
clear W

resid = Y - X*betaFGLS;


sigmasq = resid'*resid/(n-size(X,2));
S = diag(resid.*resid);
% X3=(X'*X)\X';
wV = diag((((X'*X)\X')*S*((X'*X)\X')').^(1/2));
clear S

tFGLS=betaFGLS./wV;
```

```
% make [dist resid] matrix
if network
    if network-1
        load([path 'distdatak' distfilenum 'Cart']);
    else
        load([path 'distdatak' distfilenum]);
    end
else
    load([path 'distdatak' distfilenum 'Euc']);
end
varmat = calcVarMat(kDist, resid);
clear resid

varmat = CressieHawks(varmat, bins); %take this out for non cressie-
hawks
out = fitvario (model,varmat,[5;3;21]);
c0 = out(1); ce = out(2); a = out(3);

% GET CDD VAR/COV
Cdd = sigmasq - variogram(full(kDist), c0, ce, a, model);
clear kDist
for i=1:size(Cdd,1)
    Cdd(i,i) = sigmasq;
    for j=i+1:size(Cdd,2)
        Cdd(j,i) = Cdd(i,j);
    end
end

eigens=eig(Cdd);

Cdd = eye(size(Cdd))/Cdd; %Cdd is now its inverse
beta = (X'*Cdd*X)\X'*Cdd*Y;

tWLS=beta./wV;

% GET CPD COVARIANCE
if network
    if network-1
        load([path 'distdatap' distfilenum 'Cart']);
    else
    load([path 'distdatap' distfilenum]);
    end
else
    load([path 'distdatap' distfilenum 'Euc']);
end
Cdp = full(pDist); %convert to full
clear pDist
Cdp = sigmasq - variogram(Cdp, c0, ce, a, model);

%Create var/cov Cd0
invU = eye(size(X,2))/(X'*Cdd*X);
```

```
load([path 'data5']);
zPred = [pMat(:,2), BCtrans(pMat(:,3), lam), zeros(n2,2), pMat(:,3),
zeros(n2,3)];
clear kMat pMat
%zPred(:,2);                                          % tActual
zPred(:,3) = (Wp - Cdp'*Cdd*X)*beta + Cdp'*Cdd*Y;     % tPred
% zPred(:,3) = Wp*beta;
zPred(:,4) = diag((Wp - Cdp'*Cdd*X)*invU*(Wp - Cdp'*Cdd*X)' + (sigmasq-
Cdp'*Cdd*Cdp));%prediction variance
%zPred(:,5);                                          % Actual
zPred(:,6) = InvBCtrans(zPred(:,3),lam);              % Pred
zPred(:,7) = zPred(:,6)-zPred(:,5);                   % Error
zPred(:,8) = zPred(:,7)./zPred(:,5);                  % %Error

zPred(n2+1,8) = mean(abs(zPred(:,8)));
zPred(n2+2,8) = median(zPred(:,8));
zPred(n2+1,7) = sum(zPred(1:n2,7).^2)/n2;
meanErr = [zPred(n2+1,8) zPred(n2+2,8) zPred(n2+1,7)*n2];
beta = [betaFGLS tFGLS beta tWLS];
load([path 'data5']);
newMat(:,2)=zPred(1:size(pMat,1),8);
newMat(:,1)=pMat(:,2);
if network
    if network-1
        save([path name 'Cart' num2str(model)], 'zPred', 'out',
'beta');
    else
        save([path name num2str(model)], 'zPred', 'out', 'beta');
    end
else
    save([path name 'Euc' num2str(model)], 'zPred', 'out', 'beta');
end

end
```

calcVarMat.m

```
function varmat = calcVarMat(kDist, resids)

% varmat=zeros(size(kDist,1)^2,2);
k=0;
n=size(kDist,1);
varmat=zeros(n^2,2);

for i=1:n
    for j=i:n
        if kDist(i,j)~=0
            k=k+1;
            varmat(k,1)= kDist(i,j);
            varmat(k,2)= (resids(i,1)-resids(j,1))^2;
```

```
        end
    end
end

varmat=varmat(1:k,:);
```

CressieHawks.m

```
function vhisto = CressieHawks(varmat, bins)
%cressie-hawkins estimator
tempbins = zeros(bins,2);
N=zeros(bins,1);
maxdist = max(varmat(:,1))+.001;
interval = maxdist/bins;
vhisto=[interval*(1:bins)' zeros(bins,1)];
% Bivariate Gauss rand fields
% (Z1-Z2)/sqrt(2*vario(h)) ~ Gaussian(0,1)

% Estimator eq for each band h
% vario(h)=.5*((1/N)*sum(sqrt(Z1-Z2)))^4/(0.457+.494/N+.045/N^2);
% data = [dist vario(h)] length k, where k is number of bins

for i=1:size(varmat,1) %sum the sq rt of error differences
    ind=floor(varmat(i,1)/interval)+1;
    if ind==0
    end
    tempbins(ind,2) = tempbins(ind,2) + varmat(i,2)^(1/4);
    N(ind)=N(ind)+1;
end

entries=0;
for i=1:bins
    if tempbins(i,2)>0
%         vhisto(i,1) = tempbins(i,1);
        vhisto(i,2) = .5*((1/N(i))*tempbins(i,2))^4/(0.457+.494/N(i));
        entries=entries+1;
    end
end
vhisto = vhisto(1:entries,:);
```

fitvario.m

```
function out = fitvario (model,data,t0)

  global m
  m = model;

% Least-square fitting
lb = [0;0;0];
ub = [10;10;25];
```

```
%0   [lam,option] = leastsq ('fun',lam,[],[],data);
[theta,resnorm,residual,exitflag]=lsqnonlin(@(theta)fun(theta,data),t0,
lb,ub)
% [theta,fval,exitflag]=fminunc(@(theta)fun2(theta,data),t0);
out = [theta;resnorm;exitflag];
```

variogram.m

```
function D = variogram(D, c0, ce, a, model)

D=D./a;

if model == 1 % spherical
    temp= D>1; D(temp)=1;
    temp= D==0; D(temp)=1;
    clear temp
    D = c0 + ce*(3/2*(D)-1/2*(D).^3);

elseif model == 2 %exponential
    temp= D==0; D(temp)=5;
    clear temp
    D = c0 + ce*(1-exp(-D));

elseif model == 3 %gaussian
    temp= D==0; D(temp)=5;
    clear temp
    D = c0 + ce*(1-exp(-D.^2));
end
```

batchGWR.m

```
t1 =clock; disp(t1(4:6));
npoints = 160;%(160:95:350)';
scores1 = zeros(11,19);
scores2 = zeros(11,19);
scores3 = zeros(11,19);
% access=[1 0; 2 3; 2 4]; % use first access then 2 (5mi) and 3 (10mi),
2 and 4 (25mi)
access=[(1:30)' zeros(30,1); 26 28; 26 29; 27 28; 27 29; 27 30];
betasArr = cell(6,1);
for network=0:1
    for i=6
        switch i
            case 1
                cols=[4;5;6;7;9;11];
                path='data\houstonNoIS\';
                name='houstonNoIS2';
            case 2
                cols=[4;5;6;7;8;9;10;11];
                name='houston';
                path='data\houston\';
            case 3
```

```
                cols=[4;5;6;7;8;9;10;11];
                name='austin';
                path='data\austin\';
            case 4
                cols=[4;5;6;7;8];
                name='IS';
                path='data\OnlyIS\';
            case 5
                cols=[4;5;6;7];
                name='minorL';
                path='data\minorL\';
            case 6
                cols=[4;5;6;7;10;11];
                name='urban';
                path='data\urban\';
        end

        for model=1:3
            for accInd=1:35
                for j=1:size(npoints,1)
                    t =clock;
                    id=i*100+model*10+network;
                    disp([t(4:6) id]);
                    [score betas] =
mainGWR(path,name,model,network,cols, npoints(j), access(accInd,:));

                    col=18*(j-1)+(model-1)*6+i;              %col for
every subset
                    row=1+35*network+accInd;        % 24 rows per
network
                    score(1);
                    scores1(row,col) = score(1); scores1(1,col) = id;
%mean abs % err
                    scores2(row,col) = score(2); scores2(1,col) = id;
%SSR
                    scores3(row,col) = score(3); scores3(1,col) = id;
%median % err

                    betasArr{i} = betas;
                end
            end
        end
    end
end
name2 = [name 'GWR-all'];
t2 =clock; disp(t(4:6));
```

mainGWR.m

```
function [CVscore betas] = mainGWR(path, name,model,network,cols,
nPointsGWR, accInd)
```

```
lam=.15;

load([path 'data5']);
[n dwidth] = size(kMat);  n2 = size(pMat,1);
Y = BCtrans(kMat(:,3), lam);
X = [ones(n,1) zeros(n,size(cols,1))];
for i=1:size(cols,1)
    X(:,i+1) = kMat(:,cols(i));
end
clear kMat


%Create X for prediction
Xp = [ones(n2,1) zeros(n2,size(cols,1))];
load([path 'data5']);
for i=1:size(cols,1)
    Xp(:,i+1) = pMat(:,cols(i));
end

%Accessibility index test
load([path 'access5']);
X(:,5) = kAcc(:,accInd(1)+1);
Xp(:,5) = pAcc(:,accInd(1)+1);
if accInd(2)~=0 %use if more than once accessibility
    X(:,size(X,2)+1) = kAcc(:,accInd(2)+1);
    Xp(:,size(Xp,2)+1) = pAcc(:,accInd(2)+1);
end
clear kAcc pAcc

zPred = [pMat(:,2), BCtrans(pMat(:,3), lam), zeros(n2,2), pMat(:,3),
zeros(n2,3)];

% GET WEIGHTS by dist from known to pred
if network
    if network-1
        load([path 'distdatapallCart']);
    else
    load([path 'distdatapall']);
    end
else
    load([path 'distdatapallEuc']);
end

if 0 % max distance formula with gaussian (?)
    Wmaster = makeGwrW(pDist,kernel);
    clear pDist
    for i=1:n2
        W=diag(Wmaster(:,i)); %make diagonal of row
        beta = (X'*W*X)\X'*W*Y;
        zPred(i,3) = Xp(i,:)*beta;
    end
end
```

```
betas = zeros(n2,(1+size(X,2))*2);
SSE=0;
S=zeros(n2,n);
CC=cell(n2,1);

pointsInd=zeros(n,1); % # obs = kMat
for i=1:n
    pointsInd(i,1)=i;
end
TEMPCOND=zeros(n2,1);
%loop for estimation/prediction
for i=1:n2
    W = makeWind(full(pDist(:,i)),pointsInd, nPointsGWR, model); %get W
for point i
    Xcurr = Xp(i,:);
    Xt=X(W(:,2),:); % set X for i
    Yt=Y(W(:,2),1); % set Y for i
    j=size(Xt,2)+1; k=6;
    dropped=[];
    while k<j %remove X cols with 0s only
        if sum(Xt(:,k))==0
            Xt = [Xt(:,1:k-1) Xt(:,k+1:size(Xt,2))];
            Xcurr = [Xcurr(:,1:k-1) Xcurr(:,k+1:size(Xcurr,2))];
            j=j-1;
            dropped=[dropped k];
        else
            k=k+1;
        end
    end
    W=diag(W(:,1));
    C = (Xt'*W*Xt)\Xt'*W;
    beta = C*Yt;
    zPred(i,3) = Xcurr*beta;
    zPred(i,4) = rcond((Xt'*W*Xt)\eye(size(Xt,2)));

    r(i,:) = Xcurr*C;
    CC{i,1}= C*C';
    SSE=SSE+(zPred(i,3)-zPred(i,2))^2;

    for d=1:size(dropped,2)
        beta=[beta(1:dropped(d)+d-2); 0; beta(dropped(d)+d-
1:size(beta,1))];
    end
    betas(i,1:size(betas,2)/2) = [pMat(i,2) beta'];
end
clear kMat pMat
clear pDist

%zPred(:,2);                                          % tActual
%zPred(:,3) = (Xp - Cdp'*Cdd*X)*beta + Cdp'*Cdd*Y;     % tPred
% zPred(:,3) = Xp*beta;
```

```
%zPred(:,4) = REPLACED WITH MAT CONDITION diag((Xp -
Cdp'*Cdd*X)*invU*(Xp - Cdp'*Cdd*X)' + (sigmasq-
Cdp'*Cdd*Cdp));%prediction variance
%zPred(:,5);                                        % Actual
zPred(:,6) = InvBCtrans(zPred(:,3),lam);            % Pred
zPred(:,7) = zPred(:,6)-zPred(:,5);                 % Error
zPred(:,8) = zPred(:,7)./zPred(:,5);                % %Error

% CVscore = sum(zPred(:,7).^2);
CVscore = [mean(abs(zPred(:,8))) sum(zPred(:,7).^2)
median(zPred(:,8))];

zPred(n2+1,8) = mean(abs(zPred(:,8)));
zPred(n2+2,8) = median(zPred(:,8));
zPred(n2+1,7) = sum(zPred(1:n2,7).^2)/n2;

end
```

makeWind.m

```
function out = makeWind(distVec, ind,nLocs, model) %No 0 values in dist
%out is a nLocs x 2 mat

out = [distVec ind];
out = sortrows(out,1); %sort by dist
out = out(1:nLocs,:); % take first nLocs
out = sortrows(out,2); %sort by index
dmax=max(out(:,1));
out(:,1)=out(:,1)/(dmax+.001);
if model==1 % Gaussian
    for i=1:nLocs
        out(i,1)=exp(-.5*(out(i,1))^2);
    end
elseif model==2 % bi-square
    for i=1:nLocs
        out(i,1)=(1-out(i,1)^2)^2;
    end
elseif model==3 % rank
    for i=1:nLocs
        out(i,1)=exp(-i/nLocs);
    end
end

end
```

BCtrans.m

```
function V = BCtrans(V, lam)

if lam > 0
    V = (V.^lam - 1)./lam;
```

```
elseif lam==0
    V = log(V);
end
```

invBCtrans.m

```
function V = InvBCtrans(V, lam)

if lam > 0
    V=(V*lam+1).^(1/lam);
elseif lam==0
    V = exp(V);
end
```

preProcDist.m

```
function preProcDist(network,path,name)

% preProcDist.m
% this matches dist data to the ID but requires an ID conversion
% (stationID-1)/8-590+984488
% network 0 = great circle, 1 = network dist, 2 = cartesian
% network=1;
% preProcData(path,name)

fclose('all');
kIDs = csvread([name 'k2.txt']); %format: [ID]
pIDs = csvread([name 'p2.txt']); %format: [ID]
if network==1
    fid = fopen('C:\AADT\TxDOT-
Ma\2005_Annual_and_Urban_Shapefiles\Street StratMap\ACSPedit.csv');
elseif network==0
    fid = fopen('old\PtsDist.csv');
elseif network==2
    fid = fopen('CartDist.csv');
end

n = size(kIDs,1);
n2 = size(pIDs,1);

%convert to dist ID
if network==1
    for i=1:n
        kIDs(i) = (kIDs(i)-1)/8-590+984488;
    end
    for i=1:n2
        pIDs(i) = (pIDs(i)-1)/8-590+984488;
    end
end

%make 2 matrices
```

```
kDist = zeros(n);
pDist = zeros(n,n2);

i1 = 1; i2 = 1; line = 1; entries1=0; entries2=0;
tline = fgets(fid);

t =clock; disp(t(4:6));

while tline~=-1
    if i1>n && i2>n2
        break;
    end
    %token get id
    [currID remain] = strtok(tline, ',');
    currID=str2num(currID);

    if i1<n+1                   %index in bounds?
        tempid = kIDs(i1);      %take the kID
        while tempid< currID    %past this known id in the dist list?
             i1=i1+1;           %go to the next kID
             if i1<n+1          %still in bounds?
                 tempid=kIDs(i1); %take the kID
             else               %if done the kID list
                 tempid=currID+1; %set kID past dist id to exit
             end
        end
        if tempid == currID     %if the kID and dID
            [ID2 dist] = strtok(remain, ','); %get ID2 from string
            ID2 = str2num(ID2); %convert ID2 to number
            index2 = find(kIDs==ID2,1);
            if ~isempty(index2) && tempid<ID2 %ID2 in the klist and
less than ID1
%                 fprintf(fid2, '%s', [num2str(i1) ',' num2str(index2)
',' tline]);
                kDist(i1, index2) = str2num(dist); %put dist in kDist
mat
                entries1=entries1+1;
            end
        end
    end

    if i2<n2+1                  %index in pIDs bounds?
        tempid = pIDs(i2);      %take the pID
        while tempid< currID    %past this pred id in the dist list?
             i2=i2+1;           %go to next pID
             if i2<n2+1         %still in bounds?
                 tempid=pIDs(i2); %get next pID
             else               %done the list
                 tempid=currID+1; %set pID past dist list to exit
             end
        end
        if tempid== currID    %ID found in dist list
            [ID2 dist] = strtok(remain, ','); %get ID2 from string
```

```
            ID2 = str2num(ID2); %convert to number
            index2 = find(kIDs==ID2,1);
            if ~isempty(index2)  %if ID2 is in known list
%                 fprintf(fid3, '%s', tline);
                pDist(index2, i2) = str2num(dist); %put it into pDist
mat
                entries2=entries2+1;
            end
        end
    end
    tline = fgets(fid);         %get next line
    line = line+1;
    if floor(line/1000000)==line/1000000
        disp(line);
        t =clock;
        disp(t(4:6));
    end
end
fclose('all');

if network==1
    save([path 'distdatap3'], 'pDist'); save([path 'distdatak3'],
'kDist');
elseif network==0
    save([path 'distdatap3Euc'], 'pDist'); save([path 'distdatak3Euc'],
'kDist');
elseif network==2
    save([path 'distdatap3Cart'], 'pDist'); save([path
'distdatak3Cart'], 'kDist');
end
end
```

preProcDistEuc.m

```
function preProcDistEuc(path,name)

% preProcDist2.m
% this matches dist data to the ID but requires an ID conversion
% (stationID-1)/8-590+984488
% network 0 = great circle, 1 = network dist, 2 = cartesian
locs = 10840;
fclose('all');
kIDs = csvread([name 'k2.txt']); %format: [ID]
pIDs = csvread([name 'p2.txt']); %format: [ID]
fid = fopen('PtsDist2.csv');

n = size(kIDs,1);
n2 = size(pIDs,1);
t =clock; disp(t(4:6));
allIDs = zeros(locs,1);
kIndex = zeros(n+1,1);
pIndex = zeros(n2+1,1);
```

```
ik=1; ip=1;

fseek(fid, 0, 'bof');

for i=1:locs                    % finds indices
    [tossed remain] = strtok(fgets(fid), ',');
    allIDs(i) = str2double(strtok(remain, ',')); % get 2nd ID
    if ik<n+1
        while kIDs(ik)<allIDs(i) && kIDs(ik)>0 % if we are past that ID
            kIndex(ik) = -1;    % put in kIndex
            ik = ik+1;          % increment ik
        end
        if kIDs(ik)==allIDs(i)  % if its one of k's IDs
            kIndex(ik) = i;     % put in kIndex
            ik = ik+1;          % increment ik
        end
    end
    if ip<n2+1
        while pIDs(ip)<allIDs(i) && pIDs(ip)>0 % if we are past that ID
            pIndex(ip) = -1;    % put in pIndex
            ip = ip+1;          % increment ip
        end
        if pIDs(ip)==allIDs(i)  % if its one of p's IDs
            pIndex(ip) = i;     % put in pIndex
            ip = ip+1;          % increment ip
        end
    end
end

if min(kIndex(1:n,1))<1
    error('The list of indices in kIndex contains a 0');
end
if min(pIndex(1:n2,1))<1
    error('The list of indices in pIndex contains a 0');
end
fseek(fid, 0, 'bof');           % go to the beginning of file
clear ip

ik=1;
kDist = zeros(n);
pDist = zeros(n,n2);

for i = 1:kIndex(n)             % loop for ID 1, up to kIndex
    if kIndex(ik)==i            % proceed if its a k Index
        fileplace1=ftell(fid);
        ik2=1;ip2=1;% start at first loc of each
        for j = 1:locs        % loop for ID 2, all locations
            if kIndex(ik2)==j% if ID 2 is also a k Index
                [tossID1 remain] = strtok(fgets(fid), ',');  % remove
token1
                if str2double(tossID1)~= kIDs(ik)
                    error(['Error in k at ' num2str(i) ' '
num2str(j)]);
```

```
                end
                [tossID2 remain] = strtok(remain, ',');      % remove
token2
                if str2double(tossID2)~= kIDs(ik2)
                    error(['Error in k at ' num2str(i) ' '
num2str(j)]);
                end
                kDist(ik,ik2)= str2double(strtok(remain, ','));% put
dist in ij
                ik2=ik2+1;                                   % increment
ik2
            elseif pIndex(ip2)==j %if ID 2 is also a p Index
                [tossed remain] = strtok(fgets(fid), ',');  % remove
token1
                [tossed remain] = strtok(remain, ',');      % remove
token2
                if str2double(tossed)~= pIDs(ip2)
                    error(['Error in p at ' num2str(i) ' '
num2str(j)]);
                end
                pDist(ik,ip2)= str2double(strtok(remain, ','));% put
dist in ij
                ip2=ip2+1;                                   % increment
ip2
            else
                fgets(fid);     % skip other lines
            end
        end
        ik = ik+1;              % increment ik for each ID1
    else
        for j = 1:locs
            fgets(fid);         % skip all lines if its not a k ind
        end
    end

    if floor(i/1500)==i/1500
        disp([i ik]);
        t =clock;
        disp([t(4:6)]);
    end
end

fclose('all');
save([path 'distdatapallEuc'], 'pDist'); save([path 'distdatakallEuc'],
'kDist');
end
```

preProcData.m

```
% preProcData.m
function preProcData(path, name)
t =clock;
```

```
disp(t(4:6));

dataNum='5';
accessNum='5';

datamat = csvread(['datamat' dataNum '.csv']); %format: [index ID count
pop class jobs...
kIDs = csvread([name 'k2.txt']); %format: [ID]
pIDs = csvread([name 'p2.txt']); %format: [ID]

n = size(kIDs,1);
n2 = size(pIDs,1);
[nd dcol] = size(datamat);

kMat=zeros(n,dcol);
pMat=zeros(n2,dcol);

accessmat = csvread(['accessmat' accessNum '.csv']); %format: [ID acc1
acc2... ac11]
kAcc=zeros(n,size(accessmat,2));
pAcc=zeros(n2,size(accessmat,2));

missingk = []; missingp = [];

for i=1:n
    ind = find(datamat(:,2)==kIDs(i));
    if ~isempty(ind)
        kMat(i,:) = datamat(ind,:);
    else
        missingk = [missingk; kIDs(i)];
    end

    kAcc(i,:) = accessmat(ind,:);
    if kAcc(i,1) ~= kMat(i,2)
        error(['Access ID(' num2str(kAcc(i,1)) ') and Mat ID('
num2str(kMat(i,2)) ') do not match']);
    end
end

for i=1:n2
    ind = find(datamat(:,2)==pIDs(i));
    if(i==31)
        ind;
    end
    if ~isempty(ind)
        pMat(i,:) = datamat(ind,:);
    else
        missingp = [missingp; pIDs(i)];
    end

    pAcc(i,:) = accessmat(ind,:);
    if pAcc(i,1) ~= pMat(i,2)
```

```
        error(['Access ID(' num2str(pAcc(i,1)) ') and Mat ID('
num2str(pMat(i,2)) ') do not match']);
    end
end

save([path 'access' accessNum], 'pAcc', 'kAcc');

if ~isempty(missingp) || ~isempty(missingk)
    missingp;
end

t =clock;
disp(t(4:6));
end
```

Preprocbatch.m

```
net=0;
name = 'Austin';
path = 'data\Austin\';
preProcDist(net,path, name);
name = 'Houston';
path = 'data\Houston\';
preProcDist(net,path, name);
name = 'HoustonNoIS';
path = 'data\HoustonNoIS\';
preProcDist(net,path, name);
name = 'minorL';
path = 'data\minorL\';
preProcDist(net,path, name);
name = 'IS';
path = 'data\OnlyIS\';
preProcDist(net,path, name);
name = 'urban';
path = 'data\urban\';
preProcDist(net,path, name);
```

countNeighbors

```
% countNeighbors ~ for analysis only
n=size(pDist,2);
counts=zeros(n,7);

for i=1:n
    for j=1:size(pDist,1)
        if pDist(j,i)>0
            if pDist(j,i)>15
                counts(i,7)=counts(i,7)+1;
            elseif pDist(j,i)>12
                counts(i,6)=counts(i,6)+1;
            elseif pDist(j,i)>10
```

```
                counts(i,5)=counts(i,5)+1;
            elseif pDist(j,i)>5
                counts(i,4)=counts(i,4)+1;
            elseif pDist(j,i)>2
                counts(i,3)=counts(i,3)+1;
            elseif pDist(j,i)>1
                counts(i,2)=counts(i,2)+1;
            else
                counts(i,1)=counts(i,1)+1;
            end
        end
    end
end
```

APPENDIX 2: Complete Results for Part 1's AADT Prediction

GWR – Average Absolute Percentage Errors

	GWR - 160 Neighbors, Gaussian						GWR - 160 Neighbors, Bi-squared						GWR - 160 Neighbors, Rank Weighting					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	80%	77%	78%	29%	94%	70%	72%	71%	62%	25%	88%	67%	82%	80%	89%	30%	95%	71%
d=1,a=0.5	80%	77%	76%	28%	94%	70%	72%	71%	61%	24%	87%	67%	82%	80%	87%	29%	95%	70%
d=1,a=0.25	80%	77%	75%	28%	93%	69%	73%	71%	59%	24%	87%	67%	82%	80%	86%	29%	94%	70%
d=1,a=0.1	80%	77%	74%	28%	93%	69%	73%	71%	58%	24%	86%	67%	82%	80%	86%	29%	94%	69%
d=2,a=1	80%	77%	76%	28%	94%	69%	72%	71%	61%	25%	87%	67%	82%	80%	88%	29%	95%	70%
d=2,a=0.5	80%	77%	75%	27%	93%	68%	73%	71%	58%	24%	86%	66%	82%	79%	87%	28%	94%	68%
d=2,a=0.25	79%	77%	79%	27%	91%	67%	73%	71%	58%	23%	84%	65%	82%	79%	92%	28%	92%	67%
d=2,a=0.1	79%	77%	81%	27%	90%	66%	73%	71%	59%	23%	83%	65%	82%	79%	94%	28%	91%	67%
d=5,a=1	79%	77%	74%	27%	93%	69%	73%	71%	59%	23%	86%	66%	82%	79%	85%	28%	94%	70%
d=5,a=0.5	78%	76%	80%	26%	87%	67%	73%	71%	61%	22%	80%	64%	81%	78%	92%	28%	88%	67%
d=5,a=0.25	77%	75%	82%	27%	84%	67%	72%	70%	63%	22%	78%	64%	79%	77%	94%	28%	85%	67%
d=5,a=0.1	76%	74%	83%	27%	83%	67%	71%	69%	64%	22%	77%	64%	78%	75%	95%	28%	84%	68%
d=10,a=1	78%	76%	72%	26%	91%	68%	72%	70%	58%	23%	85%	66%	81%	79%	82%	27%	92%	69%
d=10,a=0.5	75%	73%	77%	26%	81%	67%	71%	69%	60%	22%	76%	65%	77%	75%	89%	28%	82%	68%
d=10,a=0.25	72%	70%	78%	26%	78%	67%	70%	68%	61%	22%	74%	65%	73%	72%	90%	28%	79%	68%
d=10,a=0.1	71%	69%	78%	26%	78%	67%	68%	67%	61%	22%	75%	65%	72%	70%	90%	28%	79%	68%
d=25,a=1	77%	75%	65%	26%	92%	67%	71%	69%	55%	23%	85%	66%	79%	77%	72%	27%	92%	68%
d=25,a=0.5	74%	72%	59%	25%	88%	66%	71%	69%	51%	23%	81%	65%	76%	74%	64%	26%	89%	66%
d=25,a=0.25	74%	72%	58%	26%	92%	66%	70%	69%	52%	23%	83%	65%	75%	74%	63%	26%	93%	67%
d=25,a=0.1	74%	72%	59%	26%	93%	67%	**70%**	**69%**	**52%**	**23%**	**85%**	**65%**	76%	74%	63%	27%	94%	67%
d=50,a=1	76%	74%	67%	25%	92%	67%	70%	69%	55%	22%	85%	66%	77%	76%	75%	27%	92%	68%
d=50,a=0.5	75%	74%	64%	25%	91%	67%	70%	69%	53%	22%	84%	65%	77%	75%	71%	27%	92%	67%
d=50,a=0.25	75%	74%	69%	26%	95%	68%	70%	69%	57%	23%	85%	66%	77%	76%	76%	27%	96%	68%
d=50,a=0.1	76%	74%	75%	26%	95%	68%	70%	69%	60%	23%	85%	66%	78%	76%	85%	28%	96%	69%
to1	79%	77%	74%	27%	92%	69%	73%	71%	58%	24%	86%	66%	82%	79%	85%	28%	93%	69%
to2	79%	76%	82%	27%	89%	66%	73%	71%	60%	23%	83%	64%	82%	79%	95%	28%	90%	67%
to5	75%	73%	83%	27%	83%	67%	70%	68%	64%	22%	77%	64%	77%	75%	95%	28%	84%	68%
to10	70%	69%	78%	26%	78%	68%	68%	66%	61%	22%	75%	65%	72%	70%	90%	28%	79%	68%
to25	74%	72%	59%	26%	93%	67%	70%	69%	53%	24%	86%	66%	76%	74%	64%	27%	94%	67%
to50	76%	74%	81%	27%	95%	69%	71%	69%	62%	24%	85%	67%	78%	76%	93%	28%	96%	69%
to2&to10	72%	70%	78%	26%	77%	65%	68%	66%	58%	22%	73%	63%	74%	71%	89%	28%	78%	65%
to2&to25	75%	73%	58%	25%	89%	64%	71%	69%	51%	22%	80%	63%	77%	75%	63%	26%	90%	64%
to5&to10	71%	70%	75%	26%	78%	66%	68%	66%	60%	21%	73%	63%	73%	71%	86%	28%	79%	66%
to5&to25	74%	72%	58%	25%	82%	64%	69%	68%	51%	22%	76%	63%	75%	73%	62%	26%	84%	65%
to5&to50	75%	73%	77%	24%	82%	66%	70%	68%	59%	20%	75%	64%	76%	74%	89%	25%	84%	66%

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR – Average Absolute Percentage Errors

	GWR - 160 Neighbors, Gaussian, Network Distances						GWR - 160 Neighbors, Bi-squared, Network Distances						GWR - 160 Neighbors, Rank Weighting, Network Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	81%	78%	78%	29%	96%	71%	76%	73%	63%	25%	92%	67%	83%	81%	90%	30%	96%	72%
d=1,a=0.5	81%	79%	76%	29%	96%	71%	76%	74%	61%	24%	92%	67%	83%	81%	88%	30%	96%	72%
d=1,a=0.25	81%	79%	75%	28%	96%	70%	76%	74%	60%	24%	91%	67%	83%	81%	87%	29%	96%	71%
d=1,a=0.1	81%	79%	74%	28%	95%	70%	76%	74%	59%	24%	90%	67%	83%	81%	87%	29%	95%	71%
d=2,a=1	81%	79%	77%	29%	96%	71%	76%	74%	62%	24%	92%	67%	83%	81%	89%	30%	96%	72%
d=2,a=0.5	81%	78%	76%	28%	95%	69%	76%	74%	59%	23%	90%	66%	83%	81%	89%	29%	96%	70%
d=2,a=0.25	81%	78%	79%	27%	94%	68%	76%	74%	59%	23%	88%	65%	83%	81%	93%	29%	95%	69%
d=2,a=0.1	81%	78%	81%	27%	92%	68%	76%	73%	60%	23%	87%	64%	83%	81%	95%	29%	93%	68%
d=5,a=1	80%	78%	75%	28%	95%	70%	76%	74%	60%	23%	90%	66%	83%	80%	86%	28%	95%	71%
d=5,a=0.5	80%	78%	80%	27%	89%	68%	76%	74%	61%	22%	84%	65%	82%	80%	92%	28%	90%	69%
d=5,a=0.25	78%	77%	82%	27%	86%	68%	75%	73%	63%	22%	81%	64%	80%	78%	94%	28%	87%	69%
d=5,a=0.1	77%	76%	83%	27%	85%	68%	74%	72%	64%	22%	80%	64%	79%	78%	95%	28%	86%	69%
d=10,a=1	80%	78%	73%	27%	94%	70%	76%	73%	59%	23%	89%	66%	82%	80%	83%	28%	94%	71%
d=10,a=0.5	77%	75%	77%	27%	83%	69%	74%	72%	61%	22%	79%	65%	78%	77%	89%	28%	84%	69%
d=10,a=0.25	74%	72%	78%	27%	80%	69%	72%	70%	62%	22%	77%	65%	76%	74%	89%	28%	81%	69%
d=10,a=0.1	73%	71%	78%	27%	80%	69%	70%	68%	62%	22%	77%	65%	74%	73%	89%	28%	82%	70%
d=25,a=1	78%	76%	66%	26%	94%	69%	74%	72%	55%	23%	89%	66%	80%	78%	74%	27%	94%	70%
d=25,a=0.5	76%	75%	60%	26%	91%	67%	74%	72%	51%	23%	84%	64%	78%	76%	66%	26%	91%	68%
d=25,a=0.25	76%	74%	60%	26%	94%	68%	73%	71%	52%	23%	88%	65%	77%	76%	65%	26%	95%	68%
d=25,a=0.1	76%	74%	60%	26%	96%	68%	73%	71%	53%	24%	90%	65%	78%	76%	65%	27%	97%	68%
d=50,a=1	78%	76%	68%	26%	94%	68%	74%	72%	56%	22%	89%	66%	79%	77%	77%	26%	94%	69%
d=50,a=0.5	77%	76%	65%	25%	94%	68%	73%	71%	54%	22%	86%	65%	79%	77%	72%	27%	94%	69%
d=50,a=0.25	78%	76%	69%	26%	97%	69%	73%	71%	58%	23%	89%	66%	79%	77%	77%	27%	98%	70%
d=50,a=0.1	78%	76%	75%	26%	98%	69%	73%	71%	60%	23%	89%	67%	80%	78%	85%	28%	99%	70%
to1	81%	79%	74%	28%	94%	70%	76%	74%	58%	24%	90%	66%	83%	81%	86%	29%	95%	70%
to2	80%	78%	82%	27%	91%	68%	76%	73%	61%	23%	86%		83%	81%	96%	29%	92%	68%
to5	77%	75%	83%	27%	85%	68%	73%	71%	65%	22%	80%	64%	79%	77%	95%	28%	86%	69%
to10	72%	71%	78%	27%	81%	69%	70%	68%	62%	22%	77%	65%	74%	72%	89%	28%	82%	70%
to25	76%	74%	60%	27%	96%	68%	73%	71%	53%	24%	90%	66%	78%	76%	66%	27%	97%	69%
to50	78%	76%	81%	26%	97%	70%	73%	71%	62%	23%	88%	67%	80%	78%	93%	28%	98%	71%
to2&to10	73%	71%	77%	27%	79%	66%	70%	68%	59%	22%	75%	63%	75%	73%	89%	28%	80%	67%
to2&to25	77%	75%	60%	26%	91%	65%	73%	71%	52%	23%	84%	63%	79%	77%	65%	26%	93%	66%
to5&to10	73%	72%	75%	27%	81%	67%	70%	68%	60%	21%	76%	63%	75%	73%	85%	28%	82%	67%
to5&to25	75%	74%	59%	26%	85%	65%	72%	70%	52%	22%	79%	63%	77%	75%	64%	26%	86%	66%
to5&to50	76%	74%	76%	24%	85%	67%	72%	70%	59%	20%	78%	64%	78%	76%	87%	25%	86%	68%

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR – Average Absolute Percentage Errors

	GWR - 255 Neighbors, Gaussian, Euclidean Distances						GWR - 255 Neighbors, Bi-squared, Euclidean Distances						GWR - 255 Neighbors, Rank Weighting, Euclidean Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	82%	80%	88%	29%	95%	73%	77%	75%	71%	27%	90%	68%	85%	83%	102%	30%	96%	74%
d=1,a=0.5	82%	80%	86%	29%	95%	72%	77%	75%	70%	26%	90%	67%	85%	83%	100%	30%	95%	74%
d=1,a=0.25	82%	80%	86%	29%	94%	72%	77%	75%	69%	26%	89%	67%	85%	83%	100%	29%	94%	73%
d=1,a=0.1	82%	80%	86%	29%	94%	71%	77%	75%	68%	26%	88%	67%	85%	83%	100%	29%	94%	73%
d=2,a=1	82%	80%	87%	29%	95%	72%	77%	75%	70%	26%	90%	67%	85%	83%	100%	30%	95%	74%
d=2,a=0.5	82%	80%	90%	28%	94%	70%	77%	75%	71%	25%	89%	66%	85%	82%	104%	29%	94%	71%
d=2,a=0.25	81%	79%	93%	28%	93%	69%	77%	75%	74%	25%	87%	65%	84%	82%	108%	29%	93%	71%
d=2,a=0.1	81%	78%	95%	28%	92%	69%	77%	74%	75%	25%	86%	65%	83%	81%	109%	28%	92%	71%
d=5,a=1	82%	80%	85%	28%	94%	71%	77%	75%	69%	25%	89%	67%	85%	83%	99%	29%	94%	73%
d=5,a=0.5	80%	78%	93%	27%	89%	70%	76%	74%	74%	24%	83%	65%	83%	80%	107%	27%	90%	71%
d=5,a=0.25	78%	76%	94%	27%	86%	70%	75%	73%	75%	24%	81%	65%	81%	79%	109%	27%	87%	71%
d=5,a=0.1	78%	76%	95%	27%	86%	70%	74%	73%	76%	24%	81%	65%	80%	78%	109%	27%	87%	72%
d=10,a=1	81%	79%	83%	27%	93%	71%	76%	74%	68%	24%	87%	67%	84%	82%	95%	28%	93%	72%
d=10,a=0.5	78%	76%	89%	27%	83%	70%	74%	72%	72%	24%	78%	66%	80%	78%	102%	28%	84%	72%
d=10,a=0.25	75%	73%	89%	27%	80%	71%	72%	70%	72%	24%	76%	66%	77%	75%	103%	28%	81%	72%
d=10,a=0.1	74%	72%	89%	27%	80%	71%	71%	69%	72%	24%	76%	66%	76%	74%	103%	28%	81%	72%
d=25,a=1	79%	77%	74%	27%	94%	69%	75%	73%	62%	24%	88%	66%	82%	80%	84%	27%	93%	71%
d=25,a=0.5	77%	75%	68%	26%	92%	68%	73%	71%	56%	24%	85%	65%	79%	77%	76%	27%	92%	69%
d=25,a=0.25	77%	75%	68%	27%	95%	69%	73%	71%	56%	24%	88%	66%	79%	76%	75%	27%	95%	70%
d=25,a=0.1	77%	75%	68%	27%	97%	69%	73%	71%	57%	24%	90%	66%	79%	77%	76%	28%	97%	70%
d=50,a=1	79%	77%	76%	26%	94%	69%	74%	73%	63%	24%	88%	66%	81%	79%	87%	27%	94%	70%
d=50,a=0.5	79%	77%	75%	26%	96%	68%	74%	72%	61%	24%	88%	66%	80%	78%	84%	27%	95%	69%
d=50,a=0.25	80%	77%	80%	27%	99%	69%	74%	72%	64%	24%	91%	66%	81%	79%	89%	28%	99%	70%
d=50,a=0.1	80%	78%	87%	28%	99%	70%	75%	73%	69%	25%	91%	67%	82%	80%	98%	28%	99%	70%
to1	81%	80%	87%	28%	93%	71%	77%	75%	68%	25%	88%	67%	84%	82%	101%	29%	93%	72%
to2	80%	78%	95%	28%	91%	69%	77%	74%	76%	25%	85%	65%	83%	81%	110%	28%	92%	71%
to5	77%	75%	95%	27%	86%	70%	74%	72%	76%	24%	80%	65%	79%	77%	109%	27%	87%	72%
to10	74%	72%	89%	27%	81%	71%	70%	69%	72%	24%	76%	66%	75%	73%	102%	28%	82%	72%
to25	77%	75%	69%	27%	97%	69%	73%	71%	57%	25%	90%	66%	79%	77%	77%	28%	98%	70%
to50	81%	78%	92%	28%	98%	70%	75%	73%	73%	25%	90%	67%	83%	80%	106%	28%	98%	71%
to2&to10	74%	72%	89%	27%	80%	69%	71%	69%	72%	24%	75%	64%	75%	73%	103%	28%	82%	70%
to2&to25	77%	75%	68%	26%	93%	66%	74%	72%	56%	24%	85%	63%	79%	77%	77%	27%	94%	67%
to5&to10	74%	72%	87%	27%	82%	70%	71%	69%	70%	24%	77%	64%	75%	73%	100%	27%	83%	71%
to5&to25	76%	74%	68%	25%	86%	67%	73%	71%	56%	23%	80%	63%	77%	75%	77%	25%	88%	68%
to5&to50	78%	76%	89%	25%	86%	68%	74%	72%	70%	22%	79%	64%	79%	77%	102%	25%	87%	68%

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR – Average Absolute Percentage Errors

	GWR - 255 Neighbors, Gaussian, Network Distances						GWR - 255 Neighbors, Bi-squared, Network Distances						GWR - 255 Neighbors, Rank Weighting, Network Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	83%	82%	88%	30%	98%	73%	79%	77%	71%	27%	93%	68%	85%	84%	103%	30%	98%	75%
d=1,a=0.5	83%	82%	86%	30%	98%	73%	79%	77%	69%	26%	93%	68%	85%	84%	101%	30%	97%	74%
d=1,a=0.25	83%	81%	86%	29%	97%	72%	79%	77%	68%	26%	92%	68%	85%	84%	101%	30%	97%	73%
d=1,a=0.1	83%	81%	86%	29%	96%	72%	79%	77%	68%	26%	91%	67%	85%	83%	101%	30%	96%	73%
d=2,a=1	83%	82%	86%	30%	98%	73%	79%	77%	70%	26%	93%	68%	85%	84%	101%	30%	98%	74%
d=2,a=0.5	83%	81%	89%	29%	97%	70%	79%	77%	70%	25%	92%	66%	84%	83%	104%	30%	97%	72%
d=2,a=0.25	82%	80%	92%	29%	96%	70%	79%	77%	73%	25%	90%	65%	84%	82%	107%	29%	96%	71%
d=2,a=0.1	81%	79%	94%	28%	94%	69%	79%	76%	75%	25%	89%	65%	83%	81%	109%	29%	95%	71%
d=5,a=1	83%	81%	85%	29%	97%	71%	79%	77%	69%	25%	92%	67%	85%	83%	99%	29%	97%	73%
d=5,a=0.5	81%	79%	92%	27%	91%	70%	78%	76%	73%	24%	86%	65%	83%	81%	107%	28%	92%	71%
d=5,a=0.25	80%	78%	93%	27%	89%	70%	77%	75%	75%	24%	84%	65%	82%	80%	108%	29%	90%	71%
d=5,a=0.1	80%	78%	94%	28%	88%	70%	76%	74%	76%	24%	83%	65%	81%	79%	108%	29%	89%	72%
d=10,a=1	82%	80%	82%	28%	96%	71%	78%	76%	67%	25%	91%	67%	84%	82%	96%	29%	96%	72%
d=10,a=0.5	79%	77%	88%	27%	85%	70%	76%	74%	71%	24%	81%	66%	81%	79%	102%	29%	86%	72%
d=10,a=0.25	76%	74%	88%	28%	82%	71%	73%	72%	72%	24%	79%	67%	78%	76%	102%	29%	83%	72%
d=10,a=0.1	75%	73%	88%	28%	82%	71%	72%	70%	72%	24%	79%	67%	76%	74%	102%	29%	83%	72%
d=25,a=1	80%	79%	73%	27%	96%	69%	77%	75%	61%	24%	91%	67%	82%	81%	85%	28%	96%	71%
d=25,a=0.5	77%	76%	69%	27%	94%	68%	75%	73%	57%	24%	88%	66%	79%	77%	77%	28%	94%	69%
d=25,a=0.25	77%	75%	69%	28%	97%	69%	74%	73%	57%	24%	91%	66%	78%	76%	76%	29%	97%	69%
d=25,a=0.1	77%	75%	69%	28%	99%	69%	74%	73%	57%	25%	93%	66%	78%	76%	77%	29%	98%	69%
d=50,a=1	81%	79%	76%	27%	96%	69%	77%	75%	63%	24%	91%	66%	82%	81%	88%	28%	95%	70%
d=50,a=0.5	81%	79%	75%	28%	98%	68%	76%	74%	61%	24%	90%	66%	82%	80%	84%	28%	97%	69%
d=50,a=0.25	81%	79%	80%	28%	101%	69%	76%	74%	64%	25%	93%	67%	83%	80%	89%	29%	101%	70%
d=50,a=0.1	82%	80%	86%	29%	101%	70%	77%	75%	69%	25%	93%	67%	83%	81%	97%	29%	101%	71%
to1	83%	81%	86%	29%	95%	72%	79%	77%	68%	26%	91%	67%	84%	83%	102%	30%	95%	73%
to2	81%	79%	94%	28%	94%	69%	78%	76%	76%	25%	88%	65%	83%	81%	109%	29%	94%	71%
to5	79%	77%	94%	28%	88%	70%	76%	74%	76%	24%	83%	66%	80%	78%	108%	29%	89%	72%
to10	75%	73%	88%	28%	83%	71%	71%	70%	72%	24%	79%	67%	76%	74%	102%	29%	84%	72%
to25	77%	75%	70%	28%	99%	69%	75%	73%	57%	25%	93%	67%	78%	76%	78%	29%	99%	69%
to50	82%	80%	92%	29%	100%	71%	77%	75%	72%	25%	93%	68%	84%	81%	106%	29%	100%	71%
to2&to10	74%	73%	88%	28%	82%	69%	72%	70%	71%	24%	77%	64%	75%	74%	102%	29%	83%	70%
to2&to25	77%	76%	69%	27%	94%	66%	75%	73%	57%	24%	87%	64%	78%	76%	78%	28%	95%	67%
to5&to10	75%	73%	86%	27%	84%	70%	72%	70%	69%	24%	79%	65%	76%	74%	100%	28%	85%	71%
to5&to25	77%	75%	69%	26%	88%	67%	74%	72%	56%	24%	82%	64%	78%	76%	78%	27%	90%	68%
to5&to50	79%	77%	88%	26%	87%	68%	75%	73%	69%	22%	81%	65%	80%	78%	101%	26%	89%	69%

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR – Average Absolute Percentage Errors

	GWR - 350 Neighbors, Gaussian, Euclidean Distances						GWR - 350 Neighbors, Bi-squared, Euclidean Distances						GWR - 350 Neighbors, Rank Weighting, Euclidean Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	84%	81%	95%	31%	98%	75%	79%	77%	81%	28%	92%	69%	86%	84%	111%	31%	99%	75%
d=1,a=0.5	84%	81%	93%	30%	97%	74%	79%	77%	79%	27%	92%	69%	86%	84%	107%	31%	98%	75%
d=1,a=0.25	83%	81%	92%	30%	97%	74%	79%	77%	78%	27%	91%	68%	86%	83%	106%	30%	97%	74%
d=1,a=0.1	83%	81%	93%	30%	96%	73%	79%	77%	79%	27%	91%	68%	85%	83%	107%	30%	97%	74%
d=2,a=1	84%	81%	93%	30%	97%	74%	79%	77%	80%	27%	92%	69%	86%	84%	107%	31%	98%	75%
d=2,a=0.5	83%	80%	95%	29%	97%	72%	79%	77%	82%	26%	91%	67%	85%	83%	110%	29%	97%	73%
d=2,a=0.25	82%	79%	99%	29%	95%	71%	79%	76%	85%	26%	90%	66%	84%	82%	114%	29%	96%	72%
d=2,a=0.1	81%	79%	101%	29%	94%	71%	78%	76%	86%	26%	89%	66%	83%	81%	115%	29%	95%	72%
d=5,a=1	83%	81%	91%	29%	97%	73%	79%	77%	78%	26%	91%	68%	85%	83%	105%	29%	97%	74%
d=5,a=0.5	80%	78%	99%	28%	91%	71%	78%	76%	85%	25%	85%	66%	82%	80%	113%	28%	92%	72%
d=5,a=0.25	79%	77%	101%	28%	88%	72%	76%	74%	86%	25%	83%	67%	81%	79%	115%	28%	89%	73%
d=5,a=0.1	79%	77%	101%	28%	88%	72%	76%	74%	87%	25%	83%	67%	80%	78%	116%	28%	89%	73%
d=10,a=1	82%	80%	88%	28%	96%	73%	78%	76%	76%	25%	90%	68%	84%	82%	100%	29%	96%	73%
d=10,a=0.5	79%	77%	95%	28%	86%	72%	76%	74%	81%	25%	80%	67%	80%	78%	108%	29%	87%	73%
d=10,a=0.25	77%	75%	95%	29%	84%	72%	74%	72%	82%	25%	78%	68%	78%	77%	109%	29%	85%	73%
d=10,a=0.1	77%	75%	95%	29%	84%	73%	73%	71%	82%	25%	78%	68%	78%	76%	109%	29%	85%	73%
d=25,a=1	80%	78%	78%	28%	96%	71%	77%	75%	68%	25%	91%	67%	82%	80%	88%	29%	97%	71%
d=25,a=0.5	79%	77%	74%	29%	94%	70%	75%	73%	63%	25%	89%	66%	80%	78%	82%	29%	95%	70%
d=25,a=0.25	78%	77%	75%	29%	97%	70%	75%	73%	63%	26%	91%	67%	80%	78%	83%	30%	98%	70%
d=25,a=0.1	79%	77%	76%	29%	99%	70%	75%	73%	63%	26%	93%	67%	80%	78%	85%	30%	99%	70%
d=50,a=1	80%	78%	81%	28%	97%	70%	77%	75%	70%	25%	91%	67%	82%	80%	92%	28%	97%	70%
d=50,a=0.5	81%	79%	82%	28%	99%	70%	77%	74%	68%	25%	92%	67%	82%	80%	90%	29%	99%	70%
d=50,a=0.25	82%	80%	90%	29%	101%	70%	77%	75%	73%	26%	94%	67%	84%	81%	99%	30%	102%	70%
d=50,a=0.1	83%	81%	98%	29%	101%	71%	78%	75%	79%	26%	94%	68%	85%	82%	109%	30%	102%	71%
to1	83%	80%	93%	29%	95%	73%	79%	77%	79%	27%	90%	68%	85%	83%	107%	30%	96%	74%
to2	81%	78%	102%	29%	93%	71%	78%	76%	87%	26%	88%	66%	83%	80%	116%	29%	94%	72%
to5	78%	76%	101%	28%	88%	72%	75%	74%	87%	25%	82%	67%	80%	78%	116%	28%	89%	73%
to10	76%	75%	95%	29%	84%	73%	72%	71%	82%	25%	78%	68%	78%	76%	108%	29%	85%	73%
to25	79%	77%	77%	29%	99%	70%	75%	73%	64%	26%	93%	67%	80%	78%	87%	30%	100%	70%
to50	83%	81%	101%	29%	101%	71%	78%	76%	84%	26%	94%	68%	85%	83%	113%	30%	102%	71%
to2&to10	76%	74%	95%	28%	83%	70%	73%	71%	82%	25%	77%	65%	77%	75%	109%	28%	84%	71%
to2&to25	78%	76%	77%	28%	94%	68%	76%	74%	63%	25%	89%	64%	79%	77%	86%	28%	95%	68%
to5&to10	77%	75%	93%	28%	84%	71%	73%	71%	79%	25%	79%	66%	77%	76%	107%	29%	86%	72%
to5&to25	78%	76%	77%	27%	89%	69%	75%	73%	63%	24%	83%	65%	79%	77%	87%	28%	90%	69%
to5&to50	79%	78%	96%	27%	88%	69%	76%	74%	80%	23%	82%	65%	80%	79%	109%	27%	90%	69%

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR – Average Absolute Percentage Errors

	GWR - 350 Neighbors, Gaussian, Network Distances						GWR - 350 Neighbors, Bi-squared, Network Distances						GWR - 350 Neighbors, Rank Weighting, Network Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	86%	84%	95%	30%	100%	75%	81%	79%	80%	28%	95%	70%	88%	85%	111%	31%	101%	77%
d=1,a=0.5	86%	84%	93%	30%	100%	75%	81%	79%	78%	27%	95%	69%	88%	85%	108%	31%	101%	76%
d=1,a=0.25	86%	83%	92%	30%	99%	74%	81%	79%	78%	27%	94%	69%	88%	85%	107%	30%	100%	76%
d=1,a=0.1	86%	83%	92%	29%	98%	74%	81%	79%	78%	27%	93%	69%	88%	85%	107%	30%	99%	76%
d=2,a=1	86%	84%	93%	30%	100%	75%	81%	79%	79%	27%	95%	69%	88%	85%	108%	31%	101%	76%
d=2,a=0.5	85%	82%	95%	29%	99%	73%	81%	78%	81%	26%	94%	68%	87%	84%	110%	29%	100%	74%
d=2,a=0.25	84%	81%	99%	29%	97%	72%	80%	78%	84%	26%	93%	67%	86%	83%	113%	29%	98%	74%
d=2,a=0.1	83%	81%	100%	29%	96%	72%	80%	77%	86%	26%	91%	67%	85%	83%	115%	29%	97%	74%
d=5,a=1	85%	83%	91%	29%	99%	74%	81%	78%	77%	26%	94%	69%	87%	85%	105%	29%	100%	75%
d=5,a=0.5	83%	80%	98%	28%	93%	72%	79%	77%	84%	25%	88%	67%	85%	82%	113%	28%	94%	74%
d=5,a=0.25	82%	80%	100%	28%	90%	73%	78%	76%	85%	25%	86%	67%	83%	81%	115%	29%	91%	74%
d=5,a=0.1	81%	79%	100%	29%	89%	73%	78%	76%	86%	25%	85%	67%	82%	80%	115%	29%	91%	74%
d=10,a=1	84%	82%	88%	28%	98%	73%	80%	78%	75%	25%	93%	68%	86%	84%	101%	29%	99%	75%
d=10,a=0.5	81%	79%	94%	29%	88%	73%	77%	75%	81%	25%	82%	68%	82%	80%	108%	29%	89%	74%
d=10,a=0.25	78%	77%	95%	29%	85%	73%	75%	73%	81%	26%	80%	68%	80%	78%	108%	29%	87%	74%
d=10,a=0.1	78%	76%	95%	29%	86%	73%	74%	73%	81%	26%	80%	68%	79%	77%	108%	29%	87%	74%
d=25,a=1	83%	80%	78%	28%	99%	72%	78%	77%	68%	25%	94%	68%	85%	82%	90%	29%	99%	73%
d=25,a=0.5	79%	78%	75%	29%	97%	70%	76%	75%	64%	25%	91%	67%	80%	79%	82%	30%	97%	71%
d=25,a=0.25	79%	77%	75%	29%	99%	71%	76%	74%	63%	26%	94%	67%	80%	79%	82%	30%	100%	71%
d=25,a=0.1	79%	78%	76%	29%	101%	71%	76%	74%	64%	26%	95%	67%	80%	79%	84%	30%	101%	71%
d=50,a=1	83%	81%	81%	28%	99%	71%	79%	77%	70%	25%	93%	67%	85%	82%	93%	28%	99%	72%
d=50,a=0.5	83%	81%	82%	28%	102%	70%	79%	77%	68%	25%	94%	67%	84%	82%	90%	29%	102%	71%
d=50,a=0.25	84%	82%	89%	29%	104%	71%	79%	77%	73%	26%	97%	68%	86%	84%	97%	30%	105%	72%
d=50,a=0.1	85%	83%	96%	29%	104%	72%	80%	77%	78%	26%	97%	68%	87%	85%	107%	30%	105%	72%
to1	85%	83%	93%	29%	97%	74%	81%	79%	78%	27%	93%	68%	87%	85%	107%	30%	98%	75%
to2	83%	80%	101%	29%	95%	72%	79%	77%	86%	26%	90%	67%	85%	82%	116%	29%	96%	74%
to5	80%	78%	101%	29%	89%	73%	77%	75%	86%	25%	85%	67%	81%	79%	116%	29%	91%	74%
to10	77%	76%	94%	29%	86%	73%	74%	72%	81%	26%	80%	68%	79%	77%	108%	29%	87%	74%
to25	79%	78%	77%	30%	102%	71%	76%	74%	64%	26%	96%	67%	81%	79%	85%	30%	102%	72%
to50	86%	83%	100%	29%	104%	72%	80%	78%	83%	27%	96%	69%	87%	85%	112%	30%	105%	73%
to2&to10	77%	75%	94%	29%	85%	71%	74%	72%	81%	25%	79%	66%	78%	76%	108%	29%	86%	72%
to2&to25	79%	77%	76%	28%	96%	69%	77%	75%	64%	25%	91%	65%	80%	78%	85%	28%	97%	69%
to5&to10	78%	76%	92%	29%	86%	72%	74%	73%	78%	25%	81%	67%	78%	77%	107%	29%	87%	73%
to5&to25	80%	78%	77%	28%	90%	70%	76%	74%	63%	25%	85%	65%	81%	79%	86%	28%	91%	70%
to5&to50	82%	80%	96%	27%	90%	70%	78%	76%	79%	23%	84%	66%	83%	81%	108%	28%	91%	71%

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR – Median Percentage Errors

	GWR - 160 Neighbors, Gaussian, Euclidean Distances						GWR - 160 Neighbors, Bi-squared, Euclidean Distances						GWR - 160 Neighbors, Rank Weighting, Euclidean Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	12.5%	10.8%	-1.5%	-3.0%	3.2%	-0.2%	7.5%	8.8%	3.0%	-7.9%	6.4%	-0.2%	13.4%	10.9%	1.4%	-9.8%	2.0%	-0.7%
d=1,a=0.5	11.4%	10.1%	0.0%	-5.0%	2.1%	-0.3%	7.6%	7.1%	2.3%	-7.1%	7.1%	0.5%	11.8%	11.6%	2.8%	-9.5%	2.8%	-0.7%
d=1,a=0.25	11.0%	9.4%	1.0%	-7.3%	2.7%	-0.1%	8.1%	8.4%	2.3%	-6.7%	7.1%	0.9%	12.8%	11.3%	3.7%	-10.9%	3.3%	-0.6%
d=1,a=0.1	10.3%	8.5%	1.4%	-7.8%	2.3%	-0.3%	8.7%	8.7%	1.6%	-5.4%	7.3%	0.3%	12.6%	11.1%	4.8%	-10.5%	4.5%	-0.8%
d=2,a=1	11.0%	10.4%	0.6%	-4.9%	2.4%	-0.1%	7.0%	7.4%	3.4%	-6.7%	6.4%	-0.1%	12.4%	11.0%	0.7%	-9.2%	2.9%	-0.2%
d=2,a=0.5	10.5%	7.0%	3.0%	-7.0%	2.9%	0.2%	6.9%	7.1%	1.9%	-4.5%	5.6%	1.3%	11.4%	11.4%	3.0%	-9.7%	3.6%	0.0%
d=2,a=0.25	8.8%	7.6%	-2.1%	-8.3%	1.4%	-0.3%	6.9%	6.4%	2.1%	-4.8%	4.9%	0.5%	9.9%	10.5%	-1.0%	-8.4%	2.2%	-1.2%
d=2,a=0.1	6.9%	5.4%	-0.4%	-7.7%	1.9%	-0.5%	7.0%	7.0%	1.9%	-5.2%	5.5%	0.8%	8.7%	9.2%	-1.5%	-7.5%	1.6%	-1.8%
d=5,a=1	9.5%	6.9%	0.7%	-6.4%	2.3%	0.7%	7.3%	6.2%	2.0%	-5.1%	6.5%	0.9%	10.2%	9.7%	3.5%	-9.5%	1.8%	-0.3%
d=5,a=0.5	6.8%	6.2%	0.9%	-3.9%	4.5%	-0.5%	6.3%	5.8%	3.2%	-3.7%	5.7%	0.7%	6.5%	7.8%	2.5%	-3.5%	4.9%	-2.3%
d=5,a=0.25	5.3%	5.4%	1.3%	-2.8%	7.1%	-0.9%	5.5%	5.6%	2.6%	-2.9%	6.3%	1.1%	5.8%	6.3%	3.4%	-3.7%	8.4%	-1.8%
d=5,a=0.1	4.7%	5.6%	1.1%	-2.5%	5.5%	-0.6%	6.2%	6.0%	3.7%	-2.5%	4.1%	0.9%	4.6%	5.3%	2.6%	-3.5%	6.8%	-1.6%
d=10,a=1	7.7%	6.1%	2.3%	-5.1%	2.6%	-0.9%	6.1%	6.0%	2.8%	-4.9%	7.5%	0.9%	9.8%	9.7%	3.6%	-9.0%	2.3%	-0.7%
d=10,a=0.5	4.1%	4.7%	0.9%	-6.2%	1.9%	-2.1%	7.2%	6.8%	-0.9%	-3.2%	5.3%	0.3%	5.5%	5.6%	1.3%	-8.0%	1.6%	-2.7%
d=10,a=0.25	2.9%	2.6%	-0.9%	-6.5%	3.6%	-2.6%	6.3%	5.1%	-1.2%	-3.3%	2.4%	-0.4%	2.9%	1.7%	1.1%	-8.6%	2.3%	-2.9%
d=10,a=0.1	4.2%	3.4%	-1.3%	-5.8%	2.0%	-2.3%	5.3%	3.7%	-0.5%	-3.5%	2.2%	0.4%	2.6%	1.7%	-1.3%	-8.0%	4.2%	-2.8%
d=25,a=1	5.3%	5.4%	1.9%	-6.8%	2.9%	-1.2%	5.7%	5.5%	-0.6%	-5.5%	7.2%	0.8%	8.1%	7.4%	3.3%	-9.4%	2.2%	-1.0%
d=25,a=0.5	5.7%	7.4%	0.1%	-6.4%	2.5%	-1.2%	5.9%	5.1%	1.7%	-6.4%	4.9%	0.7%	9.6%	9.8%	-0.2%	-8.0%	1.5%	-1.7%
d=25,a=0.25	5.7%	4.8%	-2.2%	-6.3%	1.3%	-1.9%	7.3%	7.0%	0.2%	-6.1%	5.8%	0.0%	8.6%	8.9%	1.3%	-7.9%	-0.2%	-1.5%
d=25,a=0.1	5.8%	5.9%	-3.6%	-5.7%	2.1%	-1.9%	7.8%	7.4%	1.1%	-6.7%	5.0%	0.0%	8.6%	8.5%	-0.5%	-7.1%	1.6%	-1.9%
d=50,a=1	6.5%	5.7%	1.2%	-8.6%	3.6%	-1.6%	6.5%	6.0%	0.1%	-7.4%	5.2%	0.7%	9.2%	7.5%	3.2%	-10.3%	2.4%	-1.2%
d=50,a=0.5	7.2%	5.4%	-0.5%	-7.1%	4.0%	-2.3%	5.8%	5.1%	-0.8%	-9.4%	8.3%	-0.8%	8.7%	7.9%	-0.5%	-8.5%	2.5%	-1.9%
d=50,a=0.25	6.5%	5.4%	-1.8%	-6.1%	4.0%	-1.6%	6.5%	6.2%	-1.3%	-8.9%	6.1%	0.0%	8.5%	8.9%	1.3%	-7.4%	2.7%	-1.9%
d=50,a=0.1	7.7%	7.8%	0.5%	-7.5%	3.1%	-1.7%	7.5%	7.5%	-3.3%	-10.3%	3.6%	0.9%	9.7%	9.5%	2.1%	-8.5%	3.2%	-2.0%
to1	9.7%	8.5%	0.6%	-7.6%	2.8%	-0.5%	8.3%	8.7%	1.1%	-5.8%	7.1%	-0.3%	11.9%	10.5%	4.4%	-9.5%	4.3%	-1.3%
to2	5.4%	5.1%	-1.2%	-7.2%	2.5%	-1.4%	6.1%	6.8%	3.2%	-5.2%	4.3%	0.4%	7.2%	7.6%	0.5%	-7.5%	1.7%	-2.4%
to5	4.3%	6.1%	0.7%	-2.5%	5.1%	-0.6%	6.1%	6.0%	3.9%	-2.3%	4.1%	0.8%	4.1%	4.8%	2.4%	-3.5%	7.0%	-1.9%
to10	4.3%	4.0%	-1.6%	-5.4%	2.4%	-2.2%	4.3%	4.4%	-1.1%	-3.5%	1.7%	0.3%	3.9%	2.5%	-1.6%	-7.7%	2.0%	-2.7%
to25	5.8%	6.0%	-1.1%	-5.0%	3.6%	-1.3%	7.6%	7.2%	2.7%	-6.9%	3.9%	-0.7%	8.4%	8.2%	0.8%	-7.0%	3.3%	-1.7%
to50	7.5%	6.5%	1.9%	-8.0%	2.8%	-1.3%	7.6%	7.5%	-3.1%	-10.4%	3.9%	0.6%	10.9%	9.9%	0.4%	-9.9%	3.8%	-1.4%
to2&to10	5.4%	4.8%	-2.5%	-7.5%	0.0%	-2.1%	5.0%	5.3%	0.2%	-3.9%	2.2%	0.2%	5.1%	3.4%	-1.3%	-8.4%	1.2%	-2.2%
to2&to25	5.1%	5.1%	-0.8%	-6.2%	0.7%	-0.7%	6.1%	5.3%	3.0%	-6.2%	4.1%	0.6%	8.2%	8.0%	-2.8%	-7.3%	-0.7%	-1.5%
to5&to10	5.0%	4.9%	-1.1%	-3.3%	6.2%	-1.3%	4.5%	5.3%	-2.3%	-2.8%	2.4%	0.2%	3.8%	3.7%	-0.5%	-6.6%	5.6%	-2.0%
to5&to25	4.5%	5.8%	2.0%	-5.0%	5.3%	-1.0%	7.7%	6.7%	1.6%	-4.1%	4.1%	0.9%	5.2%	5.5%	0.7%	-7.1%	7.2%	-1.5%
to5&to50	5.4%	6.5%	3.4%	-6.3%	6.9%	-0.5%	5.8%	5.9%	-0.3%	-7.9%	6.1%	0.4%	5.6%	6.3%	0.2%	-8.3%	9.0%	-0.9%

GWR – Median Percentage Errors

	GWR - 160 Neighbors, Gaussian, Network Distances						GWR - 160 Neighbors, Bi-squared, Network Distances						GWR - 160 Neighbors, Rank Weighting, Network Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	11.4%	11.0%	0.7%	-3.4%	5.5%	-0.8%	11.8%	10.8%	4.8%	-4.9%	7.3%	0.0%	12.4%	10.2%	2.2%	-7.0%	4.7%	-0.6%
d=1,a=0.5	11.2%	10.7%	2.1%	-6.1%	4.5%	0.3%	10.9%	10.8%	2.1%	-5.0%	7.5%	0.6%	10.9%	11.4%	2.1%	-6.8%	4.3%	0.2%
d=1,a=0.25	11.0%	10.3%	1.8%	-7.5%	5.8%	0.3%	10.5%	11.7%	2.8%	-4.7%	8.9%	0.5%	10.8%	10.2%	4.7%	-8.2%	4.4%	-0.1%
d=1,a=0.1	10.0%	9.7%	2.2%	-6.8%	5.5%	-0.3%	10.6%	10.6%	2.7%	-4.6%	8.7%	0.3%	10.3%	10.1%	6.2%	-7.6%	5.7%	-1.0%
d=2,a=1	10.9%	11.0%	1.4%	-4.8%	4.6%	0.5%	11.0%	10.2%	3.8%	-4.9%	7.9%	0.3%	10.8%	11.0%	1.0%	-7.2%	4.2%	0.2%
d=2,a=0.5	10.3%	8.9%	2.0%	-7.5%	5.8%	-0.6%	9.9%	10.3%	2.1%	-3.9%	7.8%	0.9%	11.6%	10.5%	4.8%	-9.0%	4.9%	-0.4%
d=2,a=0.25	8.6%	7.2%	1.3%	-8.9%	6.1%	-1.1%	7.8%	8.4%	3.9%	-4.3%	7.8%	0.4%	10.7%	9.7%	2.6%	-8.1%	5.7%	-1.3%
d=2,a=0.1	7.6%	7.0%	0.0%	-8.1%	6.8%	-1.4%	7.5%	8.2%	5.3%	-4.1%	6.7%	0.7%	10.6%	8.8%	2.7%	-6.6%	4.3%	-2.1%
d=5,a=1	9.8%	9.2%	3.6%	-6.5%	4.5%	-0.4%	11.1%	9.5%	4.3%	-4.3%	7.7%	0.5%	11.0%	9.8%	4.4%	-8.6%	3.2%	0.1%
d=5,a=0.5	7.4%	7.9%	2.1%	-2.0%	8.3%	-0.5%	8.1%	8.9%	3.6%	-3.1%	7.9%	0.5%	8.5%	7.6%	3.0%	-1.6%	7.0%	-1.6%
d=5,a=0.25	6.4%	6.2%	2.4%	-1.7%	9.3%	-1.0%	7.0%	6.5%	6.4%	-3.1%	7.8%	0.5%	7.8%	6.7%	2.5%	-2.0%	10.3%	-1.0%
d=5,a=0.1	6.9%	6.7%	1.8%	-1.2%	7.5%	-1.1%	8.0%	8.2%	7.7%	-3.1%	7.3%	0.6%	7.9%	7.6%	3.6%	-2.0%	7.4%	-1.3%
d=10,a=1	8.5%	8.3%	1.6%	-7.9%	4.8%	-1.2%	10.2%	10.1%	3.6%	-4.3%	8.3%	0.7%	9.3%	8.1%	5.7%	-5.2%	4.0%	-1.2%
d=10,a=0.5	7.0%	7.6%	1.2%	-4.8%	5.4%	-2.2%	7.8%	7.1%	3.1%	-4.1%	7.2%	0.3%	6.7%	7.4%	2.9%	-6.5%	5.0%	-1.8%
d=10,a=0.25	2.4%	4.8%	0.7%	-5.6%	5.8%	-2.4%	6.7%	5.9%	3.1%	-3.8%	5.0%	-0.1%	3.7%	4.1%	3.2%	-7.2%	4.9%	-1.2%
d=10,a=0.1	2.3%	3.6%	0.4%	-5.3%	5.2%	-2.3%	6.7%	6.0%	2.5%	-3.9%	4.3%	0.2%	1.9%	3.9%	4.1%	-5.2%	6.0%	-1.2%
d=25,a=1	8.6%	7.8%	2.9%	-7.4%	5.0%	-1.1%	6.9%	6.6%	1.9%	-5.2%	7.5%	0.4%	7.8%	8.7%	4.0%	-9.1%	2.6%	-1.0%
d=25,a=0.5	9.0%	8.5%	-0.6%	-5.9%	5.9%	-1.1%	8.7%	7.3%	2.3%	-6.5%	6.7%	1.1%	9.9%	7.6%	-2.2%	-8.3%	4.0%	-1.3%
d=25,a=0.25	7.7%	7.8%	-3.8%	-6.1%	3.0%	-2.3%	9.3%	8.3%	2.5%	-6.7%	6.9%	-0.2%	9.9%	7.1%	-0.6%	-6.8%	0.9%	-1.6%
d=25,a=0.1	7.3%	6.8%	-5.8%	-5.4%	4.1%	-2.2%	9.5%	8.7%	3.3%	-7.3%	6.2%	-0.1%	9.7%	7.6%	-3.7%	-6.2%	4.2%	-2.1%
d=50,a=1	8.1%	7.3%	2.7%	-8.2%	5.3%	-1.1%	8.3%	7.8%	1.3%	-7.3%	6.9%	1.0%	9.3%	9.0%	4.5%	-10.4%	2.5%	-1.4%
d=50,a=0.5	6.2%	4.5%	1.0%	-7.2%	4.4%	-1.8%	7.6%	7.3%	1.3%	-8.6%	7.1%	-0.1%	7.4%	5.9%	-1.1%	-8.3%	3.5%	-1.3%
d=50,a=0.25	6.8%	6.3%	0.1%	-6.5%	5.3%	-1.6%	8.2%	8.0%	0.9%	-8.2%	6.3%	-0.1%	10.3%	8.7%	0.6%	-5.5%	4.4%	-1.7%
d=50,a=0.1	9.5%	8.4%	2.4%	-8.1%	5.5%	-1.1%	9.3%	9.1%	1.4%	-9.1%	6.1%	0.7%	11.5%	9.6%	2.6%	-7.0%	5.5%	-1.4%
to1	10.5%	10.0%	1.0%	-6.5%	5.8%	-0.5%	9.8%	11.2%	2.8%	-4.9%	8.4%	-0.2%	11.0%	10.5%	5.6%	-7.8%	5.8%	-1.4%
to2	7.0%	6.8%	-0.2%	-7.7%	5.8%	-1.2%	8.2%	8.7%	6.1%	-4.2%	3.9%	0.5%	8.9%	8.8%	3.0%	-6.2%	3.9%	-2.0%
to5	7.2%	7.2%	1.6%	-0.9%	8.0%	-1.2%	9.1%	9.4%	7.7%	-2.9%	7.2%	0.5%	8.1%	7.2%	3.5%	-2.0%	7.2%	-1.1%
to10	2.1%	3.5%	0.1%	-4.3%	5.8%	-2.0%	6.8%	5.8%	2.6%	-3.9%	4.1%	0.2%	2.0%	3.7%	3.4%	-4.0%	5.6%	-1.9%
to25	7.4%	6.5%	-6.2%	-4.7%	4.5%	-1.6%	9.2%	9.0%	3.6%	-7.7%	5.4%	-0.2%	9.2%	8.6%	-4.4%	-5.6%	4.2%	-2.3%
to50	10.4%	9.1%	2.9%	-8.5%	7.1%	-0.9%	8.8%	8.9%	7.0%	-9.5%	6.8%	0.5%	11.4%	10.2%	2.0%	-8.3%	6.4%	-0.4%
to2&to10	5.2%	6.1%	0.4%	-5.7%	5.1%	-1.5%	7.2%	4.9%	3.2%	-4.0%	5.4%	-0.3%	5.9%	6.7%	3.3%	-6.0%	2.7%	-2.1%
to2&to25	6.1%	5.2%	-2.4%	-7.0%	2.9%	-0.7%	8.0%	7.3%	4.3%	-6.9%	3.6%	0.2%	8.7%	6.0%	-3.4%	-7.5%	1.7%	-2.0%
to5&to10	6.6%	7.2%	0.5%	-2.1%	5.7%	-1.0%	7.3%	6.4%	0.1%	-2.4%	6.3%	-0.1%	2.6%	5.4%	2.3%	-2.0%	4.7%	-1.3%
to5&to25	7.1%	6.5%	-1.2%	-5.3%	7.2%	-0.6%	8.6%	8.2%	2.4%	-5.2%	5.6%	0.8%	8.0%	7.6%	-0.7%	-6.5%	4.8%	-0.9%
to5&to50	8.0%	6.9%	5.4%	-6.1%	10.8%	-0.7%	7.8%	8.2%	5.4%	-7.2%	8.4%	0.3%	10.1%	9.9%	3.1%	-5.4%	8.2%	-0.4%

GWR – Median Percentage Errors

	GWR - 255 Neighbors, Gaussian, Euclidean Distances						GWR - 255 Neighbors, Bi-squared, Euclidean Distances						GWR - 255 Neighbors, Rank Weighting, Euclidean Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	11.8%	13.1%	-5.3%	-5.1%	4.3%	0.1%	9.7%	9.3%	-1.6%	-7.4%	3.8%	-0.8%	13.6%	14.1%	-2.2%	-7.6%	4.7%	-0.2%
d=1,a=0.5	12.8%	12.5%	-4.1%	-6.1%	4.1%	0.2%	8.6%	9.0%	-0.5%	-7.3%	4.1%	-1.0%	12.4%	11.8%	-1.2%	-7.9%	4.1%	0.6%
d=1,a=0.25	12.1%	12.2%	-4.7%	-6.3%	3.9%	0.2%	8.2%	8.3%	0.8%	-8.4%	3.6%	0.2%	12.5%	12.3%	-2.2%	-9.0%	4.5%	0.4%
d=1,a=0.1	11.6%	12.5%	-5.1%	-6.5%	6.3%	0.7%	7.7%	7.7%	0.6%	-7.9%	2.4%	0.4%	11.8%	12.0%	-1.6%	-9.7%	3.3%	0.1%
d=2,a=1	12.5%	12.7%	-2.6%	-6.7%	4.4%	0.6%	8.8%	9.3%	0.6%	-7.0%	2.9%	-0.3%	12.3%	12.5%	-4.0%	-10.2%	4.1%	0.3%
d=2,a=0.5	11.9%	10.2%	-6.6%	-7.3%	3.8%	0.0%	8.1%	7.8%	0.8%	-8.4%	2.5%	0.3%	10.7%	10.3%	-6.8%	-8.7%	4.9%	-0.4%
d=2,a=0.25	10.6%	10.4%	-4.0%	-5.6%	4.6%	-0.8%	7.2%	6.6%	0.7%	-6.9%	2.2%	0.0%	10.1%	9.0%	-5.1%	-8.0%	5.0%	-0.4%
d=2,a=0.1	9.8%	7.7%	-3.6%	-5.0%	3.2%	-0.9%	6.3%	6.0%	1.8%	-6.3%	0.8%	0.5%	10.4%	9.9%	-3.9%	-6.3%	3.4%	-0.7%
d=5,a=1	12.8%	11.2%	-8.4%	-9.0%	4.0%	0.0%	7.9%	8.0%	2.2%	-8.9%	2.8%	0.2%	13.2%	11.5%	-7.6%	-9.6%	5.0%	-0.7%
d=5,a=0.5	7.8%	8.1%	-2.6%	-1.3%	3.2%	-0.5%	7.6%	7.7%	0.8%	-2.2%	6.1%	-0.1%	8.6%	8.4%	-3.6%	-3.2%	5.0%	-0.3%
d=5,a=0.25	6.6%	6.4%	-2.4%	-0.1%	6.1%	-0.9%	6.5%	5.8%	1.4%	-1.7%	7.2%	-0.1%	6.7%	7.4%	-2.5%	-1.7%	8.4%	0.0%
d=5,a=0.1	6.4%	5.9%	-3.1%	0.3%	5.7%	-1.0%	6.9%	6.6%	0.3%	-1.3%	6.7%	-0.1%	6.7%	5.5%	-2.5%	-1.5%	9.0%	-0.7%
d=10,a=1	9.0%	8.6%	-7.6%	-7.1%	4.1%	-0.4%	6.2%	7.4%	1.9%	-6.6%	3.7%	-0.8%	10.0%	10.7%	-7.1%	-7.7%	3.7%	-0.9%
d=10,a=0.5	6.0%	5.7%	-6.3%	-2.0%	3.9%	-0.9%	6.2%	6.4%	-1.2%	-3.3%	3.1%	-0.7%	6.0%	5.4%	-6.5%	-3.5%	5.3%	-1.5%
d=10,a=0.25	3.6%	2.6%	-6.9%	-1.6%	5.1%	-0.9%	5.1%	4.3%	-2.5%	-3.7%	5.5%	-0.6%	3.5%	3.6%	-6.8%	-3.5%	3.7%	-1.2%
d=10,a=0.1	3.8%	3.0%	-7.4%	-1.8%	3.3%	-1.3%	5.7%	4.1%	-2.0%	-3.4%	3.8%	-0.9%	2.7%	2.9%	-6.4%	-3.8%	2.3%	-1.0%
d=25,a=1	5.8%	6.0%	-7.7%	-6.2%	4.1%	-0.8%	5.9%	6.2%	2.1%	-8.2%	5.3%	-1.2%	8.6%	9.4%	-7.4%	-9.0%	5.4%	-1.8%
d=25,a=0.5	4.0%	4.7%	-3.0%	-5.1%	2.9%	-3.0%	6.6%	6.3%	-0.4%	-7.7%	5.7%	-1.7%	6.1%	5.7%	-3.8%	-7.5%	3.6%	-2.6%
d=25,a=0.25	4.1%	4.7%	-2.8%	-3.0%	1.4%	-3.4%	5.3%	5.8%	-0.3%	-6.0%	3.2%	-3.0%	5.3%	4.4%	-0.7%	-5.9%	3.1%	-2.6%
d=25,a=0.1	4.2%	4.3%	-4.0%	-2.2%	2.0%	-4.1%	5.4%	6.0%	-0.5%	-5.2%	3.6%	-2.7%	4.5%	4.3%	-1.9%	-5.6%	4.3%	-2.9%
d=50,a=1	8.3%	5.7%	-5.7%	-6.3%	4.3%	-1.4%	7.5%	8.0%	3.3%	-9.3%	4.5%	-1.8%	11.0%	10.1%	-8.1%	-9.5%	5.5%	-1.3%
d=50,a=0.5	7.7%	6.0%	-2.6%	-3.7%	3.0%	-2.6%	5.9%	5.9%	0.6%	-6.9%	6.4%	-2.2%	8.7%	5.8%	-3.2%	-5.8%	4.6%	-2.7%
d=50,a=0.25	9.3%	6.5%	-1.1%	-4.3%	4.5%	-2.4%	7.3%	6.1%	-0.8%	-8.7%	4.7%	-1.4%	9.4%	7.3%	-2.3%	-6.8%	5.3%	-2.5%
d=50,a=0.1	10.6%	8.0%	-0.9%	-4.6%	4.9%	-2.0%	8.4%	6.3%	-2.2%	-8.6%	4.4%	-0.8%	10.0%	7.8%	2.1%	-7.1%	5.5%	-1.4%
to1	12.4%	11.9%	-4.7%	-6.8%	5.5%	0.5%	8.0%	7.7%	0.6%	-7.7%	2.5%	0.1%	10.0%	11.2%	-0.5%	-9.5%	3.9%	-0.8%
to2	9.6%	8.1%	-3.4%	-4.9%	3.2%	-0.6%	5.3%	5.3%	1.7%	-6.5%	2.4%	0.3%	11.3%	9.6%	-3.4%	-6.2%	4.1%	-0.8%
to5	6.0%	6.0%	-3.4%	0.2%	5.7%	-1.2%	7.3%	7.3%	0.2%	-1.2%	6.7%	-0.1%	5.0%	6.4%	-2.7%	-1.3%	9.9%	-1.0%
to10	5.5%	4.3%	-7.0%	-2.0%	3.4%	-1.2%	6.6%	5.2%	-1.8%	-3.4%	3.4%	-0.6%	3.2%	3.3%	-6.6%	-3.8%	4.2%	-0.8%
to25	3.7%	3.9%	-4.1%	-2.4%	2.1%	-4.0%	5.3%	5.3%	-1.0%	-5.1%	4.6%	-2.5%	4.9%	3.5%	0.8%	-4.8%	4.3%	-2.9%
to50	10.8%	9.2%	-1.5%	-4.6%	5.4%	-1.0%	7.4%	6.2%	2.0%	-9.0%	4.5%	-1.2%	10.9%	9.2%	2.5%	-6.9%	5.7%	-1.0%
to2&to10	4.6%	3.8%	-6.9%	-1.7%	4.2%	-1.0%	5.4%	5.5%	-1.3%	-3.0%	3.0%	-0.7%	2.2%	2.5%	-5.5%	-4.5%	3.7%	-0.8%
to2&to25	4.4%	2.5%	-4.9%	-3.1%	3.2%	-1.5%	5.8%	5.5%	1.1%	-7.5%	2.1%	-0.9%	5.5%	1.5%	-3.6%	-6.6%	3.7%	-1.1%
to5&to10	2.7%	2.9%	-7.5%	-1.5%	3.3%	-0.7%	5.1%	6.1%	-1.6%	-2.7%	6.7%	-0.6%	2.7%	2.1%	-5.3%	-3.2%	4.9%	-0.3%
to5&to25	4.1%	4.3%	-3.3%	-1.4%	6.6%	-1.4%	7.4%	6.9%	1.1%	-3.3%	6.8%	-0.7%	4.3%	3.7%	-1.2%	-3.3%	10.0%	-1.4%
to5&to50	8.3%	5.3%	-1.9%	-1.5%	6.8%	-0.2%	7.9%	6.8%	0.5%	-6.1%	9.3%	0.4%	7.9%	6.0%	-1.4%	-2.5%	9.8%	-1.9%

GWR – Median Percentage Errors

	GWR - 255 Neighbors, Gaussian, Network Distances						GWR - 255 Neighbors, Bi-squared, Network Distances						GWR - 255 Neighbors, Rank Weighting, Network Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	17.7%	14.6%	-4.9%	-5.2%	5.6%	0.3%	11.6%	12.0%	-1.3%	-4.6%	6.7%	0.0%	18.5%	17.4%	-6.6%	-8.1%	6.9%	1.3%
d=1,a=0.5	17.3%	14.1%	-5.3%	-6.5%	5.7%	-0.1%	11.6%	11.8%	0.2%	-5.1%	5.4%	-0.7%	17.1%	16.9%	-7.5%	-8.5%	5.3%	0.7%
d=1,a=0.25	17.4%	14.3%	-7.5%	-7.1%	3.7%	0.5%	12.1%	12.2%	2.6%	-6.5%	5.9%	0.0%	16.7%	16.2%	-8.2%	-9.1%	5.3%	-0.1%
d=1,a=0.1	15.5%	13.6%	-7.7%	-7.7%	3.9%	0.9%	11.9%	11.5%	4.1%	-6.4%	6.0%	0.3%	15.6%	15.6%	-7.1%	-9.6%	4.3%	0.6%
d=2,a=1	17.4%	14.5%	-7.5%	-7.6%	5.5%	0.4%	11.7%	11.8%	1.0%	-6.4%	5.3%	-0.3%	18.6%	16.9%	-6.8%	-9.4%	5.7%	1.1%
d=2,a=0.5	14.1%	12.1%	-8.8%	-8.0%	6.0%	0.4%	11.7%	12.0%	3.1%	-6.3%	5.2%	0.2%	15.7%	14.9%	-8.4%	-9.9%	5.3%	-0.3%
d=2,a=0.25	13.7%	11.7%	-4.4%	-6.2%	5.3%	-0.3%	9.6%	9.3%	2.7%	-7.2%	5.0%	0.3%	14.8%	13.0%	-5.3%	-8.6%	4.9%	-0.6%
d=2,a=0.1	11.6%	11.2%	-4.2%	-4.7%	4.2%	0.0%	8.5%	7.8%	2.4%	-7.2%	4.8%	0.3%	12.7%	12.7%	-4.3%	-5.8%	2.3%	-0.5%
d=5,a=1	15.8%	12.3%	-8.4%	-9.5%	5.8%	-0.3%	10.7%	11.8%	3.7%	-7.7%	5.1%	0.3%	15.7%	15.2%	-8.6%	-9.1%	6.0%	0.0%
d=5,a=0.5	8.6%	9.8%	-2.4%	-1.3%	6.3%	-0.5%	9.9%	9.8%	2.2%	-0.9%	8.2%	-0.1%	10.7%	10.8%	-2.6%	-3.3%	7.8%	0.4%
d=5,a=0.25	8.4%	7.9%	-3.6%	-0.4%	8.2%	-0.7%	8.4%	7.4%	2.5%	-0.5%	10.0%	-0.9%	7.9%	6.9%	-2.4%	-1.3%	10.5%	-0.8%
d=5,a=0.1	7.6%	7.5%	-3.0%	-0.1%	8.0%	-1.3%	7.6%	8.1%	2.4%	-0.2%	9.3%	-0.9%	7.0%	6.3%	-3.0%	-1.2%	10.5%	-0.6%
d=10,a=1	11.8%	12.4%	-7.1%	-6.7%	5.6%	-0.4%	9.5%	10.5%	4.1%	-6.7%	5.6%	-0.7%	14.4%	15.7%	-7.9%	-8.1%	6.3%	-0.6%
d=10,a=0.5	7.9%	8.2%	-6.3%	-2.3%	5.2%	-1.5%	7.1%	7.5%	1.9%	-4.4%	5.6%	-0.4%	9.2%	8.8%	-5.6%	-3.5%	6.2%	-1.5%
d=10,a=0.25	7.9%	7.4%	-5.8%	-2.7%	5.3%	-1.7%	6.4%	7.1%	0.7%	-4.2%	7.1%	-0.7%	7.1%	6.7%	-5.5%	-4.2%	4.7%	-0.9%
d=10,a=0.1	7.3%	5.5%	-5.4%	-2.9%	4.3%	-1.6%	7.3%	6.9%	0.2%	-3.7%	5.4%	-0.8%	6.2%	6.0%	-6.1%	-4.0%	4.5%	-0.6%
d=25,a=1	11.1%	10.7%	-6.5%	-5.4%	6.3%	-0.9%	9.3%	9.8%	3.0%	-7.0%	6.5%	-1.4%	12.4%	10.9%	-5.7%	-9.0%	6.7%	-0.9%
d=25,a=0.5	9.5%	8.8%	-4.8%	-4.4%	5.1%	-3.2%	9.9%	9.0%	-0.1%	-5.9%	6.2%	-1.9%	8.4%	7.2%	-4.7%	-7.2%	6.1%	-2.6%
d=25,a=0.25	8.6%	7.8%	-4.4%	-3.0%	3.0%	-3.4%	8.4%	8.1%	0.0%	-5.0%	5.3%	-3.1%	8.2%	6.8%	-2.8%	-5.2%	4.8%	-3.4%
d=25,a=0.1	8.8%	7.9%	-4.8%	-3.1%	4.2%	-3.6%	7.9%	7.6%	-0.7%	-5.4%	5.2%	-2.8%	8.2%	6.3%	-3.4%	-4.5%	5.3%	-2.7%
d=50,a=1	13.4%	12.6%	-6.1%	-5.9%	5.8%	-1.5%	11.1%	11.1%	4.4%	-7.3%	7.0%	-1.7%	13.4%	12.1%	-6.1%	-7.9%	7.1%	-1.4%
d=50,a=0.5	12.0%	10.1%	-1.2%	-5.5%	4.4%	-2.4%	8.4%	8.0%	0.7%	-7.2%	8.7%	-2.4%	12.1%	10.2%	-2.4%	-7.5%	4.9%	-1.8%
d=50,a=0.25	12.2%	10.6%	-1.4%	-5.2%	5.8%	-2.8%	9.0%	8.1%	0.0%	-8.7%	7.4%	-1.4%	13.1%	10.3%	-3.7%	-5.4%	6.2%	-2.6%
d=50,a=0.1	13.8%	11.1%	-2.5%	-5.5%	7.6%	-2.0%	10.9%	8.7%	-0.3%	-8.8%	6.5%	-0.8%	13.7%	11.1%	0.2%	-6.5%	6.9%	-1.7%
to1	13.9%	13.7%	-6.9%	-7.8%	7.7%	0.8%	11.3%	10.8%	4.5%	-6.3%	6.6%	0.7%	15.5%	15.2%	-5.8%	-9.8%	4.7%	0.1%
to2	12.3%	11.4%	-3.3%	-4.1%	4.6%	0.2%	7.8%	7.0%	2.3%	-7.2%	5.0%	-0.4%	12.4%	12.3%	-3.8%	-5.8%	3.7%	-0.5%
to5	8.0%	7.5%	-3.1%	0.0%	8.2%	-1.2%	9.4%	9.1%	2.3%	0.0%	9.8%	-1.0%	6.9%	7.1%	-3.2%	-1.1%	10.6%	-0.7%
to10	7.5%	5.6%	-5.5%	-3.1%	4.9%	-1.5%	8.6%	8.0%	-0.2%	-3.9%	5.3%	-1.1%	7.7%	6.4%	-6.7%	-4.2%	3.6%	-0.6%
to25	8.9%	7.9%	-5.1%	-3.0%	3.1%	-3.7%	8.1%	7.6%	-1.1%	-5.2%	5.8%	-2.5%	8.4%	6.4%	-3.9%	-4.4%	4.5%	-2.6%
to50	14.6%	11.3%	-2.3%	-5.2%	8.0%	-1.6%	11.5%	8.9%	2.0%	-10.0%	7.1%	-0.8%	14.3%	11.8%	5.3%	-7.1%	7.1%	-0.9%
to2&to10	8.2%	7.2%	-5.4%	-2.8%	4.9%	-1.8%	6.7%	6.8%	2.0%	-3.5%	3.1%	-0.5%	5.6%	5.1%	-5.5%	-4.6%	6.0%	-1.7%
to2&to25	7.6%	5.4%	-5.9%	-4.2%	3.6%	-1.5%	5.8%	6.2%	0.9%	-5.9%	4.2%	-1.2%	6.0%	5.0%	-3.2%	-6.7%	3.3%	-2.1%
to5&to10	5.6%	6.7%	-6.3%	-2.6%	5.4%	-1.0%	7.5%	7.8%	1.5%	-1.3%	9.5%	-0.6%	6.8%	6.3%	-6.4%	-3.4%	8.1%	-0.3%
to5&to25	5.8%	4.9%	-3.2%	-1.5%	9.5%	-2.0%	7.2%	8.2%	2.8%	-3.8%	9.5%	-1.0%	2.9%	4.4%	-2.3%	-2.4%	10.8%	-2.5%
to5&to50	8.0%	7.6%	-1.0%	-2.3%	8.1%	-1.1%	9.7%	8.4%	4.1%	-6.7%	10.5%	-0.5%	9.8%	8.2%	-3.4%	-2.6%	10.1%	-1.7%

GWR – Median Percentage Errors

	GWR - 350 Neighbors, Gaussian, Euclidean Distances						GWR - 350 Neighbors, Bi-squared, Euclidean Distances						GWR - 350 Neighbors, Rank Weighting, Euclidean Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	14.5%	13.7%	-6.9%	-5.4%	1.4%	0.6%	10.5%	9.7%	-4.1%	-5.7%	3.1%	-1.1%	13.5%	13.4%	-7.7%	-6.1%	6.2%	0.5%
d=1,a=0.5	14.0%	11.4%	-9.0%	-6.3%	3.3%	1.3%	9.8%	9.4%	-2.5%	-6.2%	2.9%	-1.7%	13.4%	13.7%	-5.8%	-6.9%	7.7%	0.8%
d=1,a=0.25	13.0%	11.3%	-9.2%	-8.1%	5.3%	1.9%	10.5%	10.4%	-3.2%	-6.5%	3.3%	-1.0%	13.6%	12.0%	-6.2%	-9.1%	6.7%	1.6%
d=1,a=0.1	12.1%	10.2%	-9.1%	-7.8%	7.5%	1.5%	11.9%	10.1%	-2.9%	-6.0%	2.0%	-0.5%	13.2%	11.6%	-6.2%	-9.5%	8.2%	1.6%
d=2,a=1	14.8%	13.5%	-9.1%	-6.6%	1.4%	1.4%	9.9%	9.9%	-2.7%	-6.3%	1.7%	-1.5%	14.3%	13.3%	-6.1%	-6.8%	5.9%	0.8%
d=2,a=0.5	12.9%	12.0%	-9.7%	-6.6%	5.5%	0.3%	9.4%	9.3%	-4.5%	-8.0%	3.1%	-0.1%	12.9%	10.0%	-7.4%	-7.3%	7.3%	0.6%
d=2,a=0.25	9.8%	9.6%	-8.7%	-5.2%	6.3%	-0.1%	9.6%	8.9%	-2.5%	-8.2%	3.9%	-1.2%	10.8%	7.5%	-5.7%	-5.7%	6.3%	0.1%
d=2,a=0.1	7.2%	8.9%	-8.0%	-4.2%	6.2%	-0.9%	7.2%	6.5%	-2.2%	-7.3%	2.9%	0.0%	9.0%	8.2%	-4.8%	-4.7%	6.0%	-0.2%
d=5,a=1	14.2%	10.0%	-10.0%	-6.5%	4.4%	0.7%	10.5%	10.2%	-4.5%	-9.0%	3.2%	-0.3%	13.7%	11.6%	-8.4%	-7.8%	7.9%	0.4%
d=5,a=0.5	6.1%	6.1%	-8.6%	-1.9%	0.9%	0.9%	8.4%	8.1%	-1.4%	-1.5%	4.9%	-0.3%	5.9%	5.8%	-8.2%	-2.8%	2.6%	1.0%
d=5,a=0.25	5.6%	3.8%	-7.2%	0.6%	3.7%	0.3%	5.9%	5.3%	-1.3%	-1.6%	7.0%	-0.9%	6.1%	4.8%	-9.1%	-1.7%	4.3%	0.3%
d=5,a=0.1	5.9%	4.5%	-6.0%	1.0%	4.6%	0.0%	6.7%	7.7%	-1.8%	-1.9%	6.1%	-0.8%	4.4%	4.3%	-8.6%	-1.5%	5.0%	0.3%
d=10,a=1	11.0%	10.2%	-10.7%	-3.1%	3.6%	0.5%	9.9%	9.4%	-3.1%	-7.5%	3.7%	-0.9%	11.3%	10.1%	-8.7%	-3.8%	6.0%	0.5%
d=10,a=0.5	6.5%	4.7%	-10.1%	0.7%	5.3%	0.0%	5.2%	5.8%	-3.2%	-2.9%	5.5%	-1.6%	4.7%	3.3%	-9.9%	-1.3%	3.6%	1.0%
d=10,a=0.25	6.2%	4.6%	-7.5%	1.0%	4.1%	-0.9%	3.2%	4.0%	-3.5%	-3.5%	5.2%	-1.5%	4.1%	2.9%	-8.4%	-1.2%	4.7%	0.6%
d=10,a=0.1	7.4%	6.2%	-6.9%	0.9%	5.0%	-1.3%	2.0%	2.9%	-3.3%	-3.4%	4.7%	-1.5%	5.9%	4.8%	-8.5%	-1.3%	4.7%	0.5%
d=25,a=1	8.7%	7.0%	-9.2%	-4.8%	6.0%	0.6%	8.4%	7.9%	-4.1%	-6.0%	4.1%	-1.7%	7.8%	6.0%	-6.3%	-6.4%	9.9%	-0.2%
d=25,a=0.5	2.8%	6.2%	-6.7%	-3.0%	4.8%	-1.5%	6.1%	6.6%	-2.4%	-6.5%	4.1%	-3.3%	3.2%	2.7%	-2.6%	-5.1%	5.4%	-2.7%
d=25,a=0.25	3.6%	3.5%	-3.8%	-2.7%	5.2%	-2.8%	5.0%	4.7%	-2.3%	-3.1%	3.3%	-3.6%	2.7%	2.9%	-4.6%	-4.0%	4.8%	-2.2%
d=25,a=0.1	3.6%	4.8%	-5.7%	-2.1%	5.8%	-2.5%	5.1%	3.9%	-3.9%	-2.0%	4.2%	-3.2%	2.0%	1.7%	-5.6%	-4.3%	5.4%	-2.4%
d=50,a=1	8.0%	6.9%	-6.5%	-3.8%	6.8%	-0.8%	10.5%	6.9%	-3.9%	-6.5%	5.0%	-2.2%	7.7%	6.1%	-6.6%	-4.5%	8.7%	-1.3%
d=50,a=0.5	6.8%	5.3%	-6.1%	-3.2%	4.2%	-2.4%	6.5%	6.9%	-3.0%	-3.1%	5.2%	-3.3%	4.7%	4.3%	-5.5%	-4.8%	7.0%	-3.0%
d=50,a=0.25	9.2%	7.6%	-4.3%	-4.5%	7.1%	-2.2%	9.2%	6.6%	-0.4%	-6.1%	3.7%	-2.5%	9.0%	8.6%	-5.0%	-5.0%	8.2%	-1.9%
d=50,a=0.1	10.3%	8.9%	-3.0%	-4.5%	7.0%	-1.9%	9.9%	7.8%	-2.0%	-6.9%	3.7%	-1.9%	13.1%	9.8%	-5.7%	-5.1%	7.7%	-2.0%
to1	11.3%	9.7%	-8.4%	-8.3%	9.0%	1.9%	11.5%	9.4%	-2.1%	-6.7%	3.2%	-0.4%	13.0%	11.9%	-7.1%	-9.6%	8.3%	1.8%
to2	8.1%	7.6%	-7.4%	-4.1%	5.9%	-0.6%	7.3%	6.0%	-2.9%	-7.3%	2.9%	0.2%	6.9%	7.5%	-4.3%	-4.5%	4.1%	-0.7%
to5	5.1%	4.1%	-5.8%	1.0%	3.9%	-0.4%	7.6%	8.2%	-1.9%	-2.0%	6.3%	-0.7%	5.0%	5.4%	-8.3%	-1.4%	4.9%	-0.2%
to10	6.7%	7.0%	-6.8%	0.8%	4.4%	-1.3%	3.3%	3.5%	-3.5%	-3.4%	4.7%	-1.6%	6.6%	4.1%	-8.5%	-1.6%	3.8%	0.6%
to25	4.4%	4.8%	-5.9%	-2.4%	5.8%	-2.3%	5.0%	4.1%	-4.7%	-1.8%	4.1%	-3.4%	3.1%	1.5%	-0.3%	-4.4%	5.2%	-2.8%
to50	10.4%	9.8%	-7.1%	-5.2%	6.3%	-1.7%	10.2%	8.9%	-1.3%	-6.6%	6.1%	-1.2%	14.5%	12.3%	-5.8%	-5.7%	6.9%	-1.2%
to2&to10	5.3%	3.9%	-7.3%	-0.1%	6.1%	-1.0%	3.8%	5.2%	-2.7%	-4.4%	3.0%	-0.8%	3.7%	2.7%	-8.7%	-2.0%	4.6%	-1.3%
to2&to25	2.6%	0.9%	-7.4%	-2.7%	6.7%	-1.7%	4.8%	3.9%	-4.3%	-6.1%	2.7%	-1.2%	3.2%	0.8%	-7.0%	-5.3%	7.3%	-1.7%
to5&to10	5.3%	4.0%	-5.3%	0.2%	5.6%	-0.4%	4.8%	5.2%	-5.4%	-1.9%	5.4%	0.0%	4.2%	3.9%	-8.3%	-1.5%	6.9%	0.1%
to5&to25	3.2%	3.0%	-6.1%	-1.9%	7.8%	-2.2%	3.1%	3.3%	-1.2%	-1.2%	8.1%	-1.0%	4.4%	2.7%	-5.6%	-3.2%	8.9%	-1.3%
to5&to50	7.1%	5.2%	-1.9%	-2.5%	7.2%	-1.5%	7.4%	6.4%	0.3%	-1.3%	8.1%	-0.6%	8.4%	6.6%	-7.6%	-2.8%	8.9%	-2.3%

GWR – Median Percentage Errors

	GWR - 350 Neighbors, Gaussian, Network Distances						GWR - 350 Neighbors, Bi-squared, Network Distances						GWR - 350 Neighbors, Rank Weighting, Network Distances					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	17.0%	18.9%	-6.0%	-2.1%	5.0%	1.7%	16.3%	13.8%	-4.4%	-3.4%	5.0%	-1.0%	18.9%	18.3%	-5.5%	-4.1%	6.4%	2.7%
d=1,a=0.5	19.2%	17.4%	-8.2%	-4.7%	6.1%	2.2%	15.7%	13.8%	-3.4%	-5.6%	5.7%	-1.3%	18.8%	18.1%	-7.3%	-5.6%	9.0%	1.6%
d=1,a=0.25	19.2%	16.8%	-9.0%	-6.2%	9.4%	2.2%	15.0%	13.9%	-3.6%	-6.6%	5.5%	-1.1%	17.9%	17.3%	-5.4%	-6.5%	9.1%	1.5%
d=1,a=0.1	17.9%	15.9%	-9.2%	-6.2%	9.0%	2.0%	14.2%	13.5%	-3.8%	-6.3%	5.1%	-0.6%	16.7%	15.8%	-4.8%	-6.8%	9.4%	1.6%
d=2,a=1	18.4%	18.2%	-7.7%	-4.0%	4.9%	2.0%	15.3%	14.3%	-3.5%	-5.5%	5.5%	-1.0%	19.3%	18.1%	-6.2%	-4.8%	7.5%	1.3%
d=2,a=0.5	16.9%	15.5%	-10.3%	-5.1%	7.1%	0.9%	13.6%	12.1%	-3.6%	-7.8%	5.2%	-0.6%	15.9%	15.6%	-6.5%	-5.9%	7.2%	0.7%
d=2,a=0.25	14.6%	10.8%	-9.7%	-3.2%	7.3%	0.4%	10.7%	10.0%	-2.4%	-8.2%	6.7%	-0.5%	12.8%	12.2%	-6.5%	-4.3%	4.6%	0.7%
d=2,a=0.1	12.1%	10.5%	-9.1%	-2.5%	6.9%	0.3%	9.8%	10.3%	-1.3%	-7.7%	5.7%	0.0%	12.0%	10.7%	-4.7%	-3.9%	5.6%	0.0%
d=5,a=1	18.4%	14.3%	-8.7%	-5.0%	6.7%	1.0%	14.6%	13.5%	-4.2%	-8.4%	5.0%	-0.9%	17.0%	16.4%	-7.1%	-5.1%	7.5%	1.6%
d=5,a=0.5	7.8%	7.8%	-10.0%	-0.3%	3.5%	1.8%	10.0%	10.0%	-0.7%	-0.4%	7.4%	-0.6%	10.7%	10.4%	-8.5%	-1.5%	5.3%	2.5%
d=5,a=0.25	9.4%	6.4%	-9.7%	1.7%	6.0%	1.0%	9.3%	8.0%	-0.4%	0.4%	10.4%	-0.8%	9.9%	9.0%	-8.0%	1.0%	5.5%	1.5%
d=5,a=0.1	10.6%	8.3%	-8.6%	2.2%	6.7%	0.6%	8.8%	9.3%	-0.7%	0.3%	10.4%	-1.2%	9.7%	8.6%	-7.0%	1.2%	4.9%	1.0%
d=10,a=1	14.8%	15.6%	-8.3%	-2.5%	5.5%	0.7%	13.1%	12.7%	-1.2%	-6.6%	4.3%	-1.0%	14.4%	11.3%	-7.4%	-1.9%	6.6%	1.3%
d=10,a=0.5	11.0%	8.9%	-9.4%	2.7%	6.4%	-0.1%	8.2%	8.5%	-4.0%	-2.0%	6.7%	-1.8%	10.8%	6.6%	-8.7%	-0.2%	5.4%	0.9%
d=10,a=0.25	9.7%	7.1%	-8.1%	3.1%	8.2%	0.0%	5.4%	6.5%	-3.0%	-2.1%	6.5%	-1.3%	10.2%	6.7%	-8.3%	0.2%	8.9%	1.2%
d=10,a=0.1	9.6%	7.6%	-7.5%	2.9%	6.7%	0.1%	6.7%	7.7%	-2.6%	-2.2%	6.6%	-1.5%	10.2%	6.6%	-8.3%	0.2%	6.6%	1.3%
d=25,a=1	12.2%	13.3%	-6.8%	-4.2%	8.8%	0.6%	10.2%	10.1%	-4.4%	-5.2%	6.7%	-2.0%	11.1%	10.5%	-4.9%	-4.8%	11.6%	-0.1%
d=25,a=0.5	9.1%	7.8%	-7.4%	-1.1%	7.1%	-1.6%	10.7%	10.1%	-2.4%	-5.3%	5.7%	-2.7%	6.4%	6.1%	-3.6%	-2.8%	7.9%	-2.3%
d=25,a=0.25	8.4%	6.1%	-4.5%	-1.4%	6.6%	-2.2%	9.2%	8.7%	-3.7%	-3.1%	4.1%	-3.1%	5.7%	5.6%	-5.1%	-2.0%	6.0%	-1.7%
d=25,a=0.1	7.8%	5.7%	-5.4%	-1.2%	7.1%	-2.0%	8.7%	7.7%	-4.4%	-2.6%	5.4%	-2.9%	7.3%	5.0%	-4.7%	-1.4%	7.8%	-2.3%
d=50,a=1	12.7%	12.8%	-5.9%	-3.2%	8.5%	-0.3%	10.9%	11.0%	-3.0%	-5.6%	5.2%	-2.1%	10.8%	10.1%	-6.7%	-3.5%	10.0%	0.6%
d=50,a=0.5	10.9%	7.1%	-4.9%	-2.9%	9.0%	-2.3%	10.5%	7.3%	-0.3%	-3.4%	7.5%	-2.7%	10.4%	7.5%	-6.3%	-4.6%	11.1%	-2.7%
d=50,a=0.25	12.8%	9.9%	-2.9%	-3.0%	9.3%	-2.0%	10.8%	8.2%	-1.2%	-5.9%	5.1%	-2.0%	11.8%	11.5%	-4.1%	-4.6%	12.0%	-2.9%
d=50,a=0.1	16.3%	13.1%	-4.4%	-3.6%	10.4%	-0.9%	13.0%	9.5%	-2.1%	-7.3%	6.2%	-2.2%	13.6%	13.1%	-7.3%	-4.4%	11.1%	-1.3%
to1	16.2%	12.9%	-9.6%	-5.7%	9.6%	2.0%	13.3%	12.5%	-2.1%	-7.0%	5.0%	-0.1%	15.2%	14.0%	-5.0%	-7.0%	9.7%	2.3%
to2	14.6%	11.3%	-8.8%	-3.0%	6.3%	0.3%	10.6%	9.6%	-1.7%	-7.0%	7.0%	0.2%	10.6%	10.3%	-3.5%	-3.8%	5.9%	0.3%
to5	11.2%	8.1%	-8.2%	2.4%	6.2%	0.3%	8.6%	8.5%	-0.8%	0.2%	9.8%	-1.5%	9.4%	8.4%	-6.4%	1.2%	4.8%	0.7%
to10	10.3%	7.5%	-7.4%	2.7%	5.9%	0.0%	7.4%	7.7%	-2.8%	-2.1%	6.1%	-1.5%	10.5%	6.1%	-8.3%	0.2%	6.2%	1.4%
to25	7.5%	5.5%	-4.2%	-1.4%	6.3%	-2.4%	8.7%	6.8%	-2.9%	-2.4%	5.8%	-3.0%	8.0%	4.6%	-2.8%	-1.5%	7.4%	-2.6%
to50	16.2%	14.4%	-6.9%	-3.8%	8.9%	-0.6%	13.9%	10.5%	-2.0%	-8.1%	6.4%	-1.0%	14.1%	15.2%	-5.3%	-4.6%	10.5%	-0.6%
to2&to10	8.1%	4.9%	-7.2%	1.7%	6.7%	-0.4%	8.2%	8.5%	-2.1%	-3.0%	3.4%	-1.3%	8.8%	6.2%	-8.4%	-0.9%	6.4%	-0.3%
to2&to25	5.4%	3.3%	-6.9%	-1.5%	7.9%	-1.6%	8.4%	6.5%	-4.4%	-7.0%	4.8%	-1.4%	6.6%	3.3%	-5.2%	-2.8%	6.9%	-1.7%
to5&to10	8.7%	7.4%	-6.0%	3.1%	7.7%	0.7%	8.5%	9.0%	-2.8%	0.1%	8.0%	-0.8%	10.0%	6.1%	-7.0%	0.5%	6.6%	1.1%
to5&to25	7.2%	4.3%	-4.9%	-0.6%	9.0%	-1.3%	8.7%	7.4%	-0.3%	-2.1%	8.9%	-1.6%	8.0%	5.0%	-3.6%	-1.7%	12.2%	-0.5%
to5&to50	9.8%	8.4%	-0.9%	-1.6%	10.3%	-1.1%	8.3%	8.3%	0.9%	-0.9%	8.8%	-0.7%	8.2%	7.1%	-7.0%	-2.9%	10.1%	-2.0%

Mean Square Error - GWR

	GWR - 160 Neighbors, Gaussian, Euclidean Distances						GWR - 160 Neighbors, Bi-squared, Euclidean Distances						GWR - 160 Neighbors, Rank Weighting, Euclidean Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	8.95E+10	2.03E+11	3.75E+10	6.42E+10	5.58E+10	5.25E+11	1.35E+11	2.2E+11	2.71E+10	5.16E+10	5.09E+10	5.08E+11	8.52E+10	2.11E+11	4.2E+10	6.97E+10	5.99E+10	5.44E+11
d=1,a=0.5	9.24E+10	2.3E+11	3.67E+10	6.18E+10	5.66E+10	5.18E+11	1.98E+11	2.96E+11	2.63E+10	5.02E+10	5.17E+10	5.08E+11	8.46E+10	2.34E+11	4.1E+10	6.71E+10	6.13E+10	5.36E+11
d=1,a=0.25	9.8E+10	2.54E+11	3.65E+10	5.88E+10	5.74E+10	5.13E+11	2.49E+11	3.39E+11	2.63E+10	4.77E+10	5.28E+10	5.1E+11	8.39E+10	2.58E+11	4.05E+10	6.45E+10	6.27E+10	5.3E+11
d=1,a=0.1	1.04E+11	2.63E+11	3.67E+10	5.67E+10	5.79E+10	5.11E+11	2.7E+11	3.42E+11	2.66E+10	4.61E+10	5.35E+10	5.11E+11	8.48E+10	2.71E+11	4.05E+10	6.28E+10	6.33E+10	5.29E+11
d=2,a=1	9.27E+10	2.04E+11	3.64E+10	6.26E+10	5.62E+10	5.15E+11	1.67E+11	2.53E+11	2.62E+10	5.22E+10	5.1E+10	5.04E+11	8.63E+10	2.07E+11	4.01E+10	6.77E+10	6.05E+10	5.33E+11
d=2,a=0.5	9.89E+10	2.01E+11	3.52E+10	5.63E+10	5.66E+10	4.85E+11	1.92E+11	2.48E+11	2.76E+10	4.86E+10	5.09E+10	4.95E+11	8.92E+10	2.04E+11	3.72E+10	6.25E+10	6.11E+10	4.99E+11
d=2,a=0.25	9.92E+10	1.88E+11	3.53E+10	5.4E+10	5.68E+10	4.75E+11	1.75E+11	2.17E+11	2.84E+10	4.61E+10	5.09E+10	4.93E+11	9.17E+10	1.94E+11	3.73E+10	6.09E+10	6.1E+10	4.89E+11
d=2,a=0.1	9.86E+10	1.82E+11	3.55E+10	5.34E+10	5.76E+10	4.73E+11	1.66E+11	2.04E+11	2.86E+10	4.51E+10	5.14E+10	4.93E+11	9.23E+10	1.9E+11	3.74E+10	6.05E+10	6.19E+10	4.86E+11
d=5,a=1	8.59E+10	1.9E+11	3.37E+10	5.44E+10	5.55E+10	4.82E+11	1.44E+11	2.16E+11	2.54E+10	4.57E+10	5E+10	4.9E+11	8.11E+10	1.93E+11	3.55E+10	6.17E+10	6E+10	4.98E+11
d=5,a=0.5	8.28E+10	1.71E+11	3.28E+10	4.53E+10	5.46E+10	4.41E+11	1.17E+11	1.63E+11	2.66E+10	3.44E+10	4.82E+10	4.55E+11	7.93E+10	1.78E+11	3.41E+10	5.48E+10	5.85E+10	4.55E+11
d=5,a=0.25	8.22E+10	1.7E+11	3.29E+10	4.46E+10	5.46E+10	4.42E+11	1.11E+11	1.56E+11	2.64E+10	3.17E+10	4.79E+10	4.55E+11	7.89E+10	1.79E+11	3.42E+10	5.42E+10	5.82E+10	4.55E+11
d=5,a=0.1	8.19E+10	1.7E+11	3.29E+10	4.43E+10	5.45E+10	4.43E+11	1.09E+11	1.55E+11	2.62E+10	3.09E+10	4.79E+10	4.56E+11	7.87E+10	1.79E+11	3.42E+10	5.4E+10	5.81E+10	4.56E+11
d=10,a=1	8.1E+10	1.77E+11	3.19E+10	5.37E+10	5.48E+10	4.7E+11	1.39E+11	2.02E+11	2.4E+10	4.06E+10	4.93E+10	4.86E+11	7.67E+10	1.81E+11	3.34E+10	6.41E+10	5.88E+10	4.85E+11
d=10,a=0.5	7.98E+10	1.67E+11	3.06E+10	4.97E+10	5.34E+10	4.44E+11	1.13E+11	1.57E+11	2.44E+10	3.17E+10	4.79E+10	4.6E+11	7.63E+10	1.76E+11	3.18E+10	6.09E+10	5.65E+10	4.57E+11
d=10,a=0.25	7.96E+10	1.66E+11	3.08E+10	5.11E+10	5.34E+10	4.5E+11	1.09E+11	1.51E+11	2.39E+10	3.23E+10	4.79E+10	4.64E+11	7.62E+10	1.76E+11	3.22E+10	6.21E+10	5.64E+10	4.62E+11
d=10,a=0.1	7.94E+10	1.66E+11	3.1E+10	5.21E+10	5.34E+10	4.54E+11	1.07E+11	1.49E+11	2.36E+10	3.3E+10	4.81E+10	4.67E+11	7.61E+10	1.75E+11	3.24E+10	6.3E+10	5.64E+10	4.66E+11
d=25,a=1	8.01E+10	1.76E+11	3.24E+10	5.85E+10	5.53E+10	4.68E+11	1.36E+11	1.95E+11	2.43E+10	4.38E+10	4.99E+10	4.85E+11	7.56E+10	1.81E+11	3.4E+10	7.07E+10	5.88E+10	4.8E+11
d=25,a=0.5	7.97E+10	1.68E+11	3.08E+10	6.07E+10	5.16E+10	4.45E+11	1.09E+11	1.55E+11	2.51E+10	4.36E+10	4.75E+10	4.63E+11	7.65E+10	1.78E+11	3.16E+10	7.12E+10	5.47E+10	4.52E+11
d=25,a=0.25	7.99E+10	1.7E+11	3.24E+10	6.59E+10	5.15E+10	4.56E+11	1.05E+11	1.54E+11	2.63E+10	5.04E+10	4.73E+10	4.76E+11	7.67E+10	1.81E+11	3.32E+10	7.53E+10	5.48E+10	4.62E+11
d=25,a=0.1	8E+10	1.71E+11	3.47E+10	6.9E+10	5.18E+10	4.65E+11	1.04E+11	1.54E+11	2.79E+10	5.44E+10	4.75E+10	4.88E+11	7.68E+10	1.83E+11	3.63E+10	7.77E+10	5.51E+10	4.72E+11
d=50,a=1	7.92E+10	1.79E+11	3.28E+10	5.61E+10	5.57E+10	4.7E+11	1.4E+11	2.04E+11	2.47E+10	4.19E+10	4.99E+10	4.84E+11	7.47E+10	1.82E+11	3.44E+10	6.79E+10	5.95E+10	4.83E+11
d=50,a=0.5	7.72E+10	1.67E+11	2.95E+10	5.55E+10	5.54E+10	4.4E+11	1.14E+11	1.59E+11	2.37E+10	3.8E+10	4.97E+10	4.55E+11	7.41E+10	1.76E+11	3.02E+10	6.6E+10	5.92E+10	4.49E+11
d=50,a=0.25	7.7E+10	1.69E+11	3.17E+10	6.17E+10	5.55E+10	4.58E+11	1.09E+11	1.55E+11	2.47E+10	4.51E+10	5E+10	4.7E+11	7.43E+10	1.8E+11	3.29E+10	7.04E+10	5.9E+10	4.65E+11
d=50,a=0.1	7.72E+10	1.72E+11	3.7E+10	6.39E+10	5.54E+10	4.78E+11	1.08E+11	1.54E+11	2.69E+10	4.9E+10	5E+10	4.91E+11	7.48E+10	1.84E+11	4.03E+10	7.18E+10	5.89E+10	4.81E+11
to1	1.09E+11	2.66E+11	3.68E+10	5.56E+10	5.83E+10	5.12E+11	2.78E+11	3.36E+11	2.68E+10	4.53E+10	5.41E+10	5.13E+11	8.68E+10	2.76E+11	4.06E+10	6.18E+10	6.37E+10	5.3E+11
to2	9.81E+10	1.8E+11	3.55E+10	5.32E+10	5.82E+10	4.73E+11	1.6E+11	1.98E+11	2.86E+10	4.47E+10	5.2E+10	4.94E+11	9.23E+10	1.87E+11	3.75E+10	6.05E+10	6.27E+10	4.86E+11
to5	8.17E+10	1.7E+11	3.29E+10	4.42E+10	5.45E+10	4.44E+11	1.08E+11	1.54E+11	2.61E+10	3.05E+10	4.8E+10	4.56E+11	7.85E+10	1.79E+11	3.42E+10	5.39E+10	5.8E+10	4.57E+11
to10	7.94E+10	1.66E+11	3.1E+10	5.28E+10	5.34E+10	4.57E+11	1.07E+11	1.48E+11	2.35E+10	3.35E+10	4.83E+10	4.69E+11	7.6E+10	1.75E+11	3.26E+10	6.37E+10	5.64E+10	4.68E+11
to25	8.02E+10	1.72E+11	3.68E+10	7.08E+10	5.19E+10	4.73E+11	1.03E+11	1.55E+11	2.89E+10	5.67E+10	4.74E+10	4.99E+11	7.69E+10	1.84E+11	3.97E+10	7.92E+10	5.51E+10	4.8E+11
to50	7.91E+10	1.72E+11	3.85E+10	6.43E+10	5.66E+10	4.96E+11	1.04E+11	1.49E+11	2.69E+10	5.01E+10	5.04E+10	5.05E+11	7.66E+10	1.87E+11	4.31E+10	7.18E+10	6.04E+10	5.03E+11
to2&to10	9.69E+10	1.73E+11	3.09E+10	4.92E+10	5.57E+10	4.64E+11	1.52E+11	1.77E+11	2.44E+10	3.37E+10	4.94E+10	5.04E+11	8.94E+10	1.82E+11	3.23E+10	5.9E+10	5.96E+10	4.66E+11
to2&to25	9.01E+10	1.78E+11	3.44E+10	5.67E+10	5.51E+10	4.49E+11	1.55E+11	1.95E+11	2.93E+10	4.51E+10	4.86E+10	5.04E+11	8.37E+10	1.84E+11	3.6E+10	6.58E+10	5.83E+10	4.52E+11
to5&to10	8.23E+10	1.68E+11	3.04E+10	4.34E+10	5.33E+10	4.59E+11	1.08E+11	1.5E+11	2.39E+10	3.13E+10	4.58E+10	4.72E+11	7.8E+10	1.78E+11	3.19E+10	5.24E+10	5.74E+10	4.7E+11
to5&to25	8.74E+10	1.76E+11	3.16E+10	4.95E+10	4.99E+10	4.41E+11	1.09E+11	1.59E+11	2.63E+10	4E+10	4.46E+10	4.85E+11	8.19E+10	1.85E+11	3.27E+10	5.65E+10	5.23E+10	4.48E+11
to5&to50	8.02E+10	1.64E+11	3.32E+10	3.96E+10	5.43E+10	4.47E+11	1.05E+11	1.49E+11	2.57E+10	2.66E+10	4.64E+10	4.89E+11	7.72E+10	1.72E+11	3.5E+10	4.95E+10	5.82E+10	4.5E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR - Mean Square Error

	GWR - 160 Neighbors, Gaussian, Network Distances						GWR - 160 Neighbors, Bi-squared, Network Distances						GWR - 160 Neighbors, Rank Weighting, Network Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	9.81E+10	2.11E+11	3.72E+10	6.37E+10	5.6E+10	5.22E+11	1.37E+11	2.11E+11	2.73E+10	5.27E+10	5.07E+10	4.99E+11	9.65E+10	2.2E+11	4.11E+10	6.71E+10	5.96E+10	5.41E+11
d=1,a=0.5	1.12E+11	2.3E+11	3.64E+10	6.18E+10	5.69E+10	5.15E+11	1.96E+11	2.7E+11	2.66E+10	5.13E+10	5.15E+10	4.98E+11	1.1E+11	2.37E+11	3.99E+10	6.55E+10	6.1E+10	5.34E+11
d=1,a=0.25	1.29E+11	2.5E+11	3.61E+10	5.91E+10	5.79E+10	5.11E+11	2.45E+11	3.05E+11	2.66E+10	4.87E+10	5.26E+10	4.98E+11	1.26E+11	2.54E+11	3.93E+10	6.33E+10	6.24E+10	5.29E+11
d=1,a=0.1	1.41E+11	2.58E+11	3.61E+10	5.72E+10	5.87E+10	5.11E+11	2.67E+11	3.08E+11	2.69E+10	4.7E+10	5.35E+10	5E+11	1.37E+11	2.64E+11	3.93E+10	6.19E+10	6.34E+10	5.28E+11
d=2,a=1	1.08E+11	2.08E+11	3.63E+10	6.21E+10	5.64E+10	5.11E+11	1.69E+11	2.4E+11	2.65E+10	5.32E+10	5.07E+10	4.93E+11	1.05E+11	2.12E+11	3.92E+10	6.57E+10	6.04E+10	5.29E+11
d=2,a=0.5	1.28E+11	2.04E+11	3.52E+10	5.58E+10	5.7E+10	4.83E+11	2E+11	2.41E+11	2.78E+10	4.85E+10	5.08E+10	4.79E+11	1.26E+11	2.05E+11	3.68E+10	6.15E+10	6.12E+10	4.98E+11
d=2,a=0.25	1.25E+11	1.93E+11	3.55E+10	5.32E+10	5.78E+10	4.75E+11	1.85E+11	2.13E+11	2.84E+10	4.6E+10	5.11E+10	4.77E+11	1.23E+11	1.98E+11	3.71E+10	5.96E+10	6.17E+10	4.88E+11
d=2,a=0.1	1.22E+11	1.88E+11	3.56E+10	5.25E+10	5.87E+10	4.74E+11	1.75E+11	2.01E+11	2.85E+10	4.5E+10	5.18E+10	4.78E+11	1.19E+11	1.94E+11	3.73E+10	5.91E+10	6.28E+10	4.87E+11
d=5,a=1	1.06E+11	1.96E+11	3.36E+10	5.41E+10	5.6E+10	4.78E+11	1.53E+11	2.14E+11	2.57E+10	4.61E+10	4.97E+10	4.76E+11	1.05E+11	1.98E+11	3.48E+10	5.96E+10	6.02E+10	4.94E+11
d=5,a=0.5	9.51E+10	1.77E+11	3.28E+10	4.4E+10	5.54E+10	4.42E+11	1.26E+11	1.63E+11	2.65E+10	3.39E+10	4.83E+10	4.45E+11	9.31E+10	1.84E+11	3.4E+10	5.18E+10	5.95E+10	4.56E+11
d=5,a=0.25	9.19E+10	1.77E+11	3.29E+10	4.34E+10	5.53E+10	4.44E+11	1.19E+11	1.56E+11	2.63E+10	3.15E+10	4.81E+10	4.47E+11	8.96E+10	1.85E+11	3.42E+10	5.12E+10	5.91E+10	4.58E+11
d=5,a=0.1	9.06E+10	1.77E+11	3.29E+10	4.32E+10	5.51E+10	4.45E+11	1.16E+11	1.54E+11	2.62E+10	3.08E+10	4.81E+10	4.48E+11	8.84E+10	1.86E+11	3.42E+10	5.11E+10	5.89E+10	4.59E+11
d=10,a=1	9.99E+10	1.84E+11	3.16E+10	5.27E+10	5.53E+10	4.68E+11	1.52E+11	2.04E+11	2.43E+10	4.08E+10	4.91E+10	4.74E+11	9.84E+10	1.87E+11	3.25E+10	5.95E+10	5.94E+10	4.83E+11
d=10,a=0.5	8.87E+10	1.73E+11	3.03E+10	4.86E+10	5.47E+10	4.46E+11	1.24E+11	1.59E+11	2.41E+10	3.23E+10	4.84E+10	4.52E+11	8.58E+10	1.82E+11	3.13E+10	5.63E+10	5.83E+10	4.59E+11
d=10,a=0.25	8.66E+10	1.72E+11	3.05E+10	5.01E+10	5.43E+10	4.52E+11	1.19E+11	1.52E+11	2.37E+10	3.33E+10	4.84E+10	4.56E+11	8.38E+10	1.82E+11	3.17E+10	5.76E+10	5.79E+10	4.65E+11
d=10,a=0.1	8.59E+10	1.72E+11	3.06E+10	5.11E+10	5.42E+10	4.57E+11	1.17E+11	1.5E+11	2.35E+10	3.42E+10	4.86E+10	4.6E+11	8.31E+10	1.82E+11	3.19E+10	5.86E+10	5.78E+10	4.69E+11
d=25,a=1	9.38E+10	1.79E+11	3.23E+10	5.61E+10	5.55E+10	4.67E+11	1.44E+11	1.93E+11	2.46E+10	4.45E+10	4.96E+10	4.73E+11	9.11E+10	1.85E+11	3.32E+10	6.27E+10	5.85E+10	4.79E+11
d=25,a=0.5	8.28E+10	1.72E+11	3.08E+10	5.91E+10	5.21E+10	4.5E+11	1.14E+11	1.54E+11	2.51E+10	4.52E+10	4.75E+10	4.57E+11	7.92E+10	1.84E+11	3.14E+10	6.55E+10	5.48E+10	4.58E+11
d=25,a=0.25	8.1E+10	1.74E+11	3.27E+10	6.47E+10	5.16E+10	4.62E+11	1.1E+11	1.53E+11	2.62E+10	5.2E+10	4.7E+10	4.71E+11	7.77E+10	1.87E+11	3.36E+10	7.06E+10	5.42E+10	4.69E+11
d=25,a=0.1	8.06E+10	1.76E+11	3.53E+10	6.8E+10	5.17E+10	4.71E+11	1.09E+11	1.53E+11	2.79E+10	5.59E+10	4.72E+10	4.83E+11	7.73E+10	1.89E+11	3.7E+10	7.37E+10	5.41E+10	4.78E+11
d=50,a=1	9.54E+10	1.82E+11	3.26E+10	5.42E+10	5.61E+10	4.68E+11	1.49E+11	2.02E+11	2.49E+10	4.3E+10	4.96E+10	4.72E+11	9.34E+10	1.86E+11	3.36E+10	6.07E+10	5.95E+10	4.82E+11
d=50,a=0.5	8.43E+10	1.71E+11	2.92E+10	5.54E+10	5.57E+10	4.44E+11	1.22E+11	1.59E+11	2.36E+10	4E+10	4.98E+10	4.47E+11	8.13E+10	1.81E+11	2.98E+10	6.24E+10	5.87E+10	4.54E+11
d=50,a=0.25	8.25E+10	1.73E+11	3.12E+10	6.12E+10	5.57E+10	4.64E+11	1.16E+11	1.55E+11	2.45E+10	4.65E+10	4.99E+10	4.64E+11	7.98E+10	1.85E+11	3.24E+10	6.73E+10	5.86E+10	4.74E+11
d=50,a=0.1	8.26E+10	1.75E+11	3.63E+10	6.31E+10	5.55E+10	4.8E+11	1.14E+11	1.53E+11	2.7E+10	4.97E+10	4.99E+10	4.85E+11	8.06E+10	1.89E+11	3.93E+10	6.86E+10	5.85E+10	4.85E+11
to1	1.48E+11	2.61E+11	3.62E+10	5.62E+10	5.95E+10	5.12E+11	2.76E+11	3.05E+11	2.71E+10	4.61E+10	5.42E+10	5.01E+11	1.42E+11	2.68E+11	3.94E+10	6.1E+10	6.41E+10	5.3E+11
to2	1.19E+11	1.85E+11	3.57E+10	5.23E+10	5.92E+10	4.73E+11	1.7E+11	1.95E+11	2.85E+10	4.46E+10	5.23E+10	1.85E+16	1.17E+11	1.92E+11	3.74E+10	5.9E+10	6.36E+10	4.87E+11
to5	9E+10	1.77E+11	3.29E+10	4.32E+10	5.51E+10	4.46E+11	1.15E+11	1.53E+11	2.61E+10	3.04E+10	4.82E+10	4.48E+11	8.78E+10	1.87E+11	3.42E+10	5.1E+10	5.87E+10	4.6E+11
to10	8.55E+10	1.71E+11	3.07E+10	5.19E+10	5.42E+10	4.59E+11	1.16E+11	1.49E+11	2.34E+10	3.48E+10	4.87E+10	4.62E+11	8.27E+10	1.82E+11	3.21E+10	5.92E+10	5.78E+10	4.72E+11
to25	8.04E+10	1.77E+11	3.74E+10	7E+10	5.17E+10	4.78E+11	1.08E+11	1.54E+11	2.9E+10	5.81E+10	4.72E+10	4.95E+11	7.72E+10	1.9E+11	4.04E+10	7.56E+10	5.4E+10	4.87E+11
to50	8.58E+10	1.76E+11	3.83E+10	6.33E+10	5.64E+10	4.93E+11	1.1E+11	1.49E+11	2.73E+10	5.05E+10	5.02E+10	4.98E+11	8.44E+10	1.93E+11	4.26E+10	6.86E+10	5.95E+10	5.02E+11
to2&to10	1.07E+11	1.76E+11	3.1E+10	4.63E+10	5.72E+10	4.71E+11	1.53E+11	1.74E+11	2.42E+10	3.46E+10	5E+10	4.92E+11	1.02E+11	1.85E+11	3.2E+10	5.37E+10	6.15E+10	4.76E+11
to2&to25	1.02E+11	1.81E+11	3.5E+10	5.48E+10	5.62E+10	4.58E+11	1.64E+11	1.93E+11	2.94E+10	4.61E+10	4.86E+10	4.97E+11	9.38E+10	1.86E+11	3.67E+10	6.14E+10	5.88E+10	4.62E+11
to5&to10	9.03E+10	1.71E+11	3.07E+10	4.3E+10	5.46E+10	4.61E+11	1.18E+11	1.53E+11	2.38E+10	3.17E+10	4.6E+10	4.64E+11	8.58E+10	1.79E+11	3.19E+10	5.07E+10	5.92E+10	4.73E+11
to5&to25	9.43E+10	1.8E+11	3.21E+10	5.26E+10	5E+10	4.53E+11	1.19E+11	1.59E+11	2.62E+10	4.07E+10	4.46E+10	4.86E+11	8.78E+10	1.88E+11	3.34E+10	5.95E+10	5.21E+10	4.62E+11
to5&to50	9.03E+10	1.68E+11	3.3E+10	3.83E+10	5.42E+10	4.49E+11	1.13E+11	1.49E+11	2.59E+10	2.69E+10	4.64E+10	4.91E+11	8.89E+10	1.76E+11	3.51E+10	4.62E+10	5.76E+10	4.53E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR - Mean Square Error

	GWR - 255 Neighbors, Gaussian, Euclidean Distances						GWR - 255 Neighbors, Bi-squared, Euclidean Distances						GWR - 255 Neighbors, Rank Weighting, Euclidean Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	1.09E+11	2.2E+11	4.63E+10	6.51E+10	5.89E+10	5.44E+11	1.01E+11	1.97E+11	3.53E+10	5.82E+10	5.32E+10	5.17E+11	1.13E+11	2.37E+11	4.99E+10	6.78E+10	6.18E+10	5.58E+11
d=1,a=0.5	1.18E+11	2.46E+11	4.56E+10	6.25E+10	5.99E+10	5.34E+11	1.2E+11	2.22E+11	3.47E+10	5.55E+10	5.38E+10	5.13E+11	1.29E+11	2.72E+11	4.89E+10	6.57E+10	6.31E+10	5.48E+11
d=1,a=0.25	1.31E+11	2.72E+11	4.51E+10	5.9E+10	6.17E+10	5.28E+11	1.44E+11	2.46E+11	3.45E+10	5.22E+10	5.48E+10	5.1E+11	1.49E+11	3.09E+11	4.81E+10	6.28E+10	6.55E+10	5.39E+11
d=1,a=0.1	1.4E+11	2.86E+11	4.5E+10	5.64E+10	6.38E+10	5.26E+11	1.6E+11	2.55E+11	3.46E+10	5.01E+10	5.56E+10	5.09E+11	1.65E+11	3.31E+11	4.79E+10	6.06E+10	6.84E+10	5.36E+11
d=2,a=1	1.12E+11	2.16E+11	4.49E+10	6.36E+10	5.96E+10	5.33E+11	1.12E+11	1.99E+11	3.42E+10	5.66E+10	5.35E+10	5.1E+11	1.19E+11	2.32E+11	4.78E+10	6.68E+10	6.27E+10	5.45E+11
d=2,a=0.5	1.18E+11	2.05E+11	4.21E+10	5.68E+10	6.18E+10	5E+11	1.3E+11	1.94E+11	3.35E+10	4.99E+10	5.4E+10	4.84E+11	1.35E+11	2.26E+11	4.39E+10	6.2E+10	6.56E+10	5.06E+11
d=2,a=0.25	1.15E+11	1.95E+11	4.2E+10	5.5E+10	6.32E+10	4.89E+11	1.26E+11	1.81E+11	3.37E+10	4.79E+10	5.45E+10	4.73E+11	1.31E+11	2.14E+11	4.38E+10	6.08E+10	6.76E+10	4.94E+11
d=2,a=0.1	1.13E+11	1.9E+11	4.2E+10	5.46E+10	6.42E+10	4.87E+11	1.22E+11	1.75E+11	3.38E+10	4.74E+10	5.51E+10	4.7E+11	1.27E+11	2.07E+11	4.38E+10	6.06E+10	6.95E+10	4.92E+11
d=5,a=1	9.99E+10	1.97E+11	3.98E+10	5.49E+10	6.05E+10	4.97E+11	1.04E+11	1.83E+11	3.16E+10	4.72E+10	5.28E+10	4.79E+11	1.07E+11	2.09E+11	4.14E+10	6E+10	6.37E+10	5.06E+11
d=5,a=0.5	9.12E+10	1.75E+11	3.72E+10	4.54E+10	6.16E+10	4.56E+11	9.41E+10	1.58E+11	3.08E+10	3.83E+10	5.22E+10	4.37E+11	9.48E+10	1.81E+11	3.86E+10	5.25E+10	6.57E+10	4.62E+11
d=5,a=0.25	8.96E+10	1.73E+11	3.72E+10	4.49E+10	6.15E+10	4.58E+11	9.17E+10	1.57E+11	3.08E+10	3.73E+10	5.21E+10	4.37E+11	9.21E+10	1.79E+11	3.86E+10	5.19E+10	6.59E+10	4.62E+11
d=5,a=0.1	8.9E+10	1.73E+11	3.72E+10	4.47E+10	6.14E+10	4.59E+11	9.08E+10	1.57E+11	3.08E+10	3.71E+10	5.21E+10	4.38E+11	9.09E+10	1.78E+11	3.86E+10	5.17E+10	6.56E+10	4.64E+11
d=10,a=1	9.36E+10	1.83E+11	3.67E+10	5.37E+10	6.09E+10	4.83E+11	9.9E+10	1.71E+11	2.98E+10	4.48E+10	5.24E+10	4.7E+11	9.87E+10	1.92E+11	3.81E+10	6.18E+10	6.39E+10	4.91E+11
d=10,a=0.5	8.57E+10	1.72E+11	3.36E+10	4.96E+10	6.06E+10	4.58E+11	9.03E+10	1.56E+11	2.84E+10	4.12E+10	5.14E+10	4.4E+11	8.68E+10	1.78E+11	3.46E+10	5.91E+10	6.46E+10	4.62E+11
d=10,a=0.25	8.44E+10	1.71E+11	3.38E+10	5.08E+10	6.04E+10	4.64E+11	8.88E+10	1.54E+11	2.85E+10	4.27E+10	5.13E+10	4.46E+11	8.48E+10	1.77E+11	3.49E+10	6.01E+10	6.42E+10	4.67E+11
d=10,a=0.1	8.4E+10	1.71E+11	3.39E+10	5.17E+10	6.04E+10	4.68E+11	8.83E+10	1.54E+11	2.86E+10	4.37E+10	5.14E+10	4.5E+11	8.4E+10	1.77E+11	3.51E+10	6.09E+10	6.41E+10	4.71E+11
d=25,a=1	9.07E+10	1.79E+11	3.75E+10	5.76E+10	6.04E+10	4.77E+11	9.81E+10	1.68E+11	3.05E+10	4.83E+10	5.3E+10	4.7E+11	9.22E+10	1.89E+11	3.87E+10	6.81E+10	6.27E+10	4.83E+11
d=25,a=0.5	8.23E+10	1.72E+11	3.38E+10	5.97E+10	5.74E+10	4.63E+11	8.91E+10	1.56E+11	2.92E+10	5.16E+10	5.02E+10	4.49E+11	8.06E+10	1.79E+11	3.43E+10	6.94E+10	5.99E+10	4.69E+11
d=25,a=0.25	8.13E+10	1.73E+11	3.78E+10	6.45E+10	5.65E+10	4.8E+11	8.77E+10	1.57E+11	3.11E+10	5.73E+10	5E+10	4.63E+11	7.93E+10	1.8E+11	3.86E+10	7.3E+10	5.86E+10	4.88E+11
d=25,a=0.1	8.12E+10	1.74E+11	4.15E+10	6.73E+10	5.63E+10	4.89E+11	8.74E+10	1.58E+11	3.34E+10	6.07E+10	5.02E+10	4.72E+11	7.9E+10	1.82E+11	4.31E+10	7.5E+10	5.81E+10	4.99E+11
d=50,a=1	9.17E+10	1.82E+11	3.76E+10	5.51E+10	6.1E+10	4.79E+11	9.86E+10	1.71E+11	3.07E+10	4.68E+10	5.32E+10	4.71E+11	9.46E+10	1.93E+11	3.9E+10	6.38E+10	6.35E+10	4.86E+11
d=50,a=0.5	8.39E+10	1.72E+11	3.21E+10	5.77E+10	5.95E+10	4.6E+11	8.98E+10	1.56E+11	2.76E+10	5.02E+10	5.29E+10	4.42E+11	8.37E+10	1.8E+11	3.31E+10	6.33E+10	6.16E+10	4.68E+11
d=50,a=0.25	8.35E+10	1.73E+11	3.51E+10	6.19E+10	5.95E+10	4.83E+11	8.82E+10	1.56E+11	2.93E+10	5.53E+10	5.31E+10	4.62E+11	8.29E+10	1.8E+11	3.67E+10	6.6E+10	6.15E+10	4.92E+11
d=50,a=0.1	8.56E+10	1.76E+11	4.21E+10	6.32E+10	5.93E+10	4.97E+11	8.78E+10	1.57E+11	3.38E+10	5.65E+10	5.3E+10	4.76E+11	8.5E+10	1.84E+11	4.54E+10	6.68E+10	6.13E+10	5.08E+11
to1	1.46E+11	2.92E+11	4.51E+10	5.49E+10	6.61E+10	5.27E+11	1.69E+11	2.58E+11	3.47E+10	4.9E+10	5.64E+10	5.09E+11	1.75E+11	3.4E+11	4.79E+10	5.92E+10	7.13E+10	5.36E+11
to2	1.11E+11	1.87E+11	4.2E+10	5.46E+10	6.47E+10	4.86E+11	1.2E+11	1.72E+11	3.39E+10	4.73E+10	5.56E+10	4.69E+11	1.24E+11	2.03E+11	4.38E+10	6.06E+10	7.08E+10	4.91E+11
to5	8.86E+10	1.73E+11	3.72E+10	4.46E+10	6.13E+10	4.6E+11	9.03E+10	1.57E+11	3.08E+10	3.7E+10	5.21E+10	4.38E+11	9.03E+10	1.78E+11	3.85E+10	5.16E+10	6.54E+10	4.65E+11
to10	8.38E+10	1.71E+11	3.4E+10	5.23E+10	6.04E+10	4.7E+11	8.81E+10	1.54E+11	2.86E+10	4.43E+10	5.15E+10	4.52E+11	8.37E+10	1.77E+11	3.52E+10	6.14E+10	6.4E+10	4.74E+11
to25	8.12E+10	1.74E+11	4.38E+10	6.9E+10	5.62E+10	4.95E+11	8.73E+10	1.59E+11	3.49E+10	6.28E+10	5.02E+10	4.78E+11	7.9E+10	1.83E+11	4.61E+10	7.62E+10	5.79E+10	5.05E+11
to50	9.07E+10	1.8E+11	4.72E+10	6.35E+10	5.93E+10	5.15E+11	8.88E+10	1.56E+11	3.57E+10	5.66E+10	5.38E+10	4.9E+11	9E+10	1.9E+11	5.16E+10	6.7E+10	6.15E+10	5.26E+11
to2&to10	9.56E+10	1.72E+11	3.37E+10	5.07E+10	6.27E+10	4.79E+11	1.16E+11	1.63E+11	2.88E+10	4.13E+10	5.34E+10	4.65E+11	1E+11	1.79E+11	3.44E+10	5.87E+10	6.97E+10	4.79E+11
to2&to25	8.78E+10	1.72E+11	3.92E+10	5.69E+10	6.03E+10	4.6E+11	1.1E+11	1.68E+11	3.34E+10	4.95E+10	5.35E+10	4.57E+11	8.88E+10	1.78E+11	4.02E+10	6.49E+10	6.49E+10	4.65E+11
to5&to10	8.27E+10	1.68E+11	3.32E+10	4.54E+10	6.02E+10	4.8E+11	9.02E+10	1.54E+11	2.83E+10	3.78E+10	5.05E+10	4.54E+11	8.07E+10	1.71E+11	3.37E+10	5.18E+10	6.48E+10	4.83E+11
to5&to25	8.31E+10	1.73E+11	3.54E+10	4.92E+10	5.59E+10	4.58E+11	9.27E+10	1.61E+11	3.06E+10	4.52E+10	4.85E+10	4.44E+11	7.91E+10	1.76E+11	3.59E+10	5.5E+10	5.87E+10	4.64E+11
to5&to50	8.85E+10	1.69E+11	3.74E+10	4.24E+10	5.96E+10	4.55E+11	8.99E+10	1.52E+11	3.08E+10	3.26E+10	5.15E+10	4.42E+11	8.87E+10	1.75E+11	3.96E+10	5.03E+10	6.29E+10	4.6E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR - Mean Square Error

	GWR - 255 Neighbors, Gaussian, Network Distances						GWR - 255 Neighbors, Bi-squared, Network Distances						GWR - 255 Neighbors, Rank Weighting, Network Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	1.14E+11	2.25E+11	4.63E+10	6.58E+10	5.9E+10	5.49E+11	1.1E+11	2E+11	3.55E+10	5.84E+10	5.32E+10	5.11E+11	1.16E+11	2.46E+11	5.05E+10	6.91E+10	6.23E+10	5.71E+11
d=1,a=0.5	1.28E+11	2.49E+11	4.55E+10	6.33E+10	5.99E+10	5.38E+11	1.38E+11	2.31E+11	3.49E+10	5.59E+10	5.39E+10	5.07E+11	1.37E+11	2.81E+11	4.92E+10	6.68E+10	6.35E+10	5.57E+11
d=1,a=0.25	1.45E+11	2.72E+11	4.48E+10	5.99E+10	6.15E+10	5.33E+11	1.69E+11	2.58E+11	3.47E+10	5.28E+10	5.5E+10	5.05E+11	1.64E+11	3.15E+11	4.81E+10	6.41E+10	6.55E+10	5.49E+11
d=1,a=0.1	1.57E+11	2.82E+11	4.46E+10	5.75E+10	6.34E+10	5.32E+11	1.87E+11	2.66E+11	3.49E+10	5.08E+10	5.6E+10	5.03E+11	1.84E+11	3.33E+11	4.77E+10	6.22E+10	6.81E+10	5.47E+11
d=2,a=1	1.19E+11	2.22E+11	4.47E+10	6.46E+10	5.98E+10	5.36E+11	1.26E+11	2.07E+11	3.45E+10	5.68E+10	5.34E+10	5.04E+11	1.25E+11	2.43E+11	4.8E+10	6.82E+10	6.33E+10	5.54E+11
d=2,a=0.5	1.29E+11	2.11E+11	4.12E+10	5.8E+10	6.19E+10	5E+11	1.49E+11	2.07E+11	3.37E+10	4.99E+10	5.41E+10	4.77E+11	1.44E+11	2.35E+11	4.32E+10	6.41E+10	6.61E+10	5.11E+11
d=2,a=0.25	1.24E+11	1.99E+11	4.11E+10	5.61E+10	6.35E+10	4.89E+11	1.41E+11	1.91E+11	3.39E+10	4.79E+10	5.48E+10	4.67E+11	1.38E+11	2.2E+11	4.3E+10	6.31E+10	6.83E+10	4.99E+11
d=2,a=0.1	1.2E+11	1.94E+11	4.11E+10	5.57E+10	6.47E+10	4.86E+11	1.36E+11	1.83E+11	3.4E+10	4.74E+10	5.54E+10	4.65E+11	1.33E+11	2.12E+11	4.3E+10	6.29E+10	7.06E+10	4.96E+11
d=5,a=1	1.06E+11	2.01E+11	3.92E+10	5.57E+10	6.06E+10	4.96E+11	1.18E+11	1.91E+11	3.18E+10	4.76E+10	5.28E+10	4.73E+11	1.1E+11	2.15E+11	4.11E+10	6.12E+10	6.42E+10	5.09E+11
d=5,a=0.5	9.47E+10	1.79E+11	3.63E+10	4.59E+10	6.18E+10	4.54E+11	1.02E+11	1.62E+11	3.08E+10	3.87E+10	5.21E+10	4.31E+11	9.59E+10	1.86E+11	3.78E+10	5.33E+10	6.63E+10	4.64E+11
d=5,a=0.25	9.27E+10	1.77E+11	3.63E+10	4.53E+10	6.18E+10	4.55E+11	9.82E+10	1.6E+11	3.09E+10	3.8E+10	5.2E+10	4.32E+11	9.3E+10	1.84E+11	3.79E+10	5.27E+10	6.66E+10	4.66E+11
d=5,a=0.1	9.18E+10	1.77E+11	3.63E+10	4.51E+10	6.17E+10	4.57E+11	9.68E+10	1.59E+11	3.08E+10	3.78E+10	5.19E+10	4.33E+11	9.17E+10	1.84E+11	3.79E+10	5.24E+10	6.64E+10	4.68E+11
d=10,a=1	9.75E+10	1.86E+11	3.61E+10	5.41E+10	6.09E+10	4.8E+11	1.12E+11	1.79E+11	2.99E+10	4.56E+10	5.23E+10	4.63E+11	9.85E+10	1.97E+11	3.78E+10	6.2E+10	6.44E+10	4.92E+11
d=10,a=0.5	8.7E+10	1.76E+11	3.31E+10	4.99E+10	6.07E+10	4.58E+11	9.69E+10	1.58E+11	2.83E+10	4.25E+10	5.17E+10	4.35E+11	8.53E+10	1.82E+11	3.44E+10	5.93E+10	6.5E+10	4.67E+11
d=10,a=0.25	8.54E+10	1.75E+11	3.35E+10	5.11E+10	6.05E+10	4.64E+11	9.42E+10	1.56E+11	2.85E+10	4.4E+10	5.14E+10	4.42E+11	8.32E+10	1.82E+11	3.48E+10	6.04E+10	6.46E+10	4.74E+11
d=10,a=0.1	8.47E+10	1.75E+11	3.37E+10	5.2E+10	6.04E+10	4.69E+11	9.33E+10	1.55E+11	2.85E+10	4.5E+10	5.16E+10	4.46E+11	8.23E+10	1.82E+11	3.51E+10	6.12E+10	6.43E+10	4.79E+11
d=25,a=1	9.06E+10	1.81E+11	3.71E+10	5.77E+10	6.07E+10	4.75E+11	1.06E+11	1.73E+11	3.06E+10	4.91E+10	5.29E+10	4.64E+11	8.81E+10	1.91E+11	3.86E+10	6.84E+10	6.34E+10	4.85E+11
d=25,a=0.5	7.99E+10	1.73E+11	3.41E+10	5.98E+10	5.81E+10	4.64E+11	9.14E+10	1.57E+11	2.91E+10	5.28E+10	5.01E+10	4.47E+11	7.63E+10	1.8E+11	3.5E+10	7.05E+10	6.09E+10	4.75E+11
d=25,a=0.25	7.86E+10	1.73E+11	3.82E+10	6.5E+10	5.73E+10	4.81E+11	8.92E+10	1.57E+11	3.1E+10	5.85E+10	4.96E+10	4.61E+11	7.54E+10	1.82E+11	3.94E+10	7.46E+10	5.95E+10	4.94E+11
d=25,a=0.1	7.84E+10	1.74E+11	4.17E+10	6.8E+10	5.7E+10	4.9E+11	8.87E+10	1.58E+11	3.33E+10	6.19E+10	4.98E+10	4.7E+11	7.54E+10	1.83E+11	4.37E+10	7.69E+10	5.9E+10	5.05E+11
d=50,a=1	9.29E+10	1.85E+11	3.72E+10	5.54E+10	6.12E+10	4.77E+11	1.09E+11	1.78E+11	3.09E+10	4.77E+10	5.31E+10	4.65E+11	9.15E+10	1.96E+11	3.89E+10	6.44E+10	6.4E+10	4.86E+11
d=50,a=0.5	8.25E+10	1.76E+11	3.23E+10	6.11E+10	6.03E+10	4.59E+11	9.42E+10	1.58E+11	2.75E+10	5.12E+10	5.29E+10	4.38E+11	7.94E+10	1.83E+11	3.37E+10	6.63E+10	6.26E+10	4.7E+11
d=50,a=0.25	8.24E+10	1.77E+11	3.55E+10	6.37E+10	6.03E+10	4.85E+11	9.17E+10	1.58E+11	2.92E+10	5.56E+10	5.29E+10	4.6E+11	7.93E+10	1.85E+11	3.77E+10	6.77E+10	6.26E+10	4.99E+11
d=50,a=0.1	8.53E+10	1.81E+11	4.16E+10	6.41E+10	5.99E+10	5.01E+11	9.16E+10	1.58E+11	3.39E+10	5.63E+10	5.28E+10	4.73E+11	8.23E+10	1.9E+11	4.5E+10	6.77E+10	6.23E+10	5.16E+11
to1	1.64E+11	2.85E+11	4.46E+10	5.62E+10	6.55E+10	5.33E+11	1.97E+11	2.68E+11	3.5E+10	4.98E+10	5.7E+10	5.04E+11	1.97E+11	3.39E+11	4.77E+10	6.11E+10	7.07E+10	5.47E+11
to2	1.18E+11	1.92E+11	4.11E+10	5.56E+10	6.53E+10	4.85E+11	1.33E+11	1.8E+11	3.4E+10	4.73E+10	5.57E+10	4.64E+11	1.3E+11	2.09E+11	4.31E+10	6.29E+10	7.21E+10	4.95E+11
to5	9.13E+10	1.77E+11	3.63E+10	4.5E+10	6.16E+10	4.58E+11	9.61E+10	1.59E+11	3.08E+10	3.77E+10	5.19E+10	4.33E+11	9.1E+10	1.84E+11	3.78E+10	5.23E+10	6.62E+10	4.69E+11
to10	8.44E+10	1.75E+11	3.38E+10	5.27E+10	6.04E+10	4.71E+11	9.29E+10	1.54E+11	2.86E+10	4.56E+10	5.17E+10	4.48E+11	8.19E+10	1.82E+11	3.53E+10	6.18E+10	6.42E+10	4.81E+11
to25	7.84E+10	1.75E+11	4.39E+10	6.97E+10	5.68E+10	4.96E+11	8.86E+10	1.58E+11	3.49E+10	6.39E+10	4.97E+10	4.76E+11	7.55E+10	1.84E+11	4.65E+10	7.82E+10	5.88E+10	5.11E+11
to50	9.08E+10	1.86E+11	4.65E+10	6.4E+10	5.97E+10	5.18E+11	9.39E+10	1.57E+11	3.59E+10	5.61E+10	5.34E+10	4.84E+11	8.79E+10	1.98E+11	5.1E+10	6.76E+10	6.22E+10	5.36E+11
to2&to10	9.62E+10	1.71E+11	3.32E+10	5.11E+10	6.29E+10	4.79E+11	1.21E+11	1.66E+11	2.89E+10	4.16E+10	5.38E+10	4.64E+11	9.68E+10	1.76E+11	3.41E+10	5.94E+10	7.02E+10	4.85E+11
to2&to25	8.51E+10	1.7E+11	3.88E+10	5.77E+10	6.13E+10	4.58E+11	1.18E+11	1.74E+11	3.32E+10	5.06E+10	5.31E+10	4.56E+11	8.26E+10	1.76E+11	4E+10	6.59E+10	6.66E+10	4.68E+11
to5&to10	8.42E+10	1.69E+11	3.3E+10	4.55E+10	6.02E+10	4.82E+11	9.57E+10	1.55E+11	2.83E+10	3.87E+10	5.07E+10	4.51E+11	8E+10	1.73E+11	3.37E+10	5.21E+10	6.49E+10	4.92E+11
to5&to25	8.17E+10	1.72E+11	3.5E+10	4.93E+10	5.69E+10	4.56E+11	9.76E+10	1.62E+11	3.02E+10	4.8E+10	4.79E+10	4.44E+11	7.71E+10	1.77E+11	3.59E+10	5.45E+10	6.02E+10	4.67E+11
to5&to50	8.9E+10	1.76E+11	3.61E+10	4.23E+10	6.03E+10	4.52E+11	9.66E+10	1.54E+11	3.07E+10	3.27E+10	5.11E+10	4.4E+11	8.61E+10	1.84E+11	3.84E+10	4.96E+10	6.42E+10	4.64E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR - Mean Square Error

	GWR - 350 Neighbors, Gaussian, Euclidean Distances						GWR - 350 Neighbors, Bi-squared, Euclidean Distances						GWR - 350 Neighbors, Rank Weighting, Euclidean Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	1.19E+11	2.23E+11	5.11E+10	6.79E+10	6.19E+10	5.72E+11	1.03E+11	2.06E+11	4.02E+10	6.11E+10	5.52E+10	5.34E+11	1.27E+11	2.34E+11	5.38E+10	6.95E+10	6.41E+10	5.82E+11
d=1,a=0.5	1.48E+11	2.52E+11	5.04E+10	6.34E+10	6.33E+10	5.57E+11	1.18E+11	2.26E+11	3.96E+10	5.81E+10	5.61E+10	5.25E+11	1.69E+11	2.71E+11	5.3E+10	6.54E+10	6.59E+10	5.66E+11
d=1,a=0.25	1.83E+11	2.85E+11	5.01E+10	5.91E+10	6.62E+10	5.48E+11	1.35E+11	2.47E+11	3.94E+10	5.46E+10	5.75E+10	5.19E+11	2.31E+11	3.17E+11	5.23E+10	6.15E+10	6.95E+10	5.56E+11
d=1,a=0.1	2.04E+11	3.03E+11	5.03E+10	5.65E+10	7E+10	5.46E+11	1.47E+11	2.57E+11	3.94E+10	5.22E+10	5.92E+10	5.18E+11	2.81E+11	3.46E+11	5.23E+10	5.93E+10	7.41E+10	5.52E+11
d=2,a=1	1.26E+11	2.21E+11	4.93E+10	6.37E+10	6.27E+10	5.51E+11	1.11E+11	2.03E+11	3.9E+10	5.92E+10	5.57E+10	5.22E+11	1.39E+11	2.37E+11	5.16E+10	6.54E+10	6.51E+10	5.6E+11
d=2,a=0.5	1.37E+11	2.17E+11	4.66E+10	5.42E+10	6.62E+10	5.09E+11	1.22E+11	1.94E+11	3.77E+10	5.17E+10	5.71E+10	4.9E+11	1.72E+11	2.46E+11	4.79E+10	5.67E+10	6.9E+10	5.1E+11
d=2,a=0.25	1.26E+11	2.04E+11	4.66E+10	5.36E+10	6.83E+10	5.01E+11	1.18E+11	1.83E+11	3.78E+10	4.98E+10	5.83E+10	4.78E+11	1.59E+11	2.32E+11	4.78E+10	5.66E+10	7.19E+10	5E+11
d=2,a=0.1	1.2E+11	1.98E+11	4.66E+10	5.39E+10	6.91E+10	5E+11	1.15E+11	1.78E+11	3.78E+10	4.95E+10	5.9E+10	4.75E+11	1.49E+11	2.23E+11	4.78E+10	5.71E+10	7.37E+10	4.98E+11
d=5,a=1	1.13E+11	2.04E+11	4.35E+10	5.37E+10	6.41E+10	5.06E+11	1.02E+11	1.87E+11	3.54E+10	4.93E+10	5.59E+10	4.87E+11	1.28E+11	2.2E+11	4.49E+10	5.57E+10	6.63E+10	5.1E+11
d=5,a=0.5	9.43E+10	1.82E+11	4.08E+10	4.71E+10	6.62E+10	4.69E+11	9.19E+10	1.65E+11	3.39E+10	4.04E+10	5.63E+10	4.46E+11	1.05E+11	1.93E+11	4.14E+10	4.95E+10	6.91E+10	4.69E+11
d=5,a=0.25	9.11E+10	1.8E+11	4.07E+10	4.8E+10	6.64E+10	4.72E+11	8.99E+10	1.64E+11	3.39E+10	3.98E+10	5.62E+10	4.47E+11	9.9E+10	1.9E+11	4.13E+10	5.04E+10	6.96E+10	4.72E+11
d=5,a=0.1	8.99E+10	1.8E+11	4.06E+10	4.84E+10	6.63E+10	4.74E+11	8.9E+10	1.64E+11	3.39E+10	3.96E+10	5.62E+10	4.48E+11	9.69E+10	1.89E+11	4.12E+10	5.08E+10	6.95E+10	4.74E+11
d=10,a=1	1E+11	1.87E+11	3.94E+10	5.58E+10	6.5E+10	4.91E+11	9.6E+10	1.74E+11	3.3E+10	4.71E+10	5.59E+10	4.75E+11	1.13E+11	2E+11	4.03E+10	5.81E+10	6.67E+10	4.92E+11
d=10,a=0.5	8.43E+10	1.8E+11	3.49E+10	5.82E+10	6.48E+10	4.74E+11	8.7E+10	1.63E+11	3.06E+10	4.37E+10	5.51E+10	4.5E+11	8.95E+10	1.88E+11	3.54E+10	6.03E+10	6.79E+10	4.74E+11
d=10,a=0.25	8.22E+10	1.81E+11	3.48E+10	6.02E+10	6.43E+10	4.81E+11	8.56E+10	1.63E+11	3.07E+10	4.52E+10	5.49E+10	4.57E+11	8.6E+10	1.91E+11	3.54E+10	6.23E+10	6.73E+10	4.82E+11
d=10,a=0.1	8.15E+10	1.82E+11	3.48E+10	6.13E+10	6.42E+10	4.85E+11	8.52E+10	1.63E+11	3.08E+10	4.62E+10	5.5E+10	4.6E+11	8.47E+10	1.92E+11	3.55E+10	6.34E+10	6.69E+10	4.86E+11
d=25,a=1	9.16E+10	1.8E+11	4.01E+10	6.62E+10	6.31E+10	4.8E+11	9.38E+10	1.7E+11	3.38E+10	5.04E+10	5.59E+10	4.71E+11	9.73E+10	1.9E+11	4.06E+10	7.13E+10	6.38E+10	4.82E+11
d=25,a=0.5	7.92E+10	1.78E+11	3.61E+10	7.82E+10	5.87E+10	4.74E+11	8.42E+10	1.63E+11	3.11E+10	5.44E+10	5.28E+10	4.55E+11	7.94E+10	1.86E+11	3.65E+10	8.6E+10	5.96E+10	4.78E+11
d=25,a=0.25	7.85E+10	1.79E+11	4.14E+10	8.33E+10	5.73E+10	4.89E+11	8.29E+10	1.64E+11	3.41E+10	6E+10	5.24E+10	4.7E+11	7.81E+10	1.89E+11	4.24E+10	9.19E+10	5.79E+10	4.94E+11
d=25,a=0.1	7.86E+10	1.81E+11	4.55E+10	8.56E+10	5.68E+10	4.98E+11	8.26E+10	1.65E+11	3.71E+10	6.33E+10	5.25E+10	4.79E+11	7.81E+10	1.9E+11	4.71E+10	9.45E+10	5.73E+10	5.02E+11
d=50,a=1	9.57E+10	1.84E+11	4.07E+10	6.72E+10	6.42E+10	4.84E+11	9.48E+10	1.73E+11	3.39E+10	4.98E+10	5.65E+10	4.74E+11	1.04E+11	1.95E+11	4.15E+10	7.36E+10	6.49E+10	4.87E+11
d=50,a=0.5	8.12E+10	1.75E+11	3.6E+10	7.5E+10	6.19E+10	4.8E+11	8.59E+10	1.62E+11	2.95E+10	5.47E+10	5.55E+10	4.52E+11	8.28E+10	1.83E+11	3.71E+10	8.07E+10	6.24E+10	4.84E+11
d=50,a=0.25	8.06E+10	1.78E+11	4.2E+10	7.5E+10	6.16E+10	5.01E+11	8.46E+10	1.63E+11	3.16E+10	5.83E+10	5.56E+10	4.74E+11	8.14E+10	1.86E+11	4.44E+10	7.92E+10	6.24E+10	5.07E+11
d=50,a=0.1	8.29E+10	1.84E+11	4.86E+10	7.44E+10	6.16E+10	5.2E+11	8.55E+10	1.65E+11	3.68E+10	5.92E+10	5.57E+10	4.89E+11	8.33E+10	1.93E+11	5.17E+10	7.81E+10	6.28E+10	5.27E+11
to1	2.15E+11	3.1E+11	5.07E+10	5.53E+10	7.41E+10	5.47E+11	1.54E+11	2.61E+11	3.95E+10	5.1E+10	6.09E+10	5.18E+11	3.15E+11	3.61E+11	5.26E+10	5.82E+10	7.9E+10	5.52E+11
to2	1.16E+11	1.95E+11	4.66E+10	5.42E+10	6.92E+10	5E+11	1.13E+11	1.76E+11	3.79E+10	4.94E+10	5.93E+10	4.74E+11	1.43E+11	2.18E+11	4.78E+10	5.75E+10	7.44E+10	4.98E+11
to5	8.93E+10	1.8E+11	4.05E+10	4.87E+10	6.62E+10	4.75E+11	8.86E+10	1.64E+11	3.39E+10	3.95E+10	5.61E+10	4.49E+11	9.58E+10	1.89E+11	4.12E+10	5.1E+10	6.93E+10	4.76E+11
to10	8.11E+10	1.82E+11	3.49E+10	6.19E+10	6.41E+10	4.88E+11	8.5E+10	1.63E+11	3.09E+10	4.68E+10	5.51E+10	4.63E+11	8.41E+10	1.93E+11	3.55E+10	6.4E+10	6.67E+10	4.89E+11
to25	7.88E+10	1.81E+11	4.82E+10	8.69E+10	5.66E+10	5.02E+11	8.26E+10	1.65E+11	3.9E+10	6.52E+10	5.24E+10	4.84E+11	7.83E+10	1.92E+11	5.01E+10	9.58E+10	5.69E+10	5.07E+11
to50	8.75E+10	1.94E+11	5.23E+10	7.4E+10	6.19E+10	5.43E+11	8.89E+10	1.67E+11	4.02E+10	5.93E+10	5.61E+10	5.04E+11	8.76E+10	2.04E+11	5.56E+10	7.74E+10	6.33E+10	5.51E+11
to2&to10	8.21E+10	1.76E+11	3.45E+10	5.12E+10	6.6E+10	4.96E+11	1.02E+11	1.65E+11	3.07E+10	4.38E+10	5.68E+10	4.69E+11	8.5E+10	1.88E+11	3.51E+10	5.4E+10	7.18E+10	4.95E+11
to2&to25	7.97E+10	1.72E+11	4.28E+10	6.33E+10	5.99E+10	4.66E+11	9.41E+10	1.66E+11	3.65E+10	5.12E+10	5.58E+10	4.53E+11	7.91E+10	1.81E+11	4.34E+10	7E+10	6.24E+10	4.67E+11
to5&to10	7.78E+10	1.77E+11	3.51E+10	5.06E+10	6.28E+10	4.95E+11	8.6E+10	1.61E+11	3.04E+10	4.06E+10	5.43E+10	4.68E+11	7.76E+10	1.87E+11	3.55E+10	5.38E+10	6.6E+10	4.97E+11
to5&to25	8.08E+10	1.78E+11	3.86E+10	6.13E+10	5.71E+10	4.61E+11	8.69E+10	1.65E+11	3.32E+10	4.7E+10	5.15E+10	4.47E+11	7.89E+10	1.86E+11	3.88E+10	6.77E+10	5.83E+10	4.64E+11
to5&to50	8.13E+10	1.83E+11	4.16E+10	5.13E+10	6.42E+10	4.69E+11	8.83E+10	1.6E+11	3.36E+10	3.62E+10	5.56E+10	4.45E+11	8.17E+10	1.92E+11	4.32E+10	5.57E+10	6.65E+10	4.71E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

GWR - Mean Square Error

	GWR - 350 Neighbors, Gaussian, Network Distances						GWR - 350 Neighbors, Bi-squared, Network Distances						GWR - 350 Neighbors, Rank Weighting, Network Distances					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	1.23E+11	2.19E+11	5.23E+10	6.53E+10	6.15E+10	5.69E+11	1.1E+11	2.09E+11	4.05E+10	6.07E+10	5.5E+10	5.29E+11	1.35E+11	2.31E+11	5.58E+10	6.76E+10	6.37E+10	5.84E+11
d=1,a=0.5	1.55E+11	2.52E+11	5.14E+10	6.11E+10	6.29E+10	5.54E+11	1.31E+11	2.33E+11	3.99E+10	5.8E+10	5.59E+10	5.2E+11	1.93E+11	2.79E+11	5.46E+10	6.34E+10	6.54E+10	5.68E+11
d=1,a=0.25	1.89E+11	2.83E+11	5.08E+10	5.71E+10	6.58E+10	5.46E+11	1.53E+11	2.56E+11	3.96E+10	5.47E+10	5.73E+10	5.16E+11	2.65E+11	3.31E+11	5.36E+10	5.97E+10	6.88E+10	5.59E+11
d=1,a=0.1	2.05E+11	2.97E+11	5.08E+10	5.49E+10	6.96E+10	5.46E+11	1.66E+11	2.66E+11	3.97E+10	5.26E+10	5.9E+10	5.15E+11	3.11E+11	3.6E+11	5.34E+10	5.77E+10	7.32E+10	5.56E+11
d=2,a=1	1.29E+11	2.19E+11	5.03E+10	6.14E+10	6.24E+10	5.48E+11	1.2E+11	2.1E+11	3.93E+10	5.9E+10	5.56E+10	5.17E+11	1.47E+11	2.38E+11	5.32E+10	6.35E+10	6.47E+10	5.61E+11
d=2,a=0.5	1.32E+11	2.14E+11	4.71E+10	5.29E+10	6.6E+10	5.08E+11	1.34E+11	2.03E+11	3.75E+10	5.16E+10	5.72E+10	4.85E+11	1.71E+11	2.47E+11	4.87E+10	5.55E+10	6.85E+10	5.13E+11
d=2,a=0.25	1.19E+11	2E+11	4.71E+10	5.23E+10	6.82E+10	4.99E+11	1.27E+11	1.9E+11	3.76E+10	4.97E+10	5.85E+10	4.74E+11	1.5E+11	2.29E+11	4.86E+10	5.53E+10	7.14E+10	5.02E+11
d=2,a=0.1	1.13E+11	1.93E+11	4.71E+10	5.25E+10	6.91E+10	4.97E+11	1.23E+11	1.84E+11	3.76E+10	4.93E+10	5.93E+10	4.72E+11	1.39E+11	2.19E+11	4.87E+10	5.57E+10	7.32E+10	5E+11
d=5,a=1	1.09E+11	2.02E+11	4.42E+10	5.18E+10	6.38E+10	5.04E+11	1.1E+11	1.93E+11	3.53E+10	4.93E+10	5.58E+10	4.8E+11	1.27E+11	2.21E+11	4.61E+10	5.39E+10	6.58E+10	5.12E+11
d=5,a=0.5	9.08E+10	1.79E+11	4.14E+10	4.52E+10	6.58E+10	4.68E+11	9.65E+10	1.68E+11	3.35E+10	4.03E+10	5.63E+10	4.4E+11	1E+11	1.9E+11	4.26E+10	4.79E+10	6.85E+10	4.71E+11
d=5,a=0.25	8.85E+10	1.77E+11	4.14E+10	4.58E+10	6.6E+10	4.7E+11	9.37E+10	1.66E+11	3.36E+10	3.97E+10	5.62E+10	4.41E+11	9.55E+10	1.87E+11	4.26E+10	4.85E+10	6.91E+10	4.73E+11
d=5,a=0.1	8.77E+10	1.77E+11	4.13E+10	4.62E+10	6.6E+10	4.72E+11	9.26E+10	1.66E+11	3.36E+10	3.96E+10	5.61E+10	4.43E+11	9.38E+10	1.86E+11	4.26E+10	4.89E+10	6.9E+10	4.75E+11
d=10,a=1	9.49E+10	1.85E+11	4.02E+10	5.38E+10	6.46E+10	4.89E+11	1.02E+11	1.78E+11	3.29E+10	4.72E+10	5.58E+10	4.68E+11	1.07E+11	2E+11	4.18E+10	5.62E+10	6.62E+10	4.93E+11
d=10,a=0.5	8.14E+10	1.77E+11	3.6E+10	5.65E+10	6.44E+10	4.72E+11	8.97E+10	1.65E+11	3.05E+10	4.41E+10	5.52E+10	4.45E+11	8.6E+10	1.85E+11	3.73E+10	5.89E+10	6.71E+10	4.74E+11
d=10,a=0.25	7.98E+10	1.78E+11	3.6E+10	5.86E+10	6.39E+10	4.79E+11	8.77E+10	1.64E+11	3.07E+10	4.56E+10	5.51E+10	4.51E+11	8.32E+10	1.87E+11	3.74E+10	6.1E+10	6.65E+10	4.81E+11
d=10,a=0.1	7.93E+10	1.79E+11	3.61E+10	5.97E+10	6.38E+10	4.83E+11	8.71E+10	1.64E+11	3.09E+10	4.66E+10	5.52E+10	4.55E+11	8.22E+10	1.88E+11	3.76E+10	6.21E+10	6.61E+10	4.86E+11
d=25,a=1	8.68E+10	1.79E+11	4.07E+10	6.45E+10	6.29E+10	4.79E+11	9.59E+10	1.72E+11	3.37E+10	5.05E+10	5.59E+10	4.65E+11	9.27E+10	1.9E+11	4.2E+10	6.98E+10	6.35E+10	4.84E+11
d=25,a=0.5	7.76E+10	1.75E+11	3.73E+10	7.77E+10	5.88E+10	4.75E+11	8.37E+10	1.63E+11	3.13E+10	5.5E+10	5.3E+10	4.52E+11	7.83E+10	1.82E+11	3.84E+10	8.49E+10	5.96E+10	4.83E+11
d=25,a=0.25	7.74E+10	1.76E+11	4.22E+10	8.29E+10	5.75E+10	4.91E+11	8.22E+10	1.64E+11	3.44E+10	6.08E+10	5.25E+10	4.67E+11	7.75E+10	1.83E+11	4.39E+10	9.03E+10	5.8E+10	5E+11
d=25,a=0.1	7.77E+10	1.77E+11	4.61E+10	8.52E+10	5.71E+10	5E+11	8.19E+10	1.64E+11	3.73E+10	6.4E+10	5.24E+10	4.76E+11	7.76E+10	1.85E+11	4.83E+10	9.24E+10	5.74E+10	5.09E+11
d=50,a=1	9.03E+10	1.84E+11	4.14E+10	6.56E+10	6.38E+10	4.83E+11	9.85E+10	1.76E+11	3.39E+10	5E+10	5.64E+10	4.67E+11	9.87E+10	1.96E+11	4.29E+10	7.2E+10	6.45E+10	4.89E+11
d=50,a=0.5	7.93E+10	1.76E+11	3.62E+10	7.36E+10	6.17E+10	4.8E+11	8.63E+10	1.64E+11	2.95E+10	5.54E+10	5.56E+10	4.46E+11	8.14E+10	1.82E+11	3.8E+10	7.84E+10	6.19E+10	4.89E+11
d=50,a=0.25	8E+10	1.79E+11	4.27E+10	7.34E+10	6.14E+10	5.03E+11	8.49E+10	1.64E+11	3.2E+10	5.81E+10	5.57E+10	4.71E+11	8.12E+10	1.86E+11	4.56E+10	7.71E+10	6.2E+10	5.13E+11
d=50,a=0.1	8.32E+10	1.85E+11	4.93E+10	7.29E+10	6.15E+10	5.21E+11	8.64E+10	1.67E+11	3.71E+10	5.84E+10	5.57E+10	4.86E+11	8.39E+10	1.92E+11	5.27E+10	7.62E+10	6.23E+10	5.33E+11
to1	2.1E+11	3.01E+11	5.11E+10	5.38E+10	7.37E+10	5.48E+11	1.74E+11	2.68E+11	3.98E+10	5.15E+10	6.07E+10	5.16E+11	3.34E+11	3.71E+11	5.36E+10	5.67E+10	7.79E+10	5.57E+11
to2	1.1E+11	1.9E+11	4.71E+10	5.27E+10	6.92E+10	4.97E+11	1.2E+11	1.81E+11	3.76E+10	4.93E+10	5.96E+10	4.71E+11	1.33E+11	2.14E+11	4.88E+10	5.59E+10	7.39E+10	5E+11
to5	8.73E+10	1.77E+11	4.12E+10	4.64E+10	6.59E+10	4.73E+11	9.21E+10	1.66E+11	3.35E+10	3.95E+10	5.61E+10	4.43E+11	9.31E+10	1.85E+11	4.26E+10	4.91E+10	6.88E+10	4.76E+11
to10	7.9E+10	1.79E+11	3.61E+10	6.04E+10	6.37E+10	4.85E+11	8.67E+10	1.64E+11	3.1E+10	4.73E+10	5.53E+10	4.58E+11	8.17E+10	1.89E+11	3.77E+10	6.27E+10	6.59E+10	4.88E+11
to25	7.8E+10	1.78E+11	4.87E+10	8.63E+10	5.68E+10	5.05E+11	8.18E+10	1.65E+11	3.9E+10	6.6E+10	5.23E+10	4.81E+11	7.78E+10	1.85E+11	5.11E+10	9.35E+10	5.71E+10	5.14E+11
to50	8.8E+10	1.93E+11	5.29E+10	7.25E+10	6.17E+10	5.41E+11	9.07E+10	1.69E+11	4.03E+10	5.82E+10	5.59E+10	5E+11	8.8E+10	2.01E+11	5.63E+10	7.57E+10	6.27E+10	5.54E+11
to2&to10	8.11E+10	1.74E+11	3.56E+10	5.05E+10	6.59E+10	4.93E+11	1.04E+11	1.66E+11	3.08E+10	4.35E+10	5.72E+10	4.67E+11	8.43E+10	1.87E+11	3.69E+10	5.3E+10	7.11E+10	4.96E+11
to2&to25	7.75E+10	1.69E+11	4.3E+10	6.37E+10	6.06E+10	4.7E+11	9.56E+10	1.67E+11	3.6E+10	5.22E+10	5.61E+10	4.5E+11	7.68E+10	1.77E+11	4.39E+10	6.87E+10	6.3E+10	4.75E+11
to5&to10	7.68E+10	1.73E+11	3.59E+10	5.04E+10	6.23E+10	4.95E+11	8.81E+10	1.61E+11	3.05E+10	4.07E+10	5.46E+10	4.63E+11	7.64E+10	1.83E+11	3.7E+10	5.3E+10	6.51E+10	5.01E+11
to5&to25	8E+10	1.75E+11	3.91E+10	6.23E+10	5.73E+10	4.63E+11	8.8E+10	1.65E+11	3.27E+10	4.86E+10	5.14E+10	4.43E+11	7.8E+10	1.81E+11	3.98E+10	6.65E+10	5.84E+10	4.68E+11
to5&to50	8.17E+10	1.82E+11	4.11E+10	5.06E+10	6.4E+10	4.68E+11	9.11E+10	1.63E+11	3.3E+10	3.55E+10	5.54E+10	4.4E+11	8.22E+10	1.89E+11	4.3E+10	5.45E+10	6.59E+10	4.73E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging– Average Absolute Percentage Errors, Limited Distances

	Kriging - Spherical, Euclidean Distances (under 25mi)						Kriging - Exponential, Euclidean Distances (under 25mi)						Kriging - Gaussian, Euclidean Distances (under 25mi)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	66%	64%	55%	25%	62%	62%	65%	63%		25%	60%	61%	67%	65%		25%	62%	64%
d=1,a=0.5	66%	65%	54%	24%	62%	62%	65%	63%		24%	60%	62%	67%	65%		24%	63%	64%
d=1,a=0.25	66%	65%	54%	24%	62%	62%	65%	64%		24%	60%	61%	67%	65%		24%	63%	64%
d=1,a=0.1	66%	65%	55%	24%	62%	62%	65%	64%		24%	61%	61%	67%	65%		24%	63%	64%
d=2,a=1	66%	64%	54%	24%	62%	62%	65%	63%		24%	60%	62%	67%	65%		24%	62%	64%
d=2,a=0.5	66%	64%	54%	23%	61%	62%	65%	63%		23%	60%	61%	67%	65%		23%	62%	64%
d=2,a=0.25	66%	64%	55%	23%	61%	62%	65%	63%		23%	59%	61%	67%	65%	58%	23%	62%	63%
d=2,a=0.1	66%	64%	54%	23%	61%	62%	64%	63%		23%	59%	61%	67%	65%		23%	62%	63%
d=5,a=1	66%	64%	54%	23%	61%	63%	65%	63%		23%	60%	62%	67%	65%		23%	62%	64%
d=5,a=0.5	65%	65%	54%	22%	60%	62%	64%	63%		22%	60%	61%	66%	65%	57%	22%	62%	64%
d=5,a=0.25	65%	64%	55%	22%	60%	62%	64%	63%		22%	62%	61%	66%	64%	57%	22%	62%	64%
d=5,a=0.1	65%	64%	55%	22%	61%	62%	64%	63%		22%	62%	61%	66%	64%	57%	22%	63%	64%
d=10,a=1	66%	65%	55%	22%	61%	63%	65%	64%		22%	60%	62%	67%	65%	56%	23%	62%	64%
d=10,a=0.5	65%	64%	56%	22%	61%	62%	64%	63%	54%	22%	62%	62%	66%	65%	56%	22%	63%	64%
d=10,a=0.25	65%	64%	56%	22%	61%	62%	64%	63%	54%	22%	63%	62%	66%	64%	56%	22%	63%	64%
d=10,a=0.1	65%	64%	56%	22%	61%	62%	64%	63%	54%	22%	62%	62%	66%	64%	56%	22%	62%	64%
d=25,a=1	65%	64%	54%	22%	62%	63%	64%	63%		21%	60%	62%	66%	64%		22%	63%	64%
d=25,a=0.5	63%	62%	54%	21%	61%	62%	63%	62%	56%	21%	60%	61%	64%	63%	55%	21%	62%	64%
d=25,a=0.25	63%	62%	54%	22%	61%	62%	63%	62%		21%	60%	61%	64%	62%	55%	22%	62%	64%
d=25,a=0.1	63%	62%	54%	22%	61%	62%	63%	62%		21%	60%	61%	64%	62%	63%	22%	62%	64%
d=50,a=1	65%	63%	55%	21%	61%	63%	64%	63%	53%	20%	60%	62%	65%	64%	55%	21%	62%	64%
d=50,a=0.5	64%	62%	56%	21%	60%	62%	63%	62%	55%	20%	59%	61%	64%	63%	56%	21%	61%	64%
d=50,a=0.25	64%	62%	56%	21%	60%	62%	63%	62%	54%	21%	59%	61%	64%	63%	58%	21%	61%	64%
d=50,a=0.1	64%	62%	56%	21%	60%	62%	63%	62%		21%	59%	61%	64%	63%	59%	21%	61%	64%
to1	66%	65%	55%	24%	63%	62%	65%	64%		24%	61%	61%	67%	65%		24%	63%	64%
to2	66%	64%	55%	23%	61%	62%	64%	63%		23%	59%	61%	66%	65%		23%	62%	63%
to5	65%	64%	55%	22%	61%	62%	64%	63%		22%	63%	61%	66%	64%	57%	22%	63%	64%
to10	65%	64%	56%	22%	61%	62%	64%	63%	54%	22%	62%	62%	66%	64%	56%	22%	62%	64%
to25	63%	62%	54%	22%	61%	62%	63%	62%		22%	60%	61%	64%	62%	80%	22%	62%	64%
to50	64%	63%	55%	21%	60%	62%	63%	62%		21%	59%	61%	64%	63%	96%	21%	61%	64%
to2&to10	65%	64%	56%	22%	60%	62%	64%	63%	54%	22%	59%	61%	66%	65%	56%	22%	61%	64%
to2&to25	63%	62%	54%	22%	60%	62%	63%	62%	96%	22%	59%	61%	64%	63%	54%	22%	61%	63%
to5&to10	65%	64%	57%	22%	60%	62%	64%	63%	55%	22%	61%	62%	66%	64%	57%	22%	62%	64%
to5&to25	63%	62%	54%	22%	60%	62%	63%	62%		21%	63%	62%	64%	62%	55%	21%	62%	64%
to5&to50	64%	62%	56%	20%	60%	62%	63%	62%	55%	20%	61%	61%	64%	63%	56%	20%	62%	63%

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging– Average Absolute Percentage Errors, Limited Distances

	Kriging - Spherical, Network Distances (under 25mi)						Kriging - Exponential, Network Distances (under 25mi)						Kriging - Gaussian, Network Distances (under 25mi)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	68%	66%	57%	24%	64%	62%	66%	64%	55%	23%	61%	62%	68%	66%	57%	24%	65%	64%
d=1,a=0.5	68%	66%	54%	24%	64%	62%	66%	64%	54%	23%	62%	62%	68%	66%	55%	24%	65%	64%
d=1,a=0.25	68%	66%	54%	23%	64%	62%	66%	64%	54%	23%	62%	62%	68%	66%	55%	23%	65%	64%
d=1,a=0.1	68%	66%	55%	23%	64%	62%	66%	64%	54%	23%	62%	61%	68%	67%	56%	23%	65%	64%
d=2,a=1	68%	66%	54%	24%	64%	62%	66%	64%	54%	23%	61%	62%	68%	66%	56%	23%	65%	64%
d=2,a=0.5	68%	66%	54%	22%	64%	62%	65%	64%	54%	22%	61%	61%	68%	66%	54%	23%	65%	63%
d=2,a=0.25	67%	66%	56%	22%	64%	61%	65%	64%	54%	22%	61%	61%	68%	66%	56%	22%	64%	63%
d=2,a=0.1	67%	65%	55%	22%	63%	61%	65%	63%	54%	22%	60%	61%	68%	66%	55%	22%	64%	63%
d=5,a=1	67%	66%	54%	23%	64%	62%	65%	64%	54%	22%	61%	61%	68%	66%	55%	23%	65%	64%
d=5,a=0.5	66%	64%	53%	22%	64%	62%	64%	63%	54%	22%	62%	62%	67%	66%	55%	22%	67%	64%
d=5,a=0.25	66%	64%	54%	22%	63%	62%	64%	62%	54%	22%	63%	62%	67%	65%	55%	22%	68%	64%
d=5,a=0.1	66%	64%	55%	22%	63%	62%	64%	62%	54%	22%	63%	62%	67%	65%	56%	22%	68%	64%
d=10,a=1	67%	66%	56%	22%	64%	62%	65%	63%	55%	21%	61%	62%	67%	66%	56%	22%	66%	64%
d=10,a=0.5	65%	64%	57%	21%	63%	62%	63%	62%	55%	21%	62%	62%	67%	66%	57%	21%	67%	64%
d=10,a=0.25	65%	64%	57%	21%	63%	62%	63%	62%	55%	21%	62%	62%	67%	65%	57%	21%	66%	64%
d=10,a=0.1	65%	64%	57%	22%	63%	62%	63%	62%	56%	21%	62%	62%	67%	65%	57%	22%	66%	64%
d=25,a=1	66%	64%	55%	21%	64%	62%	64%	63%	55%	20%	61%	61%	66%	65%	56%	21%	65%	64%
d=25,a=0.5	64%	62%	55%	20%	63%	62%	62%	61%	53%	20%	61%	61%	65%	63%	55%	20%	64%	63%
d=25,a=0.25	64%	62%	53%	20%	63%	62%	62%	61%	53%	20%	60%	61%	64%	63%	54%	20%	64%	63%
d=25,a=0.1	63%	62%	53%	20%	63%	62%	62%	61%	53%	20%	60%	61%	64%	63%	54%	20%	64%	63%
d=50,a=1	65%	64%	57%	20%	63%	62%	64%	63%	56%	19%	61%	61%	65%	64%	57%	20%	64%	63%
d=50,a=0.5	63%	62%	57%	20%	62%	62%	62%	61%	56%	19%	60%	61%	64%	62%	57%	19%	63%	63%
d=50,a=0.25	64%	62%	59%	20%	62%	62%	63%	61%	58%	19%	60%	61%	64%	63%	58%	20%	63%	63%
d=50,a=0.1	64%	62%	58%	20%	62%	61%	63%	61%	56%	20%	60%	61%	64%	63%	58%	20%	63%	63%
to1	68%	66%	57%	23%	64%	62%	66%	65%	55%	23%	63%	61%	68%	67%	57%	23%	65%	64%
to2	67%	65%	55%	22%	63%	61%	65%	63%	54%	22%	60%	61%	68%	66%	56%	22%	64%	63%
to5	66%	64%	55%	22%	63%	62%	64%	62%	54%	22%	63%	62%	67%	65%	56%	22%	68%	64%
to10	65%	64%	57%	22%	63%	62%	63%	62%	56%	21%	62%	62%	67%	65%	57%	22%	66%	64%
to25	63%	62%	52%	20%	63%	62%	62%	61%	53%	20%	60%	61%	64%	63%	54%	20%	63%	63%
to50	64%	63%	58%	20%	62%	61%	63%	61%	56%	20%	60%	61%	64%	63%	57%	20%	63%	63%
to2&to10	65%	64%	57%	22%	63%	62%	63%	62%	56%	21%	60%	63%	67%	66%	57%	21%	64%	63%
to2&to25	64%	62%	55%	21%	62%	61%	62%	61%	53%	21%	60%	61%	64%	63%	55%	21%	63%	63%
to5&to10	65%	64%	59%	22%	63%	62%	63%	62%	57%	21%	62%	63%	67%	65%	58%	21%	67%	64%
to5&to25	63%	62%	53%	21%	63%	62%	62%	61%	53%	20%	63%	61%	64%	63%	55%	21%	67%	63%
to5&to50	64%	62%	58%	20%	62%	61%	63%	61%	57%	19%	62%	61%	65%	63%	57%	19%	66%	63%

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging– Average Absolute Percentage Errors, All Distances

	Kriging - Spherical, Euclidean Distances (all)						Kriging - Exponential, Euclidean Distances (all)						Kriging - Gaussian, Euclidean Distances (all)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	67.2%	65.0%	53.4%	25.8%	62.3%	63.0%	68.2%	67.6%	54.4%	13.3%	58.7%	62.2%	72.5%	71.2%	60.1%		61.4%	
d=1,a=0.5	67.3%	65.1%	53.4%	25.5%	64.7%	63.1%	68.8%	68.1%	53.5%	13.3%	59.4%	62.3%	72.5%	71.5%	59.2%		63.8%	
d=1,a=0.25	67.7%	65.5%	53.4%	25.3%	65.0%	63.2%	70.0%	69.6%	53.4%	13.3%	60.8%	62.5%	72.2%	70.7%	58.9%		62.0%	
d=1,a=0.1	68.0%	65.8%	53.5%	25.2%	65.3%	63.2%	71.7%	71.3%	53.8%	13.3%	61.5%	62.3%	71.8%	70.5%	59.5%		63.9%	
d=2,a=1	67.2%	64.9%	53.4%	25.5%	61.5%	63.1%	68.4%	67.9%	53.5%	13.3%	58.8%	62.5%	72.5%	71.3%	59.3%		61.7%	
d=2,a=0.5	67.2%	64.9%	53.6%	24.9%	64.6%	62.9%	69.7%	68.8%	53.1%	13.3%	59.7%	62.7%	71.6%	70.7%	58.6%		65.0%	
d=2,a=0.25	66.7%	64.8%	53.9%	24.9%	64.2%	62.6%	69.9%	69.1%	53.1%	13.4%	59.4%	62.3%	71.0%	69.8%	58.3%		63.9%	
d=2,a=0.1	66.2%	64.8%	54.5%	24.9%	61.2%	62.5%	69.9%	69.3%	53.1%	13.4%	58.9%	62.1%	70.5%	69.2%	58.2%		62.3%	
d=5,a=1	67.2%	64.6%	53.5%	24.7%	63.9%	63.2%	69.8%	68.4%	53.4%	13.3%	59.2%	63.0%	71.8%	71.3%	59.0%		62.7%	
d=5,a=0.5	65.1%	64.4%	54.7%	23.9%	60.2%	62.8%	70.7%	69.1%	53.3%	13.4%	58.2%	63.2%	69.7%	68.9%	58.0%		61.5%	
d=5,a=0.25	65.0%	64.1%	54.3%	24.0%	58.9%	62.8%	69.8%	68.4%	53.4%	13.4%	57.7%	63.1%	69.6%	68.9%	58.1%		61.7%	
d=5,a=0.1	65.0%	64.0%	54.2%	24.0%	58.3%	62.8%	69.5%	68.1%	53.5%	13.5%	57.6%	62.9%	69.7%	68.9%	58.2%		61.7%	
d=10,a=1	67.0%	64.6%	53.6%	23.7%	62.5%	63.3%	71.6%	70.0%	53.3%	13.3%	59.0%	63.2%	71.2%	70.7%	58.7%		62.1%	
d=10,a=0.5	65.0%	64.0%	54.9%	23.4%	59.3%	63.1%	71.6%	69.4%	53.5%	13.5%	57.7%	63.0%	69.7%	69.4%	58.1%		61.6%	
d=10,a=0.25	64.9%	63.8%	54.4%	23.5%	58.7%	63.1%	71.5%	68.8%	53.5%	13.5%	57.5%	62.6%	69.7%	69.7%	58.2%		61.6%	
d=10,a=0.1	64.9%	63.9%	54.3%	23.6%	58.1%	63.2%	71.5%	69.1%	53.6%	13.5%	57.4%	62.5%	69.7%	69.3%	58.3%		61.7%	
d=25,a=1	66.8%	64.7%	53.4%	23.1%	62.0%	63.2%	71.5%	71.3%	53.1%	13.3%	58.7%	62.4%	70.9%	71.2%	57.8%		61.8%	
d=25,a=0.5	66.2%	63.7%	54.8%	23.1%	60.1%	62.9%	71.1%	71.1%	52.9%	13.7%	57.5%	61.4%	71.0%	71.0%	55.2%		61.2%	
d=25,a=0.25	66.1%	63.6%	54.3%	23.4%	59.9%	62.8%	71.1%	71.1%	52.7%	13.7%	57.4%	61.2%	70.9%	71.1%	55.2%		61.1%	
d=25,a=0.1	66.0%	63.7%	53.8%	23.6%	59.9%	62.8%	71.1%	71.0%	52.6%	13.7%	57.4%	61.1%	71.1%	71.1%	55.6%		61.1%	
d=50,a=1	66.8%	65.3%	53.8%	22.3%	62.0%	63.0%	71.4%	71.2%	53.7%	13.4%	58.6%	62.2%	70.6%	70.8%	58.6%		62.1%	
d=50,a=0.5	66.2%	64.9%	55.2%	22.5%	60.4%	62.5%	71.3%	71.1%	56.4%	13.6%	57.4%	61.4%	70.1%	69.6%	55.9%		60.9%	
d=50,a=0.25	66.1%	65.0%	55.6%	23.1%	60.4%	62.5%	71.3%	71.2%	57.0%	13.5%	57.4%	61.6%	69.8%	69.1%	56.1%		60.8%	
d=50,a=0.1	65.8%	64.9%	56.0%	23.3%	60.3%	62.5%	71.3%	71.2%	55.5%	13.5%	57.3%	61.8%	69.4%	68.9%	55.9%		60.8%	
to1	67.8%	66.0%	53.5%	25.1%	65.6%	63.2%	71.7%	71.6%	54.1%	13.3%	61.8%	62.3%	71.5%	70.3%	59.4%		60.4%	
to2	65.9%	64.7%	54.6%	24.9%	61.5%	62.5%	69.9%	69.2%	53.1%	13.4%	58.6%	62.1%	70.2%	68.8%	58.1%		61.7%	
to5	64.9%	64.0%	54.2%	24.0%	58.2%	62.8%	69.4%	67.9%	53.5%	13.5%	57.5%	62.9%	69.6%	69.0%	58.2%		61.7%	
to10	65.0%	63.9%	54.3%	23.6%	58.5%	63.2%	71.5%	69.2%	53.6%	13.5%	57.4%	62.4%	69.8%	69.3%	58.3%		61.6%	
to25	66.0%	63.7%	53.5%	23.7%	59.9%	62.8%	71.1%	71.0%	52.6%	13.7%	57.4%	61.1%	71.2%	71.0%	55.8%		61.1%	
to50	65.7%	64.8%	55.7%	23.5%	60.2%	62.5%	71.4%	71.2%	54.8%	13.5%	57.3%	61.8%	69.2%	68.7%	56.6%		60.8%	
to2&to10	64.8%	64.3%	54.2%	23.5%	61.4%	62.6%	71.9%	70.5%	53.4%	13.5%	58.5%	62.6%	69.5%	68.7%	58.0%		61.6%	
to2&to25	66.3%	63.9%	53.9%	23.2%	63.1%	62.4%	71.6%	71.4%	52.6%	13.7%	58.5%	62.0%	71.1%	71.2%	55.4%		62.7%	
to5&to10	65.7%	63.9%	54.4%	23.5%	58.9%	63.0%	71.8%	69.4%	53.5%	13.6%	57.5%	62.8%	70.4%	69.6%	58.2%		61.5%	
to5&to25	66.1%	64.0%	55.1%	22.6%	59.0%	62.7%	71.7%	69.8%	52.8%	13.7%	57.4%	62.4%	71.4%	70.8%	55.5%		61.4%	
to5&to50	64.8%	64.2%	55.9%	21.6%	59.8%	62.4%	71.9%	71.5%	55.5%	13.7%	57.4%	63.1%	67.5%	68.3%	56.0%		61.0%	

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging– Average Absolute Percentage Errors, All Distances

	Kriging - Spherical, Network Distances (all)						Kriging - Exponential, Network Distances (all)						Kriging - Gaussian, Network Distances (all)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	65.5%	63.5%	52.0%	25.9%	64.9%	62.7%	64.2%	62.7%	51.8%	14.2%	59.2%	60.2%	75.7%	76.1%				
d=1,a=0.5	65.6%	63.6%	52.0%	25.7%	65.8%	62.8%	64.6%	62.7%	51.9%	14.2%	59.4%	60.2%	75.6%	76.1%				
d=1,a=0.25	65.9%	63.9%	52.0%	25.5%	66.5%	62.8%	67.5%	65.6%	51.9%	14.3%	59.7%	60.3%	74.9%	74.7%				
d=1,a=0.1	66.2%	64.1%	52.2%	25.5%	68.7%	62.8%	68.0%	68.5%	52.0%	14.3%	60.2%	60.3%	74.1%	73.8%				
d=2,a=1	65.4%	63.5%	51.9%	25.7%	65.1%	62.7%	64.3%	62.8%	51.9%	14.2%	59.2%	60.2%	75.7%	76.2%				
d=2,a=0.5	65.4%	63.4%	52.1%	25.2%	65.8%	62.6%	68.0%	66.9%	51.6%	14.3%	59.5%	60.7%	74.5%	76.1%				
d=2,a=0.25	65.1%	63.4%	52.3%	25.3%	65.5%	62.3%	68.2%	67.4%	51.6%	14.3%	59.4%	60.4%	74.1%	75.1%				
d=2,a=0.1	65.1%	63.3%	52.9%	25.3%	64.8%	62.2%	68.3%	67.6%	51.5%	14.3%	59.1%	60.2%	73.5%	74.3%				
d=5,a=1	65.5%	63.3%	51.9%	25.0%	65.5%	62.9%	68.0%	63.6%	51.7%	14.4%	59.4%	60.8%	74.7%	77.0%				
d=5,a=0.5	64.9%	63.1%	54.6%	24.6%	63.4%	62.5%	68.5%	67.4%	51.6%	14.5%	59.1%	61.1%	73.6%	75.3%				
d=5,a=0.25	64.6%	62.9%	55.2%	24.7%	63.2%	62.5%	67.9%	66.6%	51.7%	14.6%	58.9%	60.9%	74.0%	139.9%				
d=5,a=0.1	64.5%	62.8%	55.2%	24.7%	63.3%	62.5%	67.5%	66.3%	51.7%	14.6%	58.8%	60.7%	74.2%	91.4%				
d=10,a=1	65.2%	63.2%	52.1%	24.1%	65.3%	62.9%	68.2%	68.3%	51.9%	14.4%	59.4%	61.0%	74.2%	77.1%				
d=10,a=0.5	64.4%	62.7%	53.7%	23.8%	63.2%	62.7%	68.3%	67.7%	51.7%	14.7%	59.0%	60.5%	74.4%	82.1%				
d=10,a=0.25	64.2%	62.6%	54.5%	23.9%	63.3%	62.7%	68.1%	67.0%	51.9%	14.7%	58.8%	60.2%	74.6%	83.1%				
d=10,a=0.1	64.2%	62.6%	54.5%	24.0%	63.5%	62.7%	68.1%	67.3%	51.9%	14.6%	58.8%	60.1%	74.7%	81.8%				
d=25,a=1	65.2%	63.1%	51.9%	23.3%	64.5%	62.7%	68.1%	66.9%	51.8%	14.3%	59.2%	60.2%	73.2%	76.7%				
d=25,a=0.5	63.8%	62.0%	53.5%	23.3%	63.0%	62.3%	67.5%	64.0%	51.3%	14.5%	58.7%	173.0%	74.4%	94.7%				
d=25,a=0.25	63.7%	61.9%	53.4%	23.6%	62.8%	62.3%	67.4%	62.8%	51.0%	14.5%	58.6%	433.2%	74.3%	83.1%				
d=25,a=0.1	63.6%	61.9%	52.8%	23.7%	62.8%	62.3%	67.4%	62.6%	50.7%	14.5%	58.6%	61.4%	74.6%	79.8%				
d=50,a=1	65.7%	63.2%	52.8%	22.5%	64.3%	62.5%	67.9%	67.8%	52.5%	14.3%	59.0%	61.4%	71.7%	74.1%				
d=50,a=0.5	64.6%	62.3%	53.2%	22.8%	62.6%	62.0%	67.3%	67.8%	52.8%	14.4%	58.2%	61.4%	71.2%	72.9%				
d=50,a=0.25	64.9%	62.5%	54.5%	23.3%	62.5%	62.0%	67.4%	67.9%	53.4%	14.4%	58.2%	61.4%	71.0%	72.3%				
d=50,a=0.1	65.1%	62.7%	54.0%	23.5%	62.5%	62.0%	67.4%	68.0%	53.1%	14.3%	58.2%	61.4%	70.7%	72.1%				
to1	66.4%	64.3%	52.3%	25.4%	68.8%	62.8%	68.1%	68.6%	52.0%	14.3%	60.5%	61.4%	73.3%	73.1%				
to2	65.0%	63.2%	53.0%	25.3%	64.3%	62.2%	68.2%	67.6%	51.4%	14.3%	59.0%	61.4%	73.3%	73.7%				
to5	64.5%	62.8%	55.2%	24.7%	63.5%	62.5%	67.4%	66.2%	51.7%	14.6%	58.8%	61.4%	74.1%	83.3%				
to10	64.1%	62.6%	54.6%	24.0%	63.5%	62.7%	68.1%	67.4%	51.8%	14.6%	58.8%	61.4%	74.8%	81.9%				
to25	63.6%	61.9%	52.2%	23.8%	62.8%	62.3%	67.4%	62.5%	50.5%	14.5%	58.6%	61.4%	74.7%	79.3%				
to50	65.3%	62.8%	53.4%	23.7%	62.4%	62.0%	67.5%	68.0%	52.7%	14.3%	58.2%	61.4%	70.6%	71.8%				
to2&to10	64.3%	62.7%	54.3%	23.9%	64.1%	62.3%	68.6%	69.0%	51.9%	14.6%	58.9%	61.4%	74.4%	#######				
to2&to25	63.7%	62.0%	52.5%	23.4%	64.4%	61.9%	68.0%	63.1%	50.7%	14.6%	58.5%	61.4%	74.3%	79.3%				
to5&to10	64.0%	62.6%	53.5%	24.0%	63.1%	62.6%	68.3%	67.8%	51.9%	14.6%	58.8%	61.4%	74.9%	81.1%				
to5&to25	63.6%	62.1%	54.8%	23.0%	62.9%	62.3%	67.2%	62.4%	51.5%	14.7%	58.6%	61.4%	74.9%	77.2%				
to5&to50	64.9%	62.8%	54.4%	22.2%	62.5%	62.0%	68.0%	68.5%	53.7%	14.7%	58.1%	61.4%	70.4%	71.0%				

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging – Median Percentage Error, Limited Distances

	Kriging - Spherical, Euclidean Distances (under 25mi)						Kriging - Exponential, Euclidean Distances (under 25mi)						Kriging - Gaussian, Euclidean Distances (under 25mi)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	4.5%	6.2%	-3.5%	-6.1%	2.1%	-2.3%	3.3%	6.7%		-5.4%	0.3%	-3.0%	3.6%	3.8%		-4.1%	1.8%	-2.5%
d=1,a=0.5	5.1%	7.2%	-3.4%	-4.8%	2.7%	-2.3%	3.9%	6.5%		-4.4%	0.7%	-2.7%	2.6%	4.3%		-4.6%	1.9%	-2.5%
d=1,a=0.25	5.7%	6.9%	-2.1%	-4.8%	1.4%	-2.0%	4.5%	6.1%		-4.4%	0.6%	-2.7%	3.9%	5.6%		-3.9%	2.5%	-2.2%
d=1,a=0.1	5.7%	6.4%	-3.0%	-4.6%	1.9%	-2.2%	4.8%	5.3%		-3.5%	0.9%	-2.7%	3.7%	4.8%		-4.2%	2.3%	-2.0%
d=2,a=1	5.0%	6.9%	-3.6%	-5.2%	2.2%	-2.5%	3.5%	6.7%		-5.3%	0.2%	-2.7%	3.7%	3.9%		-5.0%	1.8%	-2.4%
d=2,a=0.5	5.8%	6.6%	-2.3%	-3.8%	1.4%	-2.2%	4.6%	6.5%		-2.7%	0.5%	-3.0%	4.0%	6.8%		-4.7%	1.3%	-2.1%
d=2,a=0.25	3.8%	6.8%	-3.4%	-3.3%	0.6%	-2.3%	3.8%	5.2%		-3.0%	0.1%	-3.1%	3.5%	7.0%	-3.1%	-4.3%	1.5%	-2.6%
d=2,a=0.1	3.4%	6.0%	-2.8%	-3.0%	0.8%	-2.1%	3.0%	4.1%		-2.6%	0.3%	-2.8%	2.6%	6.2%		-4.2%	1.3%	-2.8%
d=5,a=1	5.9%	7.0%	-1.4%	-4.2%	1.0%	-2.7%	4.8%	6.7%		-3.9%	0.3%	-2.5%	4.6%	6.4%		-5.7%	1.4%	-2.9%
d=5,a=0.5	4.0%	4.1%	-2.9%	-4.6%	-0.5%	-2.2%	3.4%	5.3%		-3.2%	-1.6%	-2.7%	3.4%	6.1%	-3.1%	-5.0%	2.3%	-2.3%
d=5,a=0.25	1.8%	3.9%	-3.5%	-5.2%	-0.2%	-2.5%	2.1%	4.2%		-3.2%	-1.5%	-2.4%	2.7%	4.6%	-3.9%	-5.4%	2.3%	-2.1%
d=5,a=0.1	2.2%	4.1%	-3.9%	-4.9%	-0.2%	-2.5%	2.1%	3.6%		-3.1%	-0.7%	-2.5%	4.0%	4.6%	-5.1%	-5.1%	2.4%	-2.0%
d=10,a=1	6.4%	7.4%	-2.2%	-5.5%	-0.5%	-2.2%	4.0%	7.0%		-3.8%	0.0%	-2.4%	4.3%	6.0%	-3.0%	-5.2%	1.0%	-2.4%
d=10,a=0.5	3.3%	4.0%	-6.0%	-3.2%	0.1%	-1.6%	4.5%	4.7%	-0.3%	-2.9%	-1.2%	-1.8%	4.1%	5.1%	-3.8%	-4.0%	2.3%	-2.0%
d=10,a=0.25	2.2%	4.2%	-6.4%	-3.1%	-0.1%	-2.0%	3.0%	4.9%	-0.8%	-2.9%	-0.6%	-2.1%	3.1%	4.6%	-4.2%	-4.5%	2.7%	-2.0%
d=10,a=0.1	1.6%	4.0%	-6.4%	-3.1%	0.2%	-2.0%	3.4%	4.8%	-0.2%	-2.9%	-0.5%	-2.4%	2.8%	4.2%	-3.4%	-4.3%	2.4%	-2.1%
d=25,a=1	6.9%	8.3%	-2.6%	-6.0%	0.2%	-2.4%	7.5%	7.9%		-5.0%	0.8%	-2.2%	4.4%	6.6%	2.0%	-5.5%	1.7%	-2.3%
d=25,a=0.5	4.3%	4.6%	-3.3%	-4.5%	1.3%	-1.5%	3.5%	3.7%	3.5%	-4.8%	1.2%	-2.2%	2.0%	4.3%	-5.3%	-4.2%	2.3%	-1.9%
d=25,a=0.25	3.1%	4.2%	-3.1%	-4.5%	1.2%	-1.3%	3.6%	4.0%		-4.9%	1.3%	-2.2%	2.1%	4.3%	-2.3%	-4.5%	1.7%	-1.8%
d=25,a=0.1	3.0%	4.2%	-2.5%	-4.6%	1.3%	-1.4%	3.8%	4.2%		-4.8%	1.2%	-2.0%	2.3%	4.2%	-2.3%	-4.7%	1.4%	-1.8%
d=50,a=1	7.3%	7.2%	-4.3%	-5.8%	-0.3%	-2.1%	7.0%	8.9%	-1.1%	-5.9%	0.0%	-2.2%	4.3%	6.0%	-0.6%	-5.6%	1.0%	-1.9%
d=50,a=0.5	5.4%	4.6%	-6.5%	-4.5%	0.5%	-1.8%	2.9%	3.9%	-1.1%	-4.4%	0.6%	-2.8%	0.7%	2.2%	-1.4%	-4.3%	1.1%	-1.7%
d=50,a=0.25	2.9%	3.9%	-5.2%	-4.6%	0.7%	-1.9%	3.2%	4.4%	-1.1%	-3.9%	0.8%	-2.4%	1.2%	1.7%	-7.8%	-4.5%	1.3%	-2.2%
d=50,a=0.1	2.3%	3.5%	-4.4%	-5.3%	0.7%	-1.7%	3.1%	4.5%		-3.7%	0.8%	-2.5%	1.2%	1.3%	-3.0%	-4.3%	1.1%	-2.2%
to1	5.4%	6.2%	-3.6%	-4.4%	2.5%	-2.0%	4.7%	4.5%		-3.1%	1.4%	-2.8%	3.5%	4.4%		-4.2%	1.9%	-2.1%
to2	3.5%	5.7%	-3.1%	-3.0%	1.0%	-2.0%	3.1%	3.9%		-2.6%	0.8%	-2.7%	2.0%	5.5%	-1.4%	-3.9%	1.4%	-2.9%
to5	2.0%	4.4%	-4.1%	-4.7%	0.0%	-2.5%	2.2%	3.5%		-3.2%	-0.5%	-2.6%	3.9%	4.6%	-5.2%	-4.9%	2.7%	-1.8%
to10	1.5%	4.0%	-6.3%	-3.1%	0.2%	-2.1%	3.1%	4.8%	-0.2%	-2.8%	-0.2%	-2.3%	2.7%	3.9%	-3.8%	-4.2%	2.6%	-2.1%
to25	2.9%	4.0%	-2.4%	-4.7%	1.5%	-1.4%	3.9%	4.4%		-4.7%	1.4%	-2.0%	2.5%	4.0%	-8.2%	-4.7%	1.3%	-1.9%
to50	2.7%	3.3%	-3.4%	-5.2%	0.4%	-1.6%	3.1%	4.2%		-3.6%	0.9%	-2.6%	1.3%	2.1%	-5.7%	-4.2%	1.2%	-2.1%
to2&to10	2.1%	4.2%	-5.9%	-3.5%	2.4%	-1.8%	3.3%	4.6%	-0.1%	-2.9%	1.4%	-2.4%	3.0%	5.5%	-2.7%	-4.5%	1.4%	-2.6%
to2&to25	3.8%	5.0%	-3.1%	-4.5%	2.3%	-1.9%	3.6%	3.9%	-1.1%	-4.2%	1.0%	-1.9%	2.8%	4.0%	-4.1%	-4.7%	1.8%	-2.3%
to5&to10	1.8%	3.8%	-6.2%	-3.9%	0.3%	-2.0%	2.9%	4.7%	-2.3%	-2.9%	-0.8%	-2.1%	3.6%	4.2%	-1.5%	-4.3%	3.0%	-2.0%
to5&to25	3.1%	3.8%	-4.0%	-4.4%	1.2%	-1.9%	4.0%	3.8%	0.0%	-4.3%	0.6%	-2.1%	2.5%	3.7%	-5.1%	-5.1%	1.3%	-1.9%
to5&to50	1.2%	4.6%	-0.3%	-5.0%	-0.6%	-1.9%	1.6%	3.1%	-0.9%	-4.1%	-0.4%	-2.9%	0.3%	4.3%	-1.7%	-4.8%	0.7%	-1.8%

Kriging – Median Percentage Error, Limited Distances

	Kriging - Spherical, Network Distances (under 25mi)						Kriging - Exponential, Network Distances (under 25mi)						Kriging - Gaussian, Network Distances (under 25mi)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	2.9%	3.8%	-1.1%	-5.2%	2.8%	-2.7%	3.9%	6.0%	-1.9%	-5.1%	0.1%	-2.6%	4.7%	4.7%	-2.1%	-5.9%	5.4%	-2.3%
d=1,a=0.5	4.8%	5.0%	-3.8%	-4.8%	2.2%	-2.1%	3.8%	5.7%	-0.4%	-5.3%	1.0%	-2.4%	4.5%	5.6%	-2.5%	-5.1%	5.4%	-2.6%
d=1,a=0.25	4.8%	4.7%	-3.4%	-4.9%	2.4%	-1.9%	3.6%	5.7%	-0.6%	-4.8%	1.6%	-2.1%	4.4%	5.5%	-3.3%	-4.8%	5.2%	-2.5%
d=1,a=0.1	4.7%	4.7%	-4.2%	-4.9%	2.3%	-2.4%	4.0%	5.7%	-1.0%	-4.2%	2.4%	-2.0%	4.7%	5.7%	-2.7%	-4.8%	5.3%	-2.3%
d=2,a=1	4.2%	4.9%	-4.5%	-5.4%	2.7%	-2.2%	3.5%	6.0%	-1.0%	-5.0%	0.3%	-2.9%	4.4%	5.0%	-2.2%	-5.9%	5.2%	-2.4%
d=2,a=0.5	2.9%	3.9%	-3.1%	-4.8%	3.2%	-2.9%	5.2%	6.2%	-0.5%	-4.5%	0.8%	-2.3%	3.6%	5.5%	-3.6%	-5.4%	5.9%	-2.8%
d=2,a=0.25	2.7%	5.0%	-0.4%	-4.3%	3.6%	-2.7%	4.1%	5.5%	0.3%	-4.3%	0.4%	-2.4%	2.2%	5.1%	-1.2%	-5.0%	5.7%	-1.9%
d=2,a=0.1	2.4%	3.6%	0.3%	-3.4%	4.1%	-2.9%	4.1%	5.1%	1.2%	-4.1%	0.3%	-2.5%	1.7%	3.4%	-2.2%	-4.9%	4.6%	-2.4%
d=5,a=1	3.6%	4.6%	-3.9%	-5.2%	3.1%	-2.1%	5.0%	5.7%	-1.0%	-4.1%	0.9%	-2.9%	3.8%	4.4%	-2.5%	-6.5%	4.6%	-2.4%
d=5,a=0.5	2.3%	3.6%	-1.0%	-5.6%	1.4%	-2.5%	4.7%	4.2%	-0.3%	-4.6%	-0.8%	-1.7%	1.2%	3.5%	-2.0%	-5.9%	3.5%	-2.2%
d=5,a=0.25	2.7%	1.9%	1.2%	-5.1%	1.2%	-2.2%	4.6%	3.6%	0.2%	-4.4%	-0.3%	-2.2%	3.0%	3.0%	-1.3%	-5.5%	4.4%	-2.4%
d=5,a=0.1	2.3%	1.4%	1.7%	-5.0%	1.4%	-2.4%	4.5%	3.1%	0.4%	-4.2%	-0.8%	-2.0%	2.9%	4.2%	-1.5%	-5.4%	4.2%	-2.5%
d=10,a=1	4.3%	6.1%	0.5%	-4.3%	2.8%	-2.4%	5.6%	6.3%	-2.2%	-3.3%	0.9%	-3.0%	2.9%	3.4%	-1.5%	-4.5%	3.4%	-2.4%
d=10,a=0.5	2.3%	3.2%	1.0%	-4.3%	0.8%	-2.0%	3.7%	4.4%	1.4%	-3.6%	0.7%	-2.1%	3.5%	5.1%	-0.3%	-4.4%	3.3%	-2.0%
d=10,a=0.25	1.9%	2.4%	0.3%	-4.3%	1.4%	-1.9%	3.3%	5.0%	0.2%	-4.1%	1.4%	-1.9%	3.9%	5.5%	-1.5%	-4.3%	4.4%	-2.1%
d=10,a=0.1	1.8%	2.1%	0.0%	-4.2%	1.3%	-2.0%	3.0%	4.9%	-0.8%	-4.2%	1.6%	-1.8%	4.1%	5.0%	-1.6%	-4.2%	4.2%	-2.0%
d=25,a=1	5.6%	7.2%	-2.7%	-5.2%	1.7%	-2.0%	5.6%	6.2%	-2.1%	-4.8%	1.8%	-3.3%	4.3%	5.0%	-1.0%	-5.1%	2.7%	-2.2%
d=25,a=0.5	2.1%	4.2%	0.4%	-4.7%	3.0%	-1.7%	2.7%	3.0%	1.9%	-3.9%	2.0%	-2.1%	2.0%	4.3%	-0.4%	-5.2%	4.0%	-1.4%
d=25,a=0.25	1.7%	2.9%	-4.7%	-4.6%	3.7%	-1.9%	3.4%	3.3%	-1.2%	-4.0%	1.8%	-1.5%	0.6%	3.1%	-2.6%	-4.4%	3.3%	-1.5%
d=25,a=0.1	1.5%	2.6%	-4.6%	-4.8%	3.7%	-1.9%	3.5%	3.5%	-0.5%	-4.4%	1.9%	-1.5%	1.1%	2.8%	-2.8%	-4.8%	3.5%	-1.6%
d=50,a=1	5.8%	7.0%	-2.3%	-5.5%	1.2%	-2.0%	6.9%	6.0%	-2.3%	-4.7%	1.5%	-2.9%	4.0%	6.3%	-0.9%	-6.1%	2.5%	-2.1%
d=50,a=0.5	3.0%	2.5%	-1.4%	-4.7%	1.7%	-2.3%	2.9%	4.1%	-0.3%	-3.2%	2.1%	-2.1%	2.4%	3.6%	-1.4%	-3.2%	3.1%	-2.1%
d=50,a=0.25	3.0%	1.4%	-2.1%	-4.8%	1.7%	-2.3%	2.7%	3.9%	-2.9%	-2.8%	2.5%	-2.3%	2.0%	1.7%	-3.3%	-3.2%	2.9%	-1.9%
d=50,a=0.1	2.3%	1.5%	-3.8%	-4.6%	1.7%	-2.4%	3.1%	4.0%	-1.9%	-3.0%	2.2%	-2.3%	0.4%	1.3%	-5.1%	-4.0%	2.6%	-2.4%
to1	4.7%	4.4%	0.2%	-4.7%	3.0%	-2.2%	4.5%	5.6%	0.4%	-4.1%	2.4%	-1.6%	4.7%	5.6%	-2.2%	-4.9%	5.3%	-2.1%
to2	2.6%	2.7%	0.2%	-3.6%	4.0%	-2.9%	3.8%	4.9%	0.5%	-4.1%	0.6%	-2.4%	2.3%	2.3%	-0.8%	-4.8%	4.4%	-2.9%
to5	1.8%	1.4%	1.6%	-4.9%	1.4%	-2.3%	4.4%	2.9%	0.5%	-4.1%	-0.9%	-1.9%	2.9%	4.3%	-1.5%	-5.3%	4.0%	-2.6%
to10	1.8%	2.0%	-0.1%	-4.6%	1.2%	-2.1%	3.0%	4.7%	-1.2%	-4.1%	1.3%	-2.0%	4.0%	4.9%	-1.6%	-4.0%	4.3%	-2.1%
to25	1.3%	2.7%	-4.8%	-4.7%	3.8%	-1.9%	3.6%	3.6%	-0.8%	-4.2%	1.7%	-1.6%	1.3%	2.5%	-3.0%	-4.7%	3.5%	-1.7%
to50	1.4%	1.4%	-4.8%	-4.4%	1.7%	-2.2%	2.9%	3.6%	-2.6%	-3.2%	1.7%	-2.4%	0.4%	1.2%	-3.5%	-4.5%	2.5%	-2.5%
to2&to10	1.5%	2.7%	0.5%	-4.7%	2.8%	-2.6%	3.3%	4.6%	0.8%	-4.4%	2.1%	-2.0%	2.8%	5.0%	0.9%	-4.3%	4.6%	-2.8%
to2&to25	1.7%	3.0%	0.0%	-5.5%	2.2%	-2.1%	3.7%	3.2%	-0.3%	-5.0%	1.5%	-2.4%	0.0%	2.9%	-1.3%	-5.5%	3.8%	-2.1%
to5&to10	2.0%	2.0%	0.6%	-3.4%	1.4%	-2.3%	2.8%	5.0%	-0.6%	-3.8%	1.8%	-1.8%	3.3%	5.1%	1.0%	-4.2%	4.3%	-2.9%
to5&to25	1.3%	2.9%	-5.7%	-4.8%	1.7%	-1.8%	3.7%	3.3%	-0.8%	-5.1%	-1.0%	-2.9%	0.9%	3.1%	-3.4%	-5.3%	1.5%	-2.0%
to5&to50	1.7%	1.6%	-1.3%	-4.6%	1.0%	-1.8%	4.2%	2.4%	0.3%	-4.3%	-0.3%	-2.7%	1.1%	3.4%	-0.3%	-4.5%	1.5%	-2.5%

Kriging – Median Percentage Error, All Distances

	Kriging - Spherical, Euclidean Distances (all)						Kriging - Exponential, Euclidean Distances (all)						Kriging - Gaussian, Euclidean Distances (all)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	3.5%	4.9%	-1.8%	-7.7%	0.0%	-2.5%	5.5%	6.7%	-3.0%	-0.6%	0.6%	-3.2%	1.8%	4.7%	-9.6%		-2.4%	
d=1,a=0.5	4.0%	5.1%	-1.8%	-7.3%	0.6%	-3.0%	6.4%	7.2%	-1.1%	-0.6%	1.3%	-2.9%	2.7%	4.6%	-8.0%		-2.5%	
d=1,a=0.25	4.1%	4.3%	-1.0%	-7.3%	1.7%	-3.1%	6.8%	7.3%	-1.1%	-0.6%	1.5%	-3.1%	3.4%	3.9%	-8.1%		-1.2%	
d=1,a=0.1	4.1%	4.4%	-1.5%	-7.2%	1.4%	-2.7%	7.7%	8.7%	-2.2%	-0.4%	1.3%	-2.8%	2.4%	3.4%	-6.6%		-3.3%	
d=2,a=1	3.9%	5.2%	-1.7%	-7.7%	-0.4%	-3.2%	5.7%	7.1%	-1.1%	-0.6%	0.6%	-3.1%	2.1%	4.6%	-8.0%		-1.0%	
d=2,a=0.5	3.2%	5.7%	-0.8%	-6.9%	1.7%	-3.2%	6.3%	6.9%	-0.5%	-0.6%	1.7%	-2.9%	2.2%	3.3%	-8.1%		-2.4%	
d=2,a=0.25	2.7%	6.0%	0.9%	-6.9%	2.7%	-2.7%	6.6%	7.1%	1.1%	-0.6%	1.4%	-2.4%	1.8%	3.6%	-8.4%		-2.8%	
d=2,a=0.1	2.1%	5.7%	1.0%	-6.4%	1.3%	-2.7%	6.2%	6.8%	-0.4%	-0.4%	0.9%	-2.3%	2.3%	3.8%	-8.2%		-1.6%	
d=5,a=1	4.3%	6.1%	-0.4%	-7.6%	0.6%	-3.1%	6.7%	7.2%	-1.6%	-0.8%	1.0%	-3.3%	2.8%	4.3%	-8.7%		-1.6%	
d=5,a=0.5	2.8%	4.8%	1.2%	-6.3%	0.3%	-2.0%	7.9%	7.7%	-0.7%	-0.6%	0.4%	-3.0%	2.8%	3.3%	-8.7%		-3.3%	
d=5,a=0.25	2.6%	4.5%	1.5%	-6.3%	-0.5%	-2.4%	8.1%	7.4%	-0.7%	-0.2%	0.4%	-3.0%	3.4%	4.1%	-9.2%		-4.0%	
d=5,a=0.1	2.6%	4.3%	1.5%	-6.5%	-0.6%	-2.4%	7.5%	6.6%	-0.9%	-0.5%	0.3%	-2.9%	2.8%	3.8%	-9.2%		-3.8%	
d=10,a=1	4.0%	6.4%	-1.0%	-6.1%	-0.7%	-3.0%	7.4%	7.6%	-0.9%	-1.0%	0.6%	-3.4%	2.0%	3.4%	-10.1%		-2.2%	
d=10,a=0.5	2.6%	3.9%	2.8%	-5.9%	-0.6%	-2.4%	7.3%	6.9%	-2.2%	-0.6%	0.0%	-2.9%	3.2%	4.0%	-9.5%		-4.9%	
d=10,a=0.25	2.0%	3.1%	1.4%	-5.1%	-0.6%	-2.4%	7.2%	7.2%	-1.4%	-0.3%	-0.4%	-3.2%	2.9%	3.8%	-9.5%		-5.3%	
d=10,a=0.1	2.1%	3.6%	1.5%	-4.5%	-0.6%	-2.4%	7.0%	7.6%	-1.6%	-0.3%	-0.4%	-3.0%	2.5%	3.5%	-9.8%		-4.7%	
d=25,a=1	4.7%	5.8%	-1.0%	-8.5%	-1.1%	-3.1%	7.8%	8.1%	-0.4%	-0.9%	1.2%	-2.5%	2.8%	4.2%	-8.2%		-2.7%	
d=25,a=0.5	3.2%	2.1%	3.0%	-8.1%	0.0%	-2.1%	6.8%	8.0%	0.3%	-0.7%	0.1%	-1.6%	2.7%	3.1%	-7.1%		-3.6%	
d=25,a=0.25	3.4%	2.5%	3.0%	-8.4%	0.0%	-1.9%	6.5%	7.8%	0.6%	-0.9%	0.2%	-1.9%	2.8%	2.6%	-6.7%		-3.8%	
d=25,a=0.1	3.3%	2.7%	2.6%	-8.6%	0.1%	-1.9%	6.5%	7.8%	1.2%	-1.1%	0.2%	-2.1%	2.7%	2.5%	-6.0%		-4.2%	
d=50,a=1	3.7%	3.6%	-2.2%	-8.5%	-1.3%	-3.0%	7.4%	7.6%	-0.9%	-0.7%	0.4%	-2.5%	3.1%	3.6%	-9.4%		-2.5%	
d=50,a=0.5	2.0%	3.3%	1.4%	-7.8%	0.0%	-1.6%	6.9%	7.4%	3.2%	-0.6%	0.5%	-1.9%	0.4%	1.4%	-1.8%		-3.8%	
d=50,a=0.25	2.2%	2.8%	-0.4%	-9.1%	-0.3%	-2.0%	6.8%	7.5%	0.9%	-0.4%	0.4%	-2.4%	0.8%	0.7%	-1.6%		-3.5%	
d=50,a=0.1	1.2%	2.6%	-4.6%	-10.0%	-0.4%	-2.1%	6.9%	7.4%	0.3%	-0.4%	0.0%	-2.6%	1.9%	0.0%	-5.2%		-3.2%	
to1	3.7%	4.4%	-1.5%	-7.2%	2.3%	-2.7%	7.7%	8.3%	-2.8%	-0.4%	1.7%	-2.6%	2.5%	3.7%	-7.0%		-0.2%	
to2	2.2%	5.2%	1.9%	-6.3%	1.8%	-2.5%	6.5%	6.5%	-0.9%	-0.5%	1.2%	-2.1%	2.0%	3.2%	-8.2%		-1.8%	
to5	2.7%	4.1%	1.8%	-6.9%	-0.3%	-2.4%	6.9%	5.6%	-1.0%	-0.5%	0.8%	-2.9%	2.6%	3.4%	-9.1%		-3.5%	
to10	2.1%	3.7%	1.5%	-4.6%	-0.7%	-2.5%	6.9%	7.5%	-1.6%	-0.3%	-0.4%	-2.9%	2.7%	3.3%	-10.0%		-4.8%	
to25	3.2%	2.7%	1.8%	-8.3%	0.1%	-1.9%	6.6%	7.7%	1.9%	-1.1%	0.2%	-2.1%	2.7%	2.4%	-6.2%		-4.2%	
to50	1.1%	2.5%	-3.7%	-10.4%	-0.4%	-2.1%	6.9%	7.5%	1.3%	-0.4%	0.0%	-2.7%	2.0%	0.6%	-2.6%		-3.1%	
to2&to10	1.9%	4.1%	0.9%	-4.9%	1.7%	-2.1%	8.3%	7.9%	-1.0%	-0.6%	1.0%	-2.9%	2.0%	3.6%	-9.9%		-2.6%	
to2&to25	3.2%	3.0%	2.2%	-7.7%	0.3%	-2.2%	8.2%	8.3%	1.6%	-0.7%	1.6%	-2.0%	2.1%	2.8%	-5.6%		-2.1%	
to5&to10	2.3%	3.7%	1.5%	-5.2%	-0.4%	-2.3%	6.8%	7.0%	-1.3%	-0.2%	-0.1%	-2.7%	0.8%	3.7%	-9.0%		-5.1%	
to5&to25	3.4%	2.8%	4.1%	-6.5%	-0.2%	-2.1%	6.8%	7.5%	1.0%	-0.6%	0.1%	-2.4%	2.4%	3.1%	-8.2%		-4.5%	
to5&to50	2.4%	3.3%	-6.4%	-6.3%	-0.7%	-1.6%	7.0%	7.4%	-0.3%	-0.6%	0.6%	-2.8%	3.4%	2.0%	-5.3%		-3.5%	

Kriging – Median Percentage Error, All Distances

	Kriging - Spherical, Network Distances (all)						Kriging - Exponential, Network Distances (all)						Kriging - Gaussian, Network Distances (all)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	3.8%	5.8%	-0.6%	-9.8%	2.4%	-2.5%	5.1%	5.5%	0.8%	-0.2%	3.6%	-2.3%	3.1%	3.6%				
d=1,a=0.5	3.3%	6.2%	-0.3%	-9.3%	2.2%	-1.9%	4.3%	5.1%	-0.7%	-0.2%	3.8%	-2.1%	3.0%	2.7%				
d=1,a=0.25	2.8%	6.2%	-0.6%	-9.6%	2.4%	-1.9%	7.1%	6.1%	-0.2%	-0.1%	6.3%	-2.4%	3.2%	2.3%				
d=1,a=0.1	2.3%	5.9%	-1.2%	-9.6%	3.6%	-1.9%	6.9%	6.1%	-0.5%	-0.1%	7.3%	-2.2%	2.6%	1.3%				
d=2,a=1	4.0%	6.0%	0.1%	-9.0%	2.3%	-2.0%	4.7%	5.2%	-0.6%	-0.4%	3.2%	-2.0%	2.7%	3.3%				
d=2,a=0.5	4.0%	6.6%	0.7%	-7.7%	2.8%	-3.0%	6.8%	6.4%	0.1%	-0.4%	3.7%	-2.3%	1.5%	2.8%				
d=2,a=0.25	3.8%	5.6%	0.8%	-7.0%	3.2%	-3.4%	7.0%	6.0%	-0.7%	-0.3%	3.6%	-2.3%	0.9%	2.3%				
d=2,a=0.1	3.2%	4.8%	0.7%	-6.9%	2.9%	-2.8%	7.3%	6.1%	0.5%	-0.3%	2.9%	-2.2%	0.2%	0.5%				
d=5,a=1	4.3%	6.1%	-0.3%	-9.0%	2.6%	-2.9%	7.2%	4.6%	-0.4%	-1.1%	3.2%	-3.2%	2.0%	3.8%				
d=5,a=0.5	3.4%	4.8%	0.0%	-7.4%	0.5%	-2.1%	6.3%	6.2%	1.2%	-0.7%	2.8%	-2.5%	0.0%	0.8%				
d=5,a=0.25	2.6%	2.9%	0.2%	-7.8%	-2.2%	-1.4%	6.7%	5.3%	1.7%	-0.5%	1.0%	-2.8%	0.5%	0.0%				
d=5,a=0.1	2.2%	3.1%	0.5%	-8.0%	-2.5%	-1.8%	7.4%	4.9%	2.1%	-0.4%	0.8%	-2.9%	-0.1%	3.3%				
d=10,a=1	4.4%	5.5%	-1.0%	-7.2%	2.4%	-2.4%	7.0%	6.4%	0.3%	-1.2%	3.2%	-3.1%	-0.1%	3.4%				
d=10,a=0.5	2.2%	3.0%	0.1%	-6.4%	-1.3%	-1.1%	6.9%	5.0%	1.7%	-0.7%	1.2%	-2.0%	0.8%	3.6%				
d=10,a=0.25	2.1%	3.6%	-0.4%	-7.0%	-2.6%	-1.5%	6.7%	5.1%	2.4%	-0.5%	0.8%	-1.7%	-0.3%	2.7%				
d=10,a=0.1	3.1%	3.5%	-0.4%	-7.1%	-2.9%	-1.7%	6.9%	5.5%	2.0%	-0.4%	0.7%	-1.6%	-0.7%	2.5%				
d=25,a=1	4.0%	4.9%	-0.2%	-8.4%	1.1%	-2.4%	6.6%	6.4%	1.0%	-1.2%	2.6%	-1.9%	-0.2%	5.0%				
d=25,a=0.5	2.7%	3.1%	0.8%	-8.7%	-1.1%	-1.9%	6.0%	4.0%	3.9%	0.5%	1.4%	0.0%	0.1%	3.3%				
d=25,a=0.25	3.2%	2.8%	1.0%	-9.0%	-0.7%	-2.1%	5.4%	3.4%	3.3%	0.5%	1.5%	0.0%	0.5%	2.9%				
d=25,a=0.1	2.7%	2.7%	1.5%	-9.4%	-0.6%	-2.0%	5.3%	3.2%	2.2%	0.5%	1.4%	0.0%	0.4%	1.2%				
d=50,a=1	2.9%	4.4%	-2.5%	-7.9%	1.5%	-2.1%	7.1%	5.9%	-0.8%	-0.9%	1.4%	-2.3%	0.8%	1.3%				
d=50,a=0.5	0.5%	2.6%	-3.1%	-10.9%	-0.4%	-2.1%	6.6%	5.5%	2.3%	-0.1%	1.2%	-1.0%	0.0%	1.0%				
d=50,a=0.25	0.9%	1.9%	-6.1%	-10.8%	-0.3%	-2.7%	6.0%	5.4%	0.0%	0.0%	1.4%	-1.4%	-1.0%	0.5%				
d=50,a=0.1	0.8%	1.9%	-5.1%	-10.6%	-0.7%	-2.5%	6.1%	5.4%	1.5%	0.1%	1.4%	-1.4%	-0.5%	0.3%				
to1	2.3%	5.6%	-1.3%	-9.4%	4.1%	-1.8%	6.7%	6.1%	0.2%	-0.1%	6.2%	-2.3%	2.0%	1.4%				
to2	2.4%	4.0%	0.2%	-7.1%	2.3%	-2.8%	7.9%	6.7%	1.0%	-0.2%	2.4%	-2.5%	-0.9%	0.7%				
to5	2.3%	3.1%	0.6%	-8.0%	-2.7%	-2.0%	7.0%	4.7%	2.1%	-0.4%	0.6%	-3.1%	0.0%	2.7%				
to10	3.0%	3.3%	-0.4%	-7.2%	-3.0%	-1.7%	7.0%	5.4%	1.9%	-0.4%	0.8%	-1.8%	-0.5%	2.7%				
to25	2.5%	2.4%	2.1%	-9.3%	-0.8%	-2.0%	5.2%	3.2%	2.6%	0.4%	1.4%	-40.4%	0.4%	1.5%				
to50	0.9%	2.0%	-3.9%	-10.8%	-1.0%	-2.5%	6.1%	5.5%	1.1%	0.1%	1.4%	-1.5%	-0.2%	0.1%				
to2&to10	2.7%	4.3%	0.5%	-6.4%	3.0%	-1.6%	7.0%	5.5%	1.2%	-0.4%	3.0%	-2.6%	-0.9%	0.0%				
to2&to25	2.6%	2.8%	2.6%	-8.7%	4.2%	-1.7%	6.2%	2.4%	1.8%	0.2%	3.2%	-2.3%	0.5%	0.8%				
to5&to10	2.8%	3.1%	-0.3%	-6.4%	-2.2%	-1.6%	5.9%	5.2%	2.3%	-0.4%	1.4%	-2.8%	0.4%	2.5%				
to5&to25	2.6%	3.3%	2.4%	-7.7%	-1.4%	-1.3%	5.6%	3.1%	3.6%	-0.5%	1.3%	-1.9%	0.3%	1.0%				
to5&to50	-0.1%	3.0%	-4.6%	-6.5%	-0.8%	-1.5%	6.1%	5.5%	1.9%	-0.2%	1.6%	-2.9%	1.6%	2.4%				

Kriging – Mean Squared Error, Limited Distances

	Kriging - Spherical, Euclidean Distances (under 25mi)						Kriging - Exponential, Euclidean Distances (under 25mi)						Kriging - Gaussian, Euclidean Distances (under 25mi)					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	2.03E+11	2.9E+11	4.03E+10	4.4E+10	4.08E+10	4.98E+11	1.53E+11	2.3E+11		4.09E+10	3.64E+10	5.15E+11	2.17E+11	3.1E+11		4.53E+10	4.26E+10	4.91E+11
d=1,a=0.5	2.47E+11	3.61E+11	3.99E+10	4.22E+10	4.12E+10	4.92E+11	1.79E+11	2.71E+11		3.85E+10	3.66E+10	5.08E+11	2.62E+11	3.87E+11		4.37E+10	4.27E+10	4.83E+11
d=1,a=0.25	3.3E+11	4.83E+11	3.98E+10	4.17E+10	4.19E+10	4.87E+11	2.27E+11	3.41E+11		3.76E+10	3.72E+10	5.05E+11	3.5E+11	5.23E+11		4.32E+10	4.34E+10	4.78E+11
d=1,a=0.1	4.43E+11	6.39E+11	4.02E+10	4.15E+10	4.35E+10	4.85E+11	2.89E+11	4.25E+11		3.71E+10	3.89E+10	5.05E+11	4.66E+11	6.9E+11		4.29E+10	4.51E+10	4.77E+11
d=2,a=1	2.18E+11	3.09E+11	4.03E+10	4.14E+10	4.07E+10	4.92E+11	1.62E+11	2.4E+11		3.91E+10	3.61E+10	5.08E+11	2.33E+11	3.3E+11		4.25E+10	4.25E+10	4.82E+11
d=2,a=0.5	3.22E+11	4.13E+11	4.12E+10	3.75E+10	4.18E+10	4.66E+11	2.29E+11	3.16E+11		3.74E+10	3.62E+10	4.9E+11	3.59E+11	4.8E+11		3.8E+10	4.36E+10	4.59E+11
d=2,a=0.25	3.74E+11	4.56E+11	4.22E+10	3.75E+10	4.23E+10	4.6E+11	2.79E+11	3.62E+11		3.87E+10	3.65E+10	4.88E+11	4.54E+11	5.69E+11	3.58E+10	3.77E+10	4.46E+10	4.52E+11
d=2,a=0.1	3.79E+11	4.36E+11	4.23E+10	3.75E+10	4.22E+10	4.6E+11	2.88E+11	3.61E+11		3.92E+10	3.67E+10	4.88E+11	4.73E+11	5.65E+11	3.31E+12	3.76E+10	4.51E+10	4.5E+11
d=5,a=1	2.38E+11	3.17E+11	3.99E+10	3.58E+10	4.07E+10	4.81E+11	1.76E+11	2.54E+11		3.41E+10	3.61E+10	4.99E+11	2.6E+11	3.52E+11		3.69E+10	4.31E+10	4.73E+11
d=5,a=0.5	2.45E+11	2.9E+11	4.02E+10	3.11E+10	3.98E+10	4.66E+11	2.18E+11	2.73E+11		3.19E+10	3.55E+10	4.93E+11	3.18E+11	3.47E+11	3.49E+10	3.05E+10	4.49E+10	4.51E+11
d=5,a=0.25	2.16E+11	2.55E+11	4.03E+10	3.15E+10	3.97E+10	4.72E+11	1.99E+11	2.47E+11		3.23E+10	3.61E+10	5E+11	2.82E+11	2.99E+11	3.56E+10	3.1E+10	4.53E+10	4.57E+11
d=5,a=0.1	2E+11	2.41E+11	4.03E+10	3.19E+10	3.97E+10	4.76E+11	1.87E+11	2.35E+11		3.26E+10	3.65E+10	5.03E+11	2.61E+11	2.8E+11	3.64E+10	3.14E+10	4.55E+10	4.61E+11
d=10,a=1	2.36E+11	3.05E+11	4E+10	3.18E+10	4.04E+10	4.85E+11	1.88E+11	2.66E+11		3.03E+10	3.61E+10	5.01E+11	2.88E+11	3.64E+11	3.59E+10	3.32E+10	4.34E+10	4.76E+11
d=10,a=0.5	1.99E+11	2.48E+11	4.02E+10	3.03E+10	3.89E+10	4.98E+11	1.86E+11	2.4E+11	3.72E+10	2.99E+10	3.6E+10	5.16E+11	2.76E+11	2.86E+11	4.12E+10	3.06E+10	4.37E+10	4.84E+11
d=10,a=0.25	1.76E+11	2.25E+11	4.04E+10	3.15E+10	3.88E+10	5.06E+11	1.67E+11	2.21E+11	3.76E+10	3.1E+10	3.62E+10	5.23E+11	2.46E+11	2.6E+11	4.15E+10	3.18E+10	4.34E+10	4.95E+11
d=10,a=0.1	1.68E+11	2.18E+11	4.05E+10	3.22E+10	3.87E+10	5.1E+11	1.6E+11	2.15E+11	3.8E+10	3.16E+10	3.6E+10	5.26E+11	2.35E+11	2.5E+11	4.17E+10	3.24E+10	4.31E+10	5E+11
d=25,a=1	2.61E+11	3.29E+11	4.02E+10	3.08E+10	4.06E+10	4.82E+11	1.99E+11	2.77E+11		2.96E+10	3.66E+10	4.99E+11	2.93E+11	3.63E+11	1.25E+11	3.17E+10	4.34E+10	4.77E+11
d=25,a=0.5	1.84E+11	2.26E+11	4.05E+10	3.19E+10	3.97E+10	4.96E+11	1.51E+11	2.09E+11	4.57E+10	3.13E+10	3.63E+10	5.15E+11	2.17E+11	2.49E+11	3.93E+10	3.24E+10	4.24E+10	4.98E+11
d=25,a=0.25	1.72E+11	2.17E+11	4.08E+10	3.3E+10	3.96E+10	5.01E+11	1.39E+11	1.99E+11		3.23E+10	3.62E+10	5.2E+11	1.99E+11	2.35E+11	3.91E+10	3.36E+10	4.22E+10	5.06E+11
d=25,a=0.1	1.69E+11	2.17E+11	4.08E+10	3.34E+10	3.96E+10	5.02E+11	1.35E+11	1.96E+11		3.28E+10	3.63E+10	5.22E+11	1.92E+11	2.31E+11	4.74E+10	3.4E+10	4.21E+10	5.09E+11
d=50,a=1	2.72E+11	3.46E+11	4.03E+10	2.88E+10	4.08E+10	4.81E+11	2.03E+11	2.81E+11	3.59E+10	2.74E+10	3.66E+10	4.99E+11	2.88E+11	3.61E+11	4.1E+10	2.97E+10	4.29E+10	4.8E+11
d=50,a=0.5	1.86E+11	2.35E+11	3.99E+10	3.04E+10	4.02E+10	4.96E+11	1.44E+11	2.04E+11	3.9E+10	2.92E+10	3.64E+10	5.14E+11	2E+11	2.5E+11	4.15E+10	3.12E+10	4.24E+10	4.97E+11
d=50,a=0.25	1.77E+11	2.29E+11	4.09E+10	3.2E+10	4.03E+10	5E+11	1.36E+11	1.99E+11	3.79E+10	3.06E+10	3.66E+10	5.17E+11	1.89E+11	2.45E+11	3.94E+10	3.31E+10	4.26E+10	4.99E+11
d=50,a=0.1	1.75E+11	2.29E+11	4.1E+10	3.32E+10	4.04E+10	5.01E+11	1.35E+11	1.98E+11		3.16E+10	3.66E+10	5.18E+11	1.87E+11	2.46E+11	3.88E+10	3.43E+10	4.26E+10	4.99E+11
to1	5.69E+11	7.97E+11	4.06E+10	4.14E+10	4.57E+10	4.84E+11	3.57E+11	5.05E+11		3.69E+10	4.12E+10	5.07E+11	5.95E+11	8.56E+11		4.27E+10	4.74E+10	4.78E+11
to2	3.72E+11	4.23E+11	4.23E+10	3.78E+10	4.2E+10	4.6E+11	2.84E+11	3.52E+11		3.95E+10	3.66E+10	4.89E+11	4.69E+11	5.5E+11	1.28E+11	3.78E+10	4.52E+10	4.5E+11
to5	1.93E+11	2.33E+11	4.03E+10	3.21E+10	3.97E+10	4.78E+11	1.8E+11	2.29E+11		3.28E+10	3.66E+10	5.05E+11	2.51E+11	2.71E+11	3.66E+10	3.17E+10	4.54E+10	4.64E+11
to10	1.64E+11	2.15E+11	4.06E+10	3.25E+10	3.88E+10	5.12E+11	1.56E+11	2.12E+11	3.8E+10	3.2E+10	3.62E+10	5.27E+11	2.3E+11	2.46E+11	4.18E+10	3.28E+10	4.32E+10	5.02E+11
to25	1.67E+11	2.16E+11	4.09E+10	3.36E+10	3.96E+10	5.03E+11	1.33E+11	1.94E+11		3.31E+10	3.62E+10	5.23E+11	1.89E+11	2.3E+11	9.09E+10	3.43E+10	4.21E+10	5.1E+11
to50	1.75E+11	2.29E+11	4.1E+10	3.38E+10	4.04E+10	5.01E+11	1.35E+11	1.98E+11		3.21E+10	3.66E+10	5.18E+11	1.87E+11	2.47E+11	2.03E+11	3.5E+10	4.27E+10	4.99E+11
to2&to10	2.05E+11	2.69E+11	4.16E+10	3.23E+10	4E+10	4.72E+11	1.94E+11	2.67E+11	4.01E+10	3.22E+10	3.55E+10	4.91E+11	2.97E+11	3.38E+11	4.36E+10	3.23E+10	4.25E+10	4.51E+11
to2&to25	2.16E+11	2.84E+11	4.22E+10	3.32E+10	3.99E+10	4.58E+11	1.74E+11	2.52E+11	4.57E+11	3.38E+10	3.52E+10	4.84E+11	2.5E+11	3.15E+11	3.94E+10	3.31E+10	4.19E+10	4.5E+11
to5&to10	1.63E+11	2.14E+11	4.06E+10	3.15E+10	3.89E+10	4.92E+11	1.53E+11	2.12E+11	3.88E+10	3.14E+10	3.57E+10	5.14E+11	2.26E+11	2.49E+11	4.23E+10	3.15E+10	4.35E+10	4.71E+11
to5&to25	1.71E+11	2.21E+11	4.06E+10	3.12E+10	3.83E+10	4.85E+11	1.38E+11	1.99E+11		3.12E+10	3.59E+10	5.08E+11	1.89E+11	2.31E+11	3.78E+10	3.11E+10	4.36E+10	4.75E+11
to5&to50	2.21E+11	2.4E+11	4.13E+10	2.74E+10	3.96E+10	4.78E+11	1.76E+11	2.22E+11	4.04E+10	2.72E+10	3.58E+10	5.03E+11	2.46E+11	2.67E+11	4.38E+10	2.74E+10	4.44E+10	4.73E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging – Mean Squared Error, Limited Distances

	Kriging - Spherical, Network Distances (under 25mi)						Kriging - Exponential, Network Distances (under 25mi)						Kriging - Gaussian, Network Distances (under 25mi)					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	2.08E+11	3.11E+11	3.99E+10	4.09E+10	3.68E+10	4.65E+11	1.54E+11	2.33E+11	3.86E+10	3.74E+10	3.26E+10	4.77E+11	1.99E+11	3.08E+11	3.95E+10	4.25E+10	3.81E+10	4.92E+11
d=1,a=0.5	2.59E+11	3.97E+11	3.85E+10	4.01E+10	3.68E+10	4.6E+11	1.87E+11	2.84E+11	3.72E+10	3.59E+10	3.28E+10	4.7E+11	2.5E+11	3.92E+11	3.89E+10	4.2E+10	3.8E+10	4.84E+11
d=1,a=0.25	3.63E+11	5.54E+11	3.84E+10	4E+10	3.68E+10	4.55E+11	2.53E+11	3.72E+11	3.72E+10	3.53E+10	3.34E+10	4.64E+11	3.5E+11	5.43E+11	3.88E+10	4.22E+10	3.84E+10	4.78E+11
d=1,a=0.1	5.02E+11	7.39E+11	3.91E+10	4E+10	3.83E+10	4.54E+11	3.39E+11	4.77E+11	3.85E+10	3.5E+10	3.52E+10	4.62E+11	4.8E+11	7.2E+11	4.01E+10	4.22E+10	4E+10	4.75E+11
d=2,a=1	2.27E+11	3.37E+11	3.89E+10	3.89E+10	3.66E+10	4.6E+11	1.65E+11	2.46E+11	3.79E+10	3.58E+10	3.23E+10	4.71E+11	2.18E+11	3.33E+11	3.95E+10	4.03E+10	3.79E+10	4.82E+11
d=2,a=0.5	4.09E+11	5.44E+11	3.98E+10	3.61E+10	3.74E+10	4.37E+11	2.57E+11	3.45E+11	3.93E+10	3.33E+10	3.26E+10	4.48E+11	3.83E+11	5.31E+11	4.07E+10	3.73E+10	3.82E+10	4.53E+11
d=2,a=0.25	5.61E+11	6.8E+11	4.58E+10	3.57E+10	3.83E+10	4.31E+11	3.28E+11	4.07E+11	4.29E+10	3.34E+10	3.31E+10	4.42E+11	5.24E+11	6.71E+11	4.5E+10	3.65E+10	3.86E+10	4.45E+11
d=2,a=0.1	5.87E+11	6.76E+11	4.4E+10	3.55E+10	3.87E+10	4.29E+11	3.38E+11	4.03E+11	4.21E+10	3.34E+10	3.35E+10	4.41E+11	5.53E+11	6.83E+11	4.48E+10	3.62E+10	3.89E+10	4.44E+11
d=5,a=1	2.74E+11	3.82E+11	3.88E+10	3.48E+10	3.74E+10	4.53E+11	1.84E+11	2.65E+11	3.74E+10	3.22E+10	3.28E+10	4.63E+11	2.6E+11	3.79E+11	3.91E+10	3.62E+10	3.87E+10	4.71E+11
d=5,a=0.5	3.84E+11	3.79E+11	3.91E+10	3.12E+10	3.74E+10	4.34E+11	2.43E+11	2.85E+11	3.85E+10	2.94E+10	3.59E+10	4.68E+11	4.04E+11	4.18E+11	4.1E+10	3.09E+10	4.22E+10	4.56E+11
d=5,a=0.25	3.25E+11	3.09E+11	4.04E+10	3.13E+10	3.74E+10	4.39E+11	2.16E+11	2.5E+11	3.89E+10	2.92E+10	3.72E+10	4.85E+11	3.56E+11	3.46E+11	4.17E+10	3.09E+10	4.3E+10	4.65E+11
d=5,a=0.1	2.94E+11	2.83E+11	4.05E+10	3.16E+10	3.74E+10	4.43E+11	1.99E+11	2.35E+11	3.9E+10	2.93E+10	3.77E+10	4.88E+11	3.26E+11	3.17E+11	4.17E+10	3.12E+10	4.33E+10	4.69E+11
d=10,a=1	3.3E+11	4.15E+11	3.94E+10	3.15E+10	3.75E+10	4.55E+11	2.04E+11	2.81E+11	3.85E+10	2.89E+10	3.34E+10	4.66E+11	3.2E+11	4.21E+11	3.94E+10	3.27E+10	3.94E+10	4.76E+11
d=10,a=0.5	3.05E+11	2.89E+11	4E+10	2.91E+10	3.63E+10	4.62E+11	2E+11	2.4E+11	3.96E+10	2.68E+10	3.7E+10	4.93E+11	3.51E+11	3.39E+11	3.97E+10	2.91E+10	4.07E+10	4.93E+11
d=10,a=0.25	2.66E+11	2.59E+11	4E+10	2.98E+10	3.6E+10	4.71E+11	1.75E+11	2.18E+11	3.95E+10	2.73E+10	3.66E+10	4.92E+11	3.11E+11	3E+11	3.97E+10	2.99E+10	4.02E+10	5.03E+11
d=10,a=0.1	2.52E+11	2.46E+11	3.98E+10	3.01E+10	3.57E+10	4.75E+11	1.66E+11	2.1E+11	3.96E+10	2.76E+10	3.61E+10	4.93E+11	2.96E+11	2.87E+11	3.95E+10	3.03E+10	3.98E+10	5.07E+11
d=25,a=1	3.27E+11	3.9E+11	3.95E+10	2.89E+10	3.81E+10	4.55E+11	2.15E+11	2.88E+11	3.83E+10	2.66E+10	3.43E+10	4.64E+11	3.17E+11	3.94E+11	3.94E+10	2.96E+10	3.93E+10	4.74E+11
d=25,a=0.5	2.23E+11	2.43E+11	3.87E+10	2.8E+10	3.73E+10	4.7E+11	1.54E+11	2.03E+11	3.77E+10	2.57E+10	3.44E+10	4.76E+11	2.29E+11	2.55E+11	3.85E+10	2.82E+10	3.83E+10	4.94E+11
d=25,a=0.25	2E+11	2.26E+11	3.89E+10	2.86E+10	3.71E+10	4.75E+11	1.4E+11	1.91E+11	3.73E+10	2.62E+10	3.4E+10	4.8E+11	2.04E+11	2.37E+11	3.91E+10	2.88E+10	3.8E+10	4.99E+11
d=25,a=0.1	1.92E+11	2.21E+11	3.86E+10	2.88E+10	3.71E+10	4.77E+11	1.35E+11	1.88E+11	3.67E+10	2.64E+10	3.39E+10	4.81E+11	1.95E+11	2.31E+11	3.94E+10	2.9E+10	3.79E+10	5.01E+11
d=50,a=1	3.09E+11	3.72E+11	4E+10	2.68E+10	3.79E+10	4.57E+11	2.14E+11	2.85E+11	3.96E+10	2.47E+10	3.39E+10	4.64E+11	2.97E+11	3.75E+11	3.95E+10	2.74E+10	3.85E+10	4.75E+11
d=50,a=0.5	1.95E+11	2.39E+11	4.03E+10	2.66E+10	3.7E+10	4.7E+11	1.42E+11	1.98E+11	4E+10	2.41E+10	3.34E+10	4.76E+11	1.92E+11	2.47E+11	3.96E+10	2.66E+10	3.8E+10	4.94E+11
d=50,a=0.25	1.82E+11	2.34E+11	4.3E+10	2.8E+10	3.71E+10	4.71E+11	1.34E+11	1.92E+11	4.32E+10	2.52E+10	3.34E+10	4.79E+11	1.78E+11	2.41E+11	4.22E+10	2.81E+10	3.81E+10	4.97E+11
d=50,a=0.1	1.8E+11	2.35E+11	4.31E+10	2.89E+10	3.71E+10	4.71E+11	1.32E+11	1.92E+11	4.22E+10	2.61E+10	3.33E+10	4.8E+11	1.75E+11	2.42E+11	4.21E+10	2.92E+10	3.82E+10	4.99E+11
to1	6.57E+11	9.24E+11	4.14E+10	4.01E+10	4.07E+10	4.54E+11	4.36E+11	5.82E+11	3.96E+10	3.49E+10	3.77E+10	4.61E+11	6.24E+11	8.94E+11	4.09E+10	4.22E+10	4.26E+10	4.75E+11
to2	5.75E+11	6.45E+11	4.44E+10	3.56E+10	3.86E+10	4.29E+11	3.3E+11	3.89E+11	4.24E+10	3.35E+10	3.35E+10	4.42E+11	5.47E+11	6.63E+11	4.51E+10	3.61E+10	3.9E+10	4.44E+11
to5	2.78E+11	2.72E+11	4.04E+10	3.18E+10	3.74E+10	4.45E+11	1.9E+11	2.27E+11	3.9E+10	2.94E+10	3.77E+10	4.9E+11	3.09E+11	3.04E+11	4.17E+10	3.14E+10	4.32E+10	4.72E+11
to10	2.46E+11	2.41E+11	3.98E+10	3.04E+10	3.58E+10	4.77E+11	1.62E+11	2.06E+11	3.95E+10	2.78E+10	3.61E+10	4.93E+11	2.89E+11	2.82E+11	3.94E+10	3.06E+10	3.98E+10	5.09E+11
to25	1.89E+11	2.19E+11	3.87E+10	2.9E+10	3.7E+10	4.78E+11	1.33E+11	1.87E+11	3.68E+10	2.65E+10	3.38E+10	4.81E+11	1.91E+11	2.29E+11	3.94E+10	2.92E+10	3.79E+10	5.01E+11
to50	1.79E+11	2.36E+11	4.2E+10	2.95E+10	3.71E+10	4.71E+11	1.32E+11	1.92E+11	4.09E+10	2.66E+10	3.33E+10	4.8E+11	1.75E+11	2.42E+11	4.13E+10	2.98E+10	3.82E+10	4.99E+11
to2&to10	3.08E+11	3.23E+11	4.37E+10	3.04E+10	3.68E+10	4.39E+11	2.04E+11	2.63E+11	4.28E+10	2.81E+10	3.32E+10	5.13E+11	3.55E+11	3.83E+11	4.31E+10	3.04E+10	3.7E+10	4.57E+11
to2&to25	2.58E+11	3.07E+11	4.31E+10	2.95E+10	3.72E+10	4.33E+11	1.81E+11	2.48E+11	4.1E+10	2.78E+10	3.31E+10	4.45E+11	2.56E+11	3.18E+11	4.27E+10	2.91E+10	3.68E+10	4.47E+11
to5&to10	2.45E+11	2.46E+11	4.12E+10	3.02E+10	3.59E+10	4.6E+11	1.59E+11	2.07E+11	4.09E+10	2.79E+10	3.65E+10	5.14E+11	2.84E+11	2.81E+11	3.95E+10	3.01E+10	4.04E+10	4.85E+11
to5&to25	1.98E+11	2.25E+11	3.88E+10	2.87E+10	3.65E+10	4.58E+11	1.42E+11	1.93E+11	3.78E+10	2.67E+10	3.82E+10	4.74E+11	1.97E+11	2.34E+11	4.04E+10	2.86E+10	4.16E+10	4.81E+11
to5&to50	2.72E+11	2.67E+11	4.41E+10	2.62E+10	3.74E+10	4.52E+11	1.84E+11	2.2E+11	4.27E+10	2.41E+10	3.66E+10	4.68E+11	2.73E+11	2.84E+11	4.35E+10	2.59E+10	4.21E+10	4.76E+11

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging – Mean Squared Error, All Distances

	Kriging - Spherical, Euclidean Distances (under 25mi)						Kriging - Exponential, Euclidean Distances (under 25mi)						Kriging - Gaussian, Euclidean Distances (under 25mi)					
	Houston				Minor		Houston				Minor		Houston				Minor	
Accessibility	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban	No IS	Houston	Austin	Interstate	Roads	Urban
d=1,a=1	2.0424E+11	2.4822E+11	3.877E+10	4.2518E+10	4.2558E+10	4.9639E+11	7.4424E+10	1.6745E+11	3.998E+10	1.6341E+10	2.9364E+10	5.0212E+11	2.1847E+11	2.6478E+11	4.507E+10		3.6196E+10	
d=1,a=0.5	2.2942E+11	2.7998E+11	3.8519E+10	4.1095E+10	4.5192E+10	4.894E+11	7.6954E+10	1.7829E+11	3.8542E+10	1.6319E+10	2.9526E+10	4.94E+11	2.4473E+11	2.9629E+11	4.3259E+10		3.4261E+10	
d=1,a=0.25	2.7716E+11	3.4033E+11	3.8364E+10	3.9929E+10	4.6147E+10	4.8334E+11	7.8962E+10	1.9246E+11	3.8371E+10	1.6342E+10	3.0675E+10	4.8664E+11	2.8727E+11	3.4602E+11	4.2832E+10		3.514E+10	
d=1,a=0.1	3.3906E+11	4.0996E+11	3.8638E+10	3.9277E+10	4.7051E+10	4.8087E+11	8.1366E+10	2.0589E+11	3.9255E+10	1.6375E+10	3.1904E+10	4.8463E+11	3.4064E+11	4.0788E+11	4.3817E+10		3.3938E+10	
d=2,a=1	2.108E+11	2.5499E+11	3.8946E+10	4.1254E+10	4.1457E+10	4.894E+11	7.5736E+10	1.6962E+11	3.9004E+10	1.6359E+10	2.9064E+10	4.9335E+11	2.2476E+11	2.7072E+11	4.3476E+10		3.5859E+10	
d=2,a=0.5	2.6515E+11	3.1213E+11	3.9367E+10	3.9276E+10	4.6444E+10	4.6092E+11	8.4704E+10	1.869E+11	3.9331E+10	1.7124E+10	2.8834E+10	4.6114E+11	2.6208E+11	3.1407E+11	4.2457E+10		3.3894E+10	
d=2,a=0.25	3.0392E+11	3.5283E+11	4.0246E+10	3.8639E+10	4.7207E+10	4.5247E+11	9.4918E+10	1.9695E+11	4.0125E+10	1.7612E+10	2.8931E+10	4.5425E+11	2.8443E+11	3.3643E+11	4.1793E+10		3.4647E+10	
d=2,a=0.1	3.1328E+11	3.5839E+11	4.0402E+10	3.8413E+10	4.3342E+10	4.5108E+11	9.5993E+10	1.9576E+11	4.0599E+10	1.7717E+10	2.8909E+10	4.5527E+11	2.8192E+11	3.3361E+11	4.1598E+10		3.5999E+10	
d=5,a=1	2.198E+11	2.5903E+11	3.8041E+10	3.709E+10	4.4636E+10	4.7908E+11	7.4373E+10	1.7223E+11	3.8549E+10	1.6032E+10	2.9291E+10	4.8192E+11	2.2391E+11	2.7447E+11	4.269E+10		3.4859E+10	
d=5,a=0.5	2.4122E+11	2.8003E+11	3.7911E+10	3.0002E+10	4.1624E+10	4.5492E+11	9.306E+10	1.8846E+11	3.8547E+10	1.7231E+10	2.9361E+10	4.5936E+11	2.1499E+11	2.7067E+11	4.0463E+10		3.8249E+10	
d=5,a=0.25	2.2389E+11	2.5847E+11	3.8011E+10	2.9664E+10	3.9651E+10	4.6025E+11	9.1321E+10	1.8039E+11	3.8755E+10	1.7405E+10	2.9918E+10	4.6745E+11	2.0196E+11	2.5528E+11	4.0415E+10		4.0038E+10	
d=5,a=0.1	2.1413E+11	2.4853E+11	3.7951E+10	2.9688E+10	3.8455E+10	4.6409E+11	8.7305E+10	1.7532E+11	3.8735E+10	1.745E+10	3.0116E+10	4.7324E+11	1.9568E+11	2.4877E+11	4.0431E+10		4.0327E+10	
d=10,a=1	2.3033E+11	2.675E+11	3.788E+10	3.3074E+10	4.2877E+10	4.8314E+11	7.064E+10	1.7442E+11	3.7802E+10	1.5888E+10	2.9019E+10	4.8634E+11	2.2733E+11	2.7799E+11	4.1842E+10		3.5312E+10	
d=10,a=0.5	2.2902E+11	2.5817E+11	3.7731E+10	2.9865E+10	3.9129E+10	4.9003E+11	7.2801E+10	1.7775E+11	3.8267E+10	1.6668E+10	2.9468E+10	4.9606E+11	2.1312E+11	2.6197E+11	4.026E+10		3.9086E+10	
d=10,a=0.25	2.0886E+11	2.3962E+11	3.7844E+10	3.1417E+10	3.8263E+10	5.0001E+11	6.8356E+10	1.7212E+11	3.8523E+10	1.6863E+10	2.9862E+10	5.0586E+11	1.9735E+11	2.4868E+11	4.0453E+10		3.9555E+10	
d=10,a=0.1	2.0128E+11	2.348E+11	3.7834E+10	3.2238E+10	3.6955E+10	5.0451E+11	6.6881E+10	1.7072E+11	3.856E+10	1.6944E+10	3.0083E+10	5.0937E+11	1.9161E+11	2.4128E+11	4.0582E+10		3.995E+10	
d=25,a=1	2.4466E+11	2.7585E+11	3.7991E+10	3.443E+10	4.2118E+10	4.8271E+11	7.0082E+10	1.7331E+11	3.8179E+10	1.5736E+10	2.8573E+10	4.9292E+11	2.3481E+11	2.869E+11	4.265E+10		3.595E+10	
d=25,a=0.5	2.0088E+11	2.3308E+11	3.7192E+10	3.695E+10	3.9459E+10	4.956E+11	6.5163E+10	1.6753E+11	3.7565E+10	1.6467E+10	2.8828E+10	5.1263E+11	2.0514E+11	2.5376E+11	4.2516E+10		3.7687E+10	
d=25,a=0.25	1.8916E+11	2.2471E+11	3.7246E+10	3.9078E+10	3.9251E+10	5.0079E+11	6.389E+10	1.6596E+11	3.778E+10	1.6589E+10	2.8978E+10	5.1732E+11	1.9536E+11	2.4689E+11	4.3965E+10		3.7891E+10	
d=25,a=0.1	1.8535E+11	2.2314E+11	3.7398E+10	4.0053E+10	3.928E+10	5.024E+11	6.3539E+10	1.6546E+11	3.7808E+10	1.661E+10	2.9009E+10	5.1822E+11	1.937E+11	2.4513E+11	4.4672E+10		3.7909E+10	
d=50,a=1	2.5657E+11	2.8756E+11	3.9144E+10	3.2718E+10	4.2381E+10	4.8249E+11	6.8796E+10	1.7048E+11	3.8505E+10	1.5811E+10	2.846E+10	4.9343E+11	2.4151E+11	2.9534E+11	4.2075E+10		3.5428E+10	
d=50,a=0.5	2.0053E+11	2.3727E+11	3.9246E+10	3.5446E+10	4.0544E+10	4.9543E+11	6.3406E+10	1.6323E+11	3.9411E+10	1.6372E+10	2.8798E+10	5.0782E+11	1.9502E+11	2.4591E+11	4.0917E+10		3.7353E+10	
d=50,a=0.25	1.913E+11	2.3229E+11	4.1165E+10	3.7242E+10	4.0725E+10	4.9866E+11	6.3004E+10	1.6262E+11	4.1741E+10	1.6506E+10	2.9032E+10	5.0891E+11	1.8589E+11	2.3737E+11	4.287E+10		3.7565E+10	
d=50,a=0.1	1.8722E+11	2.3123E+11	4.0378E+10	3.8014E+10	4.067E+10	4.9937E+11	6.2985E+10	1.6253E+11	4.0824E+10	1.6542E+10	2.9166E+10	5.0828E+11	1.8095E+11	2.352E+11	4.1816E+10		3.7836E+10	
to1	4.0715E+11	4.7787E+11	3.8764E+10	3.8915E+10	4.8556E+10	4.805E+11	8.6358E+10	2.1731E+11	3.9709E+10	1.6396E+10	3.3011E+10	4.8453E+11	3.9742E+11	4.7026E+11	4.3602E+10		3.6926E+10	
to2	3.1027E+11	3.5494E+11	4.0429E+10	3.833E+10	4.418E+10	4.509E+11	9.3758E+10	1.9209E+11	4.0738E+10	1.773E+10	2.8941E+10	4.5556E+11	2.7552E+11	3.2686E+11	4.155E+10		3.6966E+10	
to5	2.0863E+11	2.4363E+11	3.7896E+10	2.972E+10	3.8158E+10	4.665E+11	8.4858E+10	1.7278E+11	3.8697E+10	1.7481E+10	3.0249E+10	4.7553E+11	1.9173E+11	2.4588E+11	4.0438E+10		4.0556E+10	
to10	1.9779E+11	2.3225E+11	3.7816E+10	3.274E+10	3.7885E+10	5.0703E+11	6.6212E+10	1.7003E+11	3.8566E+10	1.6992E+10	3.0055E+10	5.1112E+11	1.8918E+11	2.383E+11	4.0664E+10		3.9805E+10	
to25	1.8383E+11	2.2259E+11	3.7573E+10	4.059E+10	3.9268E+10	5.0306E+11	6.3391E+10	1.6523E+11	3.7823E+10	1.6614E+10	2.9029E+10	5.1859E+11	1.9339E+11	2.4426E+11	4.4997E+10		3.7964E+10	
to50	1.8552E+11	2.3092E+11	4.1149E+10	3.8435E+10	4.0579E+10	4.9959E+11	6.2954E+10	1.6246E+11	4.006E+10	1.6555E+10	2.9251E+10	5.0792E+11	1.7917E+11	2.339E+11	4.0767E+10		3.7998E+10	
to2&to10	2.5503E+11	3.0852E+11	4.0158E+10	3.1403E+10	4.3036E+10	4.6162E+11	8.6561E+10	1.9248E+11	4.0196E+10	1.7288E+10	2.8641E+10	4.54E+11	2.3091E+11	2.9146E+11	4.0425E+10		3.6359E+10	
to2&to25	2.4348E+11	2.9463E+11	3.9657E+10	3.5842E+10	4.4452E+10	4.5436E+11	8.4943E+10	1.8945E+11	3.9927E+10	1.7777E+10	2.7959E+10	4.592E+11	2.4662E+11	3.0722E+11	4.3328E+10		3.4561E+10	
to5&to10	1.9929E+11	2.3376E+11	3.7771E+10	3.0163E+10	3.8922E+10	4.8187E+11	7.6574E+10	1.7453E+11	3.8481E+10	1.7338E+10	2.9695E+10	4.7597E+11	1.9446E+11	2.4126E+11	4.0278E+10		3.9445E+10	
to5&to25	1.8925E+11	2.295E+11	3.7152E+10	3.167E+10	3.8745E+10	4.8023E+11	7.7098E+10	1.7412E+11	3.8093E+10	1.7513E+10	2.9033E+10	4.8571E+11	1.9822E+11	2.4813E+11	4.2055E+10		3.8705E+10	
to5&to50	1.9718E+11	2.4415E+11	3.9873E+10	2.689E+10	4.0732E+10	4.7312E+11	8.1017E+10	1.7718E+11	3.9919E+10	1.7501E+10	2.913E+10	4.7464E+11	1.8434E+11	2.4041E+11	4.127E+10		3.801E+10	

*Best values in each column are highlighted, in order, in green, yellow and red.

Kriging – Mean Squared Error, All Distances

	Kriging - Spherical, Network Distances (under 25mi)						Kriging - Exponential, Network Distances (under 25mi)						Kriging - Gaussian, Network Distances (under 25mi)					
Accessibility	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban	Houston No IS	Houston	Austin	Interstate	Minor Roads	Urban
d=1,a=1	1.5441E+11	2.1152E+11	3.6114E+10	4.3534E+10	3.6916E+10	4.6964E+11	7.9616E+10	1.6739E+11	3.5445E+10	1.5561E+10	2.6873E+10	4.6266E+11	1.7714E+11	2.8027E+11	3.838E+10			
d=1,a=0.5	1.7232E+11	2.352E+11	3.5751E+10	4.2209E+10	3.8794E+10	4.6371E+11	8.1382E+10	1.797E+11	3.5109E+10	1.5635E+10	2.6731E+10	4.58E+11	1.9946E+11	3.0371E+11	3.9553E+10			
d=1,a=0.25	2.0975E+11	2.8547E+11	3.5512E+10	4.1157E+10	4.0567E+10	4.5837E+11	7.5182E+10	1.8692E+11	3.5025E+10	1.567E+10	2.6943E+10	4.5472E+11	2.421E+11	3.3631E+11	4.0904E+10			
d=1,a=0.1	2.617E+11	3.4558E+11	3.5847E+10	4.0573E+10	4.5666E+10	4.5618E+11	8.0522E+10	2.0675E+11	3.5377E+10	1.5677E+10	2.7428E+10	4.5427E+11	3.0028E+11	3.9028E+11	3.7672E+10			
d=2,a=1	1.5823E+11	2.1518E+11	3.6176E+10	4.2296E+10	3.7323E+10	4.6371E+11	8.0983E+10	1.698E+11	3.5547E+10	1.5728E+10	2.6654E+10	4.5835E+11	1.8034E+11	2.8346E+11	3.9139E+10			
d=2,a=0.5	1.9171E+11	2.4877E+11	3.6265E+10	4.0892E+10	3.9676E+10	4.3684E+11	7.9979E+10	1.8967E+11	3.6195E+10	1.6648E+10	2.6253E+10	4.3953E+11	2.0619E+11	3.011E+11	5.546E+11			
d=2,a=0.25	2.1117E+11	2.707E+11	3.7036E+10	4.0346E+10	4.0309E+10	4.2821E+11	9.5E+10	2.0748E+11	3.7118E+10	1.6965E+10	2.6393E+10	4.3482E+11	2.1726E+11	3.0697E+11	1.4298E+11			
d=2,a=0.1	2.143E+11	2.7098E+11	3.7332E+10	4.0076E+10	3.9241E+10	4.2676E+11	1.0102E+11	2.128E+11	3.6906E+10	1.6962E+10	2.6503E+10	4.3631E+11	2.1678E+11	3.0492E+11	1.7707E+11			
d=5,a=1	1.6155E+11	2.1372E+11	3.556E+10	3.8398E+10	3.8262E+10	4.5398E+11	6.9983E+10	1.6935E+11	3.5074E+10	1.625E+10	2.6703E+10	4.5584E+11	1.7636E+11	2.8933E+11	4.0423E+10			
d=5,a=0.5	1.6389E+11	2.1419E+11	3.7691E+10	3.2038E+10	3.3198E+10	4.2903E+11	9.1817E+10	1.9892E+11	3.5435E+10	1.8229E+10	2.7271E+10	4.4539E+11	1.7069E+11	2.7023E+11	1.6098E+12			
d=5,a=0.25	1.484E+11	1.9679E+11	3.8581E+10	3.1698E+10	3.0164E+10	4.3432E+11	9.0932E+10	1.9204E+11	3.5359E+10	1.8029E+10	2.7861E+10	4.5194E+11	1.5947E+11					
d=5,a=0.1	1.4147E+11	1.9058E+11	3.8516E+10	3.1701E+10	2.9724E+10	4.3814E+11	8.6715E+10	1.8658E+11	3.5306E+10	1.7892E+10	2.8013E+10	4.5577E+11	1.55E+11	2.6024E+11	1.2353E+13			
d=10,a=1	1.673E+11	2.2058E+11	3.5748E+10	3.4371E+10	3.7545E+10	4.5658E+11	7.1778E+10	1.8522E+11	3.5266E+10	1.6393E+10	2.6632E+10	4.5968E+11	1.804E+11	2.8788E+11	3.4543E+10			
d=10,a=0.5	1.5839E+11	2.0155E+11	3.6591E+10	3.1673E+10	3.0066E+10	4.6184E+11	8.0686E+10	1.9477E+11	3.5237E+10	1.7174E+10	2.7608E+10	4.6612E+11	1.7532E+11	2.728E+11	1.1579E+13			
d=10,a=0.25	1.4272E+11	1.8783E+11	3.7123E+10	3.3095E+10	2.9012E+10	4.7168E+11	7.4414E+10	1.8717E+11	3.5164E+10	1.6918E+10	2.7855E+10	4.6766E+11	1.6321E+11	2.8131E+11				
d=10,a=0.1	1.3758E+11	1.8586E+11	3.7078E+10	3.3842E+10	2.8723E+10	4.7616E+11	7.2067E+10	1.8716E+11	3.5116E+10	1.6815E+10	2.7993E+10	4.6761E+11	1.5929E+11	2.5711E+11				
d=25,a=1	1.8769E+11	2.3428E+11	3.5792E+10	3.5266E+10	3.5371E+10	4.5521E+11	7.4913E+10	1.8155E+11	3.515E+10	1.6181E+10	2.6888E+10	4.5905E+11	1.9861E+11	2.8314E+11	3.7424E+10			
d=25,a=0.5	1.5544E+11	1.954E+11	3.6296E+10	3.7874E+10	3.132E+10	4.6837E+11	7.1527E+10	1.6954E+11	3.4854E+10	1.5888E+10	2.798E+10		1.6822E+11	2.4232E+11	1.7292E+13			
d=25,a=0.25	1.4875E+11	1.8984E+11	3.6381E+10	3.9716E+10	3.1432E+10	4.7328E+11	6.8936E+10	1.6479E+11	3.4747E+10	1.5624E+10	2.8029E+10		1.6228E+11	2.4346E+11	1.3133E+11			
d=25,a=0.1	1.4677E+11	1.8947E+11	3.5786E+10	4.0551E+10	3.1442E+10	4.7477E+11	6.819E+10	1.6394E+11	3.4868E+10	1.5544E+10	2.8029E+10		1.6027E+11	2.4494E+11				
d=50,a=1	2.05E+11	2.478E+11	3.7125E+10	3.3407E+10	3.575E+10	4.5586E+11	7.4975E+10	1.8403E+11	3.5814E+10	1.6061E+10	2.7011E+10	4.5899E+11	2.1256E+11	2.7891E+11	4.105E+10			
d=50,a=0.5	1.6129E+11	2.0355E+11	3.7646E+10	3.5991E+10	3.2792E+10	4.6914E+11	6.7583E+10	1.7964E+11	3.6755E+10	1.5621E+10	2.7689E+10	3.3265E+12	1.7481E+11	2.3966E+11	4.0066E+10			
d=50,a=0.25	1.5665E+11	2.0121E+11	3.8469E+10	3.7585E+10	3.2827E+10	4.7191E+11	6.5565E+10	1.7815E+11	3.7971E+10	1.5561E+10	2.7617E+10	4.7502E+11	1.702E+11	2.362E+11	3.9819E+10			
d=50,a=0.1	1.569E+11	2.0142E+11	3.8216E+10	3.8302E+10	3.2585E+10	4.7248E+11	6.4965E+10	1.7748E+11	3.782E+10	1.5559E+10	2.7598E+10	4.6758E+11	1.7005E+11	2.3614E+11	3.999E+10			
to1	3.2494E+11	4.0627E+11	3.598E+10	4.0245E+10	4.7715E+10	4.5589E+11	8.6913E+10	2.1922E+11	3.5606E+10	1.5673E+10	2.8049E+10	4.5486E+11	3.7062E+11	4.5236E+11	5.1903E+10			
to2	2.1162E+11	2.6706E+11	3.748E+10	3.9961E+10	3.8004E+10	4.2657E+11	1.0122E+11	2.1228E+11	3.681E+10	1.6922E+10	2.6568E+10	4.368E+11	2.1322E+11	3.0132E+11				
to5	1.3849E+11	1.878E+11	3.8445E+10	3.1718E+10	2.9388E+10	4.4053E+11	8.4274E+10	1.8365E+11	3.5265E+10	1.7825E+10	2.8111E+10	4.5746E+11	1.5325E+11	2.6004E+11	3.9025E+12			
to10	1.352E+11	1.8471E+11	3.7132E+10	3.4301E+10	2.868E+10	4.7869E+11	7.0972E+10	1.8681E+11	3.5085E+10	1.6764E+10	2.795E+10	4.6747E+11	1.5736E+11	2.5206E+11	3.7452E+12			
to25	1.4616E+11	1.8947E+11	3.539E+10	4.101E+10	3.1393E+10	4.7538E+11	6.7877E+10	1.635E+11	3.5009E+10	1.551E+10	2.8033E+10		1.5961E+11	2.4432E+11				
to50	1.5696E+11	2.0225E+11	3.7657E+10	3.8707E+10	3.2396E+10	4.7263E+11	6.4705E+10	1.7705E+11	3.7259E+10	1.556E+10	2.7593E+10	4.6615E+11	1.6999E+11	2.36E+11	4.068E+10			
to2&to10	1.6166E+11	2.1827E+11	3.7867E+10	3.3188E+10	3.7007E+10	4.3702E+11	1.0136E+11	2.2449E+11	3.6382E+10	1.7099E+10	2.6724E+10	4.3509E+11	1.8137E+11					
to2&to25	1.7692E+11	2.2571E+11	3.6371E+10	3.6942E+10	3.7986E+10	4.2899E+11	9.7281E+10	1.9537E+11	3.6082E+10	1.6717E+10	2.7259E+10	4.3975E+11	1.918E+11	2.7425E+11	1.6573E+11			
to5&to10	1.3258E+11	1.8472E+11	3.6393E+10	3.2036E+10	2.9401E+10	4.588E+11	7.8049E+10	1.9309E+11	3.5187E+10	1.7783E+10	2.7677E+10	4.5732E+11	1.5236E+11	2.499E+11	3.8311E+11			
to5&to25	1.4722E+11	1.918E+11	3.8583E+10	3.3168E+10	3.0404E+10	4.5558E+11	7.9403E+10	1.6981E+11	3.4895E+10	1.7539E+10	2.8076E+10	4.6081E+11	1.6013E+11	2.4199E+11	3.7237E+13			
to5&to50	1.5999E+11	2.0364E+11	3.9178E+10	2.839E+10	3.2483E+10	4.4843E+11	8.5312E+10	1.9662E+11	3.9003E+10	1.7814E+10	2.7667E+10	4.5721E+11	1.7301E+11	2.3576E+11	3.8992E+10			

*Best values in each column are highlighted, in order, in green, yellow and red.

APPENDIX 3: MATLAB Code for Part 2's Vehicle Market Model

carMarket.m – Main program, runs the car market model.

```
% clear variables
clear AUC AUCsummary HHfn HHinfo buyerList hhVehList hhVehs
clear masterHHmat masterHHveh masterMkt masterVeh numVeh numVehSell
numbuyers numhh
clear oldest pick prevOwner round scrap scrapped sellerList sumbuyers
clear sumrounds sumunsold sumveh vehList vehPlist vehTypeInfo vehstats
yrIndex
filenum;
t =clock;
disp([num2str(t(4:6)) ' start']);
% HHfn='HHdata.csv';
HHfn='austin-data2.csv';
Vehfn='fake-prices.csv';
auctions=50;
scrap=500;
pVariance=.15;
fuelCoeff=1;
numVeh=0;
scrapped = 0;
crashCoeff = 5;
crashed = 0;
coeffs=[-8.514; -5.57; 0.3627; 0.8756; 0.2895; -0.4148; -1.121; 0.2632;
0.1864; -.3333; -5.57; 5.23; -.2785];
beta=[-3 -4 .4077 .251 -0.3303 0.01 -2.25*10^(-6) 1.5];

HHinfo = csvread(HHfn); %nx23 (including 5 cars)
%Hhsize,Age,Inc,Female,Urban,Suburban,#Workers,mileage,vehID1,age1,mile
age1,vehID2…
vehTypeInfo = csvread(Vehfn); %list of prices, could just hardcode
numhh=size(HHinfo,1);

masterHHveh{numhh}=[]; %set len to number HH
masterHHmat=zeros(numhh,12); % numHHx11
masterVeh{numhh}=[]; %set len to number HH
masterMkt{auctions}=[]; %set len to number of years
crashAges = zeros(1000,1);
crashID = zeros(1000,1);

for i=1:numhh %loads HH structs, creates vehicles, puts info in --
replaced large old nested ifs
    masterHHmat(i,:) = HHInit(HHinfo(i,:)); %set up struct, no veh
    for j=1:masterHHmat(i,9) %number of veh
        numVeh=numVeh+1;
        masterVeh{numVeh} = vehStruct(numVeh, HHinfo(i,6+3*j),
vehTypeInfo(HHinfo(i,6+3*j)), i, HHinfo(i,7+3*j), HHinfo(i,8+3*j));
```

```
        masterHHveh{i}(j,:)=[numVeh HHinfo(i,6+3*j) HHinfo(i,7+3*j)
vehTypeInfo(HHinfo(i,6+3*j)) 0 0];
        if -HHinfo(i,7+3*j)>masterHHmat(i,12) %is this older
            masterHHmat(i,12) = -HHinfo(i,7+3*j); %set to max age veh
        end
    end %the veh structs are made here but could take teh info and make
structs after, assume 3 cars/HH for temp mat
end %now all the initial veh are made and put into HH

tempTransArr=zeros(numhh,5);
for i=1:auctions
    t =clock;
    disp([num2str(t(4:5)) ' Auction ' num2str(i)]);

    vehList = zeros(numhh,4);
    buyerList = zeros(numhh,1);
    sellerList = zeros(numhh,2);%for ref only, not used
    numVehSell=0;
    numbuyers=0;
    for j=1:numhh %run trans model > vehList and buyerList
        transArr = transModel(masterHHmat(j,:),beta); %1 buy, 2 sell, 3
nothing %prevent selling 0 car
        pick=transArr(1,1);
        tempTransArr(j,:)=transArr;

        if pick == 1 %buy
            numbuyers=numbuyers+1;
            buyerList(numbuyers)=j;
        end

        if pick == 2 %Sell - increment # of auctions
            %only cars still owned
            hhVehs=masterHHveh{j}(:,1); % veh in houshold, dropVeh does
not automatically exclude frmr veh
            hhVehList = zeros(size(hhVehs,1),4);
            hhVehList(:,1) = hhVehs;
            %hhVehList has [id age mileage type]
            vehPlist = zeros(size(hhVehs,1),1);
            for k=1:size(hhVehs,1)
                templine = size(masterVeh{hhVehs(k)}{2}(:,1),1); %index
of mileage
                hhVehList(k,:)= [hhVehs(k) masterVeh{hhVehs(k)}{1}(6)
masterVeh{hhVehs(k)}{2}(templine,1) masterVeh{hhVehs(k)}{1}(2)];
                if masterHHveh{j}(k,5)==0 %if sold year is 0 (not yet
sold)
                    vehPlist(k,1) =
masterVeh{hhVehs(k)}{2}(templine,2); %put curr price in
                else
                    vehPlist(k,1) = 0; %dont put price in (it was sold)
                end
            end
```

```
            tempVehID = dropVeh(hhVehList, vehTypeInfo, vehPlist,
masterHHmat(j,:), coeffs, fuelCoeff);%pick vehicle to get rid of
            if tempVehID>0
                numVehSell=numVehSell+1;
                templine =
size(masterVeh{hhVehs(tempVehID)}{2}(:,1),1); %index of mileage
                masterVeh{hhVehs(tempVehID)}{1}(5) =
masterVeh{hhVehs(tempVehID)}{1}(5)+1; %+1 Auction
                vehList(numVehSell,:)=[hhVehs(tempVehID)
masterVeh{hhVehs(tempVehID)}{1}(6)
masterVeh{hhVehs(tempVehID)}{2}(templine,1)
masterVeh{hhVehs(tempVehID)}{1}(2)];
                %vehList has [id age mileage type]
                masterHHmat(j,9)=masterHHmat(j,9)-1; % one less veh
                sellerList(numVehSell,:) = [j tempVehID];
            else
                disp(['buyer ' num2str(j) ' didnt drop, but has '
num2str(masterHHmat(j,9))]);
            end
        end
    end
    vehList = vehList(1:numVehSell,:);
    buyerList = buyerList(1:numbuyers,:);
    sellerList = sellerList(1:numVehSell,:);

    AUC = doAuction(vehList, buyerList, masterHHmat, vehTypeInfo,
coeffs, scrap, pVariance, fuelCoeff);
    masterMkt{i} = AUC;
    round=AUC{1}(3);
    %vehList = [id age mileage type]      buyerList is nx1

    for j=1:AUC{1}(1) %loop of buyers, put info into HH structs

        temphh=AUC{2}(j,1); % hh's id
        masterHHmat(temphh,9) = 1+masterHHmat(temphh,9); % 1 more car
        tempveh = size(masterHHveh{temphh},1); % rows (veh) in hh
struct
        if AUC{2}(j,round+1)<1 && AUC{2}(j,round+1)>0 %if it is new
car, # will be vehID*.1
            vtype=floor(AUC{2}(j,round+1)*10); %scale back up to id
            numVeh=numVeh+1;            %(id,       type,           P,
owner, year, mileage)
            masterVeh{numVeh} = vehStruct(numVeh, vtype,
vehTypeInfo(vtype), AUC{2}(j,1), i, 0);
            if size(masterHHveh{i},2)>0 %if it already has a matrix

masterHHveh{temphh}(size(masterHHveh{temphh},1)+1,:)=[numVeh,vtype,i,ve
hTypeInfo(vtype),0,0];
            else

masterHHveh{temphh}(1,:)=[numVeh,vtype,i,vehTypeInfo(vtype),0,0];
%create first entry
            end
```

```
        else %used car
            masterHHveh{temphh}(tempveh+1,1)=abs(AUC{2}(j,round+1));
%veh id

masterHHveh{temphh}(tempveh+1,2)=masterVeh{abs(AUC{2}(j,round+1))}{1}(2
); %veh type
            masterHHveh{temphh}(tempveh+1,3)=i; %veh buy year
            masterHHveh{temphh}(tempveh+1,4:6)=[0 0 0]; %for HH that
had 0 cars
            tempvehyr=size(masterVeh{abs(AUC{2}(j,round+1))}{2},1)+1;
%size of mileage/p/owner mat +1 year
            masterVeh{abs(AUC{2}(j,round+1))}{2}(tempvehyr,3)=temphh;
%put buyer into veh struct
        end
    end

    for j=1:AUC{1}(2) %auctioned veh loop, put info into veh struct

        tempID = AUC{3}(j,1); %veh id

        if AUC{3}(j,2*(AUC{1}(3))+5)~=0 % non-zero bids, sold at market
or max price
            % masterVeh{tempID} veh's struct
            %masterVeh{tempID}{1}(5) = masterVeh{tempID}{1}(5)+1; %+1
Auction  moved to above
            yrIndex=size(masterVeh{tempID}{2},1); %size of
mileage/p/owner mat, already has year added above

masterVeh{tempID}{2}(yrIndex,2)=abs(AUC{3}(j,2*AUC{1}(3)+4));%change
price


            temp =
size(masterHHveh{masterVeh{tempID}{2}(yrIndex,3)},1); % index for
buyer's struct

masterHHveh{masterVeh{tempID}{2}(yrIndex,3)}(temp,1)=tempID;%put id
into buyer's struct

masterHHveh{masterVeh{tempID}{2}(yrIndex,3)}(temp,2)=masterVeh{tempID}{
1}(2);%put type into buyer's struct
            masterHHveh{masterVeh{tempID}{2}(yrIndex,3)}(temp,3)=i;
%put year into buyer's struct

masterHHveh{masterVeh{tempID}{2}(yrIndex,3)}(temp,4)=abs(AUC{3}(j,2*rou
nd+4)); %put price into buyer's struct

            %      size of (veh struct of     (veh frmr owner))
            prevOwner = masterVeh{tempID}{2}(yrIndex-1,3);
            temp = size(masterHHveh{prevOwner},1);% index for sellers's
struct
            while 1
                if masterHHveh{prevOwner}(temp,1)==tempID %is it the
right veh?
```

```
                    masterHHveh{prevOwner}(temp,5)=i;%put year into
sellers's struct

masterHHveh{prevOwner}(temp,6)=abs(AUC{3}(j,2*round+4));%put price into
seller's struct
                    break;
                end
                temp=temp-1;
            end

        elseif AUC{3}(j,2*(AUC{1}(3))+4)==0 % Scrapped (P=0)
            %set owner to 0
            yrIndex = size(masterVeh{tempID}{2},1)+1;

masterVeh{tempID}{2}(yrIndex,1)=masterVeh{tempID}{2}(yrIndex-1,1); %set
mileage to prev
            masterVeh{tempID}{2}(yrIndex,2)=scrap; %p=scrap, owner is 0
for new mat line no need to change
            scrapped = scrapped+1;

            %      size of (veh struct of     (veh frmr owner))
            prevOwner = masterVeh{tempID}{2}(yrIndex-1,3);
            temp = size(masterHHveh{prevOwner},1);% index for sellers's
struct
            while 1
                if masterHHveh{prevOwner}(temp,1)==tempID %is it the
right veh?
                    masterHHveh{prevOwner}(temp,5)=i;%put year into
sellers's struct
                    masterHHveh{prevOwner}(temp,6)=scrap;%put price
into seller's struct
                    break;
                end
                temp=temp-1;
            end


        elseif AUC{3}(j,2*(AUC{1}(3))+5)==0 %no bids ~ car returned to
owner
            yrIndex=size(masterVeh{tempID}{2},1)+1; %size of
mileage/p/owner mat +1 new yr

            masterVeh{tempID}{2}(yrIndex,2)=AUC{3}(j,2*round+4);%set
price (is min price)
            prevOwner = masterVeh{tempID}{2}(yrIndex-1,3); %get owner
from before
            masterVeh{tempID}{2}(yrIndex,3)=prevOwner; %same owner as
before

            masterHHmat(prevOwner,9) = masterHHmat(prevOwner,9)+1; %add
veh, which was deleted before
        else
```

```
            j;
        end

    end %auctioned veh loop

    %NEED TO SET BOUGHT/SOLD YEAR ETC, NOTE UNSOLDS
    for j=1:numVeh %updates veh stats - age, mileage, (copy P and
owner, if not bought)
        temp = size(masterVeh{j}{2},1); %years in vehicle mat
        if masterVeh{j}{2}(temp,3)>0 %if owner is not set to 0
            if masterVeh{j}{1}(4)<0 %if it was bought before simulation
                yrIndex=i+1; %info shoudl go in line i+1
            else %if it was bought during simulation
                yrIndex=i+1-masterVeh{j}{1}(4);
            end
            if temp==yrIndex && temp>1 %if this year's row is already
added
                masterVeh{j}{2}(temp,1)=masterVeh{j}{2}(temp-
1,1)+masterHHmat(masterVeh{j}{2}(temp,3),11); %put in mileage only
            elseif temp==yrIndex %and temp=1 ~ its new

masterVeh{j}{2}(temp,1)=masterHHmat(masterVeh{j}{2}(temp,3),11); %put
in mileage only
            else

masterVeh{j}{2}(temp+1,1)=masterVeh{j}{2}(temp,1)+masterHHmat(masterVeh
{j}{2}(temp,3),11); %put in mileage
                masterVeh{j}{2}(temp+1,2)=masterVeh{j}{2}(temp,2); %put
in P
                masterVeh{j}{2}(temp+1,3)=masterVeh{j}{2}(temp,3); %put
in owner
            end
            masterVeh{j}{1}(6) = masterVeh{j}{1}(6)+1; %one year older
        end
    end

    for j=1:numhh %age, HHmaxAgeVeh -- not numVeh
        % masterHHmat(j,10)=masterHHmat(j,10)+1; %increment age up
        if size(masterHHveh{j},2)>0 %is the mat empty
            oldest=0; %initialize to 0, any car will be older, EFFECT
on transModel?
            for k=1:size(masterHHveh{j},1)
                if masterVeh{masterHHveh{j}(k,1)}{1}(6)> oldest &&
masterHHveh{j}(k,5)==0
                    %if its older than 'oldest' and its not been sold
(sold yr is 0)
                    oldest=masterVeh{masterHHveh{j}(k,1)}{1}(6); %set
it as oldest
                end
            end %end owned veh loop
            masterHHmat(j,12)=oldest; %set oldest car variable
        end
    end %end hh update loop
```

```
    for j=1:numVeh %Veh crash-total loop
        crashRate=crashCoeff*exp(0.295*masterVeh{j}{1}(6)-9.25);
        currYr = size(masterVeh{j}{2},1); %get last ind in veh struct
        currOwner = masterVeh{j}{2}(currYr,3); %get ind of current
owner
        if currOwner>0 && rand<crashRate %if a (0,1)rand lower than
crash rate

            masterVeh{j}{2}(currYr,2)=scrap;  %p=scrap
            masterVeh{j}{2}(currYr,3)=0;    %owner=0

            Oind = size(masterHHveh{currOwner},1);% index for owner's
struct
            while 1
                if masterHHveh{currOwner}(Oind,1)==j %is it the right
veh?
                    masterHHveh{currOwner}(Oind,5)=i;%put year sold
into owner's struct
                    masterHHveh{currOwner}(Oind,6)=scrap;%put price
sold into owner's struct
                    break;
                end
                Oind=Oind-1;
            end
            masterHHmat(currOwner,9)=masterHHmat(currOwner,9)-1;
            crashed=crashed+1;
            crashAges(crashed)=masterVeh{j}{1}(6);
            crashID(crashed)=j;
        end
    end
    clear currVehYear currOwner currYr Oind

end %auction loop

sumbuyers=0;
sumveh=0;
sumrounds=0;
sumunsold=0;
for iter=1:20
    sumbuyers=sumbuyers+masterMkt{iter}{1}(1);
    sumveh=sumveh+masterMkt{iter}{1}(2);
    sumrounds=sumrounds+masterMkt{iter}{1}(3);
    sumunsold=sumunsold+masterMkt{iter}{1}(4);
end

%PRINT OUT RESULTS
t =clock;
printHH(masterHHmat,masterHHveh, filenum);
vehstats = printVeh(masterVeh, filenum);

printMkt(masterMkt, filenum);
```

```
crashAges=crashAges(1:crashed);
disp([num2str(t(4:6)) ' end of main'])
AUCsummary=[auctions scrap pVariance crashCoeff fuelCoeff filenum
sumbuyers sumveh sumrounds...
    sumunsold crashed mean(crashAges) scrapped numVeh vehstats coeffs'
beta];
    % vehstats~ maxAge avgAge medianYear AvgScrapAge
```

doAuction.m – runs once per "year", performs the selling, buying, and pricing. Contains *pick*, *initiatePrice*, *answer*, *newStruct*, and *getIncClass*.

```
function AUC = doAuction(vehList, buyerList, hhInfo, vehTypeInfo,
coeffs, scrap, pVariance, fuelCoeff)
numVeh = size(vehList,1);
numHH = size(buyerList,1);
AUC = AuctionStruct(vehList, buyerList);
round=1;

%vehList ~ Mx4, buyerList ~ Nx1
%vehList has [id age mileage type]

tempP = initiatePrice(vehList, vehTypeInfo, scrap, pVariance);
% [initP minP maxP] = initiatePrice(vehList, vehTypeInfo);

AUC{3}(:,6) = tempP(:,1); %initial price
minP = tempP(:,2); %minimum price
maxP = tempP(:,3); %maximum price
%each HH chooses a vehicle, vehicles count their bids
for i=1:numHH
    if AUC{2}(i,round)>0
        pickIndex = HHchoice(vehList, vehTypeInfo, AUC{3}(:,6),
hhInfo(AUC{2}(i,1),:), coeffs, fuelCoeff);
         if pickIndex>=1 %if hh selects a used car
             AUC{2}(i,2) = vehList(pickIndex,1); %put car into HH's
history
             AUC{3}(pickIndex,7) = AUC{3}(pickIndex,7)+1; %add a bid to
veh in pickIndex
         else %if hh selects new car
             AUC{2}(i,2) = pickIndex;
         end
    else
         AUC{2}(i,2) = 0;
    end
end
exitCondit = notCleared(AUC{3}(:,2*round+4:2*round+5),minP);

while exitCondit
```

```
    round=round+1;
    for i=1:numVeh %increment/decrement
        if AUC{3}(i,2*(round-1)+4)>0 && AUC{3}(i,2*(round-1)+5)~=1
            %if prev price >0 it is active & if there not was a single
bidder in prev round
            increment = 0.01*vehTypeInfo(vehList(i,4),1);
            if AUC{3}(i,2*(round-1)+5)<1 %zero bidders, decrement,
check min/scrap
                AUC{3}(i,2*round+4) = AUC{3}(i,2*(round-1)+4)-
increment;
                if AUC{3}(i,2*round+4)<scrap
                    AUC{3}(i,2*round+4)=0;
                elseif AUC{3}(i,2*round+4)<minP(i,1) %less than min
                    AUC{3}(i,2*round+4) = minP(i,1);
                end
            else %multi bidders, increment, DONT check conditions
                AUC{3}(i,2*round+4) = AUC{3}(i,2*(round-
1)+4)+increment;
                if AUC{3}(i,2*round+4)>maxP(i,1) %greater than max
                    AUC{3}(i,2*round+4) = maxP(i,1);
                end
            end
            AUC{3}(i,2*round+5) = 0; %set bidders to 0 for next round
        elseif AUC{3}(i,2*(round-1)+4)>0 %prev price is >0 (and there
is 1 bidder)
            AUC{3}(i,2*round+4) = AUC{3}(i,2*(round-1)+4); %put price
back in
            AUC{3}(i,2*round+5) = 0; %set bidders to 0 for next round
        else %if price is not positive ~ negative if sold at max, 0 if
scrapped
            AUC{3}(i,2*round+4) = AUC{3}(i,2*(round-1)+4); %put price
back in
            if AUC{3}(i,2*(round-1)+5)==1 %sold/max will have 1 bidder
and neg price
                AUC{3}(i,2*round+5) = 1; %mark it 1
            else
                AUC{3}(i,2*round+5) = 0; %scrapped, put 0 bidders in
            end
        end
    end

    for i=1:numHH %choice model
        if AUC{2}(i,round)>0 %checks prev vehID chosen by HH, neg if
locked in
            pickIndex = HHchoice(vehList, vehTypeInfo,
AUC{3}(:,2*round+4), hhInfo(AUC{2}(i,1),:), coeffs, fuelCoeff);
            if pickIndex>=1 %if hh selects a used car
                AUC{2}(i,round+1) = vehList(pickIndex,1); %put car's ID
into HH's history
                AUC{3}(pickIndex,2*round+5) =
AUC{3}(pickIndex,2*round+5)+1; %add a bid to veh in pickIndex
            else
                AUC{2}(i,round+1) = pickIndex;
```

```
            end
        else
            AUC{2}(i,round+1) = AUC{2}(i,round);
        end
    end

    for i=1:numVeh %multibidder vs maxprice
        if (AUC{3}(i,2*round+5)>1 && AUC{3}(i,2*round+4) >= maxP(i,1))
            AUC{3}(i,2*round+4)=-maxP(i,1); %set P to neg of maxP

            winner = floor(AUC{3}(i,2*round+5)*rand)+1; % #bidders *
rand(0-1) round down +1 gives winner
            temp = find(AUC{2}(:,round+1)==AUC{3}(i,1)); %get bidders

            if numel(temp)==0
                temp;
            end
            AUC{2}(temp(winner),round+1)=-AUC{3}(i,1); %sets buyer's
veh ID to neg
            for j=1:size(temp,1)
                if j~=winner %reassigns all losers
                    tID = temp(j);
                    pickIndex = HHchoice(vehList, vehTypeInfo,
AUC{3}(:,2*round+4), hhInfo(AUC{2}(tID,1),:), coeffs, fuelCoeff);
                    if pickIndex>=1 %if hh selects a used car
                        AUC{2}(tID,round+1) = vehList(pickIndex,1);
%put car's ID into HH's history
                        AUC{3}(pickIndex,2*round+5) =
AUC{3}(pickIndex,2*round+5)+1; %add a bid to veh in pickIndex
                    else
                        AUC{2}(tID,round+1) = pickIndex;
                    end
                end
            end
            AUC{3}(i,2*round+5)=1; %set bidders to 1 (to clear for
round)
        end
    end
    exitCondit = notCleared(AUC{3}(:,2*round+4:2*round+5),minP);

end %while loop of rounds
AUC{1}(3) = round;

for j=1:numVeh%vehicles
    if AUC{3}(j,2*round+5)==0  && AUC{3}(j,2*round+4)>0
        AUC{1}(4) = 1+AUC{1}(4);
    end
end

end
```

```
function answer = notCleared(vehPriceBids,minP)
answer = 0;
if max(vehPriceBids(:,2))>1
    answer = 1;
elseif min(vehPriceBids(:,2))>0
    answer = 0;
else
    for i=1:size(minP,1)
        if vehPriceBids(i,2)==0 && vehPriceBids(i,1)>minP(i,1)
            answer = 1;
            break;
        end
    end
end

end

function pick = HHchoice(vehList, vehTypeInfo, vehPlist, singhh,
coeffs, fuelCoeff) %holding model
%%vehList has [id age mileage type], vehTypeInfo (attri), info on
single hh
%singhh =[size,income,sz>5,high
inc?,fem,urban,suburb,numWkrs,numVeh,age(person),mileage/yr]
% highProb=0;
a0=-.05;
% a0=0;
del=-0.175; %must change this below also
pick=0;
if size(vehList)>0
    utilVec = zeros(size(vehList,1)+9,1);
    numUsed=size(vehList,1);
else
    utilVec = zeros(9,1);
    numUsed=0;
end

HHvars=ones(13,1);%13x1 for all vars, set to ones for non-HH values
% HHvars(1)=1;            %fuel cost
% HHvars(2)=1;            %price
HHvars(3)=(singhh(10)<30); %age x mid
HHvars(4)=(singhh(3));  %lghh? x suv
HHvars(5)=(singhh(1));  %hhsize van
% HHvars(6)=1;            %CUV
% HHvars(7)=1;            %lux
HHvars(8)=(singhh(7));  %suburb x suv
HHvars(9)=(singhh(6));  %urban x mid
HHvars(10)=(getIncClass(singhh(2))-3); %incClass^2 x used
% HHvars(11)=1;           %used *P0
% HHvars(12)=1;           %P0 x exp(del*age)
% HHvars(13)=1;           %100k mi * P
```

```
%HERE HARDCODE FUELCOSTS based on $2.50 gas
fuelCostArr = [0.1210 0.1382 0.1422 0.1343 0.1315 0.1704 0.0939 0.1655
0.1646]*fuelCoeff;
% 1 Compact
% 2 CUVs
% 3 Large
% 4 Luxury
% 5 Midsize
% 6 Pickup
% 7 Subcompact
% 8 SUVs
% 9 Vans

tempVcheck = zeros(14,numUsed+9);%THIS IS ONLY TEMPORARY XXXXXXXXX
tempVeharr = zeros(14,numUsed+9);

for i=1:numUsed+9
    %remove all references to vehPlist and vehList info from if block
below
    highMileage = 0;
    if i>numUsed
        type = i-numUsed; %TYPE?
        price = vehTypeInfo(type); %P
        fuelcost = fuelCostArr(type); %fuel cost
        age = 0; % how to handle this
        used=0;
    else
        price = vehPlist(i); %P
        type = vehList(i,4); %TYPE?
        Pnew = vehTypeInfo(type);
        fuelcost = fuelCostArr(type); %fuel cost
        age = vehList(i,2);
        if vehList(i,3)>100000
            highMileage = 1;
        end
        used=1;
    end

    if(price>0)%if P is 0 or neg it is off the market
        %vehList has [id age mileage type]
        vehVars=zeros(13,1);
%         vehVars(type)=1; % set type indicator
        vehVars(1)=fuelcost;
        vehVars(2)=price/100000; %price x 10^-5
        switch type
            case 1 %compact

            case 2 %CUV
                vehVars(6)=1;
            case 3 %Large

            case 4 %Lux
                vehVars(7)=1;
```

```
            case 5 %midsize
                vehVars(9)=1;
                vehVars(3)=1;
            case 6 %pickup

            case 7 %sub

            case 8 %suv
                vehVars(4)=1;
                vehVars(8)=1;
            case 9 %van
                vehVars(5)=1;
        end %end switch
        %vehVars(19)=1;%pickup
        vehVars(10)=used;%used indicator

        if age>0
            vehVars(11)=used*Pnew*10^-5;%used indicator
            vehVars(12)=Pnew*10^-5*exp(a0+age*del);%
        else
            vehVars(12)=0;%P0 * exp(del * age)
        end
        vehVars(13)=highMileage;%100k mileage

        V=0;
        for j=1:13 % sum the equation for utility
            V=V+coeffs(j)*HHvars(j)*vehVars(j);
             tempVeharr(j,i)=vehVars(j);%THIS IS ONLY TEMPORARY
            tempVcheck(j,i)=coeffs(j)*HHvars(j)*vehVars(j);%THIS IS
ONLY TEMPORARY
        end
        tempVcheck(14,i)=sum(tempVcheck(:,i));%THIS IS ONLY TEMPORARY
        utilVec(i,1)=exp(V);
    end % if its still on mkt
end

sumExp = sum(utilVec);


hit = rand; % grab a random number 0<R<1
totalProb =0; %initialize window
for i=1:size(vehList,1)+9 %for each veh in list
    totalProb = totalProb + utilVec(i,1)/sumExp; %set new max
    if hit < totalProb %if rand is below that max (and above any prev
        pick=i; %pick this one
        break; %break to end
    end
end

if pick > numUsed
    pick=.1*(pick-numUsed);
end
```

```
% disp(pick)
if pick==0
    disp('vehicle pick should not be 0');
end

end %hhchoice function

function newStruct = AuctionStruct(vehs, buyers)
%arrays of buyers and veh, must by Nx1 and Mx4, respectively
%veh has id age mileage type

genInfo = [size(buyers,1) size(vehs,1) 1, 0];
%number of buyers, number of vehicles, round, number unsold

buyerMat = zeros(size(buyers,1), 2);
%id vehID1 vehID2 ... vehIDi
vehMat = zeros(size(vehs,1), 7);
%id age mileage type sellcode currPrice1 numBids1 currPrice2
numBids2...currPricei numBidsi
%leaving at a single row for now
%these are history matrices, they will contain the whole auctions
history

buyerMat(:,1) = buyers;
vehMat(:,1:4) = vehs;

newStruct = {genInfo buyerMat vehMat};

end

function P = initiatePrice(vehList, vehTypeInfo, scrap, pVariance)
%returns matrix with columns initP, minP, maxP
%vehList has [id age mileage type]

% pVariance=0.15; % percent diff between curr and max/min
a0=-.05; %depreciation parameter
% a0=0;
del=-.175; %depreciation parameter
P=zeros(size(vehList,1),3); % initialize price matrix
for i=1:size(vehList,1)
    if vehList(i,2)>0 %is not new, age>0
        P(i,1)=vehTypeInfo(vehList(i,4))*exp(a0+del*vehList(i,2));
%P=Pnew*e^(a0+del*t)
        if P(i,1)<scrap
            P(i,1)=scrap;
        end
        P(i,2)=P(i,1)*(1-pVariance); %min price
        P(i,3)=P(i,1)*(1+pVariance); %max price
        if P(i,3)<scrap
            P(i,:)=[0 0 0];
        end
    end
```

```
end

end

function cl = getIncClass(inc)

switch inc
    case 5000
        cl=1;
    case 15000
        cl=2;
    case 25000
        cl=3;
    case 35000
        cl=4;
    case 45000
        cl=5;
    case 55000
        cl=6;
    case 67500
        cl=7;
    case 87500
        cl=8;
    case 112500
        cl=9;
    case 137500
        cl=10;
    case 175000
        cl=11;
    case 250000
        cl=12;
end

end
```

dropVeh.m – Uses MNL to choose the vehicle in a household which a seller will sell. Contains *getIncClass*.

```
function pick = dropVeh(vehList, vehTypeInfo, vehPlist, singhh, coeffs,
fuelCoeff) %holdingmodel
%%vehList has [id age mileage type], vehTypeInfo (attri), info on
single hh
%singhh =[size,income,sz>5,high
inc?,fem,urban,suburb,numWkrs,numVeh,age(person),mileage/yr]
lowProb=1.1;
pick=0;
a0=-0.05;
del=-0.175;

if size(vehList)>0
    %utilVec = zeros(size(vehList,1)+9,1);
```

```
    utilVec = zeros(size(vehList,1),1);
    numUsed=size(vehList,1);
end

if size(vehList,1)==1
    pick=1;
else
% coeffs=[-8.514; -5.57; 0.3627; 0.8756; 0.2895; -0.4148; -1.121;
0.2632; 0.1864; -0.4; -1; -3.5; -.2785];

HHvars=ones(13,1);%13x1 for all vars, set to ones for non-HH values
% HHvars(1)=1;            %fuel cost
% HHvars(2)=1;            %price
HHvars(3)=(singhh(10)<30); %age x mid
HHvars(4)=(singhh(3));  %lghh? x suv
HHvars(5)=(singhh(1));  %hhsize van
% HHvars(6)=1;            %CUV
% HHvars(7)=1;            %lux
HHvars(8)=(singhh(7));  %suburb x suv
HHvars(9)=(singhh(6));  %urban x mid
HHvars(10)=(getIncClass(singhh(2))-3); %incClass^2 x used
% HHvars(11)=1;           %used
% HHvars(12)=1;           %P0 x exp(del*age)
% HHvars(13)=1;           %100k mi * P

%HERE HARDCODE FUELCOSTS based on $2.50 gas
fuelCostArr = [0.1210 0.1382 0.1422 0.1343 0.1315 0.1704 0.0939 0.1655
0.1646]*fuelCoeff;

% 1 Compact
% 2 CUVs
% 3 Large
% 4 Luxury
% 5 Midsize
% 6 Pickup
% 7 Subcompact
% 8 SUVs
% 9 Vans

tempVcheck = zeros(13,numUsed);

for i=1:numUsed%+9
    %remove all references to vehPlist and vehList info from if block
below
    highMileage = 0;
    if i>numUsed
        type = i-numUsed; %TYPE?
        price = vehTypeInfo(type); %P
        fuelcost = fuelCostArr(type); %fuel cost
        age = 0; % how to handle this
        used=0;
    else
```

```
        price = vehPlist(i); %P
        type = vehList(i,4); %TYPE?
        Pnew = vehTypeInfo(type);
        fuelcost = fuelCostArr(type); %fuel cost
        age = vehList(i,2);
        if vehList(i,3)>100000
            highMileage = 1;
        end
        used=1;
    end

    if(price>0)%if P is 0 or neg it is off the market
        %vehList has [id age mileage type]
        vehVars=zeros(13,1);
%         vehVars(type)=1; % set type indicator
        vehVars(1)=fuelcost;
        vehVars(2)=price/100000; %price x 10^-5
        switch type
            case 1 %compact

            case 2 %CUV
                vehVars(6)=1;
            case 3 %Large

            case 4 %Lux
                vehVars(7)=1;
            case 5 %midsize
                vehVars(9)=1;
                vehVars(3)=1;
            case 6 %pickup

            case 7 %sub

            case 8 %suv
                vehVars(4)=1;
                vehVars(8)=1;
            case 9 %van
                vehVars(5)=1;
        end %end switch
        vehVars(10)=used;%used indicator
        vehVars(11)=used*Pnew*10^-5;%used indicator

        if age>0
            vehVars(12)=Pnew*10^-5*exp(a0+age*del);%
        else
            vehVars(12)=0;%P0 * exp(del * age)
        end
        vehVars(13)=highMileage;%100k mileage

        V=0;
        for j=1:13 % sum the equation for utility
            V=V+coeffs(j)*HHvars(j)*vehVars(j);
```

```
            tempVcheck(j,i)=coeffs(j)*HHvars(j)*vehVars(j);
        end
        tempVcheck(13+1,i)=sum(tempVcheck(:,i));
        utilVec(i,1)=exp(V);
    end % if its still on mkt
end

sumExp = sum(utilVec); %cannot include sold cars

for i=1:size(vehList,1)
    if(vehPlist(i)>0)%if P is 0 or neg it is off the market
        p = utilVec(i,1)/sumExp;
        if (p<lowProb)
            lowProb=p;
            pick=i;
        end
    end
end

if pick==0
    disp('drop pick should not be 0');
end
end
end

function cl = getIncClass(inc)

switch inc
    case 5000
        cl=1;
    case 15000
        cl=2;
    case 25000
        cl=3;
    case 35000
        cl=4;
    case 45000
        cl=5;
    case 55000
        cl=6;
    case 67500
        cl=7;
    case 87500
        cl=8;
    case 112500
        cl=9;
    case 137500
        cl=10;
    case 175000
        cl=11;
    case 250000
```

```
        cl=12;
end
end
```

transModel.m – Logit for the transaction decision for the year.

```
function pick = transModel(singhh, beta)

highProb=0;
pick=0;
expUtil=zeros(1,3);
%Acquire
expUtil(1,1)=exp(beta(1) + beta(4)*singhh(8) + beta(5)*singhh(5) +
beta(6)*singhh(12) + beta(8)*(singhh(8)-singhh(9)));
% expUtil(1,1)=exp(beta(1) + beta(4)*singhh(8) + beta(5)*singhh(5));% +
beta(6)*singhh(12));
            %    acq       acq     numWkr      acq/dis fem
acq/dis    maxVehage   numWkr-numVeh
%Dispose
expUtil(1,2)=exp(beta(2) + beta(3)*singhh(9) + beta(5)*singhh(5) +
beta(6)*singhh(12));
%expUtil(1,2)=2*expUtil(1,2); %for testing only
if singhh(9)==0
    expUtil(1,2)=0;
end
            %    disp       disp   numveh      acq/dis fem
acq/dis maxVehage
%Do Nothing
expUtil(1,3)=exp(beta(7)*singhh(2));
% 1 Acquire
% 2 Dispose
% 3 Number of vehicles in the household x Dispose
% 4 Number of workers in a house x Acquire
% 5 Female indicator x (Acquire, Dispose)
% 6 Maximum age of vehicle in household x (Acquire, Dispose)
% 7 Income of household x Do nothing

sumExp = sum(expUtil);

hit = rand;

if hit < expUtil(1,1)/sumExp
    pick=1;
elseif hit < (expUtil(1,1)+expUtil(1,2))/sumExp
    pick=2;
else
    pick=3;
end

pick = [pick hit expUtil];

end
```

HHinit.m – formats household information for struct.

```
function HHstats = HHInit(oneHH) %PUT IN OLDEST VEH??
%oneHH=[Hhsize,Age,Inc,Female,Urban,Suburban,#Workers,mileage,maxage]

HHstats = [oneHH(1,1) oneHH(1,3) 0 0 oneHH(1,4) oneHH(1,5:7) 0
oneHH(1,2) oneHH(1,8),0];
%         [size       income     0 0 fem  urban suburb numwkrs numVeh
age mileage];
% zeros are handled on the following lines
if (HHstats(1)>5) %lg household indicator
    HHstats(3)=1;
end
if (HHstats(2)>80000)%high income indicator
    HHstats(4)=1;
end
for i=1:5
    if oneHH(1,6+i*3)>0
        HHstats(9)=HHstats(9)+1;
    end
end
```

vehStruct.m – formats vehicle information for struct.

```
function newStruct = vehStruct(id, type, P, owner, year, mileage)

vehChars = [id, type, P, year, 0, 0];
    %id, type, price new, year bought, # of auctions involved in,
current age
if year<0 %neg means that it was held at begining of sim
    vehChars(6) = -year;
end
yearlyStats = [mileage P owner]; %updates yearly
    %mileage, current price, owner id
AuctionHist = [];
    %will have a cell for each auction with year and list of prices
newStruct = {vehChars yearlyStats AuctionHist};
end
```

printAuc.m – formats auction data and puts it into an text file.

```
function [] = printAuc(AUC)

fid = fopen('aucOut.txt','w');

fprintf(fid, '#buyers\t#veh\tround\tunsold\n');
fprintf(fid,
'%f\t%f\t%f\t%f\n',AUC{1}(1),AUC{1}(2),AUC{1}(3),AUC{1}(4));


fprintf(fid, 'Buyer\tchosen veh1\tchosen veh2\n');
```

```
for i=1:size(AUC{2},1) %create and print buyer line
    line = AUC{2}(i,1:2);
    format = '%6.0f\t%6.0f';
    for j=3:size(AUC{2},2)
        line = [line AUC{2}(i,j)];
        format = [format '\t%6.0f'];
    end
    format = [format '\n'];
    fprintf(fid, format, line);
end

fprintf(fid, '\n');
fprintf(fid,
'id\tage\tmileage\ttype\tsellcode\tprice\tbidders\tprice\tbidders\tpric
e\tbidders\n');
for i=1:size(AUC{3},1) %create and print veh line
    line = AUC{3}(i,1:5);
    format = '%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f';
    for j=6:size(AUC{3},2)
        line = [line AUC{3}(i,j)];
        format = [format '\t%6.0f'];
    end
    format = [format '\n'];
    fprintf(fid, format, line);
end


fclose('all')
```

printHH.m – formats household data and puts it into an text file.

```
function [] = printHH(HHmat, HHveh, filenum)

fid = fopen(['hhOut' num2str(filenum) '.txt'],'w');

fprintf(fid, 'size\tincome\tsz>5\thigh
inc?\tfem\turban\tsuburb\tnumWkrs\tnumVeh\tage (person)\tmileage
(/yr)\tmaxage(car)\n');
fprintf(fid,
'%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t
%6.0f\t%6.0f\n',HHmat');
fprintf(fid, '\n');

fprintf(fid, 'owner\tid\ttype\tbought yr\tbought p\tsold yr\tsold
p\n');
for i=1:size(HHveh,2) %create and print buyer line
    if size(HHveh{i},2)>0 %if it isnt empty
        line = [i HHveh{i}(1,1:6)];
        format = '%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\n';
        fprintf(fid, format, line);
        for j=2:size(HHveh{i},1)
              line = [i HHveh{i}(j,1:6)];
```

```
            fprintf(fid, format, line);
        end
    end
end

fclose('all');
```

printVeh.m – formats vehicle data and puts it into an text file.

```
function stats = printVeh(vehStruct, filenum)

fid = fopen(['vehOut' num2str(filenum) '.txt'],'w');
fprintf(fid, 'id\ttype\tpnew\tnew
yr\tauctions\tage\tmileage\tPcurr\towner\tmileage\tPcurr\towner\n');
maxage=0; nscrap=0; scrapAge=0; Age=0; maxauc=0;
currFleet=0;
for i=1:size(vehStruct,2) %create and print line
    currVeh = vehStruct{i};
    line = currVeh{1};
    format = '%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f';
    if size(currVeh{2},2)>0
        for j=1:size(currVeh{2},1)
            line = [line currVeh{2}(j,:)];
            format = [format '\t%6.0f\t%6.0f\t%6.0f'];
        end
    end
    format = [format '\n'];
    fprintf(fid, format, line);
    if line(size(line,2))==0
        nscrap=nscrap+1;
        scrapAge=scrapAge+currVeh{1}(6);
    else
        if currVeh{1}(6)>maxage
            maxage = currVeh{1}(6);
        end
        Age = Age + currVeh{1}(6);
        currFleet=currFleet+1;
    end
    if currVeh{1}(5)>maxauc
        maxauc = currVeh{1}(5);
    end
end

medianyear = vehStruct{size(vehStruct,2)}{1}(4);
avgScrapAge = scrapAge/nscrap;

stats = [maxage, Age/currFleet, medianyear, avgScrapAge];
fclose('all');
```

printMkt.m – formats data from the whole simulation and puts it into an text file.

```
function [] = printMkt(masterMkt, filenum)
```

```
for k=1:size(masterMkt,2)
    AUC = masterMkt{k};

    fid = fopen(['aucOutx' num2str(filenum) '-' num2str(k)
'.txt'],'w');

    fprintf(fid, '#buyers\t#veh\tround\tunsold\n');
    fprintf(fid,
'%f\t%f\t%f\t%f\n',AUC{1}(1),AUC{1}(2),AUC{1}(3),AUC{1}(4));


    fprintf(fid, 'Buyer\tchosen veh1\tchosen veh2\n');
    for i=1:size(AUC{2},1) %create and print buyer line
        line = AUC{2}(i,1:2);
        format = '%6.0f\t%6.0f';
        for j=3:size(AUC{2},2)
            line = [line AUC{2}(i,j)];
            format = [format '\t%6.0f'];
        end
        format = [format '\n'];
        fprintf(fid, format, line);
    end

    fprintf(fid, '\n');
    fprintf(fid,
'id\tage\tmileage\ttype\tsellcode\tprice\tbidders\tprice\tbidders\tpric
e\tbidders\n');
    for i=1:size(AUC{3},1) %create and print veh line
        line = AUC{3}(i,1:5);
        format = '%6.0f\t%6.0f\t%6.0f\t%6.0f\t%6.0f';
        for j=6:size(AUC{3},2)
            line = [line AUC{3}(i,j)];
            format = [format '\t%6.0f'];
        end
        format = [format '\n'];
        fprintf(fid, format, line);
    end

    fclose('all');
end
```

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