Moving Goods to Consumers: Land Use Patterns, Logistics, and Emissions

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Abstract

Moving Goods to Consumers: Land Use Patterns, Logistics, and Emissions

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Worldwide, awareness has been raised about the dangers of growing greenhouse gas emissions. In the United States, transportation is a key contributor to greenhouse gas emissions. American and European researchers have identified a potential to reduce greenhouse gas emissions by replacing passenger vehicle travel with delivery service. These reductions are possible because, while delivery vehicles have higher rates of greenhouse gas emissions than private light-duty vehicles, the routing of delivery vehicles to customers is far more efficient than those customers traveling independently. In addition to lowering travel-associated greenhouse gas emissions, because of their more efficient routing and tendency to occur during off-peak hours, delivery services have the potential to reduce congestion. Thus, replacing passenger vehicle travel with delivery service provides opportunity to address global concerns - greenhouse gas emissions and congestion.

While addressing the impact of transportation on greenhouse gas emissions is critical, transportation also produces significant levels of criteria pollutants, which impact the health of those in the immediate area. These impacts are of particular concern in urban areas, which due to their constrained land availability increase proximity of residents to the roadway network. In

the United States, heavy vehicles (those typically used for deliveries) produce a disproportionate amount of NOx and particulate matter – heavy vehicles represent roughly 9% of vehicle miles travelled but produce nearly 50% of the NOx and PM10 from transportation.

Researchers have noted that urban policies designed to address local concerns including air quality impacts and noise pollution – like time and size restrictions – have a tendency to increase global impacts, by increasing the number of vehicles on the road, by increasing the total VMT required, or by increasing the amount of CO_2 generated. The work presented here is designed to determine whether replacing passenger vehicle travel with delivery service can address both concerns simultaneously. In other words, can replacing passenger travel with delivery service reduce congestion and CO_2 emissions as well as selected criteria pollutants? Further, does the design of the delivery service impacts the results? Lastly, how do these impacts differ in rural versus urban land use patterns?

This work models the amount of VMT, CO_2, NOx, and PM10 generated by personal travel and delivery vehicles in a number of different development patterns and in a number of different scenarios, including various warehouse locations. In all scenarios, VMT is reduced through the use of delivery service, and in all scenarios, NOx and PM10 are lowest when passenger vehicles are used for the last mile of travel. The goods movement scheme that results in the lowest generation of CO_2, however, varies by municipality.

Regression models for each goods movement scheme and models that compare sets of goods movement schemes were developed. The most influential variables in all models were measures of roadway density and proximity of a service area to the regional warehouse.

These results allow for a comparison of the impacts of greenhouse gas emissions in the form of CO_2 to local criteria pollutants (NOx and PM10) for each scenario. These efforts will contribute to increased integration of goods movement in urban planning, inform policies designed to mitigate the impacts of goods movement vehicles, and provide insights into achieving sustainability targets, especially as online shopping and goods delivery becomes more prevalent.

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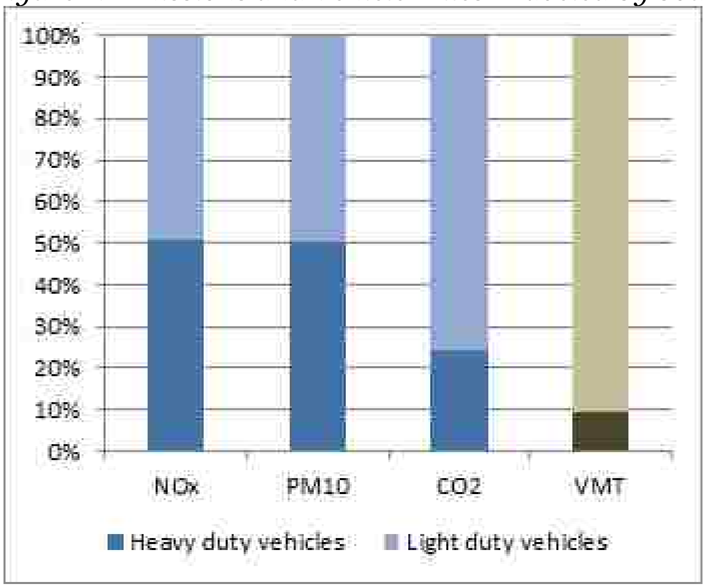
INTRODUCTION

Worldwide, awareness has been raised about the dangers of growing greenhouse gas emissions. In the United States, transportation is a key contributor to greenhouse gas emissions (US EPA 2008). American and European researchers have identified a potential to reduce greenhouse gas emissions by replacing passenger vehicle travel with delivery service (see Wygonik & Goodchild 2012 and Siikivirta et al. 2002). These reductions are possible because, while delivery vehicles have higher rates of greenhouse gas emissions than private light-duty vehicles, the routing of delivery vehicles to customers is far more efficient than those customers travelling independently. In addition to lowering travel-associated greenhouse gas emissions, because of their more efficient routing and tendency to occur during off-peak hours, delivery services have the potential to reduce congestion. Thus, replacing passenger vehicle travel with delivery service provides opportunity to address global concerns - greenhouse gas emissions and congestion.

While addressing the impact of transportation on greenhouse gas emissions is critical, transportation also produces significant levels of criteria pollutants, which impact the health of those in the immediate area (US EPA 2013b, US EPA 2013c). These impacts are of particular concern in urban areas, which due to their constrained land availability increase proximity of residents to the roadway network. In the United States, heavy vehicles (those typically used for deliveries) produce a disproportionate amount of NOx and particulate matter – heavy vehicles represent roughly 9% of vehicle miles travelled but produce nearly 50% of the NOx and PM10 from transportation (US EPA 2008, Davis et al. 2013) (see Figure 1).

Figure 1: Emissions and Vehicle Miles Traveled by Source Type



Researchers have noted that urban policies designed to address local concerns including air quality impacts and noise pollution – like time and size restrictions – have a tendency to increase global impacts, by increasing the number of vehicles on the road, by increasing the total VMT required, or by increasing the amount of CO2 generated (Wygonik and Goodchild 2011, Siikavirta et al. 2002, Quak and de Koster 2007 and 2009, Allen et al. 2003, van Rooijen et al. 2008, Holguin-Veras 2013). The work presented here is designed to determine whether replacing passenger vehicle travel with delivery service can address both concerns simultaneously. In other words, can replacing passenger travel with delivery service reduce congestion and CO2 emissions as well as selected criteria pollutants? Further, does the design of the delivery service impacts the results?

In addition, while researchers have found relationships between passenger vehicle travel and smart growth development patterns, similar relationships have not been extensively studied between urban form and goods movement trip making patterns. In rural areas, where shopping choice is more limited, goods movement delivery has the potential to be relatively more important than in more urban areas. As such, this work also aims to examine the relationships between certain development pattern characteristics including density and distance from warehousing. That is, do goods movement strategy impacts differ by urban form characteristics?

This work models the amount of CO_2, NO_x, and PM_{10} generated by personal travel and delivery vehicles in a number of different scenarios, including various warehouse locations. The results allow for a comparison of the impacts of greenhouse gas emissions in the form of CO_2 to local criteria pollutants (NO_x and PM_{10}) for each scenario. These efforts will contribute to increased integration of goods movement in urban planning, inform policies designed to mitigate the impacts of goods movement vehicles, and provide insights into achieving sustainability targets, especially as online shopping and goods delivery becomes more prevalent.

LITERATURE

Reductions in externalities with delivery systems

A sizable body of research has indicated replacement of personal travel to grocery stores with grocery delivery services has significant potential to reduce VMT. Cairns (1997, 1998, 2005) observed reductions in vehicle miles travelled (VMT) between 60 and 80 percent when delivery systems replaced personal travel. The Punakivi team found reductions in VMT as high as 50 to 93 percent (Punakivi and Saranen, 2001; Punakivi et al., 2001; Punakivi and Tanskanen, 2002; Siikavirta et al., 2002). Wygonik and Goodchild (2012) saw reductions of 70-95%.

Both Siikavirta et al. (2002) and Wygonik & Goodchild (2012) examined the impact on CO_2 emissions for passenger travel replacement for grocery shopping. Wygonik & Goodchild observed reductions in CO_2 emissions between 20 and 75 percent when delivery systems served randomly selected customers and reductions 80-90% when deliver systems served clustered customers. These are comparable to the results observed by Siikavirta et al. (2002).

Hesse (2002) points out limitations in evaluations which directly replace passenger travel with delivery service as other changes to the logistics system are likely. He further comments on the likelihood for e-commerce to encourage more distal warehouse locations. The evaluation presented here attempts to address some of these concerns by incorporating the entire supply chain from regional warehouse to end consumer. Recent growth by Amazon (Wenger 2013) shows at least some retailers are not moving their warehouses further away, but instead are moving them closer to population centers.

While some research has indicated replacement of personal travel to grocery stores with grocery delivery services has significant potential to reduce VMT, these articles have not addressed criteria pollutants, which are associated with significant health impacts (EPA 2013b, EPA 2013c).

Warehouse locations

Since warehouses (including storage and distribution centers) are frequently an end point for commercial trips, their location can significantly influence the distances travelled by goods movement vehicles. Research about the optimal locations for warehouses is common. Crainic et al. (2004) found that the use of 'satellite" warehouses to coordinate movements of multiple shippers and carriers into smaller vehicles reduced the vehicle miles traveled of heavy trucks in the urban center but increased the total mileage and number of vehicles moving goods within the urban center. This research illustrates the close relationship between warehouse location and the vehicle choice. Likewise Dablanc and Rakotonarivo (2010) found terminal locations have moved further from the city center over the past 30 years resulting in an estimated increase in CO_2 of 15,000 tonnes per year. They compare this with estimated gains from smaller consolidation centers located close to city centers and found the increase in CO_2 from the relocated terminals was 30 times greater than the savings from the smaller consolidation centers. Filippi et al. (2010) found greater potential environmental savings through urban distribution centers than through changes to the vehicle fleet, though both were successful.

In contrast, Allen and Browne (2010) found that locating distribution facilities closer to urban centers would reduce the average length of haul and total vehicle kilometers travelled by freight vehicles in and to urban centers, and Andreoli et al. (2010) found that mega-distribution centers, located to serve multiple regions, increased the distance travelled between the distribution center and the final outlet.

While this area of the literature is well-studied, clear consensus about the CO_2 impacts of warehouse location has not been reached and little research exists on the impacts of warehouse location on criteria pollutants. This research examines the results of shifting shopping behavior from personal travel to delivery service and examines the influence on warehouse structure on those results. It also provides insight into the trade-offs between local impacts (criteria pollutants – NO_x and PM_{10}) and global ones (VMT and CO_2).

Influence of Urban Form

An extensive literature has examined the role of density and urban form on automobile travel. Dense development, strong road connectivity, and a mix of land uses are three of the key features of Smart Growth development (Smart Growth Network 2011, Moudon et al. 2003). These features are associated with reduction in travel cost (Porter et al. 2005), trip making, trip length (Cervero 1989; Cervero 1996; Cervero and Landis 1997), total VMT (Frank et al. 2007;Frank et al. 2006; Ewing et al. 2002; Ewing and Cervero 2001; Handy et al. 2005; Porter et al. 2005), and emissions (TRB 2009). While there is reasonable consensus about the household travel benefits of dense development patterns, only a few studies have touched on the impact of density on freight vehicle impacts and those studies are not conclusive. Klastorin et al. (1995) found demand for truck trips is increased in urban areas, but Wygonik and Goodchild (2011) found the cost and environmental impact per delivery order to be less in denser areas.

Daganzo (2010) in discussing the traveling salesman problem, proposes an approximation summarized in Equation 1. The approximate travel length for a single delivery vehicle serving a set of customers is a function of the number of customers and service area size (or customer density) along with a factor for the type of road network connectivity (straight line paths – Euclidean/L2 or grid connections – Manhattan/L1). He extends that approximation for the vehicle routing problem (in which more than one vehicle serves a set of customers) in Equation 2. Here in addition to the number of customers and service area, he includes the capacity of the vehicle and the distance from the depot to the service area centroid.

Equation 1: Daganzo's (2010) approximation for the Traveling Salesman Problem

$$L^* \sim k\sqrt{(AN)} = kN/\sqrt{\delta}$$

Where

L: travel length

k : network constant (k =0.72 for L2 (Euclidean), .92 for L1 (grid))

A : service area

N : number of customers

δ : customer density

Equation 2: Daganzo's(2010) approximation for the Vehicle Routing Problem

$$L_{vrp} \leq L_{tsp} + 2Dr/v_m$$

Where

L_{vrp}: travel length for the vehicle routing problem estimation

L_{tsp}: travel length for the traveling salesman problem estimation

r: distance from depot to center of tour area

D: total demand (units)

v_m: vehicle capacity

The findings from these studies indicate that customer density, road network density and connectivity, service area size, the mix of land uses, and the distance from the warehouse or depot to the service area centroid all may influence VMT and, thus, emissions associated with goods movement.

Hypotheses & Research Questions
In response to the above literature, the following questions arise:

1) Is it possible to reduce VMT, CO_2, NOx, or PM_{10} from personal travel through the use of delivery systems?
2) Does warehouse location matter?
3) Does the structure of the delivery system matter?
4) Is there any tradeoff between global impacts (VMT and CO_2) and local ones (NOx and PM_{10})?
5) Can the relationships between the impacts of goods movement systems be described numerically?
6) Are there any differences in impacts of goods movement strategies in less dense environments?

Based on the findings in the literature, the following hypotheses are presented:

1) Yes it is possible to reduce VMT, CO_2, NOx, and PM_{10} with delivery systems. Other studies have shown large reductions in VMT and significant reductions in CO_2. While NOx and PM_{10} are produced at a much higher rate by delivery vehicles, the reductions in VMT would imply that an associated reduction in criteria pollutants is at least possible, if not probable.
2) Warehouse location should impact the outcome. Most of the literature implies distant warehouses yield higher total VMT. When local warehouses do not reduce overall VMT, they do reduce VMT by large vehicles and thus may reduce emissions.

3) The literature implies the structure of the delivery system will complicate the results, as closer consolidation centers have differing impacts on total and vehicle-specific VMT.
4) Because of the significant difference in criteria pollutant generation by vehicle type, some trade-off between global and local impacts is expected. Further, a handful of studies have identified on-going tension between strategies to address local impacts exacerbating global ones.
5) Based on the extensive literature for passenger vehicles as well as the approximation developed by Daganzo, it is expected that an empirical model can be developed to estimate the impacts of different goods movement strategies and that customer density will be an important component of those models.
6) Based on the work of Wygonik and Goodchild (2011), less dense environments are expected to have the same proportional reductions in emissions but greater absolute reductions.

DATA

Network Data Set

The base network is pulled from the ESRI StreetMap North America data set (ESRI 2006) and was modified in a number of ways. First, the data set was trimmed to only include road segments in King County, Washington to reduce processing time. Next, the length in feet of each road segment was calculated and appended to the data table. Travel time was calculated using the segment length and the speed limit information and appended to the data table. Finally, information regarding the CO_2, NO_x, and PM_{10} emissions associated with each road segment for each vehicle type was also appended to the data table, based on the MOVES emissions factors, the roadway speed limit, the roadway functional class, the roadway length, and the vehicle type.

Once the data were added to the StreetMap layer, it was built as a Network for use in the Network Analyst tool set in ArcGIS.

While this evaluation considers link-level travel speeds, it does not include various real-time travel components, including congestion and queuing. These factors may affect the results but are outside the scope of this analysis.

Emissions Factors

Emissions factors were obtained from the 2010b MOVES model (EPA 2013a). EPA's MOVES model was used to identify emissions rates as it is the most current emissions model supported by the United States government. The factors in MOVES are sensitive to a number of different parameters considered within this analysis, including speed and vehicle type. This analysis assumed uncongested conditions, so speed limit data from the StreetMap North America data set was used as the default flow speed for each road segment. Running exhaust emissions are tracked.

Personal travel is represented by the emissions factors for personal cars using gasoline. The home delivery vehicle travel uses emissions factors for single-unit short haul trucks with diesel fuel, and the emissions rates for the vehicles used to move goods from the warehouse to stores relies on data for combination short-haul trucks and diesel fuel. A weighted average of the previous 15 years of data was used according to the vehicle age distribution reported in the Transportation Energy Data Book (Davis et al. 2013) for passenger cars and trucks, respectively. Because of data restrictions, the distribution of the previous 15 years data is only released as of 2001. This distribution is applied to 2014.

Emission factors were selected for an analysis year of 2014. Hourly kilograms per mile of CO2 equivalents, NOx, and PM10 were extracted and averaged over each hour of the day, for weekdays, throughout the year for the King County, Washington region. Roadways with speeds of 5, 20, 25, and 35 miles per hour used urban unrestricted roadtype emissions factors, and roadways with speeds of 45 and 55 miles per hour used urban restricted roadtype emissions factors (see Table 1). Since the trucks work with hot engines due to their short stopping time, only running exhaust emissions are tracked.

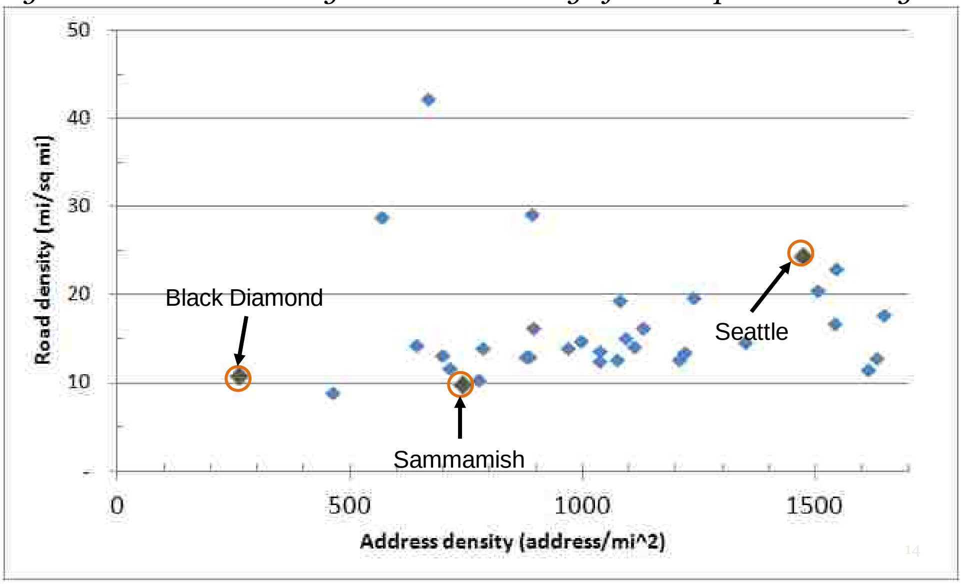
Table 1: Emissions Factors (kilograms per mile of CO2 Equivalents, NOx, and PM10) from EPA's MOVES model (EPA 2013a)

		Urban Unrestricted				Urban Restricted	
		5	20	25	35	45	55
Passenger Cars	CO2	1.05917	0.41817	0.37320	0.33967	0.30813	0.29773
	NOx	0.0004980	0.0002969	0.0002943	0.0003189	0.0003020	0.0003128
	PM10	0.00002615	0.00000865	0.00000842	0.00001183	0.00000736	0.00000720
Single Unit Short Haul	CO2	3.8027	1.4837	1.3319	1.1308	0.8667	0.7403
	NOx	0.016566	0.005898	0.005196	0.004357	0.003390	0.002950
	PM10	0.0007268	0.0002548	0.0002240	0.0001876	0.0001566	0.0001448
Combination Short Haul	CO2	4.8386	2.5148	2.3542	1.9788	1.9175	1.7228
	NOx	0.023531	0.010781	0.009821	0.008475	0.008198	0.007719
	PM10	0.0010048	0.0005433	0.0005058	0.0003797	0.0003296	0.0002410

Selected Municipalities

To consider the impact of urban form and density on delivery impacts, a set of municipalities was selected to reflect a range of development patterns. To maintain consistent data, the municipalities within King County, Washington were evaluated. Earlier work focused on Seattle, which is a large urban area. To enable comparison with the earlier work, Seattle was included here. To select the additional locations, the number of addresses, road length, and municipal area for each municipality in King County were calculated in ArcGIS. These values were used to calculate the address density (number of addresses per square mile) and the road density (linear feet per square feet) for each municipality (see Figure 2).

Figure 2: Address Density and Road Density of Municipalities in King County, Washington



As illustrated in Figure 2, Seattle has relatively high address density and moderate road density. After eliminating outliers and places with fewer than 1000 residents, Black Diamond and Sammamish were selected as two of the most contrasting locations, with low address and road densities. Their relative locations, sizes, and road densities are illustrated in Figure 3. Table 2 illustrates the descriptive statistics for each municipality.

Figure 3: Map of Selected Municipalities – Seattle, Black Diamond, and Sammamish – Illustrating Relative Locations, Sizes, and Road Densities

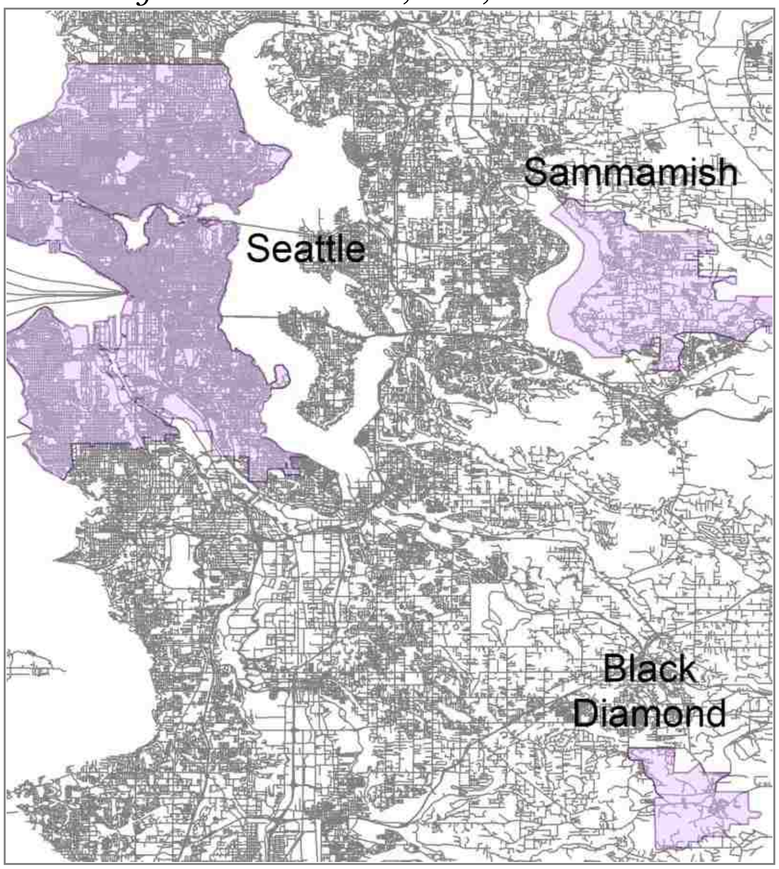


Table 2: Descriptive Statistics for Selected Municipalities – Seattle, Black Diamond, and Sammamish

	Seattle	Black Diamond	Samammish
Area (sq mi)	143.4	7.2	22.0
Average depot service area (sq mi)	28.7	7.2	22.0
Linear Road Miles	2017	78	215
Number of Addresses	211,501	1,881	16,339
Address Density (addresses/ sq mi)	1,475	261	742
Customer Density (customers/sq mi)	1.2	4.9	1.6
Est. Market Share	0.1%	1.9%	0.2%
Stores in City Limit	42	0	2
Stores Serving Customers	42	1	6
Depots	5	1	1
Avg. Miles to Warehouse from Depots	19.5	12.5	25.2

Depot Locations

Delivery services are generally clustered into two primary types – ones that rely on existing brick-and-mortar retail locations for depots and those that use warehouses as depots. While other models exist, this research compares these two main types: a brick-and-mortar storefront depot with a warehouse-based model. This analysis considers replacing one roundtrip by an addressto its nearest grocery store with delivery from a local store-based delivery service or service from a regional warehouse. Earlier work by the authors (Wygonik and Goodchild 2012) used one service area for personal travel and delivery service, and this work is designed to develop a more realistic model of the delivery service. For companies operating a delivery service out of a store-front, they are unlikely to operate that company out of every store front. Rather, they would likely pick a small subset of available options which would serve as depots for different quadrants of the city. This change reflects more realistic catchment areas for retail stores versus a delivery depot.

Puget Sound Regional Council provided a shapefile with the locations of the major grocery stores within King, Kitsap, and Snohomish counties. The service areas of the stores were calculated (using the Service Area tool within ArcGIS Network Analyst) and addresses were assigned to their closest store's service area for the personal travel calculations. Cairns (1995) summarizes the results from six surveys to describe the typical grocery shopping patterns in the United Kingdom. She cites a 1993 survey showing nearly two-thirds of housewives grocery shop less than two miles from home and a survey by Telephone Survey LTD, which indicated "62% of car shoppers use the nearest store to their home 'of its type' for main food shopping" (Cairns 1995, pg. 412). Her summary also indicated the vast majority of households with a car (99.6%) in the UK use a car for shopping, though in certain districts that percentage is somewhat lower (Cairns 1995). Siikvavirta et al. (2002) indicate in Finland only 55%of households use a car to grocery shop. Similarly detailed data are not available in the United States, where the National Household Travel Survey (US DOT 2003) consolidates all shopping into one category. Analysis of the 2001 NHTS by Pucher and Renne (2003) indicates 91.5% of all shopping trips in the U.S. were made by personal automobile. Market research by the Nielsen Company indicates value is the primary consideration for 60% of U.S. shoppers when choosing a grocery store, followed by goods selection (28%) and closest store (23%) (2007). While value is considered more important than proximity for more Americans, the survey report did not indicate secondary and tertiary considerations. For this analysis, assigning customers to their nearest store is reasonable, and provides a baseline for comparisons between personal travel and delivery vehicles.

One in 5 stores throughout King County were selected to serve as local depots. This value compares with the roughly 1 in 3 stores Tesco.com uses as local depots in the UK (Punakivi and Tanskanen, 2002). As a result, a subset of five stores was selected to serve as depots for the store-based delivery service in Seattle. These stores are distributed throughout Seattle and are illustrated in Figure 4. Black Diamond and Sammamish are each served by one local depot. In

Black Diamond that depot is outside the city limits. One existing warehouse location in Kent, Washington was selected to serve as the depot location for the warehouse-based delivery service, as well as the warehouse serving the grocery stores themselves (Figure 5).

Figure 4: Warehouse, Depot, and Store Locations in Seattle

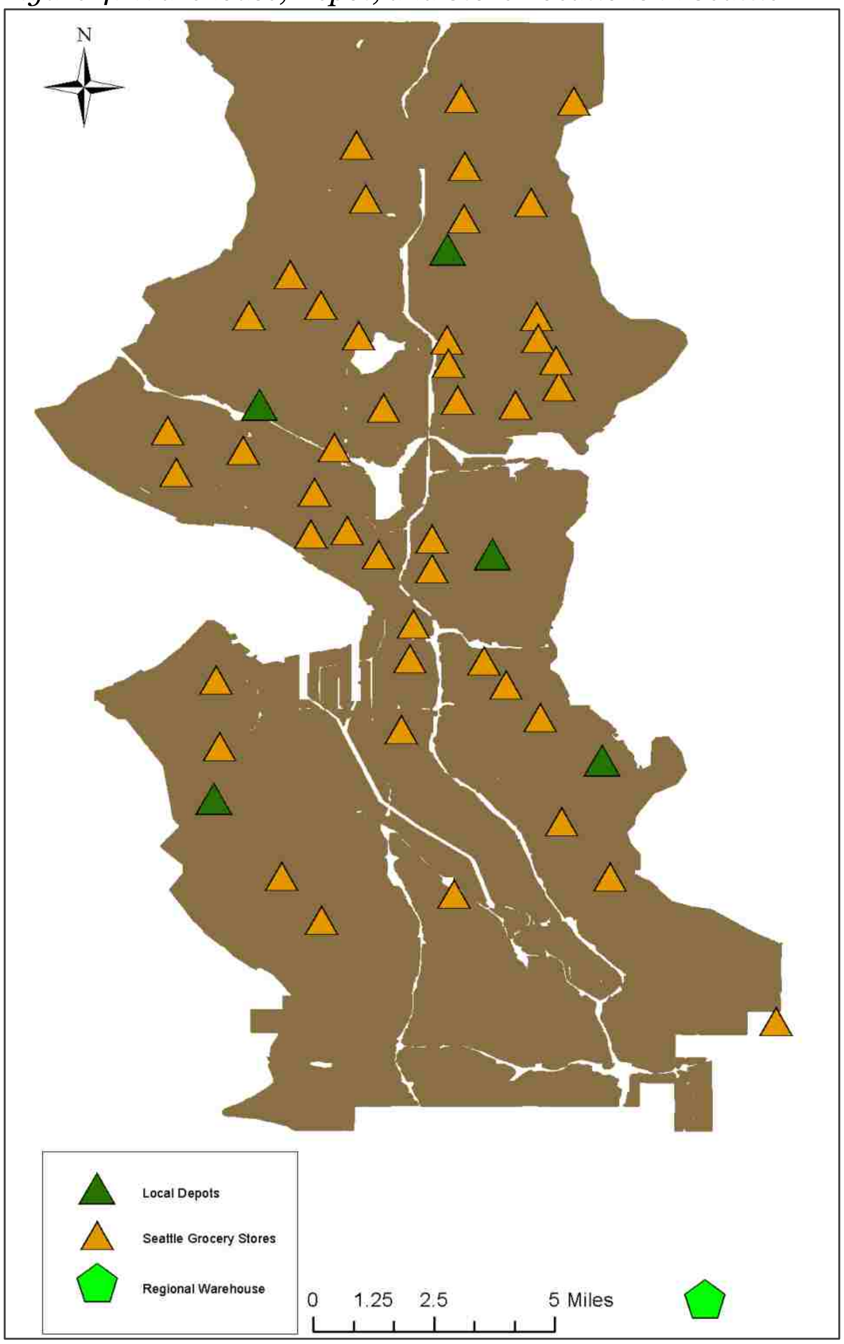
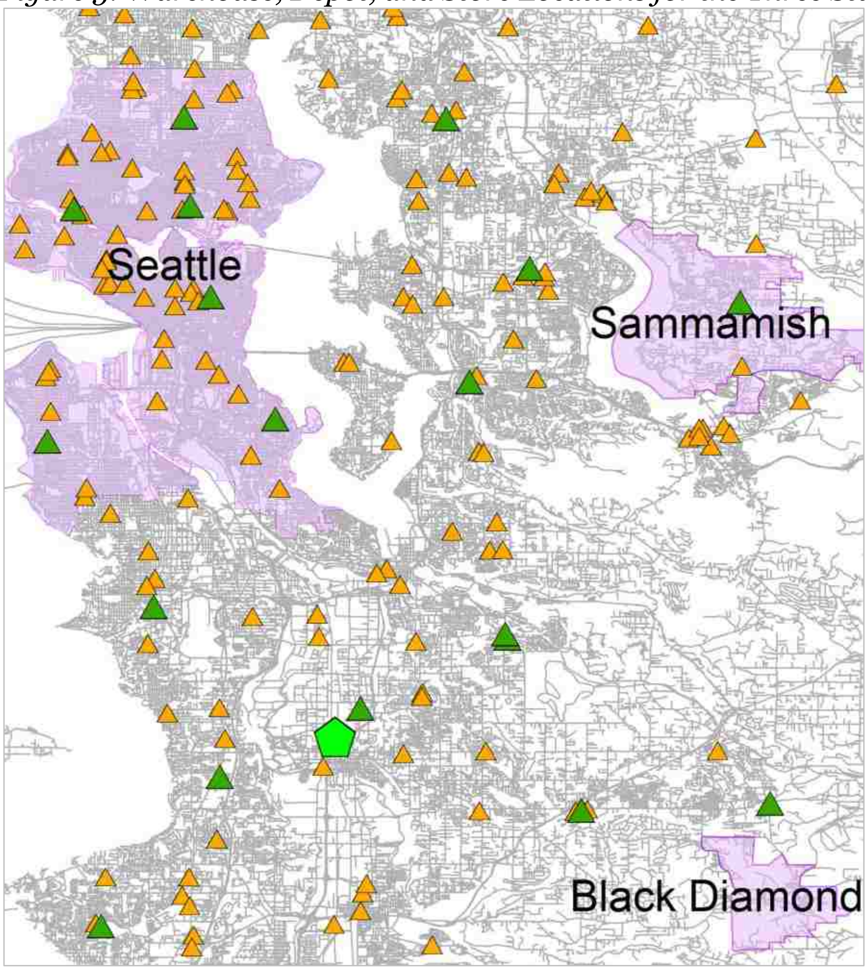


Figure 5: Warehouse, Depot, and Store Locations for the Three Studied Municipalities



Household Data

Geographic data regarding households and parcels were gathered from the Washington State Geospatial Data Archive (WAGDA) and the Urban Ecology Lab at the University of Washington. To maintain consistency with prior work, in Seattle only household location were selected. That effort required joining the WAGDA King County parcels file (containing address data) to the Urban Ecology Lab King County parcels file (containing the residential units data) to geocode the parcels with residential units information, and selecting out the residential parcels. For Black Diamond and Sammamish, all addresses were used as potential customers, reflecting that both households and businesses receive delivery services.

As personal communication with local delivery providers indicate each truck can hold approximately 35 households worth of orders, 35-household samples are used here. A total of 25 samples for each municipality were gathered, as that ensured adequate statistical power while providing reasonable computation time. For Seattle, 5 samples were gathered for each of the 5 local depot service areas. For Black Diamond and Sammamish, 25 samples were gathered for the local depot service area. These samples were used for all three travel types – household travel to their proximate store, delivery service from their assigned store-based depot, and delivery service from the regional warehouse – enabling direct comparison between each. The sampling was conducted randomly, with replacement, from all available customers in the local depot service area. To evaluate the impacts of personal travel, the sampled customers were then assigned to their closest store.

METHODS

Scenarios

Three scenarios were considered in this evaluation:

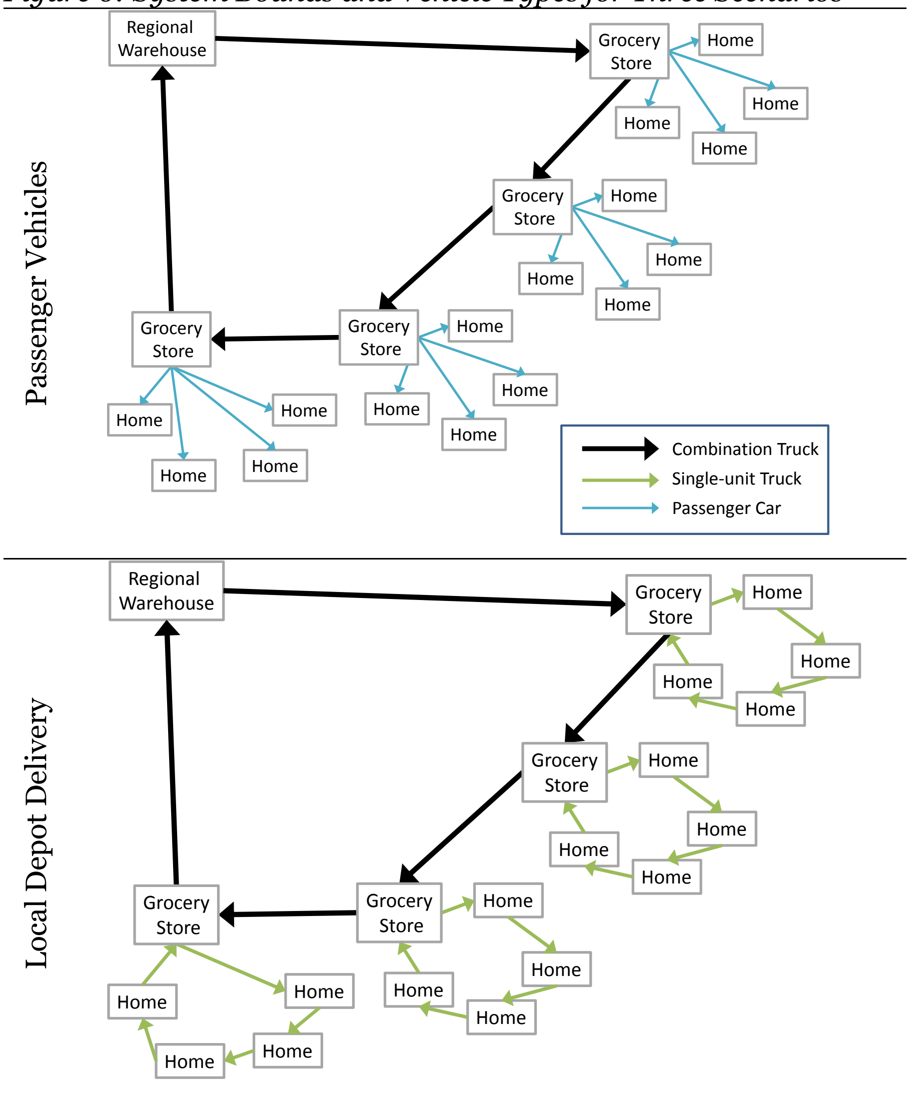
1) The baseline scenario, Passenger Vehicles, represents a common form of travel for grocery shopping. A large, combination truck stocks the grocery stores from the regional warehouse. Individual customers use passenger vehicles to complete roundtrips from their addresses to their closest grocery store and back.

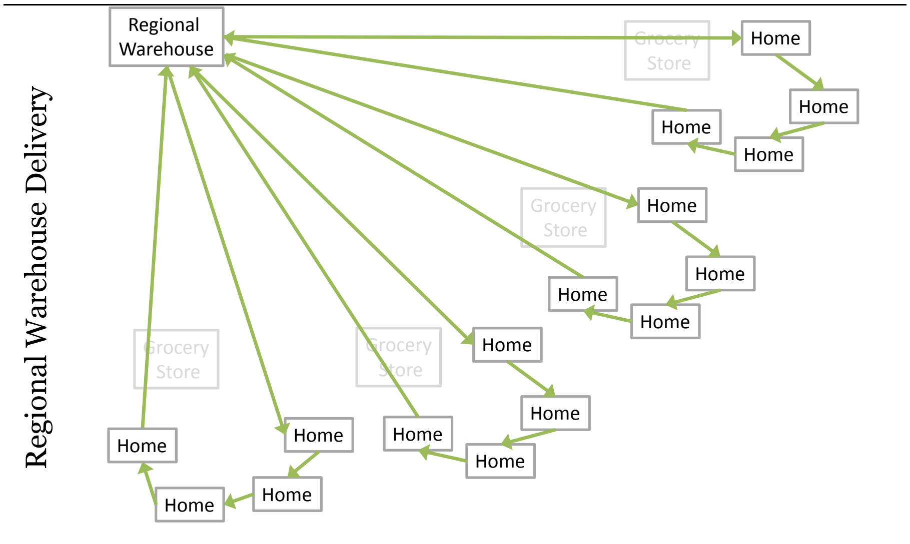
2) The second scenario, Local Depot Delivery, provides delivery service from selected grocery retail locations distributed throughout the region. In this scenario, the local depots are stocked from the regional warehouse using large, combination trucks. Then smaller box trucks complete delivery via a milk-run starting and ending at the select stores and stopping at the sampled customers along the way.

3) The third scenario, Regional Warehouse Delivery, provides delivery service directly from the regional warehouse using small, box trucks. The routes start and end at the regional warehouse and stop at the sampled customers along the way.

These scenarios are illustrated in Figure 6.

Figure 6: System Bounds and Vehicle Types for Three Scenarios





Vehicle Travel

To estimate the distances traveled and the associated emissions, routing tools within ArcGIS Network Analyst were used.

To complete the routing estimates, the Network Analyst Closest Facility tool was used to calculate the distance traveled to each grocery store for each household in the sample for the Passenger Vehicle scenario. The StreetMap network was loaded for use with Network Analyst. Output from Network Analyst includes the one-way distance traveled for each residential unit and the one-way emissions associated with each residential unit's grocery store trip when the trip is optimized for shortest time. These outputs were doubled, to reflect round trip distances and emissions. Using round trips for the Passenger Vehicle scenario represents a simplification, as some grocery shopping does occur within chained trips. However, the available data do indicate most grocery shopping occurs via passenger vehicle making exclusive trips (as discussed above and outlined in Wygonik and Goodchild 2012). Not all trips would be replaced by this type of service, but it is a reasonable estimation of the impact of replacing main household stocking trips.

To complete the routing estimates, the Network Analyst Routing tool was used to calculate the distance traveled by a delivery vehicle starting and ending at the depots and serving a sample of 35 households. The StreetMap network was loaded for use with Network Analyst. Network Analyst was run to identify the fastest path to serve the given households. The analysis reordered the stops to identify the fastest route, but kept the first and last stops (the depot) constant. Output from Network Analyst includes the distance traveled for each delivery vehicle and emissions associated with each tour, with the route optimized for shortest time.

Vehicle travel to stock the grocery stores from the regional warehouse was also included to maintain a constant system boundary for all scenarios. For the personal travel, 10 tractor trailers were required to stock the 49 grocery store locations proximate to Seattle. The Network Analyst Routing tool was used to calculate the distance traveled and emissions for 10 tractor trailers leaving the regional warehouse and each serving 5 stores (one served 4). The results were then divided by 10 to represent the average values for one truck. For Black Diamond, the 5 stores closest to the one serving Black Diamond were selected and served by a tractor trailer. For Sammamish, the 10 closest stores were selected and served by two tractor trailers for stocking runs.

For the scenario involving the local, store-based depots, the Network Analyst Routing tool was used to calculate the distance traveled and emissions for one tractor trailer serving the 5 store-based depots in Seattle and the closest 5 depots to Black Diamond and Sammamish. Figure 6 above illustrates the 3 scenarios.

The Python code used to complete the routing estimates is included in Appendix A.

Assumptions

A number of assumptions were required within the modeling system. First, all optimizations used hard time windows, guaranteeing that promised delivery times would be met. The problem is also simplified to an urban delivery system, disregarding pickup. The model does not consider real-time routing changes. It is a planning tool and is not intended to provide dynamic routing information. In addition, this model currently assumes uncongested conditions.

Regression Modeling

The regression modeling was conducted using the R statistical package. Sample R code and detailed intermediate results are presented in Appendix B.

This evaluation relied on the same set of sampled addresses used above, but in this case each address represented a data point with information about VMT and CO_2, PM_{10}, and NO_x emissions associated with each of the three goods movement scenarios along with descriptive data about an addresses associated land use environment (address density, distance to the warehouse, etc.). As a result, the regression estimates were conducted on the entire set of sampled addresses, with a sample size of 2625 (25 addresses, sampled 35 times, in 3 municipalities). Because of the sampling with replacement initially conducted, a small subset of the sampled addresses may be included more than once. This value is expected to be small enough to not affect the outcome.

To estimate the models, a modified forward selection was conducted on the likely variables. Each variable was tested for fit, and the variable with the highest explanatory power that was also significant was added to the model. This new model was tested with each of the remaining variables. If any of those remaining variables were significant, the model with the new highest predictive power was selected as the current active model. This process was repeated until either all variables were added to the model or new variables were not significant.

Two difference sets of models were developed. The first set of models represented the Best Fit models, and these models included all variables that tested significant within the model estimation. The second set of models represent the Parsimonious models. These models include only the variables that meaningfully improve the explanatory power.

Models for each dependent variable (VMT, CO_2, NOx, and PM10) were developed for each goods movement structure, for a total of 12 models in each of the two sets.

The variables selected in these models were then tested for influence in the comparative relationships between goods movement strategies. The two sets of models were again developed for each dependent variable, but this time a subset of models was created representing the differences between passenger vehicle travel and local depot delivery, between passenger vehicle travel and warehouse-based delivery, and between local depot delivery and warehouse-based delivery. Again, a total of 24 models were estimated.

Based on the literature, the following variables were tested for each goods movement strategy. For Passenger Travel, the tested variables include:

- Address Density : the number of addresses in the store service area divided by the store service area size (units = 1/square mile)
- Store Service Area Size : the store service area size (square mile)
- Distance from the Warehouse to the Store : the on-road travelled distance between the warehouse and the assigned store (miles), calculated using Google maps and the location addresses
- Store Service Area Road Density : the linear feet of road in a store service area divided by the store service area size (feet/square feet)
- Store Service Area Junction Density : the number of junctions in a store service area divided by the store service area size (1/square feet)

A similar set of variables was tested for the Local Depot Delivery models, but these variables were standardized by the depot service area instead of the store service area.

- Customer Density : the number of customers in the depot service area divided by the depot service area size (units = 1/square mile)

- Depot Service Area Size : the store service area size (square mile)
- Distance from the Warehouse to the Depot : the on-road travelled distance between the warehouse and the assigned depot (miles) , calculated using Google maps and the location addresses
- Depot Service Area Road Density : the linear feet of road in a depot service area divided by the depot service area size (feet/square feet)
- Depot Service Area Junction Density : the number of junctions in a depot service area divided by the depot service area size (1/square feet)
- Distance from the Depot to the Depot Service Area Centroid : the on-road travelled distance between the depot and the geographic centroid of the depot service area (miles), calculated using Network Analyst tools in ArcGIS

The variables tested for Warehouse Delivery were the same as those tested for Local Depot delivery, except a different measure for travel distance from the warehouse was used.

- Customer Density
- Depot Service Area Size
- Depot Service Area Road Density
- Depot Service Area Junction Density
- Distance from the Warehouse to the Depot Service Area Centroid : the on-road travelled distance between the warehouse and the geographic centroid of the depot service area (miles) , calculated using Network Analyst tools in ArcGIS

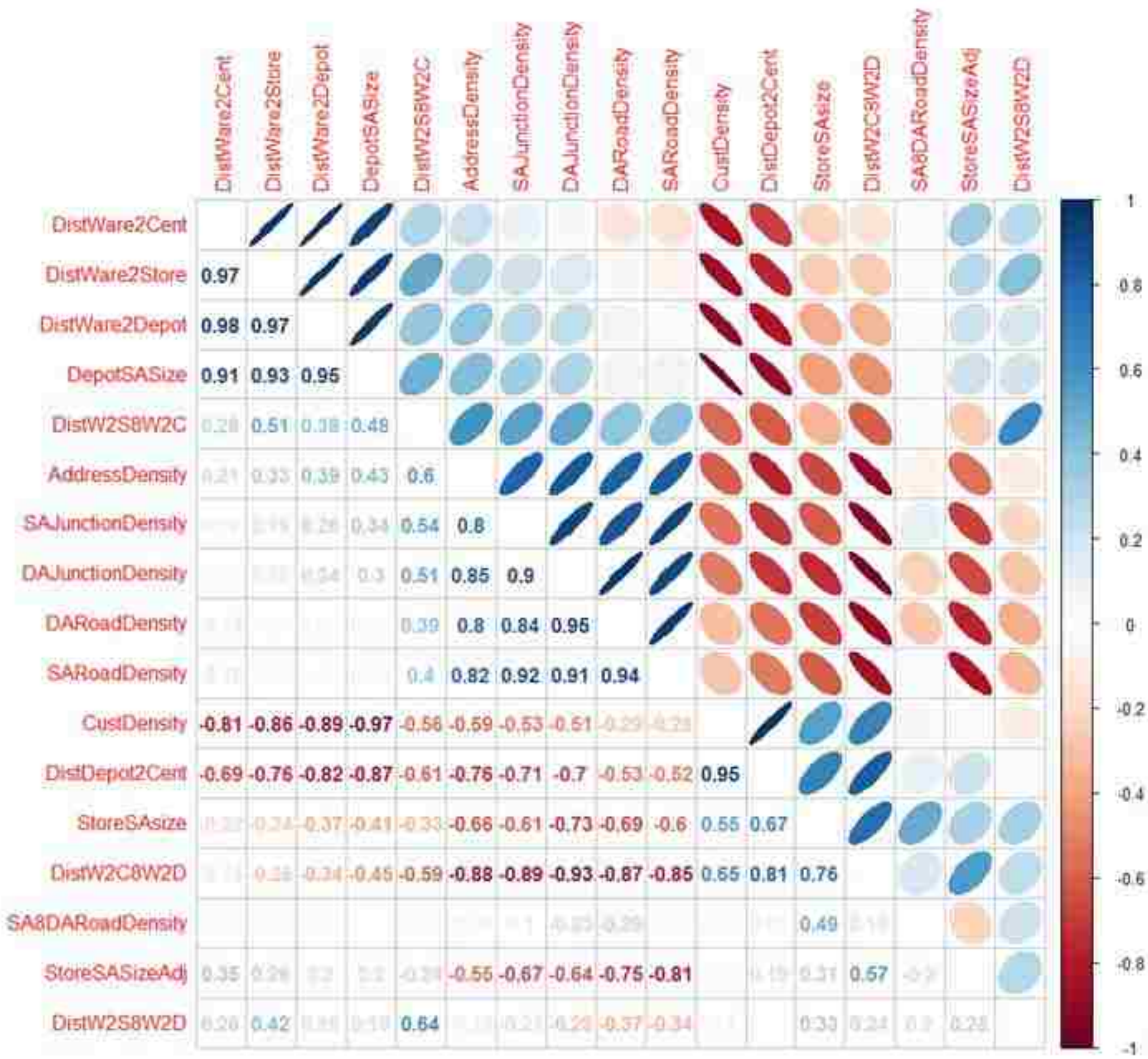
Additional variables were developed for the goods movement strategy comparisons. These were ratios between like variables. For example, the passenger travel models were evaluated for the road density in the store service area, while the delivery models were evaluated for the road density in the depot service area. For the comparison models, an extra variable representing the ratio of store service area road density to depot service area road density was included.

Descriptive statistics for all evaluated variables are included in Table 3. The correlation plot between these variables is illustrated in Figure 7. As is shown, the different measures of distance among the warehouse, stores, depots, and centroids were highly correlated. The various measures of road and junction density were highly correlated.

Table 3: Descriptive Statistics for Evaluated Independent Variables

	Minimum Value	Mean	Maximum Value	Standard Deviation	Units
Store Service Area Road Density	6.0	15.6	37.5	7.81	miles/square mile
Distance: Warehouse to Store	10.8	19.2	29.4	6.31	miles
Address Density	20.5	1009.1	2886.5	760.56	1/square miles
Store Service Area Junction Density	56.6	179.9	637.0	116.88	1/square miles
Store Service Area Size	0.5	6.6	20.6	3.95	square miles
Customer Density	1.6	2.9	4.9	1.43	1/square miles
Depot Service Area Road Density	9.8	16.3	31.9	8.64	miles/square mile
Distance: Warehouse to Depot	12.5	19.1	25.7	5.80	miles
Depot Service Area Junction Density	70.3	204.8	530.0	146.49	1/square miles
Distance: Depot to Centroid	0.2	2.1	4.2	1.51	miles
Distance: Warehouse to Centroid	12.8	20.0	27.0	5.89	miles
Store:Depot Service Area Road Density	0.60	0.98	1.31	0.17	
Distance - Warehouse to Store: Warehouse to Centroid	0.72	0.96	1.25	0.09	
Distance - Warehouse to Centroid: Warehouse to Depot	0.93	1.05	1.14	0.08	
Distance - Warehouse to Store: Warehouse to Depot	0.67	1.00	1.19	0.07	

Figure 7: Correlations between Evaluated Independent Variables



RESULTS

Evaluation of Goods Movement Schemes by Municipality

Figure 8 and Figure 9 illustrate the service areas for the grocery stores and local depots. The 35-household samples were drawn from the households within each depot service area. One of the stocking routes used to supply the stores or local depots is shown in Figure 8. One of the household samples and the associated routes for passenger travel and for local-depot-based delivery are shown in Figure 9.

Figure 8: Illustrations of Example Stock Routes

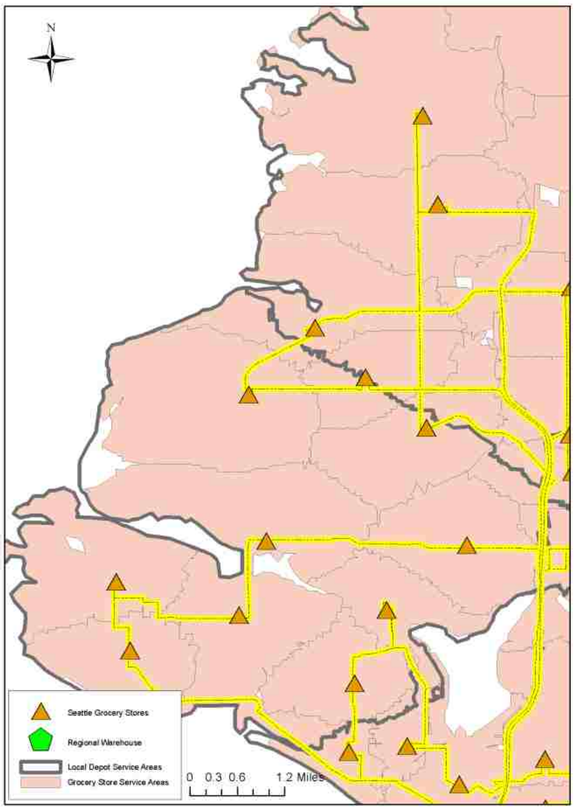
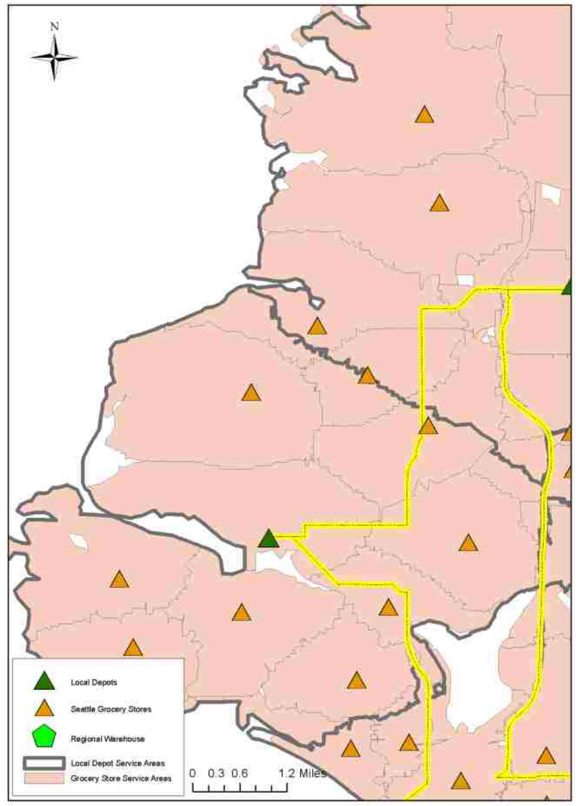
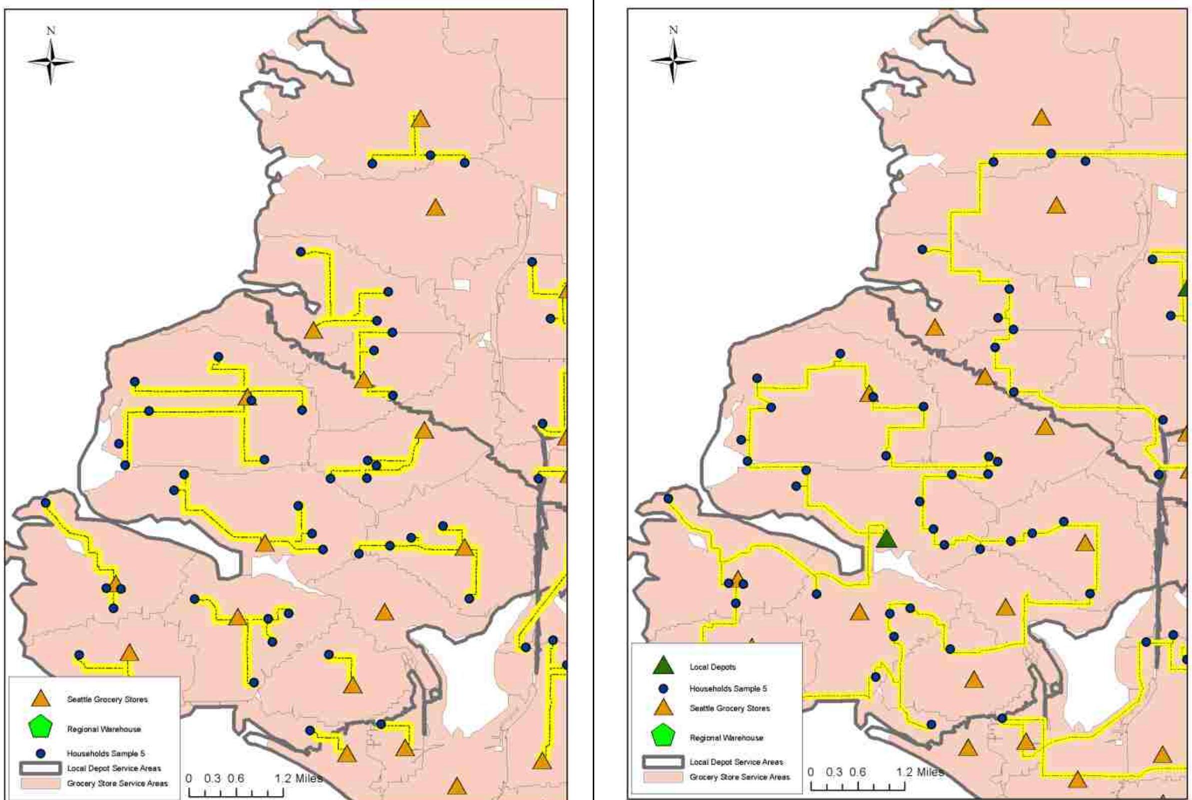
Warehouse to Stores (Combination Short Haul Truck)	Warehouse to Local Depots (Combination Short Haul Truck)
	

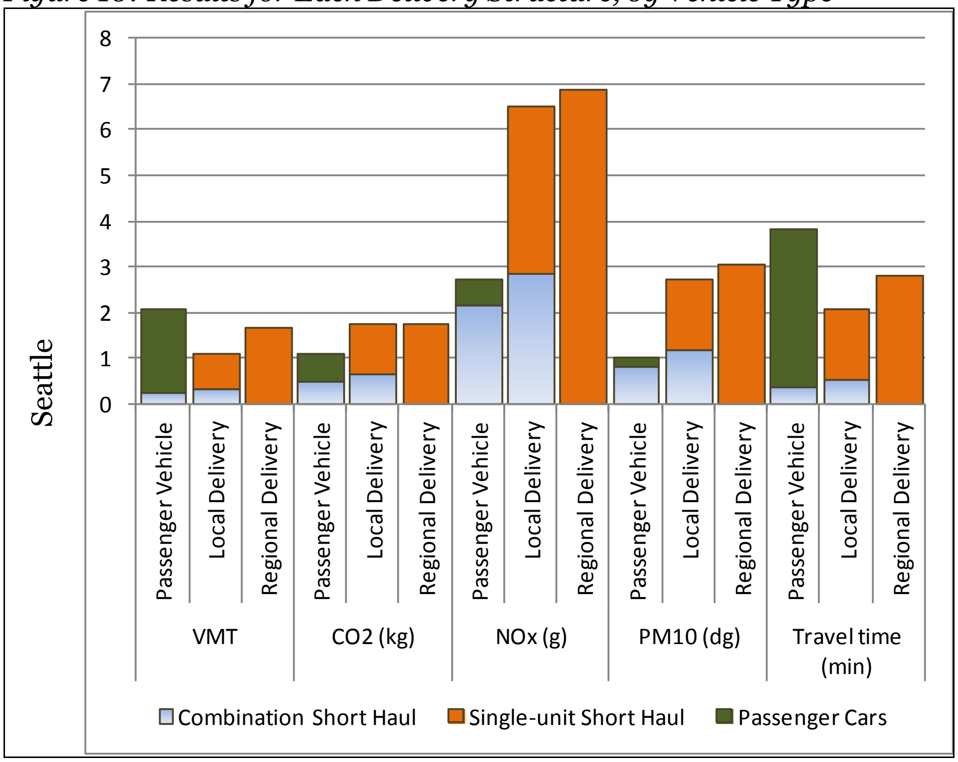
Figure 9: Illustrations of Example Final Travel to Homes

Passenger Vehicles (Passenger Cars)	Delivery Vehicle (Single-Unit Short Haul Truck)

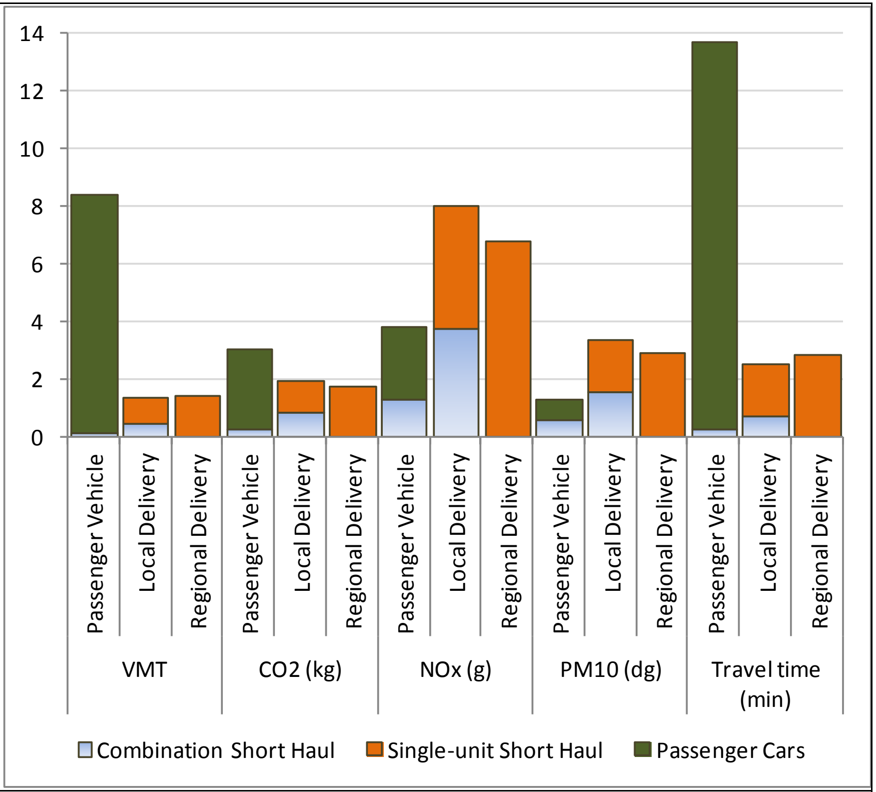


Looking at the results from the three different delivery structures (Figure 10), the relative contributions of the different legs of the supply chain become apparent. Personal travel requires the largest number of vehicle miles traveled but generates moderate levels of pollutants. Any use of a combination short haul truck within a supply chain involves significant emissions production, while the passenger cars contribute very small amounts of the studied emissions and practically no PM10. Combination short haul trucks have particularly high rates of NOx emissions, relatively. In Black Diamond, where the regional warehouse delivery system generates only slightly higher levels of VMT than the local depot delivery system but fewer emissions of NOx and PM10, the relative impact of the combination short haul trucks is apparent.

Figure 10: Results for Each Delivery Structure, by Vehicle Type



Black Diamond



Sammamish

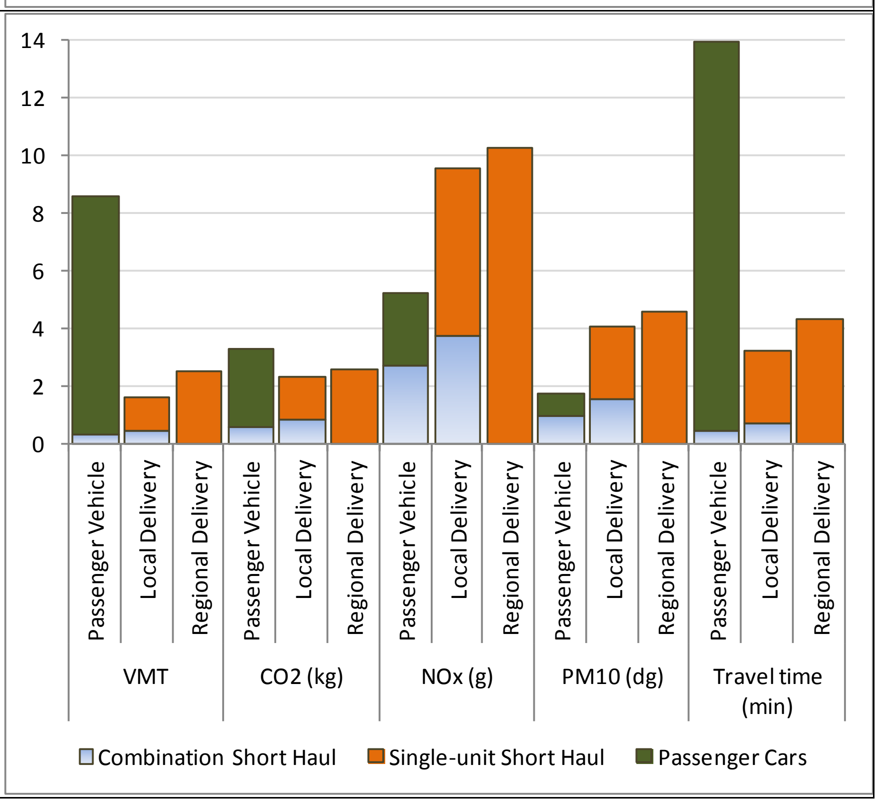


Table 4 displays the data that supports Figure 10. It includes averaged data about each leg of the supply chain for each scenario: the trip from warehouse to store or depot and the trip from the store or depot to the addresses or the trip directly from the warehouse to the addresses.

Local Depot Delivery service – where a single-unit short haul truck delivers to homes from a local depot stocked by a combination short haul truck – requires the lowest amount of VMT. The efficiency of delivery is highlighted by comparing the amount of VMT generated by passenger cars compared to the corresponding final-leg delivery vehicle. Even when the delivery vehicle is serving homes from a regional warehouse, it still requires fewer VMT than if individual homes travel directly to their closest grocery store.

The results in Table 4 also highlight the benefit of delivering to stops that are clustered together. While the combination trucks all serve 5 stores or depots, the stores are clustered together in the routes. The depots are spread throughout the city or region and require more travel to serve from the warehouse. Further, the personal vehicles require twice as much travel to get from the homes to the stores as the delivery vehicle requires to serve those homes from a local depot even though the personal travel goes to the closest store and the local depot is serving an entire quadrant of the city.

By leveraging the efficiency of a delivery structure, local depot delivery directly has the lowest VMT any of the cases. A goods movement system relying on passenger vehicles for the last mile has the highest levels of VMT and the highest levels of CO_2 for two of the municipalities. It does, however, produce the lowest levels of the studied criteria pollutants (NO_x and PM_{10}) for the three municipalities. The goods movement system producing the lowest levels of CO_2 varies by municipality, with each of the three studied locations relying on a different goods movement structure to minimize carbon dioxide generation. The two delivery systems produce the highest criteria pollutants, but the least efficient system varies by municipality.

Table 4: Vehicle Miles Traveled, Emissions, and Travel Time by Supply Chain Leg and Design

			VMT	CO2 (kg)	Nox (g)	PM10 (dg)	Travel time (min)
Seattle	Last Mile Personal Travel	To stores	0.3	0.5	2.2	0.8	0.4
		To addresses	1.8	0.6	0.6	0.2	3.5
		Total	**2.1**	**1.1**	**2.7**	**1.0**	**3.8**
	Local Depot Truck Delivery	To depots	0.3	0.7	2.8	1.2	0.5
		To addresses	0.8	1.1	3.7	1.6	1.6
		Total	**1.1**	**1.7**	**6.5**	**2.8**	**2.1**
	Regional Truck Delivery	**To addresses**	**1.7**	**1.8**	**6.9**	**3.1**	**2.8**
Black Diamond			VMT	CO2 (kg)	Nox (g)	PM10 (dg)	Travel time (min)
	Last Mile Personal Travel	To 5 stores	0.2	0.3	1.3	0.6	0.3
		To addresses	8.3	2.7	2.5	0.7	13.5
		Total	**8.4**	**3.0**	**3.8**	**1.3**	**13.8**
	Local Depot Truck Delivery	To 5 depots	0.5	0.9	3.8	1.6	0.7
		To addresses	0.9	1.1	4.2	1.8	1.9
		Total	**1.4**	**2.0**	**8.0**	**3.4**	**2.6**
	Regional Truck Delivery	**To addresses**	**1.5**	**1.7**	**6.8**	**2.9**	**2.9**
Sammamish			VMT	CO2 (kg)	Nox (g)	PM10 (dg)	Travel time (min)
	Last Mile Personal Travel	To 10 stores	0.3	0.6	2.7	1.0	0.5
		To addresses	8.3	2.7	2.5	0.7	13.5
		Total	**8.6**	**3.3**	**5.2**	**1.7**	**14.0**
	Local Depot Truck Delivery	To 5 depots	0.5	0.9	3.8	1.6	0.7
		To addresses	1.2	1.5	5.8	2.5	2.6
		Total	**1.6**	**2.4**	**9.6**	**4.1**	**3.3**
	Regional Truck Delivery	**To addresses**	**2.5**	**2.6**	**10.3**	**4.6**	**4.3**

Table 5 summarizes the goods movement system that produces the highest and lowest levels of VMT, CO2, Nox, PM10, and Travel Time for each municipality.

Table 5: Summary of Delivery Structure Impacts

		VMT	CO2 (kg)	Nox (g)	PM10 (g)	Travel time (min)
lowest	Seattle	1.1	1.1	2.7	0.10	2.1
	Black Diamond	1.4	1.7	3.8	0.13	2.6
	Sammamish	1.6	2.4	5.2	0.17	3.3
highest	Seattle	2.1	1.8	6.9	0.3	3.8
	Black Diamond	8.4	3.0	8.0	0.34	13.8
	Sammamish	8.6	3.3	10.3	0.46	14.0

Passenger Vehicles
Local Depot Delivery
Regional Warehouse Delivery

The results were also evaluated for significance using the two-tailed t-test. All comparisons were significantly different with p-values ($p \leq 0.001$), except for the difference in pollution generation between the two delivery systems in Seattle and the difference in VMT for the two delivery systems in Black Diamond. In Seattle, no significant difference between the two delivery systems was observed in the generation of CO2. The difference in NOx generation in Seattle between the two delivery systems was significant only at the $p \leq 0.1$ level, and the difference in PM10 generation was significant at the $p \leq 0.01$ level. The difference in VMT between the two delivery systems in Black Diamond was significant at the $p \leq 0.005$ level.

Detailed results of the t-tests are included in Table 6 and illustrate that variations across samples are small compared to the variation between scenarios.

Table 6: t-test Results

			VMT	CO2 (kg)	Nox (g)	PM10 (g)	Travel time (min)
Seattle	Passenger Vehicle vs Local Depot	t statistic	27.18	10.85	54.23	57.34	27.32
		d.f.	461	26	27	26	406
		p-value	0.000	0.000	0.000	0.000	0.000
	Passenger Vehicle vs Regional Warehouse	t statistic	5.42	11.53	19.27	19.84	10.07
		d.f.	36	26	24	24	52
		p-value	0.000	0.000	0.000	0.000	0.000
	Local Depot vs Regional Warehouse	t statistic	8.09	0.39	1.73	2.96	8.43
		d.f.	26	48	29	28	30
		p-value	0.000	0.701	0.094	0.006	0.000
			VMT	CO2 (kg)	Nox (kg)	PM10 (kg)	Travel time (min)
Black Diamond	Passenger Vehicle vs Local Depot	t statistic	95.08	26.70	32.88	38.24	78.89
		d.f.	680	56	25	24.88	560
		p-value	0.000	0.000	0.000	0.00	0.000
	Passenger Vehicle vs Regional Warehouse	t statistic	95.85	35.70	27.57	35.25	78.13
		d.f.	822	73	26	25.26	684
		p-value	0.000	0.000	0.000	0.00	0.000
	Local Depot vs Regional Warehouse	t statistic	3.11	5.04	7.49	6.75	4.49
		d.f.	46	47	47	46.51	47
		p-value	0.003	0.000	0.000	0.00	0.000
			VMT	CO2 (kg)	Nox (kg)	PM10 (kg)	Travel time (min)
Sammamish	Passenger Vehicle vs Local Depot	t statistic	95.80	27.95	42.24	52.71	77.60
		d.f.	817	80	27	26	735
		p-value	0.000	0.000	0.000	0.000	0.000
	Passenger Vehicle vs Regional Warehouse	t statistic	83.80	22.79	59.69	77.24	71.15
		d.f.	824	120	28	26	853
		p-value	0.000	0.000	0.000	0.000	0.000
	Local Depot vs Regional Warehouse	t statistic	30.51	7.81	5.55	9.98	19.17
		d.f.	48	46	46	47	45
		p-value	0.000	0.000	0.000	0.000	0.000

Developing Regression Models for Each Goods Movement Scheme

The results of the previous section indicate some aspects of urban form do influence the impacts of a goods movement system. In Seattle, a fairly dense urban area, passenger vehicle use resulted in the least of all three studied emissions, despite its overall high level of VMT generation. In the two more rural municipalities – Black Diamond and Sammamish – delivery options were able to reduce CO2 emissions even if they could not reduce criteria pollutants. However, there are a number of differences among these places. They vary in terms of their customer density, network density, number of stores and depots, and their distance to the regional warehouse. To shed some light into the factors that influence VMT and emissions generation, regression models were developed for each of the three goods movement methods. As discussed in the Methods section, a modified forward selection was conducted to develop Best Fit and Parsimonious models. For this analysis, all of the delivery addresses for all three municipalities were combined into one data set to enable testing of the variables discussed above, resulting in a sample size of 2625 addresses. Table 7 illustrates the resulting models for each of 4 dependent variables for each of the three goods movement strategies.

Table 7: Best Fit Models for Each Goods Movement Strategy

Passenger Vehicle

	r^2	Intercept	Store Service Area Road Density	Distance: Warehouse to Store	Address Density	Store Service Area Junction Density	Store Service Area Size
VMT	0.686	10.990	-0.286	0.045	-0.001		
Co2	0.659	3.598	-0.088	0.031	-0.0003		
NOx	0.698	2.879	-0.034	0.111	-0.0003	-0.001	0.013
PM10	0.600	0.102	-0.001	0.003	-0.00001	-0.00003	0.0004

Local Depot Delivery

	r^2	Intercept	Depot Service Area Road Density	Distance: Warehouse to Depot	Depot Service Area Junction Density	Distance: Depot to Centroid
VMT	0.822	1.190	-0.028	0.024	0.001	0.032
Co2	0.647	1.833	-0.035	0.029	0.001	0.020
NOx	0.873	7.006	-0.181	0.135	0.004	0.229
PM10	0.871	0.294	-0.008	0.006	0.0002	0.010

Regional Warehouse Delivery	r^2	Intercept	Customer Density	Depot Service Area Road Density	Depot Service Area Junction Density	Distance: Warehouse to Centroid
VMT	0.969	0.567	-0.008	-0.018	0.001	0.077
Co2	0.945	0.930	0.022	-0.028	0.001	0.067
NOx	0.948	3.602	0.075	-0.112	0.003	0.266
PM10	0.956	0.149	0.002	-0.005	0.0001	0.013

As seen in Table 7, a relatively small number of variables influences each model. Further, the variables that influence the models for each delivery structure are consistent, with the same variables appearing in all four models across each of the local depot and regional warehouse delivery models. For the passenger vehicle structure, the models for VMT and CO2 result in the same set of selected variables, as do the models for NOx and PM10. The models shown here all explain at least 60 percent of the variation observed, with as much as 95 percent of the variation observed for regional warehouse delivery explained. All of the models rely on a form of road density and distance from the warehouse to some part of the service area. Junction density and customer or address density appear in a majority of the models.

Lastly, the coefficients have consistent signs across most of the models. Road density always has a negative influence (increased road density results in lower VMT, CO2, NOx, and PM10). An increased distance between the warehouse and service area always results in higher values for the dependent variables. Increased customer density results in lower VMT but higher CO2, NOx, and PM10 for the regional warehouse delivery. In contrast, increased address density for passenger vehicle travel results in lower VMT and lower CO2, NOX, and PM10 emissions. The junction density variables have consistent signs for the delivery models (increased junction density increases the VMT, CO2, NOx, and PM10), but those signs are opposite the signs for junction density in the passenger travel models for NOx and PM10.

While these models are explanatory, they have two primary limitations. First, simpler models explain much of the variation observed in the Best Fit models. Second, some of the independent variables included in the Best Fit models covary. For example, the variables for junction density and road density are highly correlated. For these reasons, Parsimonious Models were developed. These models are seen in Table 8.

Table 8: Parsimonious Models for Each Goods Movement Strategy

Passenger Vehicle		r^2	Intercept	Store Service Area Road Density	Distance: Warehouse to Store
	VMT	0.677	12.127	-0.369	
	Co2	0.641	4.300	-0.114	
	NOx	0.692	3.507	-0.081	0.094
	PM10	0.596	0.118	-0.002	0.003

Local Depot Delivery		r^2	Intercept	Depot Service Area Road Density	Distance: Warehouse to Depot
	VMT	0.818	1.343	-0.021	0.020
	Co2	0.643	1.876	-0.024	0.028
	NOx	0.865	8.054	-0.129	0.109
	PM10	0.864	0.034	-0.006	0.005

Regional Warehouse Delivery		r^2	Intercept	Depot Service Area Road Density	Distance: Warehouse to Centroid
	VMT	0.967	0.424	-0.009	0.081
	Co2	0.942	0.980	-0.016	0.066
	NOx	0.945	3.700	-0.062	0.266
	PM10	0.953	0.149	-0.003	0.013

As seen in Table 8, these models can be reduced to one or two variables: some measure of road density and some measure reflecting the distance from the warehouse to the service area. The r^2 values for the Best Fit models are no more than 0.018 better, and as little as 0.002 improvement is seen. In all of the Parsimonious Models, road density negatively influences the dependent variables, and the distance from the warehouse to the service area has a positive influence.

Developing Regression Models for Goods Movement Scheme Comparisons

The variables identified in the previous section, which influence the studied impacts of the three goods movement strategies, were used to focus evaluations of the comparative impacts of the strategies. Models were developed for each comparison (passenger vehicle travel vs. local depot delivery, passenger vehicle travel vs. regional warehouse delivery, and regional warehouse delivery vs. local depot delivery) for each of the studied impacts. The variables that appear in the Parsimonious models for the two goods movement strategies under consideration were included in the regression analysis. For example, when evaluating the variables that influence the relative impacts of passenger vehicle travel versus local depot delivery, Store Service Area Road Density, Depot Service Area Road Density, Distance from Warehouse to Store, and Distance from Warehouse to Depot were included. Further, ratios comparing Store Service Area Road Density to Depot Service Area Road Density and the two distances were also developed and included. This model therefore had six potential variables included. The results for the Best Fit models are shown in Table 9.

Table 9: Best Fit Models for Goods Movement Strategy Comparisons

Passenger Vehicles vs. Local Depot Delivery	r^2	Intercept	Store Service Area Road Density	Distance: Warehouse to Store	Depot Service Area Road Density	Distance: Warehouse to Depot	Store:Depot Service Area Road Density
VMT	0.699	9.084	-0.187	-0.017	-0.155		1.706
Co2	0.556	1.455	-0.066		-0.023	-0.009	0.620
NOx	0.238	-5.050	-0.033		0.077		0.331
PM10	0.546	-0.230			0.004	-0.001	

Passenger Vehicles vs. Warehouse Delivery	r^2	Intercept	Store Service Area Road Density	Distance: Warehouse to Store	Depot Service Area Road Density	Distance: Warehouse to Centroid	Store:Depot Service Area Road Density	Distance Warehouse to Store: Warehouse to Centroid
VMT	0.708	9.548	-0.198	-0.072	-0.151		1.895	
Co2	0.609	3.723	-0.057	0.057	-0.033	-0.098	0.517	-1.545
NOx	0.653	-1.174	-0.067		0.055	-0.162	0.615	
PM10	0.838	-0.053	-0.002		0.003	-0.010	0.021	

Regional Warehouse vs. Local Depot Delivery

	r^2	Intercept	Depot Service Area Road Density	Distance: Warehouse to Depot	Distance: Warehouse to Centroid	Distance Warehouse to Centroid: Warehouse to Depot
VMT	0.979	-0.710	0.003	0.052	0.010	
Co2	0.644	-0.813	0.005		0.038	
NOx	0.953	-7.938	0.009	0.581	-0.403	4.469
PM10	0.966	-0.265	0.001	0.020	-0.011	0.106

Most of the Best Fit models were able to explain more than half the variation in the comparisons. However, once again, the Best Fit models included variables that covary and did not provide significantly more explanatory power than simpler models. Table 10 illustrates the resulting Parsimonious models.

Table 10: Parsimonious Models for Goods Movement Strategy Comparisons

Passenger Vehicles vs. Local Depot Delivery

	r^2	Intercept	Depot Service Area Road Density	Distance: Warehouse to Depot
VMT	0.691	10.252	-0.322	
Co2	0.544	1.840	-0.082	
NOx	0.235	-4.754	0.047	
PM10	0.546	-0.230	0.004	-0.001

Passenger Vehicles vs. Warehouse Delivery

	r^2	Intercept	Distance: Warehouse to Store	Depot Service Area Road Density	Distance: Warehouse to Centroid
VMT	0.701	11.086	-0.065	-0.328	
Co2	0.599	2.620	-0.040	-0.085	
NOx	0.644	-0.789			-0.158
PM10	0.835	-0.037		0.001	-0.010

Regional Warehouse vs. Local Depot Delivery

	r^2	Intercept	Depot Service Area Road Density	Distance: Warehouse to Depot	Distance: Warehouse to Centroid
VMT	0.978	-0.662		0.062	
Co2	0.644	-0.813	0.005		0.038
NOx	0.949	-3.565	0.030	0.159	
PM10	0.965	-0.165	0.001	0.008	

As with the individual models, one or two variables was able to explain much of the variation observed. Variable selection for the parsimonious models relied only on direct measures of distance and road density, and none of the ratios were selected for these models. Further, once again the r^2 values are not substantially larger with the Best Fit models than the parsimonious models. Differences as little as 0.001 and not larger than 0.012 are observed between the r^2 values.

Using this information along with the differences observed in the estimated impacts for each municipality allows us to evaluate the tipping point for CO2 reduction when replacing Passenger Vehicle travel. Solving for 0 with Equation 3(below), indicates that when the road density in the depot service area is at least 22.43 miles/square mile, passenger travel will result in lower CO2 emissions than local depot delivery. Black Diamond's 78 linear miles of road represent 10 linear miles of road for every square mile, and Sammamish's 215 linear miles of road represent about 9.7 linear miles of road for every square mile. In contrast, Seattle's over 2000 linear miles of road represent more than 24 linear miles of road for every square mile of land – just above the threshold. The relationships between the studied municipalities and the identified threshold is illustrated in Figure 11.

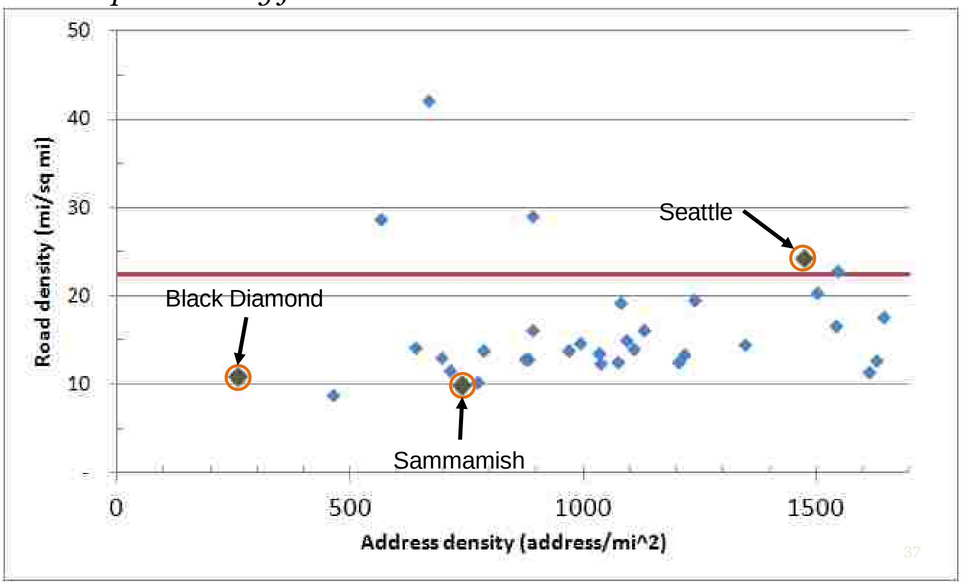
Equation 3: Difference in CO2 between Passenger Travel and Local Depot Delivery

$$CO2_{\text{passenger travel-local depot delivery}} = 1.840-0.082 * \delta$$

Where

δ : Depot Service Area Road Density

Figure 11: Studied Municipalities and Other King County, Washington Municipalities Compared to Address Density and Road Density Thresholds between Passenger Travel and Local Depot Delivery for CO2 Emissions



Because the parallel equation comparing passenger vehicle travel and warehouse delivery relies on two variables (Equation 4) the tipping point cannot be solved. However, the graph below illustrates the sensitivity analysis for the two variables. Any point below the line is a scenario in which Warehouse-based Delivery is estimated to generate lower CO_2 emissions than Passenger vehicle travel (see Figure 12). Figure 13 illustrates where the municipalities in King County, Washington – including the ones studied here – fall relative to that line.

Equation 4: Difference in CO2 between Passenger Travel and Warehouse-Based Delivery

$$CO2_{\text{passenger travel-warehouse-based delivery}} = 2.620-0.04*L-0.085*\delta$$

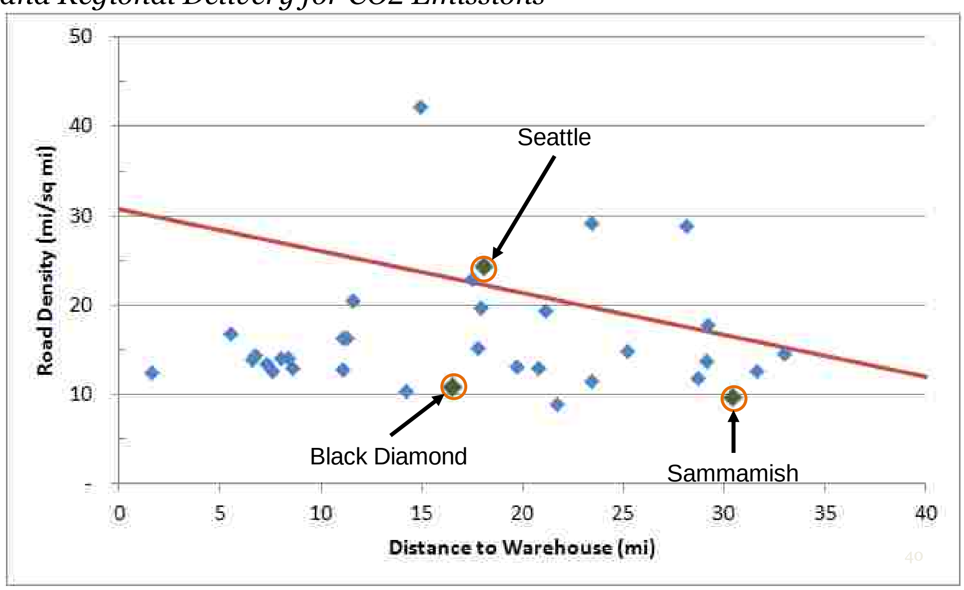
Where

L : Distance from Warehouse to Store

δ : Depot Service Area Road Density

Figure 12: Sensitivity Analysis Threshold Comparing Influences on CO2 Emissions between Passenger Vehicles and Warehouse Delivery Goods Movement Schemes

Figure 13: Studied Municipalities and Other King County, Washington Municipalities Compared to Distance to Warehouse and Road Density Thresholds between Passenger Travel and Regional Delivery for CO2 Emissions



CONCLUSIONS

This work supports earlier findings that VMT can be reduced by delivery schemes. Earlier efforts found VMT reduction between passenger travel and delivery vehicles to range from 50 to 95 percent (Cairns 1997, 1998, 2005; Punakivi and Saranen, 2001; Punakivi et al., 2001;

Punakivi and Tanskanen, 2002; Siikavirta et al., 2002; Wygonik and Goodchild 2012). This work, which included both urban and more rural areas and more realistic comparisons between delivery service areas and retail customer sheds, found a wider range in the VMT reduction. In Seattle, reductions in VMT as small as 20% were observed when passenger vehicle travel was replaced by warehouse-based delivery service. However, in the more rural areas, where passenger vehicle trips are longer and the delivery service areas more closely resemble the retail store customer sheds, the reductions in VMT were between 70 and 85 percent. Likewise, the work here saw reductions in CO2 only in the more rural areas, and observations of 20 to 45 percent were at the low end of the 20-90 percent reduction range observed in the earlier studies (Wygonik & Goodchild 2012, Siikavirta et al. 2002).

The results show there is some trade-off between VMT and pollutants. While the Local Depot Delivery has the lowest VMT levels, in some cases it generates the highest levels of criteria pollutants. Further, the passenger travel system generates the highest VMT but the lowest levels of criteria pollutants. Frequently, transportation policies and operating systems are designed to address VMT and congestion. If a region is also concerned with pollution, it will have to decide how to value the different impacts to decide how to shape policy. Combination trucks produce exceptionally high levels of NOx and PM10. These criteria pollutants have localized impacts. Policies that limit big trucks near population centers my increase VMT, but they may be worth it to ameliorate local health impacts from NOx and PM10.

Linear models were estimated via regression modeling for each dependent variable for each goods movement strategy and their comparisons. Parsimonious models maintained nearly all of the explanatory power of more complex models and relied on one or two variables – a measure of road density and a measure of distance to the warehouse. Increasing road density or decreasing the distance to the warehouse reduces the impacts as measured in the dependent variables (VMT, CO_2, NOx, and PM10).

Limitations

This work provided useful insight regarding the relationship between land use and VMT, and CO_2, PM10, and NOx emissions. However, a number of limitations remain.

This work relied on data from King County, Washington. While the selected municipalities reflected the range of densities observed in that county, it is not reflective of the entire range of densities observed across the United States or in other countries.

The work also assumed a roundtrip was conducted between addresses and stores and that roundtrip was replaced by a delivery service. While carpooling or using transit service to replace a commute trip would be purely substitutional, the same relationship is not guaranteed with shopping behavior. Personal shopping trips that are replaced by delivery service may be backfilled with other trips, including other shopping trips. Further, a replacement may occur between final purchase in store with an online purchase, but recent data indicates customers will still shop in the store to gather data before making their purchase, so-called showrooming. Lastly, while the evidence indicates most shopping transportation does occur with personal vehicles and does involve roundtrips, some shopping does occur using walking, biking or transit and some shopping is part of chained trips. In addition, this analysis assumed customers would travel to the closest store. While the available data indicates this assumption is mostly true (recall, customers were reported to shop at the closest store of its type), it is not strictly true and has the effect of underestimating the impacts of the personal travel scenario. Some minor error is introduced in that addresses but not individual units were sampled. Since zoning laws tend to focus multifamily homes and multiple-occupant commercial space toward central business districts and arterials, this sampling error has the potential to bias the results in the other direction – overestimating the impacts from personal travel. These units are, however, the most likely to take advantage of alternative modes to conduct shopping activities due to their proximity.

Another limitation to generalizing these results, reflects the number and location of the warehouses and depots. The results point to the influence of the distance to the warehouse on the measures. Because of the land use patterns and physical constraints in King County, Washington (due to bodies of water, mountains, and existing urban areas), the range of distances to the warehouse was relatively small. Less geographically-constrained regions of the country may have much longer distances to warehouses.

While some reductions in CO_2 emissions were estimated through the use of delivery service, this model is not able to include secondary benefits to CO_2 emissions from congestion reduction. This secondary effect will have the largest impact in urban areas which are already significantly impacted by high levels of congestion. The more dense areas are the places where reductions in CO_2 emissions are not observed directly by replacing personal travel with delivery service. While rural areas would be less impacted by secondary effects of congestion reduction, the significant reductions seen in CO_2 generation when personal travel is replaced by delivery service could be eliminated if some of the personal travel trips are not eliminated but are replaced by other travel.

Finally, this analysis assumed trucks would utilize existing diesel engine technology. Diesel engines generate high levels of the evaluated pollutants and will limit the potential advantage of VMT reductions. Leveraging other types of engine technology may allow delivery services to positively affect all evaluated measures and eliminate the observed trade-offs.

Discussion

These results show notable sensitivity to the structure of the depot, the depot location, routes traveled, and business model. Earlier work by Wygonik and Goodchild (2012) found delivery services reduced VMT and CO2 emissions when used in lieu of passenger vehicle travel. These results conditionally support those findings. Understanding operational details and including them in modeling efforts is necessary to evaluate the efficacy of these services. On-going work should pursue the influence of customer density thresholds, depot density, regional warehouse location sensitivity, and engine technology. Delivery service is one method of addressing some of the externalities from transportation. Further research will inform how to best leverage this transportation strategy. Shopping travel represents 14.5 percent of household vehicle miles travelled. (Hu and Reuscher 2004) Finding methods to reduce VMT associated with shopping has significant potential to address total VMT and resulting emissions.

This analysis relied on data provided by a local supplier, in which 35-households are served from a regional warehouse using one single-unit truck within the necessary time constraints. Different regional land use patterns with higher levels of sprawl might require significantly more travel from the regional warehouse to the urban center and restrict the number of households that can be served by each truck. Alternatively, lower customer demand may alter the usage levels of the vehicles or higher customer demand may enable more tightly clustered customers. While this analysis did not show particular sensitivity to customer density, there is mathematical support for its influence. As such, testing the assumptions in this work with different customer sample sizes and different truck occupancy levels is suggested.

Distance to the warehouse was a significant variable in the models developed. However, the variation in distance was limited. In rural places that are not as proximate to a major urban center, these distances would be expected to be considerably longer. Further evaluation of the sensitivity of the models to this variable is suggested.

In structuring this work, the author had expected to find a relationship between an aspect of the store service area to an aspect of the delivery service area to explain the relative efficiency of the goods movement strategies. This did not occur. Further, the author had anticipated customer density to be an important variables. This also did not occur. In practice, only direct measures – not comparative ones – informed the relative performance of the goods movement strategies. In addition, which density was important, it was the road density, not the customer density that influenced the results. Exploring other measures of transportation density and connectivity are therefore suggested.

A key aspect of this analysis is the assumed location of the local depots and the warehouse. Given the importance of distance and road density, the results may be highly sensitive to the locations chosen. Extensive random sampling of the households was conducted, but the depots were not similarly varied. The author suggests an evaluation in which the number and location of local depots are varied, in addition to the above suggestion to pursue a wider range of warehouse distances. Another aspect that may be highly influential are the assumptions made in this analysis regarding the number of depots and stores served by the stocking routes. As the relative contributions of the combination trucks are large, the results could be sensitive to variations in these assumptions. In addition, the efficiency of these stocking routes may vary with urban form – more distant and less dense areas may require less efficient stocking routes because of the additional time required to serve those locations.

Finally, this analysis relied on business-as-usual transportation methods: diesel-engine tractor trailers serving longer routes and bigger customers with single-unit diesel engine trucks or gasoline-engine passenger vehicles serving customers. Transportation methods that rely on lower emission technology (such as hybrid, electric, compressed natural gas or human-powered vehicles) or that involve more efficient operations (trip-training for passenger vehicles) will change the impacts observed.

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Appendix A: Python code for completing routing estimates in ArcGIS Network Analyst

Code for Routing from Depots

```
##get tools
import arcpy
arcpy.CheckOutExtension("Network")
## data location
arcpy.env.workspace = "E:\ArcGIS\Dissertation\data"

## to run through all of the samples
sample_count=['sample1','sample2','sample3','sample4','sample5','sample6','sample7','s
 ample8','sample9','sample10','sample11','sample12','sample13','sample14','sample15','sa
 mple16','sample17','sample18','sample19','sample20','sample21','sample22','sample23','
 sample24','sample25']
for i in range(len(sample_count)):
   print i+1, sample_count[i]
   outNALayerName =sample_count[i]
   print outNALayerName
   sql_query="%s=1" % (outNALayerName)
   print sql_query

## name variables and layers
   outLayerFile = "E:\ArcGIS\Dissertation\data\output"+"/"
 +outNALayerName+"Route.lyr"



## make Route

 outNALayer=arcpy.na.MakeRouteLayer("KingCounty3_ND",outNALayerName,"Trave
 lTm_s","FIND_BEST_ORDER","PRESERVE_BOTH","NO_TIMEWINDOWS",["Trave
 lTm_s","length_ft","SUSH_CO2","SUSH_NOx","SUSH_PM10"],"ALLOW_UTURNS",
 ["Oneway"],"USE_HIERARCHY","","TRUE_LINES_WITH_MEASURES")

## select grocery store depots

 arcpy.SelectLayerByAttribute_management("BlackDiamondSammamishGroceryStores
 ","NEW_SELECTION", '"FID" = 12 OR "FID" = 30')

## add depots

 arcpy.na.AddLocations(outNALayer,"stops","BlackDiamondSammamishGroceryStores
 ","Name  FID  #; RouteName FID #","5000 meters",
 "FID","","MATCH_TO_CLOSEST","CLEAR")

## select customers
   arcpy.SelectLayerByAttribute_management ("BlackDiamondSammamish",
 "NEW_SELECTION", sql_query)
```

```
## add customers

   arcpy.na.AddLocations(outNALayer,"stops","BlackDiamondSammamish","Name
 FID  #; RouteName LocalDepot #","5000 meters",
 "FID","","MATCH_TO_CLOSEST","APPEND")

## add return to depot stop


 arcpy.na.AddLocations(outNALayer,"stops","BlackDiamondSammamishGroceryStores
 ","Name  FID  #; RouteName FID #","5000 meters",
 "FID","","MATCH_TO_CLOSEST","APPEND")

##solve
   arcpy.na.Solve(outNALayer)

## save output
   arcpy.management.SaveToLayerFile(outNALayer,outLayerFile,"ABSOLUTE")
```

Code for Routing from Warehouses

```
##get tools
import arcpy
arcpy.CheckOutExtension("Network")
## data location
arcpy.env.workspace = "E:\ArcGIS\Dissertation\data"

## to run through all of the samples
sample_count=['sample1','sample2','sample3','sample4','sample5','sample6','sample7','s
 ample8','sample9','sample10','sample11','sample12','sample13','sample14','sample15','sa
 mple16','sample17','sample18','sample19','sample20','sample21','sample22','sample23','
 sample24','sample25']
for i in range(len(sample_count)):
   print i+1, sample_count[i]
   outNALayerName =sample_count[i]
   print outNALayerName
   sql_query="%s=1" % (outNALayerName)
   print sql_query

## name variables and layers
   outLayerFile = "E:\ArcGIS\Dissertation\data\output"+"/"
 +outNALayerName+"WarehouseRoute.lyr"



## make Route

 outNALayer=arcpy.na.MakeRouteLayer("KingCounty3_ND",outNALayerName,"Trave
 lTm_s","FIND_BEST_ORDER","PRESERVE_BOTH","NO_TIMEWINDOWS",["Trave
 lTm_s","length_ft","SUSH_CO2","SUSH_NOx","SUSH_PM10"],"ALLOW_UTURNS",
 ["Oneway"],"USE_HIERARCHY","","TRUE_LINES_WITH_MEASURES")


## add warehouses
   arcpy.na.AddLocations(outNALayer,"stops","Warehouses2","Name  FID  #;
 RouteName DepotID #","5000 meters", "FID","","MATCH_TO_CLOSEST","CLEAR")

## select customers
   arcpy.SelectLayerByAttribute_management ("BlackDiamondSammamish",
 "NEW_SELECTION", sql_query)

## add customers
```

```
  arcpy.na.AddLocations(outNALayer,"stops","BlackDiamondSammamish","Name
 FID  #; RouteName LocalDepot #","5000 meters",
 "FID","","MATCH_TO_CLOSEST","APPEND")

## add return to warehouses stop
  arcpy.na.AddLocations(outNALayer,"stops","Warehouses2","Name  FID  #;
 RouteName DepotID #","5000 meters", "FID","","MATCH_TO_CLOSEST","CLEAR")

##solve
  arcpy.na.Solve(outNALayer)

## save output
  arcpy.management.SaveToLayerFile(outNALayer,outLayerFile,"ABSOLUTE")
```

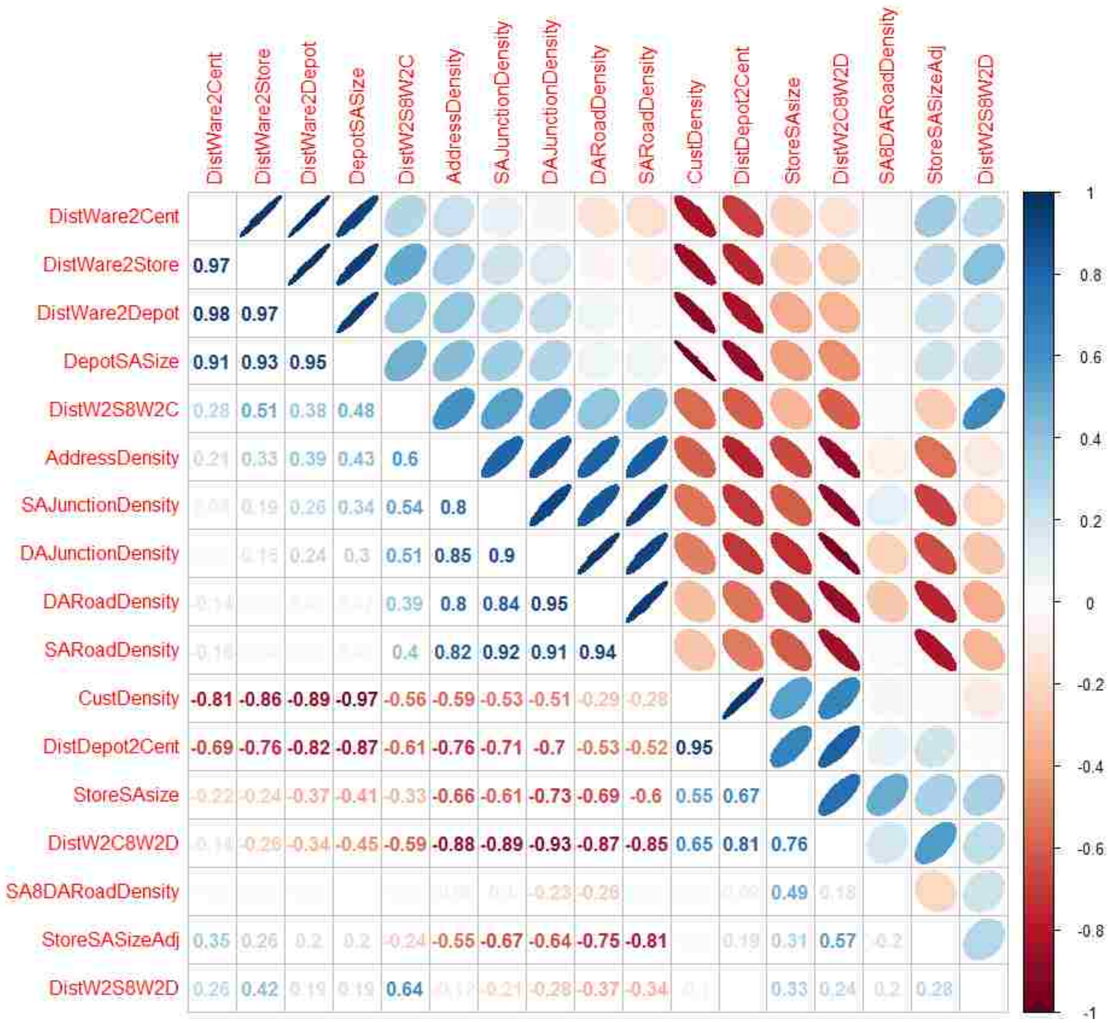
Appendix B: R Code and Results

```
setwd("C:/Documents and Settings/Eunice/My Documents/My
Dropbox/Research/Dissertation/data/Main analysis/")
Master35sRatios<-
read.csv("MasterData35sRatios.csv",header=TRUE,sep=",",quote="\"",dec=".",fill=TRUE,com
ment.char="")
summary(Master35sRatios)
           City          Sample     AddressDensity     StoreSAsize
 Black Diamond:875   Sample1-1 :   3   Min.   :  20.45   Min.   :0.470
 Sammamish    :875   Sample1-10:   3   1st Qu.: 261.12   1st Qu.:2.140
 Seattle      :875   Sample1-11:   3   Median : 993.32   Median :4.799
                     Sample1-12:   3   Mean   :1009.10   Mean   :4.921
                     Sample1-13:   3   3rd Qu.:1623.47   3rd Qu.:7.200
                     Sample1-14:   3   Max.   :2886.46   Max.   :7.528
                     (Other)   :2607
 DistWare2Store   DepotSASize     CustDensity    DistWare2Depot
 Min.   :10.83   Min.   : 7.20   Min.   :1.591   Min.   :12.50
 1st Qu.:12.50   1st Qu.: 7.20   1st Qu.:1.591   1st Qu.:12.50
 Median :18.56   Median :15.62   Median :2.241   Median :19.20
 Mean   :19.22   Mean   :15.08   Mean   :2.886   Mean   :19.07
 3rd Qu.:25.40   3rd Qu.:22.00   3rd Qu.:4.861   3rd Qu.:25.20
 Max.   :29.40   Max.   :22.00   Max.   :4.861   Max.   :25.70

 StoreSASizeAdj  SARoadDensity   SAJunctionDensity DARoadDensity
 Min.   : 0.47   Min.   : 5.98   Min.   : 56.59    Min.   : 9.77
 1st Qu.: 2.97   1st Qu.:10.69   1st Qu.: 70.28    1st Qu.: 9.77
 Median : 7.20   Median :10.79   Median :173.04    Median :10.79
 Mean   : 6.55   Mean   :15.58   Mean   :179.85    Mean   :16.26
 3rd Qu.: 7.20   3rd Qu.:22.63   3rd Qu.:278.18    3rd Qu.:25.67
 Max.   :20.59   Max.   :37.51   Max.   :636.99    Max.   :31.91

 DAJunctionDensity DistDepot2Cent  DistWare2Cent   SA8DARoadDensity
 Min.   : 70.28    Min.   :0.160   Min.   :12.81   Min.   :0.5979
 1st Qu.: 70.28    1st Qu.:0.990   1st Qu.:14.24   1st Qu.:0.9019
 Median :144.50    Median :1.230   Median :18.31   Median :1.0000
 Mean   :204.75    Mean   :2.093   Mean   :19.96   Mean   :0.9813
 3rd Qu.:348.98    3rd Qu.:4.170   3rd Qu.:26.96   3rd Qu.:1.0942
 Max.   :530.00    Max.   :4.170   Max.   :26.96   Max.   :1.3147

  DistW2S8W2D      DistW2C8W2D      DistW2S8W2C        PTVMT
 Min.   :0.6685   Min.   :0.9265   Min.   :0.7215   Min.   : 0.3312
 1st Qu.:0.9883   1st Qu.:0.9571   1st Qu.:0.8778   1st Qu.: 2.7633
 Median :1.0000   Median :1.0698   Median :0.9421   Median : 7.1007
 Mean   :1.0034   Mean   :1.0547   Mean   :0.9552   Mean   : 6.3812
 3rd Qu.:1.0119   3rd Qu.:1.1392   3rd Qu.:1.0200   3rd Qu.: 8.8393
 Max.   :1.1885   Max.   :1.1392   Max.   :1.2463   Max.   :15.3986

     PTCO2          PTNox          PTPM10            PTTT
 Min.   :0.473   Min.   :1.799   Min.   :0.07435   Min.   : 0.6072
 1st Qu.:1.444   1st Qu.:3.207   1st Qu.:0.11884   1st Qu.: 5.0987
 Median :2.748   Median :3.889   Median :0.13543   Median :11.6357
```

```
Mean   :2.523   Mean   :4.046   Mean   :0.14167   Mean   :10.5466
3rd Qu.:3.270   3rd Qu.:4.927   3rd Qu.:0.16454   3rd Qu.:13.8112
Max.   :5.730   Max.   :7.265   Max.   :0.22895   Max.   :28.8242

    LDVMT           LDCO2           LDNox           LDPM10
Min.   :0.9915   Min.   :1.444   Min.   : 5.893   Min.   :0.2483
1st Qu.:1.1605   1st Qu.:1.692   1st Qu.: 6.727   1st Qu.:0.2843
Median :1.3858   Median :2.051   Median : 8.153   Median :0.3471
Mean   :1.3710   Mean   :2.022   Mean   : 8.029   Mean   :0.3407
3rd Qu.:1.5792   3rd Qu.:2.341   3rd Qu.: 9.325   3rd Qu.:0.3955
Max.   :1.8206   Max.   :2.615   Max.   :10.546   Max.   :0.4481

     LDTT           WaVMT           WaCO2           WaNOx
Min.   :1.816   Min.   :1.170   Min.   :1.322   Min.   : 5.146
1st Qu.:2.162   1st Qu.:1.439   1st Qu.:1.703   1st Qu.: 6.603
Median :2.633   Median :1.639   Median :1.923   Median : 7.491
Mean   :2.636   Mean   :1.883   Mean   :2.048   Mean   : 7.990
3rd Qu.:3.150   3rd Qu.:2.448   3rd Qu.:2.556   3rd Qu.:10.016
Max.   :3.702   Max.   :2.776   Max.   :2.830   Max.   :11.091

    WaPM10           WaTT           PTLDVMT          PTLDCO2
Min.   :0.2266   Min.   :2.137   Min.   :-0.890   Min.   :-1.7199
1st Qu.:0.2877   1st Qu.:2.787   1st Qu.: 1.644   1st Qu.:-0.2542
Median :0.3239   Median :3.162   Median : 5.605   Median : 0.5905
Mean   :0.3542   Mean   :3.355   Mean   : 5.010   Mean   : 0.5009
3rd Qu.:0.4512   3rd Qu.:4.270   3rd Qu.: 7.355   3rd Qu.: 1.0956
Max.   :0.4995   Max.   :4.647   Max.   :13.890   Max.   : 3.5393

   PTLDNOx          PTLDPM10          PTLDTT          PTWaVMT
Min.   :-6.545   Min.   :-0.3142   Min.   :-1.657   Min.   :-1.549
1st Qu.:-4.549   1st Qu.:-0.2330   1st Qu.: 3.022   1st Qu.: 1.119
Median :-3.950   Median :-0.1968   Median : 8.693   Median : 5.137
Mean   :-3.983   Mean   :-0.1990   Mean   : 7.910   Mean   : 4.498
3rd Qu.:-3.392   3rd Qu.:-0.1637   3rd Qu.:10.902   3rd Qu.: 6.937
Max.   :-1.567   Max.   :-0.1084   Max.   :25.902   Max.   :13.701

   PTWaCO2           PTWaNOx           PTWaPM10           PTWaTT
Min.   :-1.3783   Min.   :-7.3502   Min.   :-0.37195   Min.   :-2.505
1st Qu.:-0.3580   1st Qu.:-4.8261   1st Qu.:-0.26887   1st Qu.: 2.315
Median : 0.5296   Median :-3.9180   Median :-0.20115   Median : 7.927
Mean   : 0.4755   Mean   :-3.9448   Mean   :-0.21250   Mean   : 7.191
3rd Qu.: 1.1475   3rd Qu.:-3.0857   3rd Qu.:-0.16035   3rd Qu.:10.285
Max.   : 3.6123   Max.   :-0.5294   Max.   :-0.06901   Max.   :25.580

   WaLDVMT            WaLDCO2            WaLDNOx            WaLDPM10
Min.   :-0.02442   Min.   :-0.82505   Min.   :-1.77729   Min.   :-0.07132
1st Qu.: 0.16110   1st Qu.:-0.22082   1st Qu.:-0.98492   1st Qu.:-0.03706
Median : 0.55555   Median : 0.04862   Median : 0.38945   Median : 0.03435
Mean   : 0.51201   Mean   : 0.02539   Mean   :-0.03852   Mean   : 0.01349
3rd Qu.: 0.87058   3rd Qu.: 0.27428   3rd Qu.: 0.84057   3rd Qu.: 0.05957
```

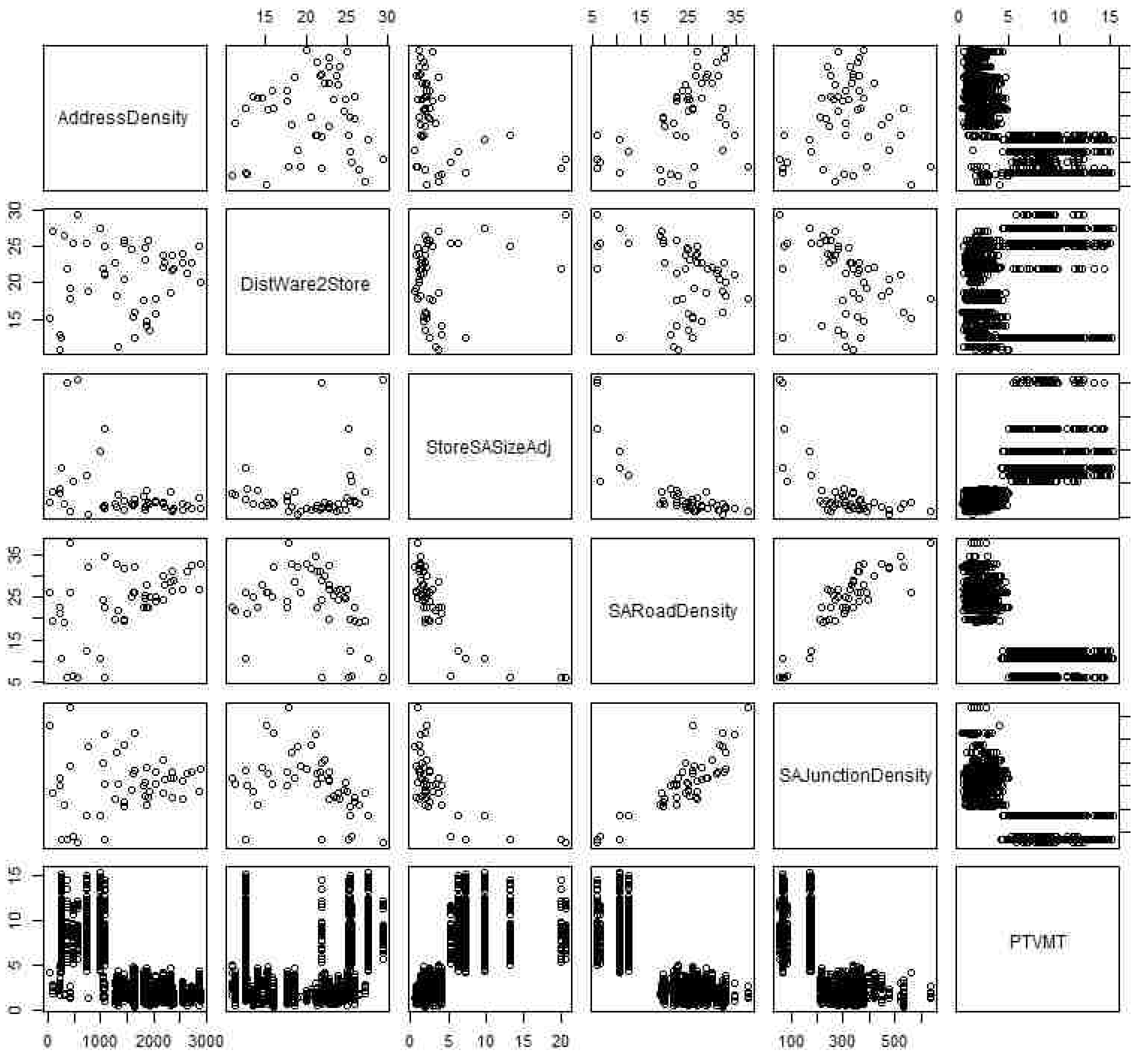
```
 Max.   : 1.03242   Max.   : 0.47510   Max.   : 1.61811   Max.   : 0.09170

    WaLDTT
 Min.   :0.1083
 1st Qu.:0.3130
 Median :0.8096
 Mean   :0.7191
 3rd Qu.:1.0902
 Max.   :1.2512
```

```
setwd("C:/Users/Erica/Documents/Dropbox/Research/Dissertation/data/Main analysis/")
Master35sRatios<-
read.csv("MasterData35sRatios.csv",header=TRUE,sep=",",quote="\"",dec=".",fill=TRUE,com
ment.char="")

DensDist=c("AddressDensity","StoreSAsize","DistWare2Store","DepotSASize","CustDensity","D
istWare2Depot","StoreSASizeAdj","SARoadDensity","SAJunctionDensity","DARoadDensity","D
AJunctionDensity","DistDepot2Cent","DistWare2Cent","SA8DARoadDensity","DistW2S8W2D"
,"DistW2C8W2D","DistW2S8W2C")
library(corrplot)
DDvars=Master35sRatios[DensDist]
M <- cor(DDvars)
ord <- corrMatOrder(M, order="AOE")
M2 <- M[ord,ord]
corrplot.mixed(M2, lower = "number", upper = "ellipse", tl.pos = "lt")
```



Other potentially useful code:
corrplot(M, method = "ellipse", order = "AOE")
tl.pos = "lt"
corrplot(M, method = "circle")

----
setwd("C:/Users/Erica/Documents/Dropbox/Research/Dissertation/data/Main analysis/")
Master35s<-
read.csv("MasterData35s.csv",header=TRUE,sep=",",quote="\"",dec=".",fill=TRUE,comment.char="")
PassVars=c("AddressDensity","DistWare2Store","StoreSASizeAdj","SARoadDensity","SAJunctionDensity","PTVMT")
PassTravel=Master35s[PassVars]
PassTravel[1:10,]
plot(PassTravel)



results1a=lm(PTVMT~SARoadDensity+StoreSASizeAdj,data=PassTravel)
summary(results1a)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTVMT	AddressDensity	StoreSASizeAdj	DistWare2Store	**SARoadDensity**	SAJunctionDensity
R^2	0.5143***	0.4394 ***	0.00229 *	**0.6768 *****	0.5518 ***
	AddressDensity	StoreSASizeAdj	DistWare2Store		SAJunctionDensity
	0.6819*/*****	0.6768 /***	0.6768 /***		0.6775 */***

		StoreSASizeAdj	**DistWare2Store**		SAJunctionDensity
		0.6823./***/***	**0.6855*****/***/***		0.6836***/***/***
		StoreSASizeAdj			SAJunctionDensity
		0.6856/***/***/***			0.6855/***/***/***

PTVMT	AddressDensity	StoreSASizeAdj	DistWare2Store	SARoadDensity	**SAJunctionDensity**
R^2	0.5143***	0.4394 ***	0.00229 *	0.6768 ***	**0.5518** ***
	AddressDensity	StoreSASizeAdj	DistWare2Store	SARoadDensity	
	0.595***/***	0.5999***/***	0.5891***/***	0.6775***/*	

PTVMT	AddressDensity	**StoreSASizeAdj**	DistWare2Store	SARoadDensity	SAJunctionDensity
R^2	0.5143***	**0.4394** ***	0.00229 *	0.6768 ***	0.5518 ***
	AddressDensity		DistWare2Store	SARoadDensity	SAJunctionDensity
	0.6196***/***		0.4563 ***/***		

PTVMT	**AddressDensity**	StoreSASizeAdj	DistWare2Store	SARoadDensity	SAJunctionDensity
R^2	**0.5143***	0.4394 ***	0.00229 *	0.6768 ***	0.5518 ***
			DistWare2Store		
			0.6036***/***		

Best fit SARoad Density, AddressDensity, DistWare2Store
Call:
lm(formula = PTVMT ~ SARoadDensity + AddressDensity + DistWare2Store,
   data = PassTravel)

Residuals:
```
    Min      1Q  Median      3Q     Max 
-4.8061 -1.3375  0.0620  0.9458  7.2358 
```

Coefficients:
```
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)   10.9935906  0.2020751  54.403  < 2e-16 ***
```

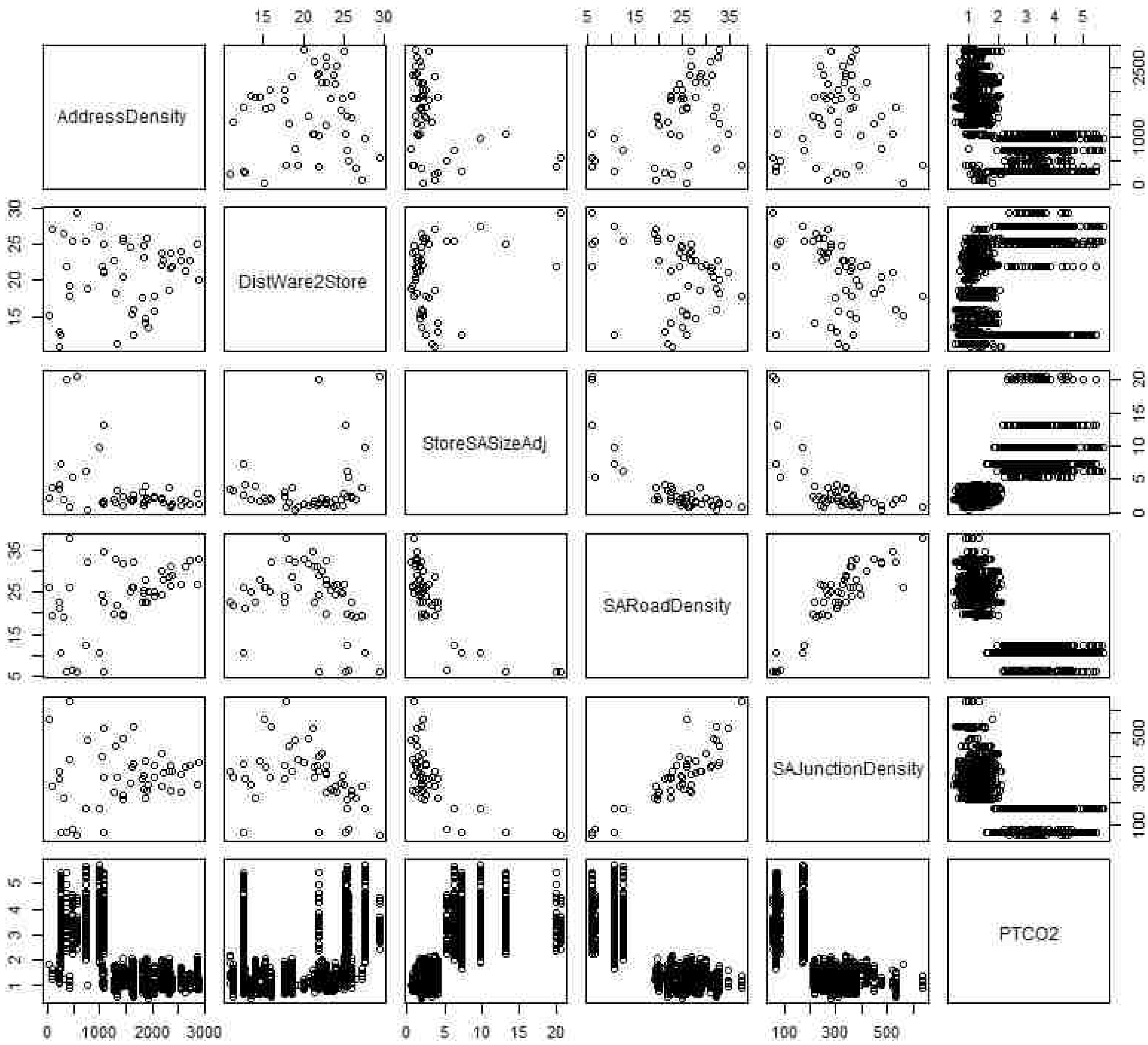
```
SARoadDensity  -0.2856866  0.0109357 -26.124  < 2e-16 ***
AddressDensity -0.0010107  0.0001186  -8.525  < 2e-16 ***
DistWare2Store  0.0446252  0.0081539   5.473 4.85e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.964 on 2621 degrees of freedom
Multiple R-squared:  0.6855,    Adjusted R-squared:  0.6851
F-statistic:  1904 on 3 and 2621 DF,  p-value: < 2.2e-16
```

============

SARoadDensity alone is most predictive/parsimonious for PTVMT:

```
> results2=lm(PTVMT~SARoadDensity,data=PassTravel)
> results2

Call:
lm(formula = PTVMT ~ SARoadDensity, data = PassTravel)

Coefficients:
  (Intercept)  SARoadDensity
      12.1269        -0.3689

> summary(results2)

Call:
lm(formula = PTVMT ~ SARoadDensity, data = PassTravel)

Residuals:
    Min      1Q  Median      3Q     Max
-4.9386 -1.4089 -0.0069  1.0257  7.5188

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   12.126949   0.086724  139.83   <2e-16 ***
SARoadDensity -0.368860   0.004977  -74.11   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.991 on 2623 degrees of freedom
Multiple R-squared:  0.6768,    Adjusted R-squared:  0.6766
F-statistic:  5492 on 1 and 2623 DF,  p-value: < 2.2e-16
```

```
PassVars=c("AddressDensity","DistWare2Store","StoreSASizeAdj","SARoadDensity","SAJunctionDensity","PTCO2")
PassCO2=Master35s[PassVars]
PassCO2[1:10,]
plot(PassCO2)
```



results10=lm(PTCO2~AddressDensity,data=PassCO2)
summary(results10)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTCO2	AddressDensity	StoreSASizeAdj	DistWare2Store	**SARoadDensity**	SAJunctionDensity
R^2	0.4361***	0.4446***	0.02129***	**0.6413*** **	0.4896***
	AddressDensity	StoreSASizeAdj	**DistWare2Store**		SAJunctionDensity
	0.6413 /***	0.6421*/***	**0.6507***/*** **		0.6485***/***
	AddressDensity	StoreSASizeAdj			SAJunctionDensity
	0.6589 */***/*** **	0.6507 /***/***			0.6517**/***/***

		StoreSASize Adj			SAJunctionDensity
		0.659 /***/***/***			0.6589 /***/***/***

SARoadDensity, DistWare 2 Store, AddressDensity best fit model

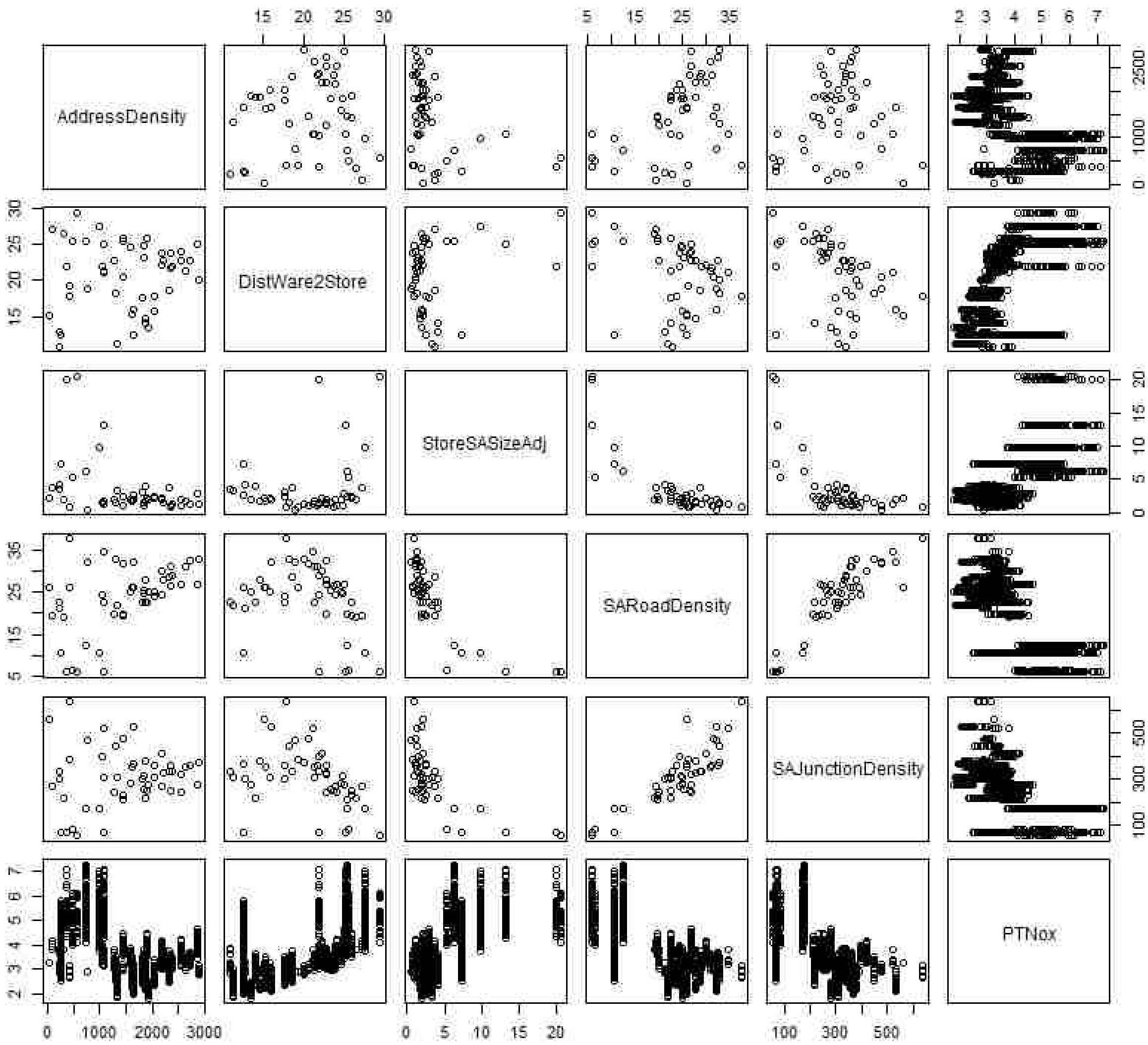
```
Call:
lm(formula = PTCO2 ~ SARoadDensity + DistWare2Store + AddressDensity,
   data = PassCO2)

Residuals:
     Min       1Q   Median       3Q      Max
-1.52434 -0.42404 -0.02623  0.28092  2.58144

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     3.598e+00  6.685e-02  53.829  < 2e-16 ***
SARoadDensity  -8.752e-02  3.618e-03 -24.192  < 2e-16 ***
DistWare2Store  3.135e-02  2.697e-03  11.624  < 2e-16 ***
AddressDensity -3.120e-04  3.922e-05  -7.953 2.68e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6498 on 2621 degrees of freedom
Multiple R-squared:  0.6589,    Adjusted R-squared:  0.6585
F-statistic:  1688 on 3 and 2621 DF,  p-value: < 2.2e-16
```

Again, SARoadDensity provides the most predictive and parsimonious model

```
results13=lm(PTCO2~SARoadDensity,data=PassCO2)
results13
Call:
lm(formula = PTCO2 ~ SARoadDensity, data = PassCO2)

Coefficients:
  (Intercept)  SARoadDensity
       4.2998        -0.1141
 summary(results13)

Call:
lm(formula = PTCO2 ~ SARoadDensity, data = PassCO2)

Residuals:
     Min       1Q   Median       3Q      Max
-1.46213 -0.44119 -0.05851  0.33555  2.78307
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    4.299838   0.029021  148.16   <2e-16 ***
SARoadDensity -0.114068   0.001666  -68.48   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6661 on 2623 degrees of freedom
Multiple R-squared:  0.6413,    Adjusted R-squared:  0.6412
F-statistic:  4690 on 1 and 2623 DF,  p-value: < 2.2e-16
```

```
PassVars=c("AddressDensity","DistWare2Store","StoreSASizeAdj","SARoadDensity","SAJuncti
onDensity","PTNox")
PassNOx=Master35s[PassVars]
PassNOx[1:10,]
plot(PassNOx)
```



results20=lm(PTNox~AddressDensity,data=PassNOx)
summary(results20)
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

PTCO2	AddressDensity	**StoreSASizeAdj**	DistWare2Store	SARoadDensity	SAJunctionDensity
R^2	0.1105***	**0.3923***	0.3447***	0.3895***	0.1923***
	AddressDensity		**DistWare2Store**	SARoadDensity	SAJunctionDensity
	0.3925/***		**0.5848***/***	0.4314***/***	0.3928/***
	AddressDensity			SARoadDensity	SAJunctionDensity

	0.6743***/***/***			0.6916***/***/	0.6683***/***/***
	AddressDensity				SAJunctionDensity
	0.696***/***/***/.				0.6917 /***/***/

PTCO2	AddressDensity	StoreSASizeAdj	DistWare2Store	**SARoadDensity**	SAJunctionDensity
R^2	0.1105***	0.3923***	0.3447***	**0.3895*** **	0.1923***
	AddressDensity	StoreSASizeAdj	DistWare2Store		SAJunctionDensity
	0.4903***/***	0.4314***/***	0.6916 ***/***		0.4995***/***
	AddressDensity	StoreSASizeAdj			SAJunctionDensity
	0.6957***/***/***	0.6916/***/***			0.6917/***/***
		StoreSASizeAdj			SAJunctionDensity
		0.696./***/***/***			0.697***/***/***/***
		StoreSASizeAdj			
		0.6977*/***/***/***			

ALL VARIABLES!! AddressDensity StoreSASizeAdj DistWare2Store SARoadDensity SAJunctionDensity

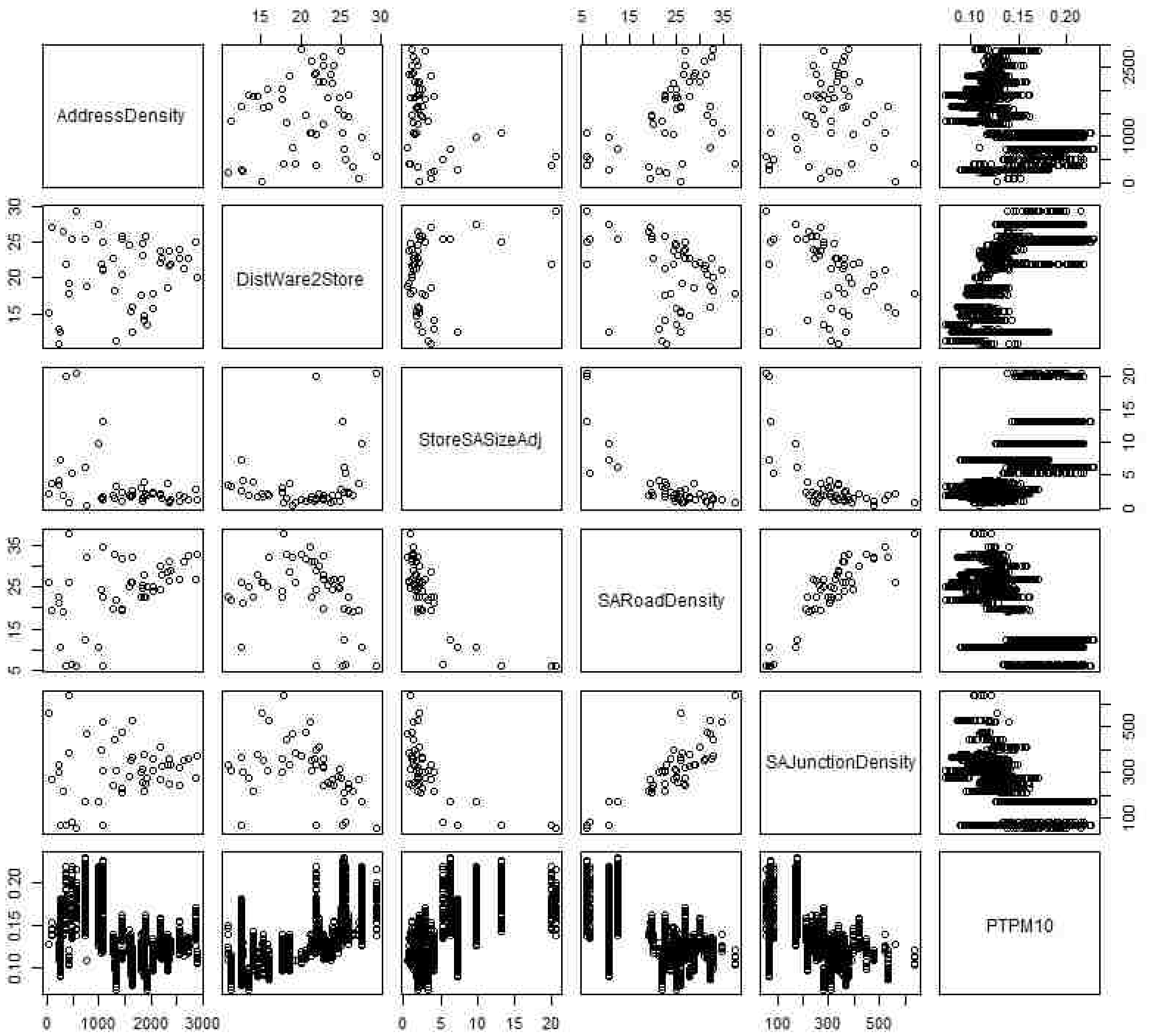
```
Call:
lm(formula = PTNox ~ SARoadDensity + DistWare2Store + AddressDensity +
    SAJunctionDensity + StoreSASizeAdj, data = PassNOx)

Residuals:
     Min       1Q   Median       3Q      Max
-1.84753 -0.36929 -0.01536  0.28991  2.34629

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       2.879e+00  1.142e-01  25.207  < 2e-16 ***
SARoadDensity    -3.427e-02  7.824e-03  -4.381 1.23e-05 ***
DistWare2Store    1.111e-01  3.309e-03  33.575  < 2e-16 ***
AddressDensity   -2.851e-04  3.972e-05  -7.178 9.18e-13 ***
```

```
SAJunctionDensity -1.301e-03  3.440e-04  -3.783 0.000158 ***
StoreSASizeAdj     1.320e-02  5.567e-03   2.371 0.017825 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5915 on 2619 degrees of freedom
Multiple R-squared:  0.6977,    Adjusted R-squared:  0.6971
F-statistic:  1209 on 5 and 2619 DF,  p-value: < 2.2e-16
```

SA RoadDensity + DistWare2Store provides most predictive, parsimonious model

```
> results23b=lm(PTNox~SARoadDensity+DistWare2Store,data=PassNOx)
results23b
Call:
lm(formula = PTNox ~ SARoadDensity + DistWare2Store, data = PassNOx)

Coefficients:
  (Intercept)   SARoadDensity  DistWare2Store
      3.50730       -0.08124        0.09385
> summary(results23b)

Call:
lm(formula = PTNox ~ SARoadDensity + DistWare2Store, data = PassNOx)

Residuals:
    Min       1Q   Median       3Q      Max
-1.65094 -0.38066 -0.00787  0.29754  2.39301

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    3.507301   0.045247   77.52   <2e-16 ***
SARoadDensity  -0.081236   0.001496  -54.31   <2e-16 ***
DistWare2Store  0.093846   0.001852   50.68   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5971 on 2622 degrees of freedom
Multiple R-squared:  0.6916,    Adjusted R-squared:  0.6914
F-statistic:  2940 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
PassVars=c("AddressDensity","DistWare2Store","StoreSASizeAdj","SARoadDensity","SAJuncti
onDensity","PTPM10")
PassPM10=Master35s[PassVars]
PassPM10[1:10,]
plot(PassPM10)
```



results30=lm(PTPM10~AddressDensity,data=PassPM10)
summary(results30)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTPM10	AddressDensity	StoreSASizeAdj	**DistWare2Store**	SARoadDensity	SAJunctionDensity
R^2	0.05777***	0.3051***	**0.355*****	0.2771***	0.1196***
	AddressDensity	StoreSASizeAdj		**SARoadDensity**	SAJunctionDensity
	0.567***/***	0.5269***/***		**0.5957*****/***	0.574***/***
	AddressDensity	StoreSASizeAdj			SAJunctionDensity

	0.5982*/*** */****	0.5958/***/***			0.5958/***/***
		StoreSASizeAdj			**SAJunctionDensity**
		0.5985/***/***/***			**0.5992*/***/*** */****
		StoreSASizeAdj			
		0.5998*/**/***/**/***			

All variables

```
Call:
lm(formula = PTPM10 ~ AddressDensity + StoreSASizeAdj + DistWare2Store +
    SARoadDensity + SAJunctionDensity, data = PassPM10)

Residuals:
     Min       1Q   Median       3Q      Max
-0.05682 -0.01312 -0.00189  0.01289  0.06296

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        1.023e-01  3.843e-03  26.607  < 2e-16 ***
AddressDensity    -6.760e-06  1.336e-06  -5.059 4.51e-07 ***
StoreSASizeAdj     3.922e-04  1.873e-04   2.093  0.03641 *
DistWare2Store     3.231e-03  1.114e-04  29.012  < 2e-16 ***
SARoadDensity     -7.930e-04  2.633e-04  -3.012  0.00262 **
SAJunctionDensity -3.376e-05  1.158e-05  -2.917  0.00357 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0199 on 2619 degrees of freedom
Multiple R-squared:  0.5998,    Adjusted R-squared:  0.5991
F-statistic: 785.2 on 5 and 2619 DF,  p-value: < 2.2e-16
```

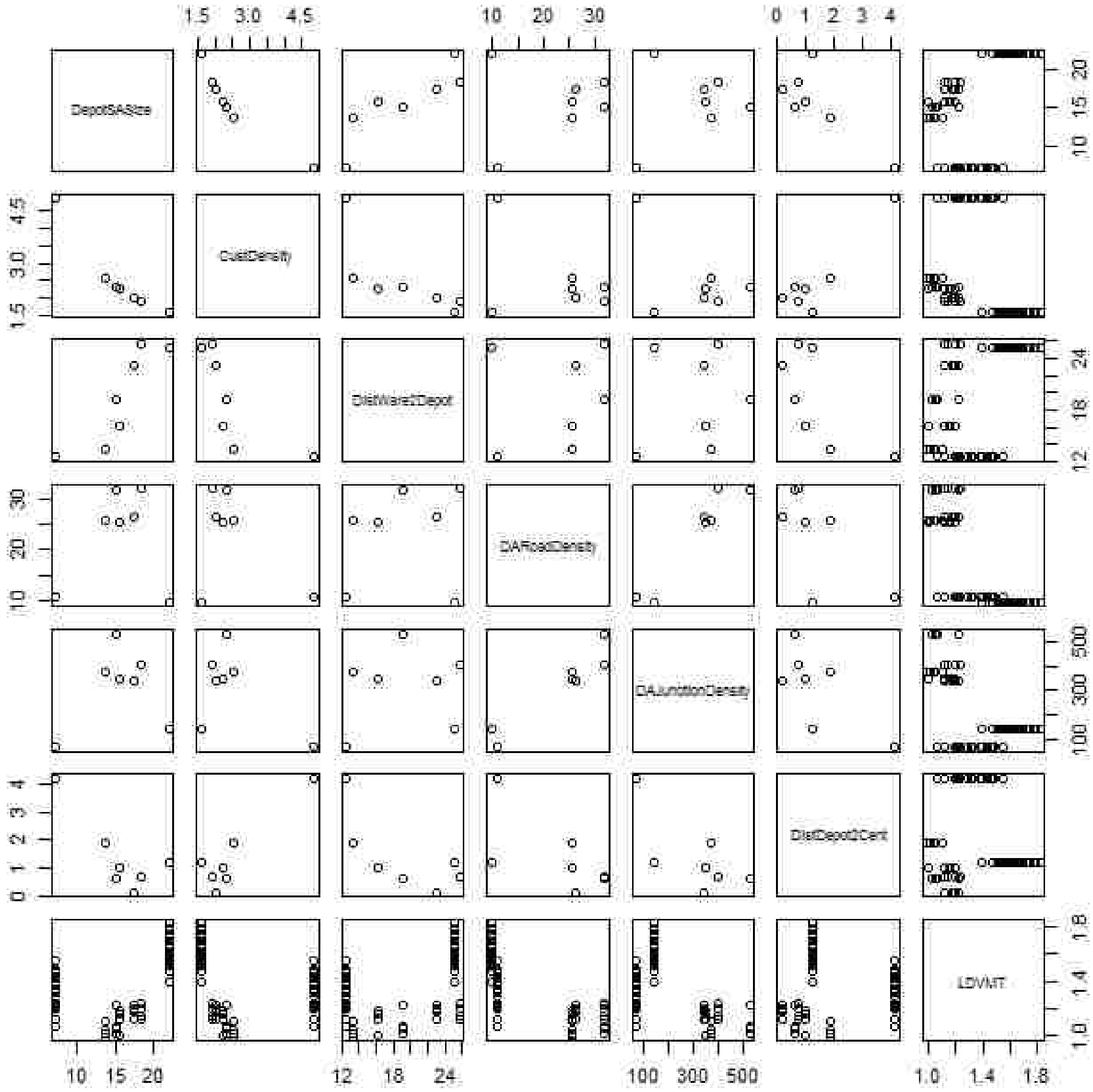
SA RoadDensity + DistWare2Store provides most predictive, parsimonious model

```
> results30c=lm(PTPM10~DistWare2Store+SARoadDensity,data=PassPM10)
> summary(results30c)

Call:
lm(formula = PTPM10 ~ DistWare2Store + SARoadDensity, data = PassPM10)

Residuals:
      Min        1Q    Median        3Q       Max
```

```
-0.051354 -0.013801 -0.001853  0.013064  0.063850

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.183e-01  1.515e-03   78.10   <2e-16 ***
DistWare2Store  2.818e-03  6.200e-05   45.45   <2e-16 ***
SARoadDensity  -1.979e-03  5.009e-05  -39.51   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01999 on 2622 degrees of freedom
Multiple R-squared:  0.5957,    Adjusted R-squared:  0.5954
F-statistic:  1932 on 2 and 2622 DF,  p-value: < 2.2e-16
```

LocalDepot Delivery

```
LDVars=c("DepotSASize","CustDensity","DistWare2Depot","DARoadDensity","DAJunctionDensity","DistDepot2Cent","LDVMT")
LDTravel=Master35s[LDVars]
LDTravel[1:10,]
plot(LDTravel)
```



results40=lm(LDVMT~DepotSASize,data=LDTravel)
 summary(results40)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

LDVMT	DepotSASize	CustDensity	DistWare2Depot	**DARoad Density**	DAJunctionDensity	DistDepot2Cent
R^2	0.1679***	0.04331***	0.1931***	**0.5797*** **	0.3905***	0.0005472
	DepotSASize	CustDensity	**DistWare2Depot**		DAJunctionDensity	DistDepot2Cent
	0.7974***/***	0.7828***/***	**0.8184***/*** **		0.6872***/***	0.7834***/***

	DepotSASize	CustDensity			DAJunctionDensity	DistDepot2Cent
	0.8185/***/***	0.8184/***/***			0.8201***/***/***	0.8184/***/***
	DepotSASize	CustDensity				DistDepot2Cent
	0.821***/***/***/***	0.8214***/****/***/***				0.8223***/***/***/***
	DepotSASize	CustDensity				
	0.8223/***/***/***	0.8223/***/***/***/***				

DARoadDensity, DistWare2Depot, DAJunctionDensit, DistDepot2Cent

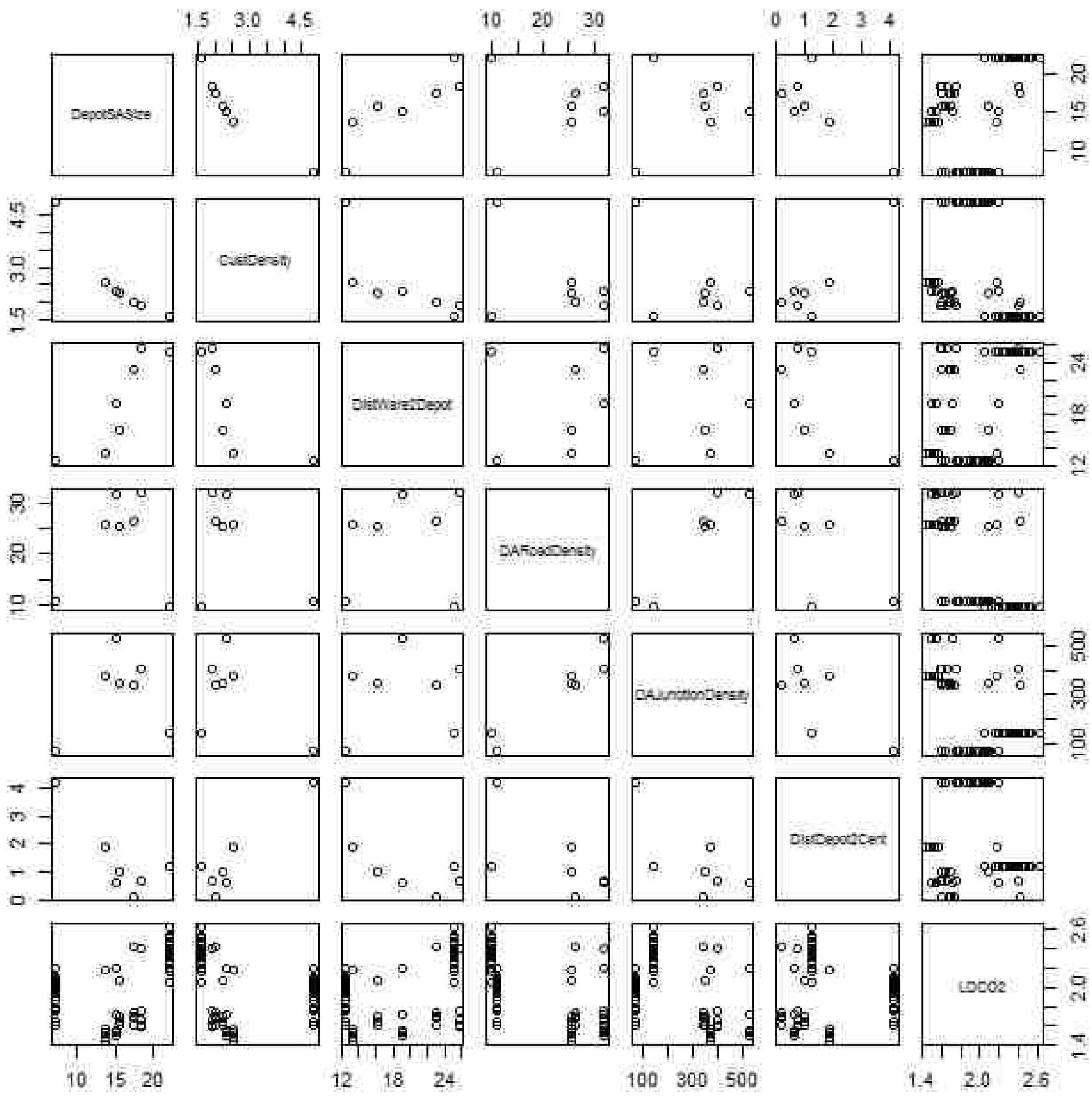
```
Call:
lm(formula = LDVMT ~ DARoadDensity + DistWare2Depot + DAJunctionDensity +
    DistDepot2Cent, data = LDTravel)

Residuals:
      Min        1Q    Median        3Q       Max
-0.285661 -0.055322 -0.003431  0.072244  0.191879

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        1.190e+00  3.541e-02   33.60  < 2e-16 ***
DARoadDensity     -2.781e-02  9.561e-04  -29.08  < 2e-16 ***
DistWare2Depot     2.363e-02  9.955e-04   23.73  < 2e-16 ***
DAJunctionDensity  5.674e-04  7.466e-05    7.60 4.10e-14 ***
DistDepot2Cent     3.183e-02  5.574e-03    5.71 1.26e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09865 on 2620 degrees of freedom
Multiple R-squared:  0.8223,    Adjusted R-squared:  0.822
F-statistic:  3031 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Most predictive, parsimonious DARoadDensity, DistWare2Depot

```
> results40c=lm(LDVMT~DARoadDensity+DistWare2Depot,data=LDTravel)
>
> summary(results40c)

Call:
lm(formula = LDVMT ~ DARoadDensity + DistWare2Depot, data = LDTravel)
```

```
Residuals:
     Min       1Q   Median       3Q      Max 
-0.286673 -0.051907  0.008009  0.071232  0.190867 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)    1.3432192  0.0074441  180.44   <2e-16 ***
DARoadDensity  -0.0214471  0.0002257  -95.01   <2e-16 ***
DistWare2Depot  0.0197387  0.0003363   58.70   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.0997 on 2622 degrees of freedom
Multiple R-squared:  0.8184,    Adjusted R-squared:  0.8182 
F-statistic:  5907 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
LDVars=c("DepotSASize","CustDensity","DistWare2Depot","DARoadDensity","DAJunctionDen
sity","DistDepot2Cent","LDCO2")
LDCO2=Master35s[LDVars]
LDCO2[1:10,]
plot(LDCO2)
```



results50=lm(LDCO2~DepotSASize,data=LDCO2)
 summary(results50)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

LDCO2	DepotSASize	CustDensity	DistWare2Depot	**DARoadDensity**	DAJunction Density	DistDepot2Cent
R^2	0.2019***	0.07842***	0.2198***	**0.3838*** **	0.2314***	0.006165***
	DepotSASize	CustDensity	**DistWare 2Depot**		DAJunction Density	DistDepot2Cent
	0.6298***/***	0.6166***/***	**0.643*** /* **		0.5111***/***	0.6167***/***

	DepotSASize	CustDensity			DAJunction Density	DistDepot2Cent
	0.6447***/***/***	0.6445**/***/***			0.6469***/***/***	0.6438*/***/***
	DepotSASize	CustDensity				DistDepot2Cent
	0.6469 /***/***/***	0.647/***/***/***				0.6474./***/***/***
	DepotSASize	CustDensity				
	0.6476/*/***/***/***	0.6475 /./***/***/***				

DARoadDensity+DistWare2Depot+DAJunctionDensity+DistDepot2Cent

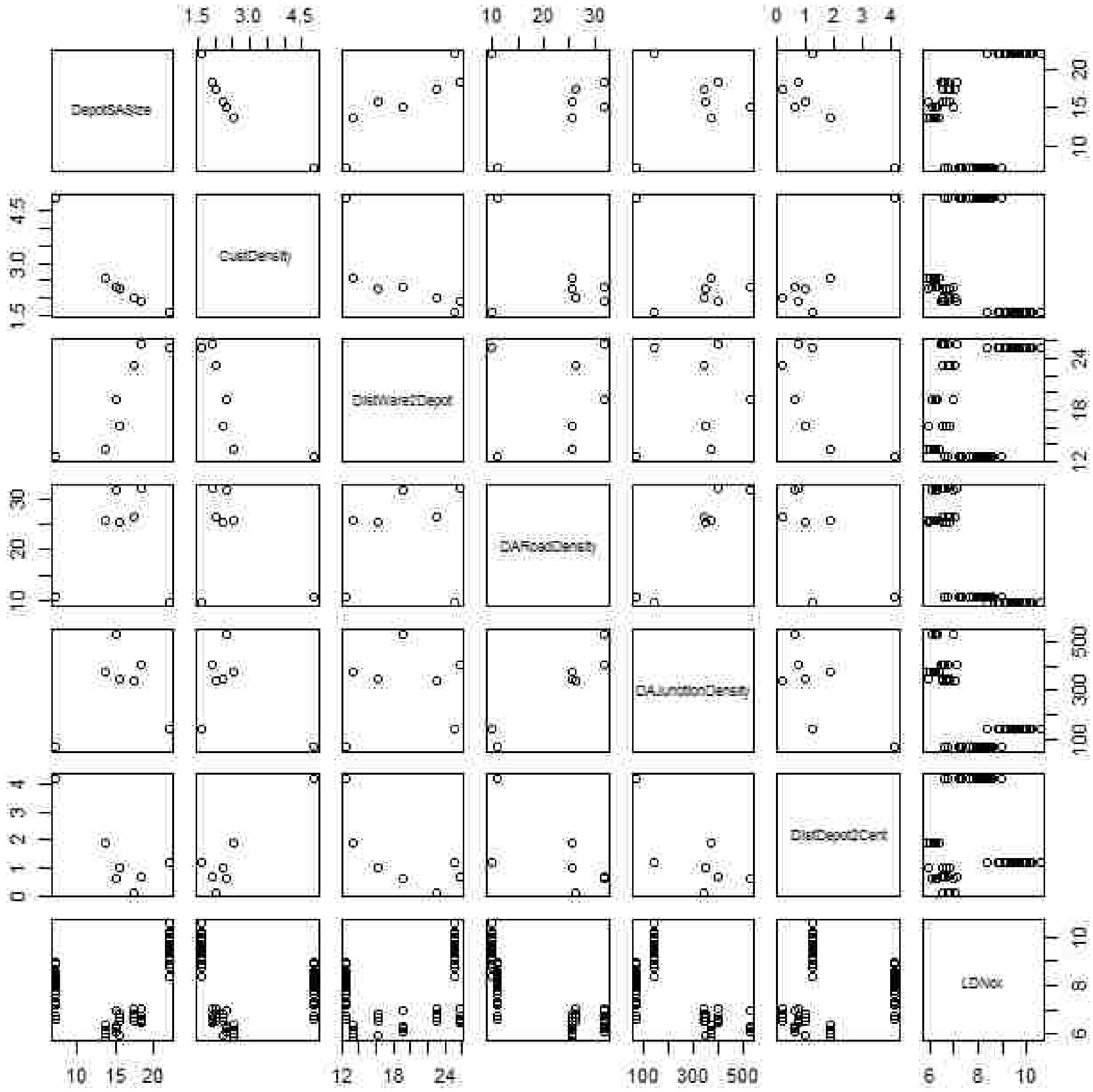
```
Call:
lm(formula = LDCO2 ~ DARoadDensity + DistWare2Depot + DAJunctionDensity +
   DistDepot2Cent, data = LDCO2)

Residuals:
     Min       1Q   Median       3Q      Max
-0.35507 -0.15557 -0.01584  0.10904  0.60003

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       1.8333006  0.0690177  26.563  < 2e-16 ***
DARoadDensity    -0.0347298  0.0018637 -18.635  < 2e-16 ***
DistWare2Depot    0.0291452  0.0019405  15.020  < 2e-16 ***
DAJunctionDensity 0.0007554  0.0001455   5.191 2.25e-07 ***
DistDepot2Cent    0.0204838  0.0108646   1.885   0.0595 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1923 on 2620 degrees of freedom
Multiple R-squared:  0.6474,    Adjusted R-squared:  0.6469
F-statistic:  1203 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Most predictive & parsimonious is DARoadDensity + DistWare2Depot

```
> results54c=lm(LDCO2~DARoadDensity+DistWare2Depot,data=LDCO2)
>  summary(results54c)

Call:
lm(formula = LDCO2 ~ DARoadDensity + DistWare2Depot, data = LDCO2)

Residuals:
```

```
    Min       1Q   Median       3Q      Max
-0.36222 -0.14500 -0.01389  0.10190  0.56475

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.8762006  0.0144406  129.93   <2e-16 ***
DARoadDensity  -0.0244142  0.0004379  -55.75   <2e-16 ***
DistWare2Depot  0.0284608  0.0006523   43.63   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1934 on 2622 degrees of freedom
Multiple R-squared:  0.643,     Adjusted R-squared:  0.6427
F-statistic:  2361 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
LDVars=c("DepotSASize","CustDensity","DistWare2Depot","DARoadDensity","DAJunctionDen
sity","DistDepot2Cent","LDNox")
LDNOx=Master35s[LDVars]
LDNOx[1:10,]
plot(LDNOx)
```



results60=lm(LDNox~DepotSASize,data=LDNOx)
summary(results60)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

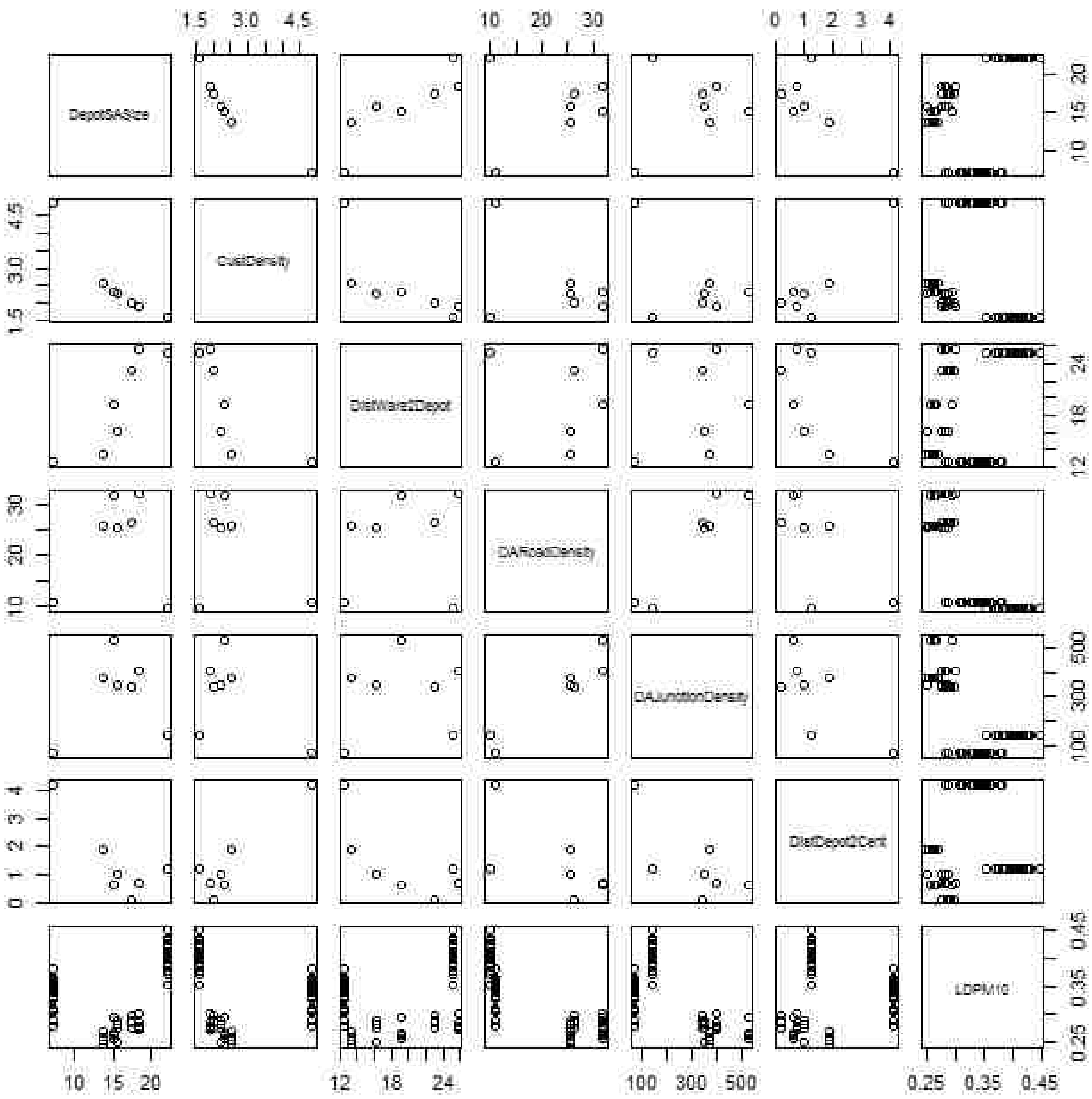
LDNOx	DepotSASize	CustDensity	DistWare2Depot	**DARoad Density**	DAJunctionDensity	DistDepot2Cent
R^2	0.1537***	0.03354***	0.1748***	**0.6445*** **	0.4391***	0.003399**
	DepotSASize	CustDensity	**DistWare2Depot**		DAJunctionDensity	DistDepot2Cent

	0.8488***/***	0.8356***/***	0.8652***/***		0.7556***/***	0.8347**/***
	DepotSASize	CustDensity			DAJunctionDensity	DistDepot2Cent
	0.8656**/***/***	0.8655*/***/***			0.8692***/***/***	0.8652/***/***
	DepotSASize	CustDensity				DistDepot2Cent
	0.8705***/***/***/***	0.8711***/***/***/***				0.8727***/***/***/***
	DepotSASize	CustDensity				
	0.8727/***/***/***/***	0.8727/***/***/***/***				

```
DARoadDensity+DistWare2Depot+DAJunctionDensity+DistDepot2Cent
Call:
lm(formula = LDNox ~ DARoadDensity + DistWare2Depot + DAJunctionDensity +
   DistDepot2Cent, data = LDNOx)

Residuals:
    Min      1Q  Median      3Q     Max
-1.38018 -0.23647 -0.01324  0.34367  0.98359

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       7.0059856  0.1716418  40.817   <2e-16 ***
DARoadDensity    -0.1809918  0.0046349 -39.050   <2e-16 ***
DistWare2Depot    0.1348199  0.0048258  27.937   <2e-16 ***
DAJunctionDensity  0.0044694  0.0003619  12.350   <2e-16 ***
DistDepot2Cent    0.2287075  0.0270194   8.465   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4782 on 2620 degrees of freedom
Multiple R-squared:  0.8727,    Adjusted R-squared:  0.8725
F-statistic:  4488 on 4 and 2620 DF,  p-value: < 2.2e-16

---------
Most predictive & parsimonious is DARoadDensity + DistWare2Depot
> results63c=lm(LDNox~DARoadDensity+DistWare2Depot,data=LDNOx)
>  summary(results63c)

Call:
lm(formula = LDNox ~ DARoadDensity + DistWare2Depot, data = LDNOx)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-1.39397 -0.30482  0.03359  0.32497  1.01387

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    8.053687   0.036716  219.35   <2e-16 ***
DARoadDensity  -0.129049   0.001113 -115.90   <2e-16 ***
DistWare2Depot  0.108696   0.001659   65.53   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4917 on 2622 degrees of freedom
Multiple R-squared:  0.8652,    Adjusted R-squared:  0.8651
F-statistic:  8417 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
LDVars=c("DepotSASize","CustDensity","DistWare2Depot","DARoadDensity","DAJunctionDen
sity","DistDepot2Cent","LDPM10")
LDPM10=Master35s[LDVars]
LDPM10[1:10,]
plot(LDPM10)
```



results70=lm(LDPM10~DepotSASize,data=LDPM10)
summary(results70)
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

LDPM10	DepotSASize	CustDensity	DistWare2Depot	**DARoad Density**	DAJunctionDensity	DistDepot2Cent
R^2	0.1449***	0.02917***	0.167***	**0.6516*****	0.4491***	0.004919***
	DepotSASize	CustDensity	**DistWare2Depot**		DAJunctionDensity	DistDepot2Cent

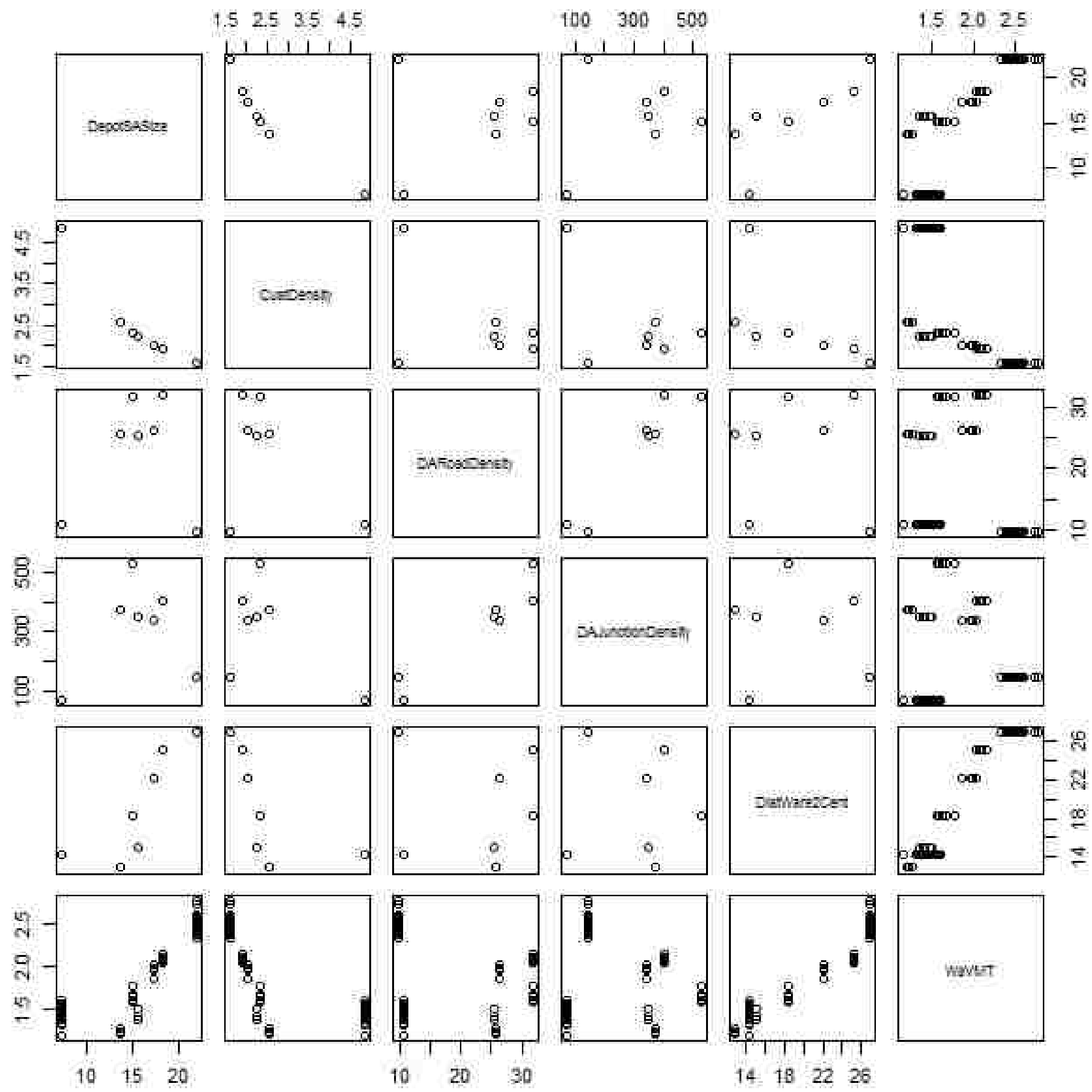
	0.8459***/***	0.8328***/***	**0.8638***/***		0.7556***/***	0.8322***/***
	DepotSASize	CustDensity			DAJunctionDensity	DistDepot2Cent
	0.864/***/***	0.8639/***/***			0.867***/***/***	0.8639/***/***
	DepotSASize	CustDensity				DistDepot2Cent
	0.8687***/***/***/***	0.8693***/***/***/***				0.8709***/***/***/***
	DepotSASize	CustDensity				
	0.8709/***/***/***/***	0.8709/***/***/***/***				

```
DARoadDensity+DistWare2Depot+DAJunctionDensity+DistDepot2Cent
Call:
lm(formula = LDPM10 ~ DARoadDensity + DistWare2Depot + DAJunctionDensity +
   DistDepot2Cent, data = LDPM10)

Residuals:
      Min        1Q    Median        3Q       Max
-0.059914 -0.010342 -0.000685  0.014458  0.042287

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        2.938e-01  7.409e-03  39.658   <2e-16 ***
DARoadDensity     -7.652e-03  2.001e-04 -38.249   <2e-16 ***
DistWare2Depot     5.836e-03  2.083e-04  28.016   <2e-16 ***
DAJunctionDensity  1.865e-04  1.562e-05  11.936   <2e-16 ***
DistDepot2Cent     1.040e-02  1.166e-03   8.921   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02064 on 2620 degrees of freedom
Multiple R-squared:  0.8709,    Adjusted R-squared:  0.8707
F-statistic:  4419 on 4 and 2620 DF,  p-value: < 2.2e-16

------
Most predictive & parsimonious is DARoadDensity + DistWare2Depot
> results73c=lm(LDPM10~DARoadDensity+DistWare2Depot,data=LDPM10)
>  summary(results73c)

Call:
lm(formula = LDPM10 ~ DARoadDensity + DistWare2Depot, data = LDPM10)

Residuals:
```

```
     Min       1Q    Median       3Q      Max
-0.060261 -0.012954  0.001946  0.013846  0.043417

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    3.439e-01  1.582e-03  217.35   <2e-16 ***
DARoadDensity  -5.558e-03  4.798e-05 -115.84   <2e-16 ***
DistWare2Depot  4.569e-03  7.147e-05   63.92   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02119 on 2622 degrees of freedom
Multiple R-squared:  0.8638,    Adjusted R-squared:  0.8637
F-statistic:  8317 on 2 and 2622 DF,  p-value: < 2.2e-16
```

Warehouse Delivery

```
setwd("C:/Documents and Settings/Eunice/My Documents/My Dropbox/Research/Dissertation/data/Main analysis/")
Master35s<-read.csv("MasterData35s.csv",header=TRUE,sep=",",quote="\"",dec=".",fill=TRUE,comment.char="")


WaVars=c("DepotSASize","CustDensity","DARoadDensity","DAJunctionDensity","DistWare2Cent","WaVMT")
WaTravel=Master35s[WaVars]
WaTravel[1:10,]
plot(WaTravel)
```



results80=lm(WaVMT~DepotSASize,data=WaTravel)
summary(results80)
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

WaVMT	DepotSASize	CustDensity	DARoadDensity	DAJunctionDensity	**DistWare2 Cent**
R^2	0.7541***	0.5476***	0.08377***	0.00908***	**0.9425*****
	DepotSASize	CustDensity	**DARoadDensity**	DAJunctionDensity	
	0.9448***/***	0.9497***/***	**0.9672***/*****	0.9626***/***	

	DepotSASize	CustDensity		DAJunctionDe nsity	
	0.9685***/***/***	0.9685***/***/***		0.9691***/***/***	
	DepotSASize	CustDensity			
	0.9692/***/***/***	0.9692./***/***/***			
	DepotSASize				
	0.9693 ***/***/***/***/***				

DistWare2Cent, DARoadDensity, DAJunctionDensity,CustDensity, DepotSASize

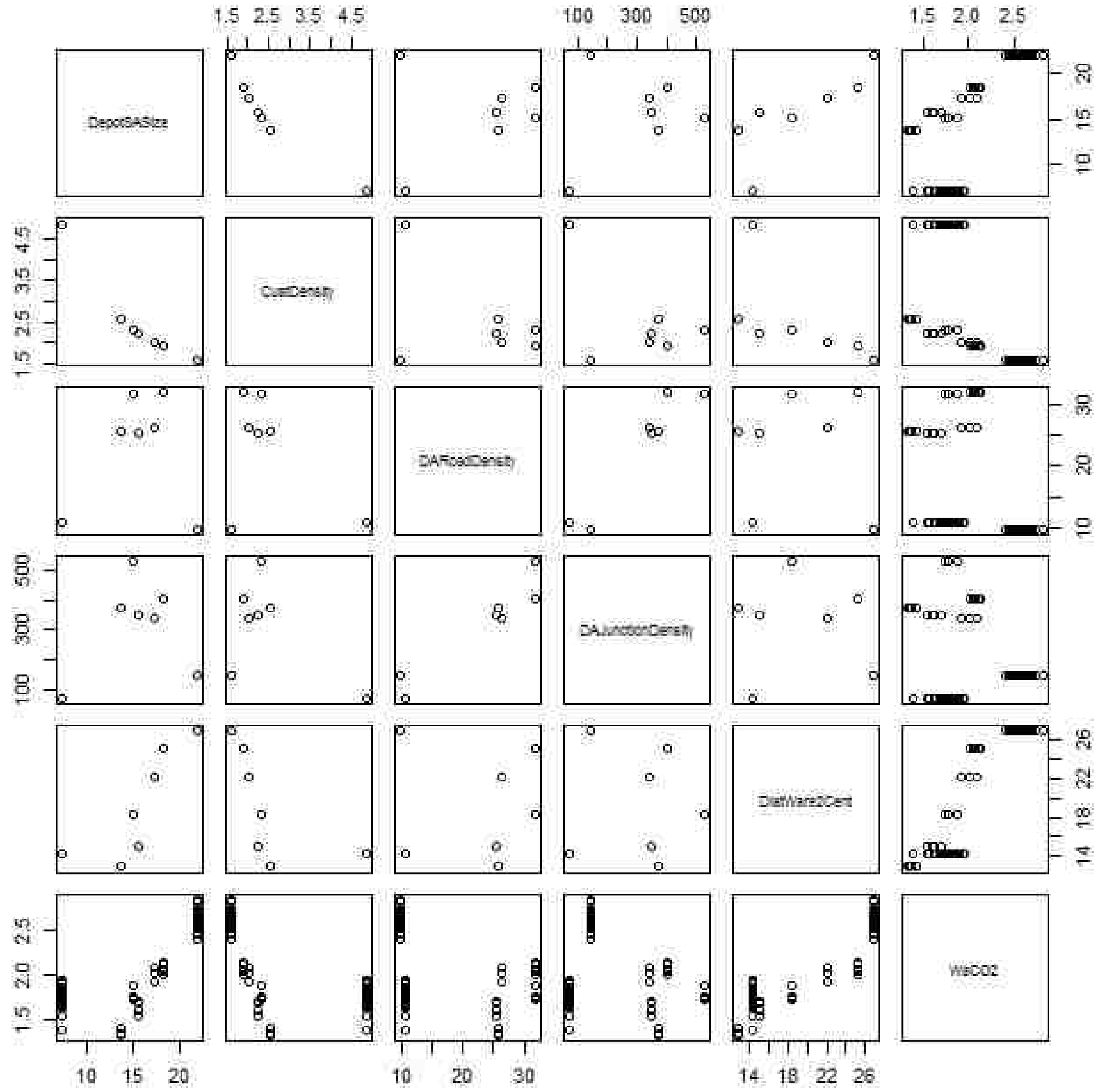
```
Call:
lm(formula = WaVMT ~ DistWare2Cent + DARoadDensity + DAJunctionDensity +
   CustDensity + DepotSASize, data = WaTravel)

Residuals:
     Min       1Q   Median       3Q      Max
-0.289906 -0.046264 -0.004518  0.061779  0.260444

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        1.736e+00  3.420e-01   5.076 4.12e-07 ***
DistWare2Cent      8.727e-02  3.193e-03  27.329  < 2e-16 ***
DARoadDensity     -2.278e-02  1.645e-03 -13.846  < 2e-16 ***
DAJunctionDensity  4.626e-04  6.929e-05   6.677 2.98e-11 ***
CustDensity       -1.940e-01  5.445e-02  -3.564 0.000372 ***
DepotSASize       -5.039e-02  1.469e-02  -3.430 0.000613 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08761 on 2619 degrees of freedom
Multiple R-squared:  0.9693,    Adjusted R-squared:  0.9693
F-statistic: 1.655e+04 on 5 and 2619 DF,  p-value: < 2.2e-16
-------------------
```

Most predictive, parsimonious DARoadDensity, DistWare2Cent

```
results84c=lm(WaVMT~DistWare2Cent+DARoadDensity,data=WaTravel)
>  summary(results84c)

Call:
```

```
lm(formula = WaVMT ~ DistWare2Cent + DARoadDensity, data = WaTravel)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.302308 -0.051849 -0.004114  0.060925  0.269968 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)    0.4235483  0.0075214   56.31   <2e-16 ***
DistWare2Cent  0.0805927  0.0003031  265.94   <2e-16 ***
DARoadDensity -0.0091937  0.0002064  -44.54   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.09048 on 2622 degrees of freedom
Multiple R-squared:  0.9672,    Adjusted R-squared:  0.9672 
F-statistic: 3.871e+04 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
WaVars=c("DepotSASize","CustDensity","DARoadDensity","DAJunctionDensity","DistWare2Cent","WaCO2")
WaCO2=Master35s[WaVars]
WaCO2[1:10,]
plot(WaCO2)
```



results90=lm(WaCO2~DepotSASize,data=WaCO2)
summary(results90)
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

WaCO2	DepotSASize	CustDensity	DARoadDensity	DAJunctionDensity	**DistWare2Cent**
R^2	0.6199***	0.3991***	0.1852***	0.05828***	0.8484***
	DepotSASize	CustDensity	DARoadDensity	DAJunctionDensity	
	0.8669***/***	0.889***/***	0.9424***/***	0.93***/***	

	DepotSASize	CustDensity		DAJunctionDensity	
	0.9427***/***/***	0.9428***/***/***		0.9445***/***/***	
	DepotSASize	CustDensity			
	0.9449***/***/***/***	0.9449***/***/***/***			
		CustDensity			
		0.945/ /***/***/***			

Best fit model

DistWare2Cent, DARoadDensity, DAJunctionDensity, CustDensity (OR DistWare2Cent, DARoadDensity, DAJunctionDensity, DepotSASize)

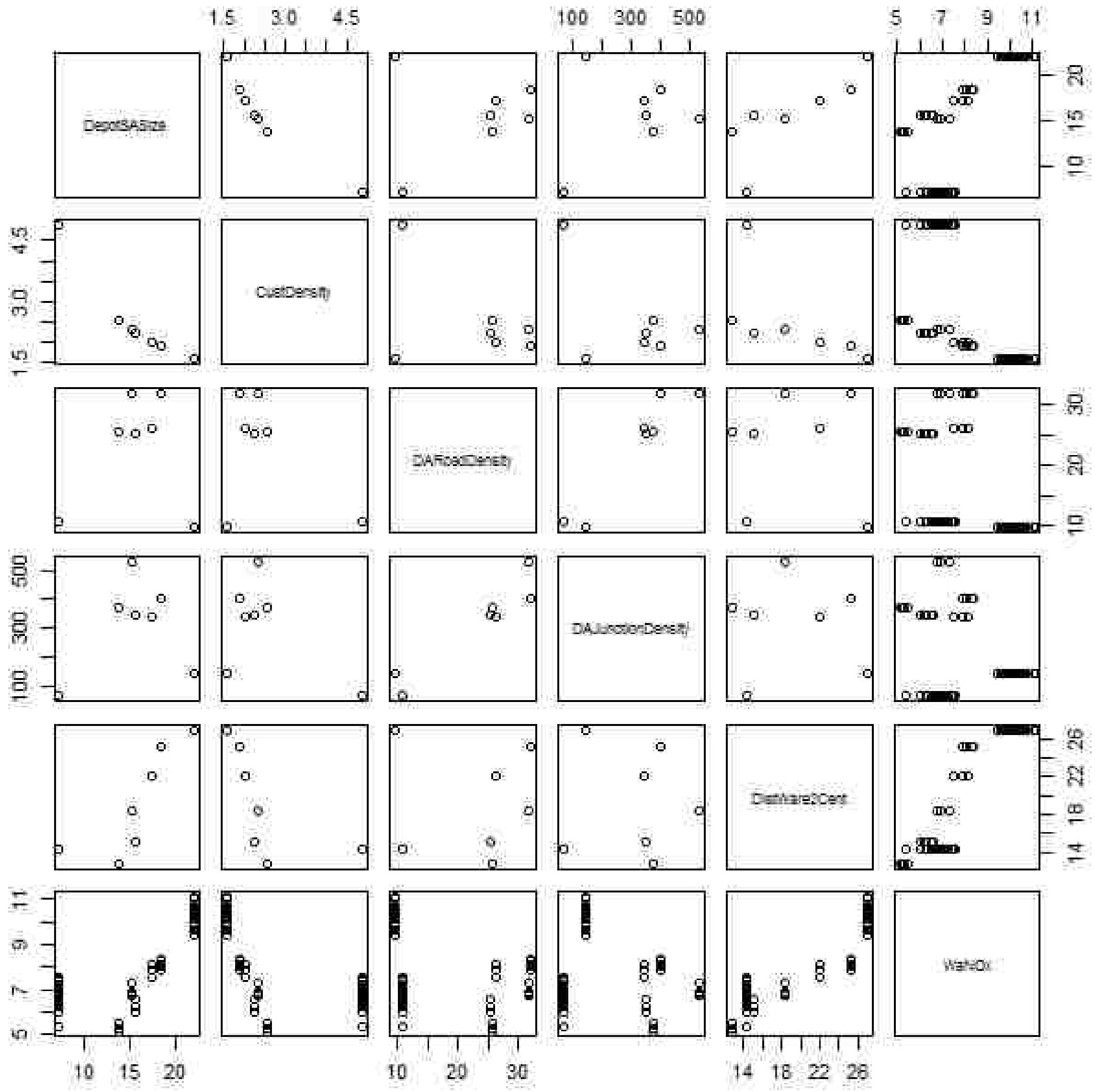
```
lm(formula = WaCO2 ~ DistWare2Cent + DARoadDensity + DAJunctionDensity +
    CustDensity, data = WaCO2)

Residuals:
     Min       1Q   Median       3Q      Max
-0.36264 -0.06695  0.00557  0.07460  0.20720

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       9.300e-01  3.386e-02  27.465  < 2e-16 ***
DistWare2Cent     6.730e-02  8.915e-04  75.486  < 2e-16 ***
DARoadDensity    -2.814e-02  1.150e-03 -24.474  < 2e-16 ***
DAJunctionDensity  8.246e-04  8.088e-05  10.195  < 2e-16 ***
CustDensity       2.170e-02  4.941e-03   4.393 1.16e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1045 on 2620 degrees of freedom
Multiple R-squared:  0.9449,	Adjusted R-squared:  0.9449
F-statistic: 1.124e+04 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Most predictive, parsimonious DARoadDensity, DistWare2Cent

```
results94c=lm(WaCO2~DistWare2Cent+DARoadDensity,data=WaCO2)
>  summary(results94c)

Call:
lm(formula = WaCO2 ~ DistWare2Cent + DARoadDensity, data = WaCO2)

Residuals:
```

```
    Min       1Q   Median       3Q      Max 
-0.36879 -0.07074  0.00235  0.06649  0.21433 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   0.9799593  0.0088852  110.29   <2e-16 ***
DistWare2Cent  0.0664650  0.0003580  185.65   <2e-16 ***
DARoadDensity -0.0159525  0.0002439  -65.42   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.1069 on 2622 degrees of freedom
Multiple R-squared:  0.9424,    Adjusted R-squared:  0.9424 
F-statistic: 2.145e+04 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
WaVars=c("DepotSASize","CustDensity","DARoadDensity","DAJunctionDensity","DistWare2Ce
nt","WaNOx")
WaNOx=Master35s[WaVars]
WaNOx[1:10,]
plot(WaNOx)
```



results100=lm(WaNOx~DepotSASize,data=WaNOx)
 summary(results100)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WaN Ox	DepotSASize	CustDensity	DARoadDens ity	DAJunctionDe nsity	**DistWare2 Cent**
R^2	0.6285***	0.4074***	0.1809***	0.05528***	**0.8541*** **

	DepotSASize	CustDensity	**DARoadDensity**	DAJunctionDensity	
	0.8708***/***	0.892***/***	**0.9447***/****	0.9322***/***	
	DepotSASize	CustDensity		DAJunctionDensity	
	0.9453***/***/***	0.9453***/***/***		0.9472***/***/***	
	DepotSASize	CustDensity			
	0.9475***/***/***/***	0.9475***/***/***/***			
	DepotSASize				
	0.9475 / /***/***/***				

Best fit model

DistWare2Cent, DARoadDensity, DAJunctionDensity, CustDensity (or DepotSASize)

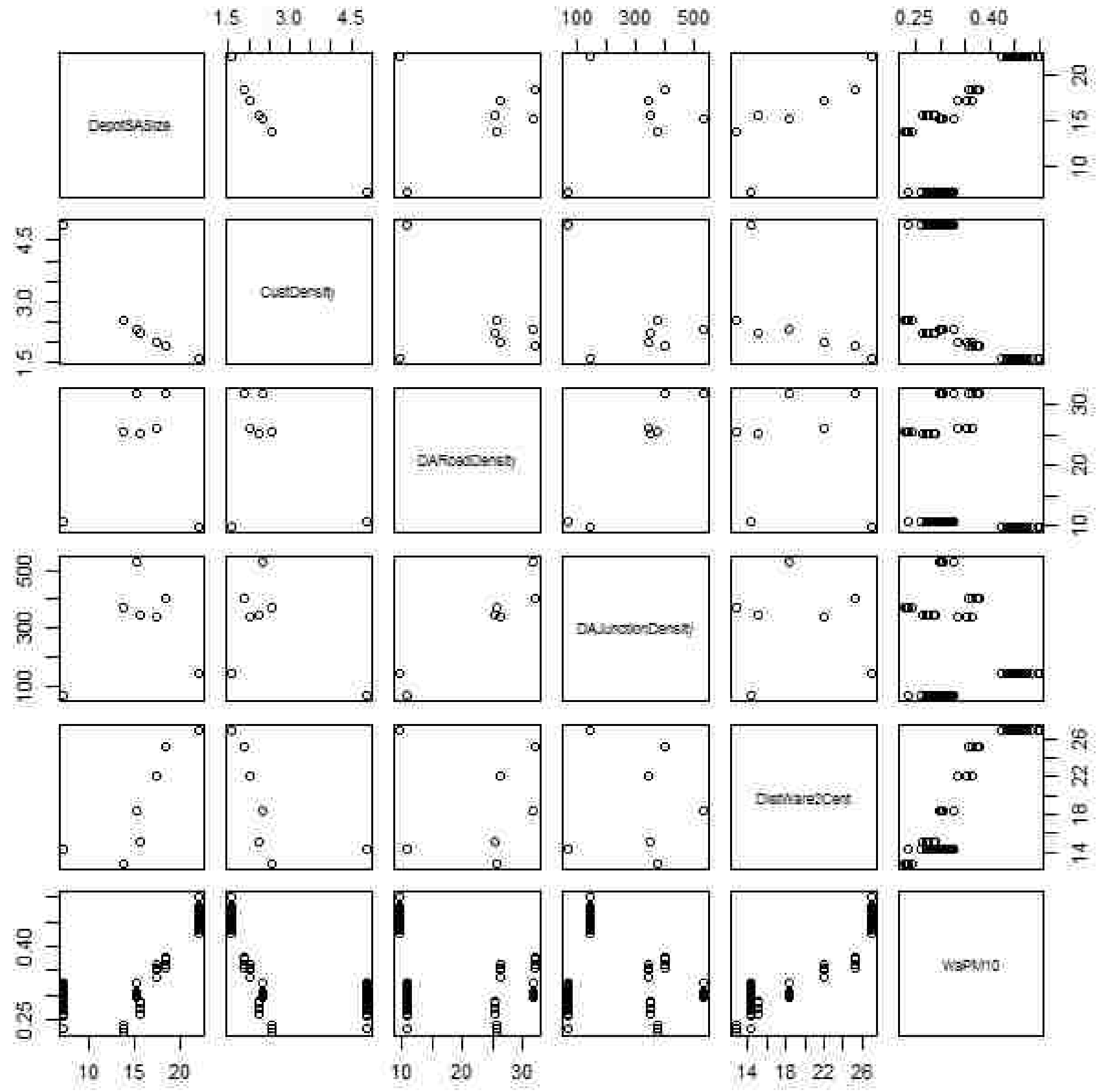
```
Call:
lm(formula = WaNOx ~ DistWare2Cent + DARoadDensity + DAJunctionDensity +
   CustDensity, data = WaNOx)

Residuals:
     Min       1Q   Median       3Q      Max
-1.41317 -0.26924  0.01067  0.28367  0.80579

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       3.6021780  0.1315925  27.374  < 2e-16 ***
DistWare2Cent     0.2663937  0.0034647  76.887  < 2e-16 ***
DARoadDensity    -0.1121097  0.0044685 -25.089  < 2e-16 ***
DAJunctionDensity  0.0033085  0.0003143  10.526  < 2e-16 ***
CustDensity       0.0745330  0.0192003   3.882 0.000106 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4063 on 2620 degrees of freedom
Multiple R-squared:  0.9475,    Adjusted R-squared:  0.9474
F-statistic: 1.182e+04 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Most predictive, parsimonious DARoadDensity, DistWare2Cent

```
> results104c=lm(WaNOx~DistWare2Cent+DARoadDensity,data=WaNOx)
>  summary(results104c)
```

```
Call:
lm(formula = WaNOx ~ DistWare2Cent + DARoadDensity, data = WaNOx)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.4428 -0.2630  0.0119  0.2515  0.8376 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)    3.6998412  0.0346361  106.82   <2e-16 ***
DistWare2Cent  0.2656896  0.0013956  190.38   <2e-16 ***
DARoadDensity -0.0623532  0.0009506  -65.59   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4167 on 2622 degrees of freedom
Multiple R-squared:  0.9447,    Adjusted R-squared:  0.9447 
F-statistic: 2.242e+04 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
WaVars=c("DepotSASize","CustDensity","DARoadDensity","DAJunctionDensity","DistWare2Ce
nt","WaPM10")
WaPM10=Master35s[WaVars]
WaPM10[1:10,]
plot(WaPM10)
```



results110=lm(WaPM10~DepotSASize,data=WaPM10)
summary(results110)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WaPM 10	DepotSASize	CustDensity	DARoadDensity	DAJunctionDensity	**DistWare2 Cent**
R^2	0.6659***	0.4459***	0.1552***	0.04028***	**0.8814*** **
	DepotSASize	CustDensity	**DARoadDensity**	DAJunctionDensity	
	0.8924***/***	0.9084***/***	**0.9528***/*** **	0.9418***/***	

	DepotSASize	CustDensity		DAJunctionDensity	
	0.9538***/***/***	0.9539***/***/***		0.9557***/***/***	
	DepotSASize	CustDensity			
	0.9558*/***/***/***	0.9558*/***/***/***/***			
	DepotSASize				
	0.9558/ /***/***/***				

Best fit model

DistWare2Cent, DARoadDensity, DAJunctionDensity, CustDensity

```
Call:
lm(formula = WaPM10 ~ DistWare2Cent + DARoadDensity + DAJunctionDensity +
    CustDensity, data = WaPM10)

Residuals:
     Min       1Q   Median       3Q      Max
-0.06130 -0.01044 -0.00085  0.01227  0.03699

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       1.489e-01  5.696e-03  26.143   <2e-16 ***
DistWare2Cent     1.252e-02  1.500e-04  83.494   <2e-16 ***
DARoadDensity    -4.899e-03  1.934e-04 -25.329   <2e-16 ***
DAJunctionDensity 1.454e-04  1.361e-05  10.685   <2e-16 ***
CustDensity       1.780e-03  8.311e-04   2.141   0.0324 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01759 on 2620 degrees of freedom
Multiple R-squared:  0.9558,    Adjusted R-squared:  0.9557
F-statistic: 1.416e+04 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Most predictive, parsimonious DARoadDensity, DistWare2Cent

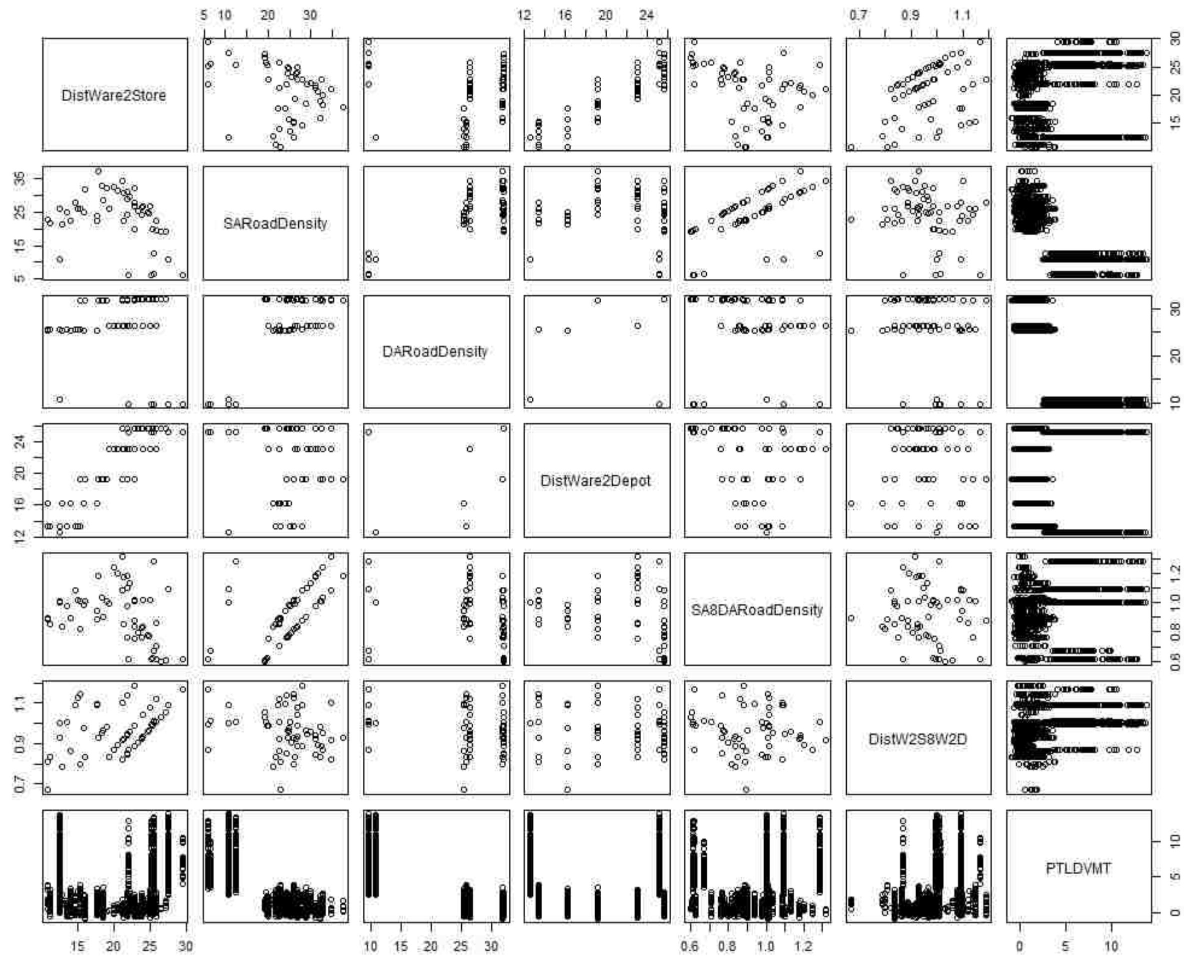
```
> results114c=lm(WaPM10~DistWare2Cent+DARoadDensity,data=WaPM10)
>  summary(results114c)

Call:
lm(formula = WaPM10 ~ DistWare2Cent + DARoadDensity, data = WaPM10)
```

```
Residuals:
      Min        1Q    Median        3Q       Max 
-0.063198 -0.010226  0.000517  0.012726  0.038783 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)    1.409e-01  1.510e-03   93.37   <2e-16 ***
DistWare2Cent  1.281e-02  6.083e-05  210.54   <2e-16 ***
DARoadDensity -2.611e-03  4.143e-05  -63.02   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 0.01816 on 2622 degrees of freedom
Multiple R-squared:  0.9528,    Adjusted R-squared:  0.9528 
F-statistic: 2.648e+04 on 2 and 2622 DF,  p-value: < 2.2e-16
```

Summary

Difference Passenger Travel to Local Depot Delivery

```
setwd("C:/Documents and Settings/Eunice/My Documents/My Dropbox/Research/Dissertation/data/Main analysis/")
Master35sRatios<-read.csv("MasterData35sRatios.csv",header=TRUE,sep=",",quote="\"",dec=".",fill=TRUE,comment.char="")


PassLDVars=c("DistWare2Store","SARoadDensity","DARoadDensity","DistWare2Depot","SA8DARoadDensity","DistW2S8W2D","PTLDVMT")
PassLDTravel=Master35sRatios[PassLDVars]
PassLDTravel[1:10,]
plot(PassLDTravel)
```



PassLDVars=c("DistWare2Store","SARoadDensity","DARoadDensity","DistWare2Depot","SA8DARoadDensity","DistW2S8W2D","PTLDVMT")

results200=lm(PTLDVMT~DistWare2Store,data=PassLDTravel)
summary(results200)

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

PTLD VMT	DistWare2Store	SARoadDensity	**DARoad Density**	DistWare2Depot	SA8DARoad Density	DistW2S8W2D
R^2	0.000215	0.6527***	**0.6913*****	0.00523***	0.03073***	0.09456***
	DistWare2Store	**SARoad Density**		DistWare2Depot	SA8DARoad Density	DistW2S8W2D
	0.6916 ./***	**0.6965*****/***		0.6917./***	0.6932***/***	0.6913/***

	DistWare2Store			DistWare2Depot	**SA8DARoadDensity**	DistW2S8W2D
	0.697*/***/***			0.6971*/***/***	**0.6978*****/***/***	0.6965/***/***
	DistWare2 Store			DistWare2Depot		DistW2S8W2D
	0.6987**/***/***/***			0.6987**/***/***/***		0.6978/***/***/***
				DistWare2Depot		DistW2S8W2D
				0.6987 / /***/***/***		0.6988/**/***/***/***

best fit
DARoadDensity, SARoadDensity,SA8DARoadDensity, DistWare2Store
Call:
lm(formula = PTLDVMT ~ DARoadDensity + SARoadDensity + SA8DARoadDensity +
    DistWare2Store, data = PassLDTravel)

Residuals:
    Min   1Q Median   3Q   Max
-4.4193 -1.1685 0.0227 0.7367 6.9046

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)   9.084155   0.435094 20.879 < 2e-16 ***
DARoadDensity   -0.155276   0.025814 -6.015 2.05e-09 ***
SARoadDensity   -0.186597   0.027625 -6.755 1.76e-11 ***
SA8DARoadDensity 1.706039   0.444168   3.841 0.000125 ***
DistWare2Store   -0.016503   0.005796 -2.847 0.004443 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.84 on 2620 degrees of freedom
Multiple R-squared: 0.6987,   Adjusted R-squared: 0.6983
F-statistic: 1519 on 4 and 2620 DF, p-value: < 2.2e-16

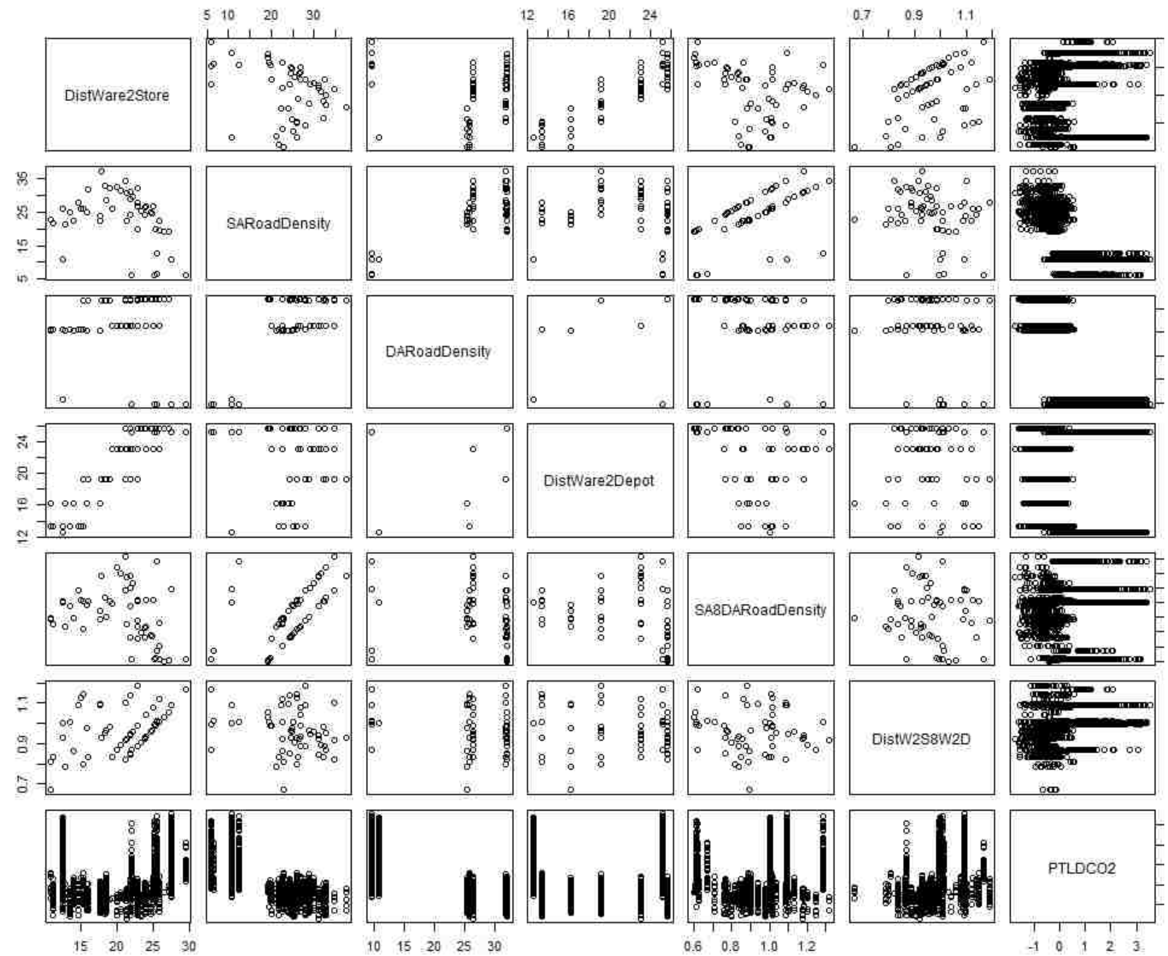
DARoad Density parsimonious model

> results202=lm(PTLDVMT~DARoadDensity,data=PassLDTravel)
> summary(results202)

Call:
lm(formula = PTLDVMT ~ DARoadDensity, data = PassLDTravel)

```
Residuals:
    Min      1Q  Median      3Q     Max 
-4.5359 -1.2556  0.0156  0.7885  6.9899 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   10.251804   0.077446  132.37   <2e-16 ***
DARoadDensity -0.322418   0.004207  -76.64   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 1.862 on 2623 degrees of freedom
Multiple R-squared:  0.6913,	Adjusted R-squared:  0.6912 
F-statistic:  5874 on 1 and 2623 DF,  p-value: < 2.2e-16
```

```
PassLDVars=c("DistWare2Store","SARoadDensity","DARoadDensity","DistWare2Depot","SA8
DARoadDensity","DistW2S8W2D","PTLDCO2")
PassLDCO2=Master35sRatios[PassLDVars]
PassLDCO2[1:10,]
plot(PassLDCO2)
```



results210=lm(PTLDCO2~DistWare2Store,data=PassLDCO2)
summary(results210)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTLD CO2	DistWare2 Store	SARoadDe nsity	**DARoadD ensity**	DistWare2D epot	SA8DARoadD ensity	DistW2S8W 2D
R^2	0.000043 22	0.523***	**0.5438*****	0.007285** *	0.02123***	0.0753***
	DistWare2 Store	**SARoadD ensity**		DistWare2D epot	SA8DARoadD ensity	DistW2S8W 2D
	0.5451**/* **	0.5508***/ ***		0.5453**/** *	0.5461***/***	0.5438/***
	DistWare2 Store			**DistWare2 Depot**	SA8DARoadD ensity	DistW2S8W 2D
	0.5526**/ ***/***			**0.5529***/ ***/*****	0.5529***/*** /**	0.5508/**/* **

	DistWare2 Store				**SA8DARoad Density**	DistW2S8W 2D
	0.553 / /***/***				**0.5556*****/*** */***/*	0.5532/***/ ***/***
	DistWare2 Store					DistW2S8W 2D
	0.5556 /***/ /***/*					0.5557 /***/***/** */*

Best fit DARoadDensity, SARoadDensity, DistWare2Depot, SA8DARoadDensity
Call:
lm(formula = PTLDCO2 ~ DARoadDensity + SARoadDensity + DistWare2Depot +
SA8DARoadDensity, data = PassLDCO2)

Residuals:
```
     Min       1Q   Median       3Q      Max
-1.60212 -0.40133 -0.02723  0.28157  2.55279
```

Coefficients:
```
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       1.454793   0.153071   9.504  < 2e-16 ***
DARoadDensity    -0.022808   0.009006  -2.533   0.0114 *
SARoadDensity    -0.065773   0.009613  -6.842 9.66e-12 ***
DistWare2Depot   -0.008761   0.002195  -3.991 6.77e-05 ***
SA8DARoadDensity  0.620091   0.154383   4.017 6.07e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.6437 on 2620 degrees of freedom
Multiple R-squared: 0.5556,   Adjusted R-squared: 0.5549
F-statistic: 819 on 4 and 2620 DF, p-value: < 2.2e-16

Parsimonious either DARoadDensity OR DARoadDensity + SARoadDensity
Call:
lm(formula = PTLDCO2 ~ DARoadDensity, data = PassLDCO2)

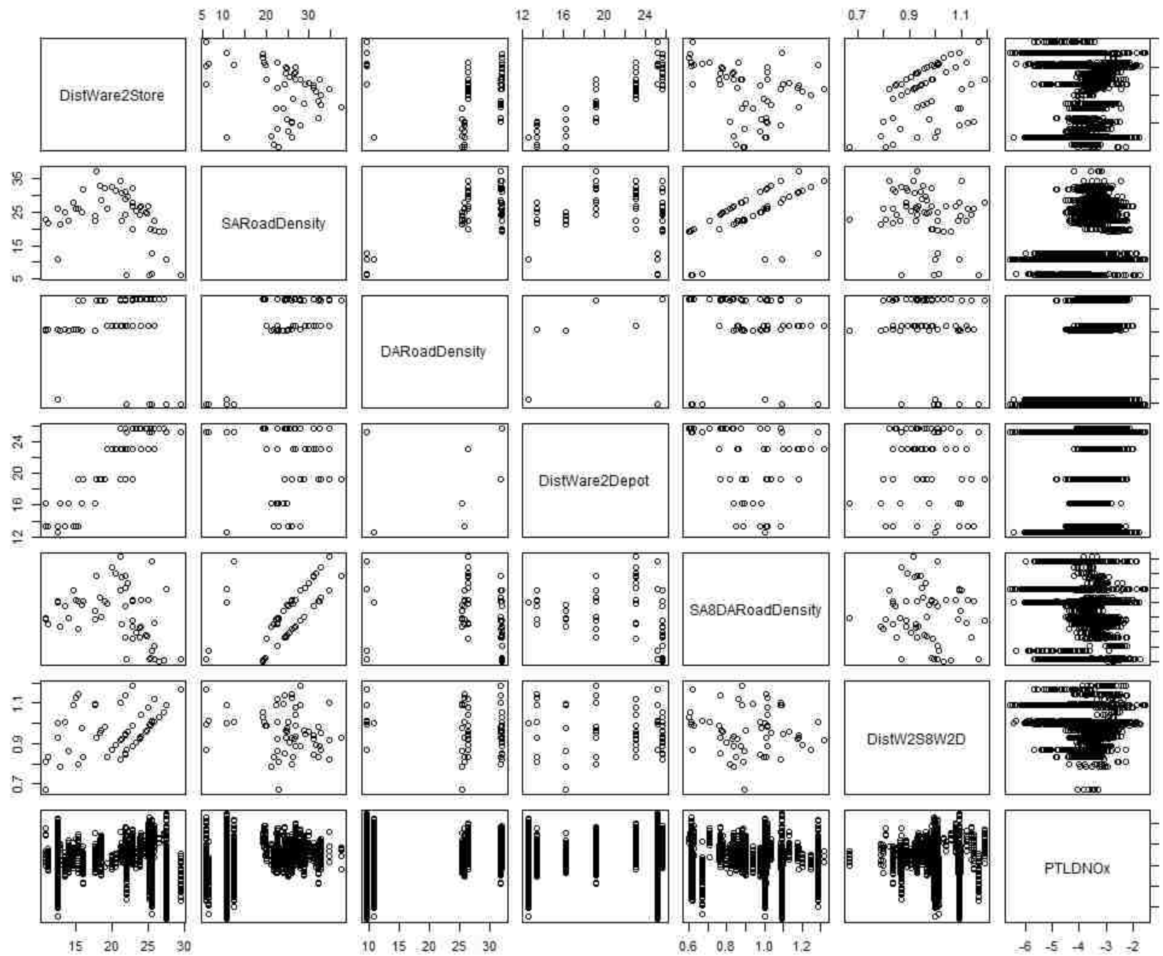
Residuals:
```
     Min       1Q   Median       3Q      Max
-1.65073 -0.40863 -0.03726  0.29978  2.50417
```

Coefficients:
```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.839819   0.027116   67.85   <2e-16 ***
DARoadDensity -0.082361   0.001473  -55.92   <2e-16 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6518 on 2623 degrees of freedom
Multiple R-squared:  0.5438,    Adjusted R-squared:  0.5436
F-statistic:  3127 on 1 and 2623 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = PTLDCO2 ~ DARoadDensity + SARoadDensity, data = PassLDCO2)

Residuals:
     Min       1Q   Median       3Q      Max
-1.63084 -0.39990 -0.03725  0.29133  2.52406

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.893301   0.028184  67.176  < 2e-16 ***
DARoadDensity -0.055920   0.004389 -12.741  < 2e-16 ***
SARoadDensity -0.031029   0.004856  -6.389 1.97e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6469 on 2622 degrees of freedom
Multiple R-squared:  0.5508,    Adjusted R-squared:  0.5504
F-statistic:  1607 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
PassLDVars=c("DistWare2Store","SARoadDensity","DARoadDensity","DistWare2Depot","SA8DARoadDensity","DistW2S8W2D","PTLDNOx")
PassLDNOx=Master35sRatios[PassLDVars]
PassLDNOx[1:10,]
plot(PassLDNOx)
```



results220=lm(PTLDNOx~DistWare2Store,data=PassLDNOx)
summary(results220)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTLD NOx	DistWare2 Store	SARoadDen sity	**DARoadD ensity**	DistWare2 Depot	SA8DARoadDe nsity	DistW2S8 W2D
R^2	0.0009566	0.1953***	**0.2352***	0.0003081	0.0222***	0.02554***
	DistWare2 Store	**SARoadD ensity**		DistWare2 Depot	SA8DARoadDe nsity	DistW2S8 W2D
	0.2353/***	**0.2373**/***		0.2354 /***	0.2357/***	0.2356/***
	DistWare2 Store			DistWare2 Depot	**SA8DARoad Density**	DistW2S8 W2D

	0.2375 /**/***			0.2376 /**/***	**0.2383 ./**/*** **	0.2377/** /***
	DistWare2 Store			DistWare2 Depot		DistW2S8 W2D
	0.2387/*/ **/***			0.2388/*/ **/***		0.2386 /./**/***

DARoadDensity, SARoadDensity, SA8DARoadDensity

```
Call:
lm(formula = PTLDNOx ~ DARoadDensity + SARoadDensity + SA8DARoadDensity,
    data = PassLDNOx)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.25924 -0.45820 -0.03624  0.42995  2.71811 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)      -5.05039    0.17352 -29.105  < 2e-16 ***
DARoadDensity     0.07689    0.01019   7.543 6.31e-14 ***
SARoadDensity    -0.03262    0.01089  -2.994  0.00278 ** 
SA8DARoadDensity  0.33131    0.17555   1.887  0.05923 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7376 on 2621 degrees of freedom
Multiple R-squared:  0.2383,	Adjusted R-squared:  0.2375 
F-statistic: 273.4 on 3 and 2621 DF,  p-value: < 2.2e-16
```

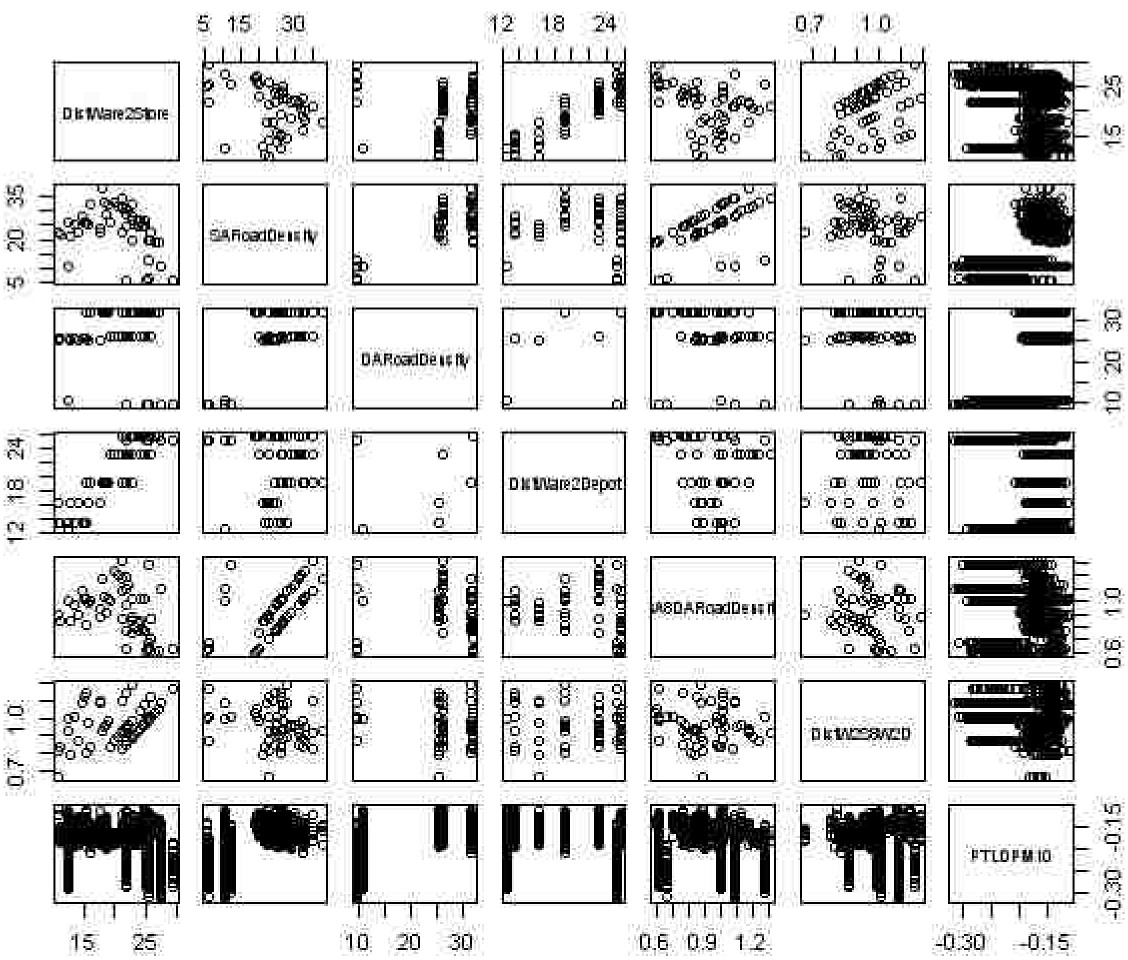
DARoadDensity best model

```
> results222=lm(PTLDNOx~DARoadDensity,data=PassLDNOx)
> summary(results222)

Call:
lm(formula = PTLDNOx ~ DARoadDensity, data = PassLDNOx)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.25362 -0.45603 -0.04707  0.43016  2.72373 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   -4.75426    0.03074  -154.7   <2e-16 ***
DARoadDensity  0.04742    0.00167    28.4   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.7389 on 2623 degrees of freedom
Multiple R-squared: 0.2352,   Adjusted R-squared: 0.2349
F-statistic: 806.6 on 1 and 2623 DF, p-value: < 2.2e-16

START HERE

```
PassLDVars=c("DistWare2Store","SARoadDensity","DARoadDensity","DistWare2Depot","SA8DARoadDensity","DistW2S8W2D","PTLDPM10")
PassLDPM10=Master35sRatios[PassLDVars]
PassLDPM10[1:10,]
plot(PassLDPM10)
```




```
results230=lm(PTLDPM10~DistWare2Store,data=PassLDPM10)
summary(results230)
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTLDPM10	DistWare2Store	SARoadDensity	**DARoadDensity**	DistWare2Depot	SA8DARoadDensity	DistW2S8W2D

R^2	0.04503***	0.4587***	**0.5097*** **	0.02097***	0.03354***	0.08243***
	DistWare2Store	SARoadDensity		**DistWare2Depot**	SA8DARoadDensity	DistW2S8W2D
	0.5434***/***	0.5099/***		**0.5459***/*** **	0.5097/***	0.5104./***
	DistWare2Store	SARoadDensity			SA8DARoadDensity	DistW2S8W2D
	0.546 /***/***	0.5459 /***/***			0.5459 /***/***	0.5462 /***/***

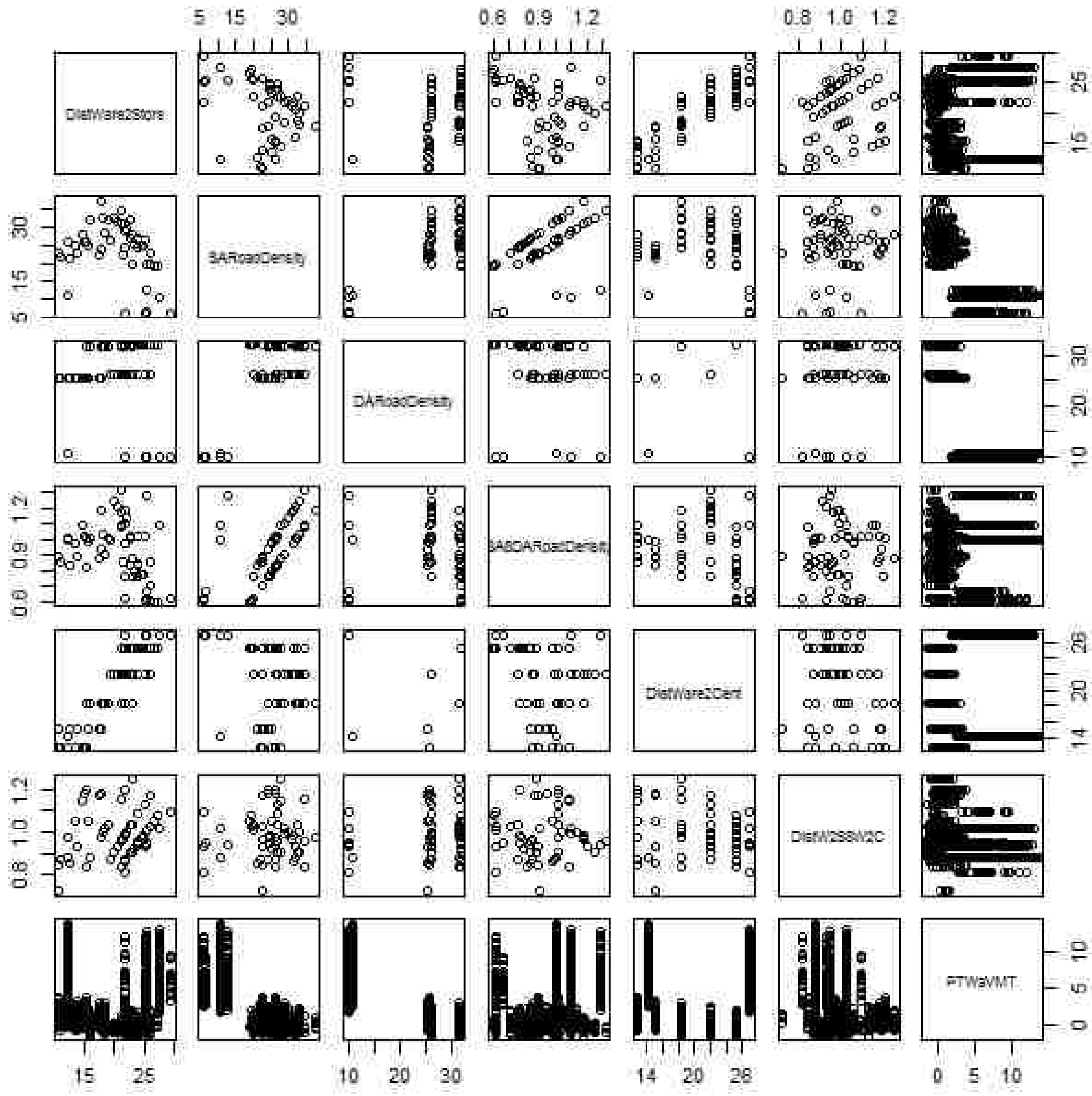
DARoadDensity + DistWare2Depot best model

```
results231a=lm(PTLDPM10~DARoadDensity+DistWare2Depot,data=PassLDPM10)
> summary(results231a)

Call:
lm(formula = PTLDPM10 ~ DARoadDensity + DistWare2Depot, data = PassLDPM10)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.083828 -0.018445 -0.000932  0.017820  0.095993 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    -2.301e-01  2.116e-03 -108.72   <2e-16 ***
DARoadDensity   3.533e-03  6.418e-05   55.06   <2e-16 ***
DistWare2Depot -1.383e-03  9.560e-05  -14.46   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02834 on 2622 degrees of freedom
Multiple R-squared:  0.5459,    Adjusted R-squared:  0.5456 
F-statistic:  1576 on 2 and 2622 DF,  p-value: < 2.2e-16
```

PassTravel to Warehouse

```
PassWaVars=c("DistWare2Store","SARoadDensity","DARoadDensity","SA8DARoadDensity","DistWare2Cent","DistW2S8W2C","PTWaVMT")
PassWaTravel=Master35sRatios[PassWaVars]
```

PassWaTravel[1:10,]
plot(PassWaTravel)



results240=lm(PTWaVMT~DistWare2Store,data=PassWaTravel)
summary(results240)

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

PTWa VMT	DistWare2 Store	SARoadDen sity	**DARoad Density**	SA8DARoadD ensity	DistWare2 Cent	DistW2S8 W2C
R^2	0.007611***	0.6441***	**0.6865*****	0.03048***	1.847e-08	0.1687***

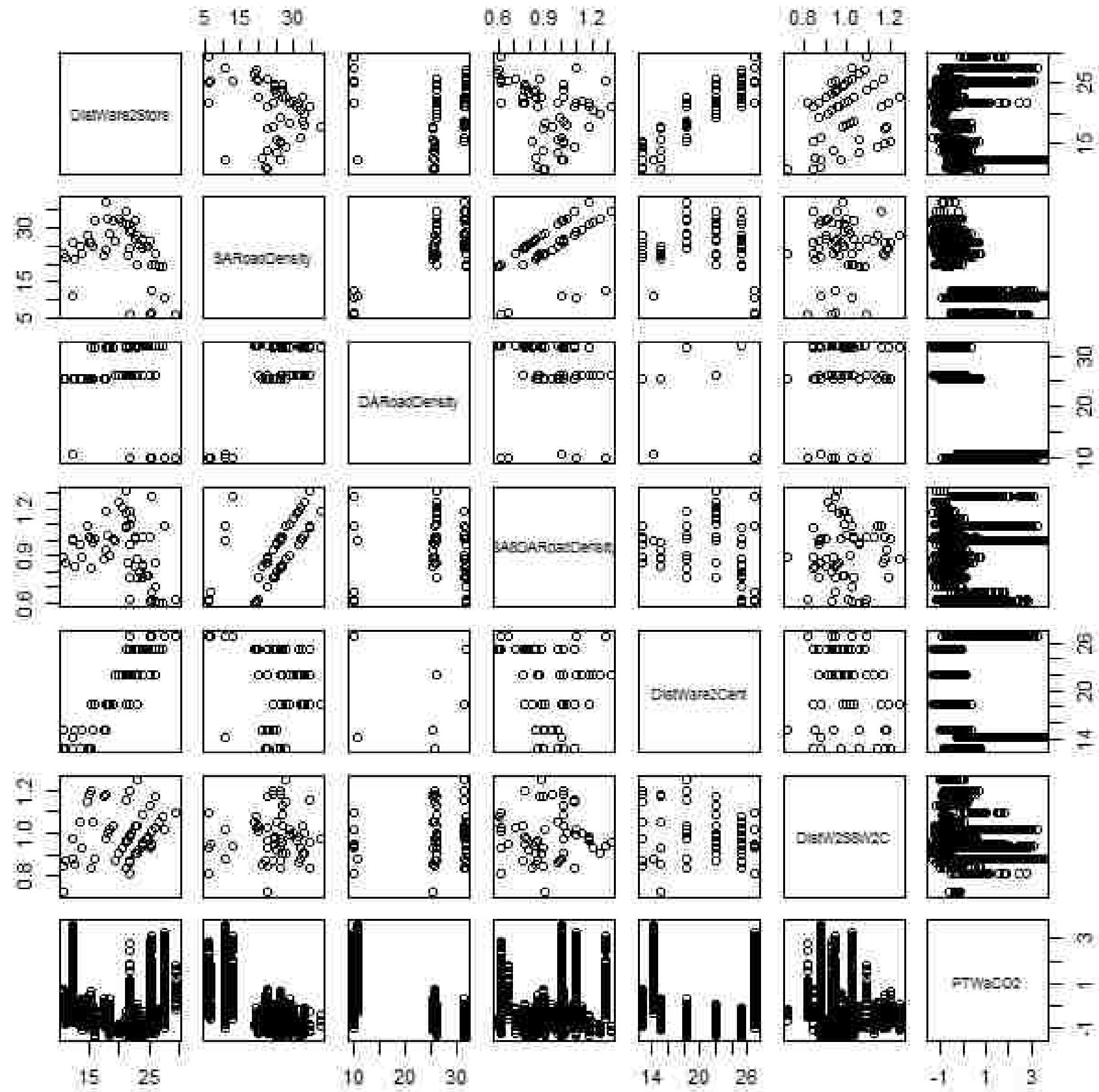
	DistWare2Store	SARoadDensity		SA8DARoadDensity	DistWare2Cent	DistW2S8W2C
	0.701***/***	0.6906***/***		0.6883***/***	0.6997***/***	0.6948***/***
		SARoadDensity		SA8DARoadDensity	DistWare2Cent	DistW2S8W2C
		0.7063***/***/***		0.7027***/***/***	0.7011/***/***	0.7018*/***/***
				SA8DARoadDensity	DistWare2Cent	DistW2S8W2C
				0.7084 ***/***/***/***	0.7063/***/**/***	0.7066/***/***/***
					DistWare2Cent	DistW2S8W2C
					0.7084 /***/***/**/***	0.7086 /***/***/***/***

Best Fit model: DARoadDensity, DistWare2Store, SARoadDensity, SA8DARoadDensity

```
results241c=lm(PTWaVMT~DARoadDensity+DistWare2Store+SARoadDensity+SA8DARoadDensity,data=PassWaTravel)
> summary(results241c)

Call:
lm(formula = PTWaVMT ~ DARoadDensity + DistWare2Store + SARoadDensity +
    SA8DARoadDensity, data = PassWaTravel)

Residuals:
    Min      1Q  Median      3Q     Max
-4.4404 -1.1409 -0.0027  0.7415  6.9477

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       9.547654   0.434723  21.963  < 2e-16 ***
DARoadDensity    -0.150529   0.025792  -5.836 5.99e-09 ***
DistWare2Store   -0.072085   0.005791 -12.448  < 2e-16 ***
SARoadDensity    -0.197500   0.027601  -7.155 1.08e-12 ***
SA8DARoadDensity  1.894986   0.443789   4.270 2.02e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.839 on 2620 degrees of freedom
```

```
Multiple R-squared:  0.7084,    Adjusted R-squared:  0.7079
F-statistic:  1591 on 4 and 2620 DF,  p-value: < 2.2e-16
------------

Parsimonious:
DARoadDensity+DistWare2Store
results241=lm(PTWaVMT~DARoadDensity+DistWare2Store,data=PassWaTravel)
> summary(results241)

Call:
lm(formula = PTWaVMT ~ DARoadDensity + DistWare2Store, data = PassWaTravel)

Residuals:
    Min      1Q  Median      3Q     Max
-4.4714 -1.2796  0.0349  0.7773  6.9705

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    11.085962   0.137420   80.67   <2e-16 ***
DARoadDensity  -0.328197   0.004208  -77.98   <2e-16 ***
DistWare2Store -0.065152   0.005764  -11.30   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.861 on 2622 degrees of freedom
Multiple R-squared:  0.701,     Adjusted R-squared:  0.7008
F-statistic:  3074 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
PassWaVars=c("DistWare2Store","SARoadDensity","DARoadDensity","SA8DARoadDensity","
DistWare2Cent","DistW2S8W2C","PTWaCO2")
PassWaCO2=Master35sRatios[PassWaVars]
PassWaCO2[1:10,]
plot(PassWaCO2)
```



results250=lm(PTWaCO2~DistWare2Store,data=PassWaCO2)
summary(results250)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTWaCO2	DistWare2Store	SARoadDensity	**DARoad Density**	SA8DARoad Density	DistWare2 Cent	DistW2S8W2C
R^2	0.05122***	0.5006***	**0.533*** **	0.02184***	0.02314***	0.1728***
	DistWare2Store	SARoadDensity		SA8DARoad Density	DistWare2 Cent	DistW2S8W2C

	0.5985*/*****	0.5363***/***		0.535***/***	0.598***/***	0.5523***/***
		SARoadDensity		SA8DARoadDensity	DistWare2Cent	DistW2S8W2C
		0.6042*/***/*** **		0.6**/***/***	0.5992*/**/***	0.5986/***/***
				SA8DARoadDensity	DistWare2Cent	DistW2S8W2C
				0.6072*/***/***/*** **	0.6057**/***/./***	0.6047./***/***/***/***
					DistWare2Cent	DistW2S8W2C
					0.6082 **/***/**/*/**	0.6077 ./***/***/***/**
						DistW2S8W2C
						0.6092 */**/***/***/./***

Best fit: all variables

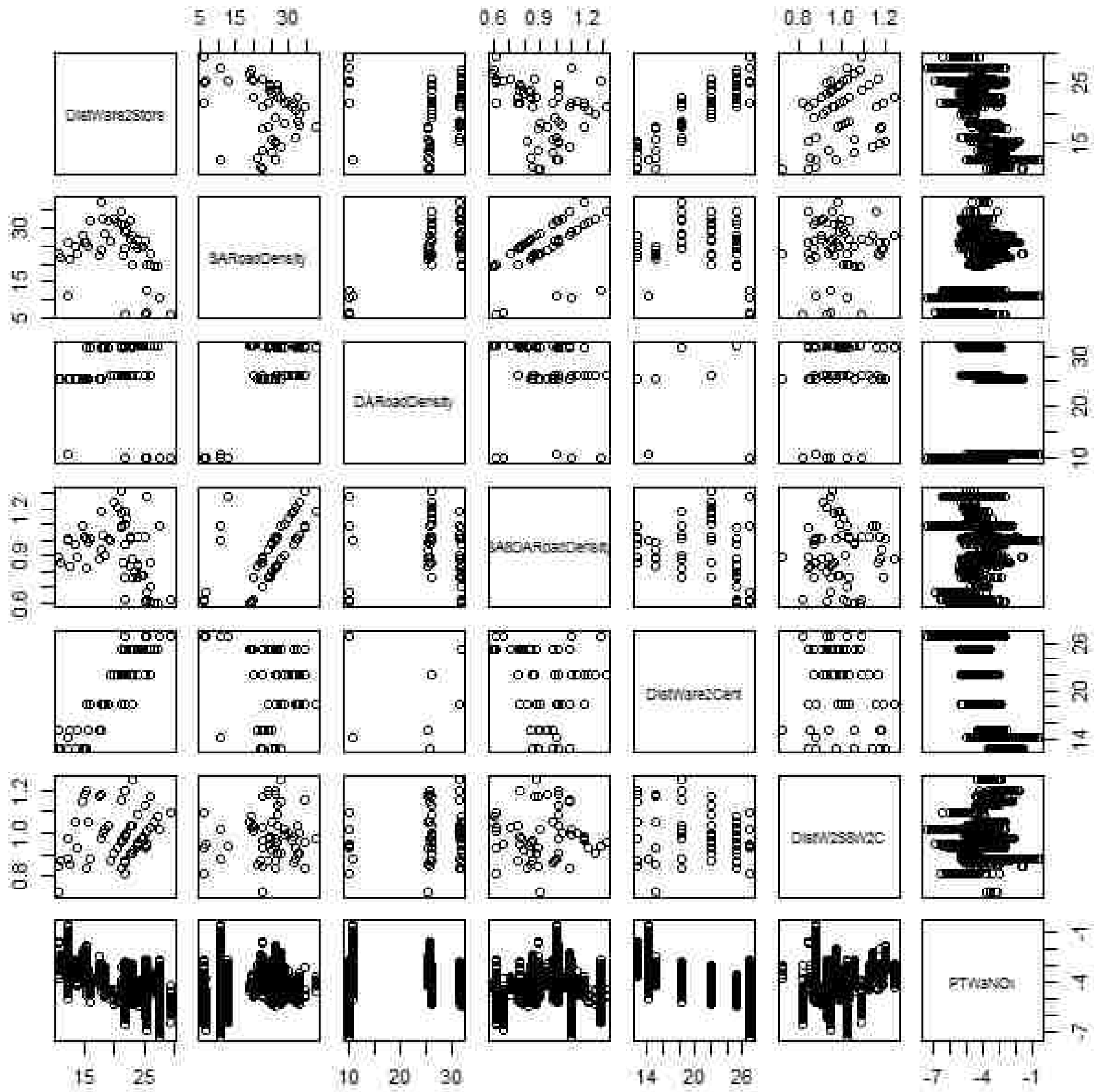
```
results252d=lm(PTWaCO2~DARoadDensity+DistWare2Store+SARoadDensity+SA8DARoadDensity+DistWare2Cent+DistW2S8W2C,data=PassWaCO2)
> summary(results252d)

Call:
lm(formula = PTWaCO2 ~ DARoadDensity + DistWare2Store + SARoadDensity + 
    SA8DARoadDensity + DistWare2Cent + DistW2S8W2C, data = PassWaCO2)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.65117 -0.36710 -0.04255  0.24908  2.53805 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)       3.723102   0.610304   6.100 1.21e-09 ***
DARoadDensity    -0.033163   0.008902  -3.725 0.000199 ***
DistWare2Store    0.057285   0.031428   1.823 0.068461 .  
SARoadDensity    -0.057225   0.009674  -5.915 3.74e-09 ***
SA8DARoadDensity  0.517001   0.155523   3.324 0.000899 ***
DistWare2Cent    -0.097678   0.030002  -3.256 0.001145 ** 
DistW2S8W2C      -1.544572   0.599459  -2.577 0.010032 *  
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6175 on 2618 degrees of freedom
Multiple R-squared:  0.6092,    Adjusted R-squared:  0.6083
F-statistic: 680.3 on 6 and 2618 DF,  p-value: < 2.2e-16
```

Parsimonious:
DARoadDensity+DistWare2Store

```
> results252a=lm(PTWaCO2~DARoadDensity+DistWare2Store,data=PassWaCO2)
> summary(results252a)

Call:
lm(formula = PTWaCO2 ~ DARoadDensity + DistWare2Store, data = PassWaCO2)

Residuals:
     Min       1Q   Median       3Q      Max
-1.62398 -0.39026 -0.04819  0.26710  2.56524

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     2.620374   0.046191   56.73   <2e-16 ***
DARoadDensity  -0.084565   0.001415  -59.78   <2e-16 ***
DistWare2Store -0.040069   0.001938  -20.68   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6255 on 2622 degrees of freedom
Multiple R-squared:  0.5985,    Adjusted R-squared:  0.5982
F-statistic:  1954 on 2 and 2622 DF,  p-value: < 2.2e-16
```

```
PassWaVars=c("DistWare2Store","SARoadDensity","DARoadDensity","SA8DARoadDensity","
DistWare2Cent","DistW2S8W2C","PTWaNOx")
PassWaNOx=Master35sRatios[PassWaVars]
PassWaNOx[1:10,]
plot(PassWaNOx)
```



results260=lm(PTWaNOx~DistWare2Store,data=PassWaNOx)
summary(results260)

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

PTWaNOx	DistWare2Store	SARoadDensity	DARoadDensity	SA8DARoadDensity	**DistWare2Cent**	DistW2S8W2C
R^2	0.6169***	0.005585***	0.005815***	0.002227*	**0.6441****	0.06807***
	DistWare2Store	**SARoad Density**	DARoadDensity	SA8DARoad Density		DistW2S8W2C

	0.6452**/***	**0.6474***/***	0.6453**/***	0.6451**/***		0.6452**/***
	DistWare2Store		**DARoadDensity**	SA8DARoad Density		DistW2S8W2C
	0.6475/***/***		**0.6508***/***/***	0.6483**/***/***		0.6474/***/***
	DistWare2Store			**SA8DARoadDensity**		DistW2S8W2C
	0.651/***/***/***			**0.6527***/***/***/***		0.6509/***/***/***
	DistWare2Store					DistW2S8W2C
	0.653/***/***/***/***					0.6528/***/***/***/***

Best fit:

```
results261a=lm(PTWaNOx~DistWare2Cent+SARoadDensity+DARoadDensity+SA8DARoadDensity,data=PassWaNOx)
> summary(results261a)

Call:
lm(formula = PTWaNOx ~ DistWare2Cent + SARoadDensity + DARoadDensity +
   SA8DARoadDensity, data = PassWaNOx)

Residuals:
    Min       1Q   Median       3Q      Max
-2.31214 -0.41814 -0.02483  0.37789  2.45947

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.174214   0.163303  -7.190 8.39e-13 ***
DistWare2Cent    -0.161768   0.002325 -69.587  < 2e-16 ***
SARoadDensity    -0.066552   0.010249  -6.494 9.99e-11 ***
DARoadDensity     0.054893   0.009551   5.748 1.01e-08 ***
SA8DARoadDensity  0.614675   0.164298   3.741 0.000187 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6835 on 2620 degrees of freedom
Multiple R-squared:  0.6527,    Adjusted R-squared:  0.6522
F-statistic:  1231 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Parsimonious:

DistWare2Cent

```
> results264=lm(PTWaNOx~DistWare2Cent,data=PassWaNOx)
> summary(results264)
```

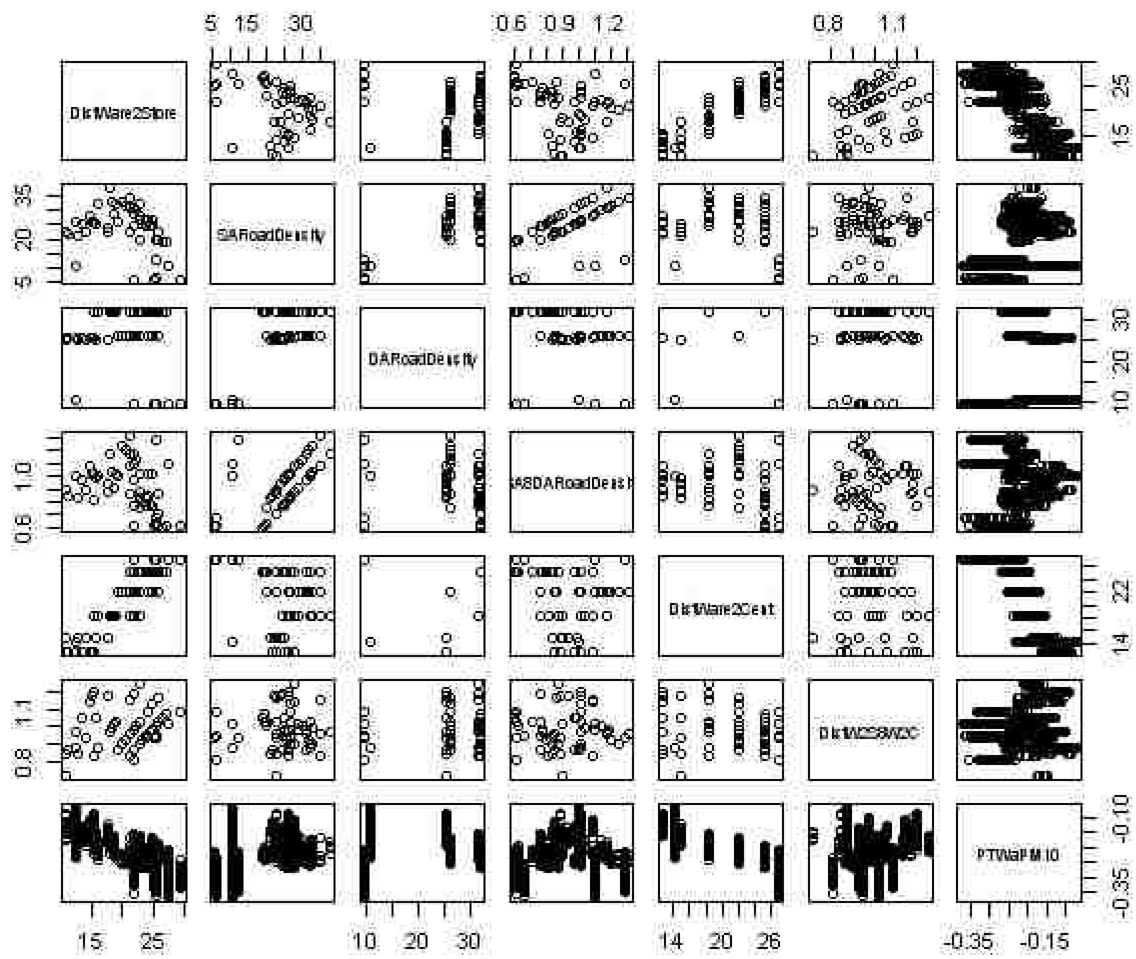
```
Call:
lm(formula = PTWaNOx ~ DistWare2Cent, data = PassWaNOx)

Residuals:
    Min       1Q   Median       3Q      Max 
-2.29956 -0.43753 -0.03954  0.40218  2.51061 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   -0.789225   0.047749  -16.53   <2e-16 ***
DistWare2Cent -0.158064   0.002294  -68.90   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.6916 on 2623 degrees of freedom
Multiple R-squared:  0.6441,    Adjusted R-squared:  0.644 
F-statistic:  4747 on 1 and 2623 DF,  p-value: < 2.2e-16


Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

PTWa CO2	**DistWare2 Store**	SARoadDe nsity	DARoadDe nsity	SA8DARoadD ensity	DistWare2 Cent	DistW2S8 W2C
R^2	**0.6169*****	0.005585***	0.005815***	0.002227*	0.6441***	0.06807***
		SARoadDe nsity	DARoadDe nsity	SA8DARoadD ensity	DistWare2 Cent	DistW2S8 W2C
		0.6176*/***	0.6189***/***	0.6174./***	0.6452***/**	0.6421***/***

```
results264a=lm(PTWaNOx~DistWare2Store,data=PassWaNOx)
> summary(results264a)

Call:
lm(formula = PTWaNOx ~ DistWare2Store, data = PassWaNOx)

Residuals:
    Min       1Q   Median       3Q      Max 
-2.26899 -0.44585 -0.03451  0.43354  2.48906 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)   -1.170806   0.044919  -26.07   <2e-16 ***
DistWare2Store -0.144333   0.002221  -65.00   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7175 on 2623 degrees of freedom
Multiple R-squared:  0.6169,    Adjusted R-squared:  0.6168
F-statistic:  4224 on 1 and 2623 DF,  p-value: < 2.2e-16
```

```
PassWaVars=c("DistWare2Store","SARoadDensity","DARoadDensity","SA8DARoadDensity","
DistWare2Cent","DistW2S8W2C","PTWaPM10")
PassWaPM10=Master35sRatios[PassWaVars]
PassWaPM10[1:10,]
plot(PassWaPM10)
```




```
results270=lm(PTWaPM10~DistWare2Store,data=PassWaPM10)
```

summary(results270)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

PTWaPM10	DistWare2Store	SARoadDensity	DARoadDensity	SA8DARoadDensity	**DistWare2Cent**	DistW2S8W2C
R^2	0.7485***	0.06773***	0.06705***	0.00558***	**0.8165*** **	0.04338***
	DistWare2Store	SARoadDensity	**DARoadDensity**	SA8DARoadDensity		DistW2S8W2C
	0.8181***/***	0.8295***/***	**0.835***/*** **	0.8199***/***		0.8191***/***
	DistWare2Store	**SARoadDensity**		SA8DARoadDensity		DistW2S8W2C
	0.8352 /***/***	**0.8368***/***/*** **		0.8356 **/***/***		0.8352 /***/***
	DistWare2Store			**SA8DARoad Density**		DistW2S8W2C
	0.8369 /***/***/***			**0.8375***/***/*** **		0.8369 /***/***/***
	DistWare2Store					DistW2S8W2C
	0.8377 /***/***/***/***					0.8376 /***/***/***/***

Best fit:

```
results274c2b=lm(PTWaPM10~DistWare2Cent+DARoadDensity+SARoadDensity+SA8DARoadDensity,data=PassWaPM10)
> summary(results274c2b)

Call:
lm(formula = PTWaPM10 ~ DistWare2Cent + DARoadDensity + SARoadDensity +
    SA8DARoadDensity, data = PassWaPM10)

Residuals:
      Min        1Q    Median        3Q       Max
-0.085128 -0.016457 -0.000811  0.015729  0.093226

Coefficients:
                Estimate Std. Error  t value Pr(>|t|)
(Intercept)     -5.347e-02  6.178e-03   -8.656  < 2e-16 ***
DistWare2Cent   -9.729e-03  8.794e-05 -110.631  < 2e-16 ***
```

```
DARoadDensity     2.991e-03  3.613e-04    8.278  < 2e-16 ***
SARoadDensity    -2.199e-03  3.877e-04   -5.671 1.58e-08 ***
SA8DARoadDensity  2.123e-02  6.215e-03    3.415 0.000648 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02586 on 2620 degrees of freedom
Multiple R-squared:  0.8375,	Adjusted R-squared:  0.8373
F-statistic:  3377 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Parsimonious

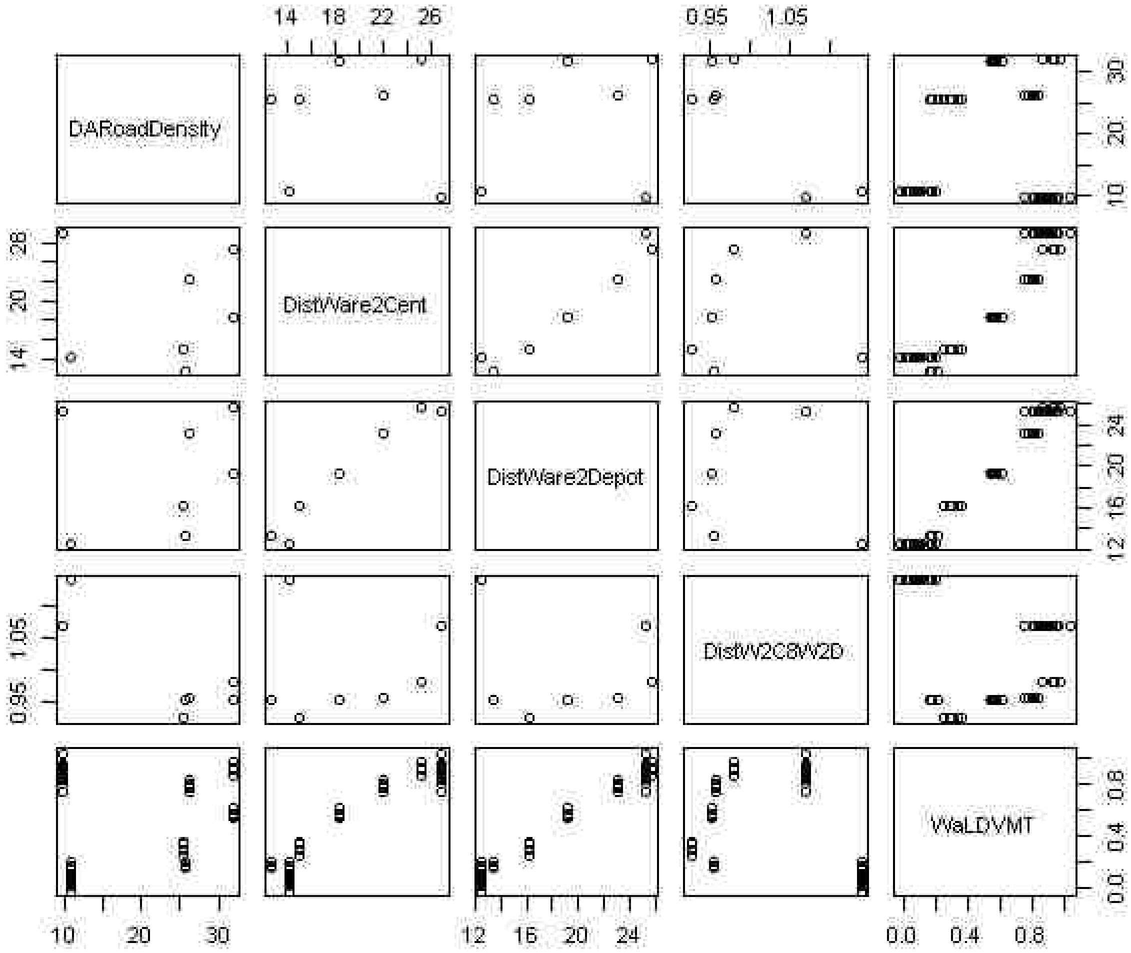
DistWare2Cent, DARoadDensity

```
results274c=lm(PTWaPM10~DistWare2Cent+DARoadDensity,data=PassWaPM10)
> summary(results274c)

Call:
lm(formula = PTWaPM10 ~ DistWare2Cent + DARoadDensity, data = PassWaPM10)

Residuals:
      Min        1Q    Median        3Q       Max
-0.085418 -0.017136 -0.000804  0.016378  0.093883

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   -3.664e-02  2.165e-03  -16.92   <2e-16 ***
DistWare2Cent -9.638e-03  8.724e-05 -110.47   <2e-16 ***
DARoadDensity  1.019e-03  5.943e-05   17.14   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02605 on 2622 degrees of freedom
Multiple R-squared:  0.835,	Adjusted R-squared:  0.8349
F-statistic:  6635 on 2 and 2622 DF,  p-value: < 2.2e-16
```

Warehouse to Local Delivery

VMT

```
WaLDVars=c("DARoadDensity","DistWare2Cent","DistWare2Depot","DistW2C8W2D","WaLD
VMT")
WaLDVMT=Master35sRatios[WaLDVars]
WaLDVMT [1:10,]
plot(WaLDVMT)
```



results280=lm(WaLDVMT~DARoadDensity,data=WaLDVMT)
summary(results280)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WaLDVMT	DARoadDensity	DistWare2Cent	**DistWare2Depot**	DistW2C8W2D
R^2	0.008549***	0.9247***	**0.9775*****	0.1293***
	DARoadDensity	DistWare2Cent		DistW2C8W2D
	0.9784***/***	0.9782***/***		0.9781***/***
		DistWare2Cent		DistW2C8W2D
		0.9785**/***/***		0.9785**/***/***
				DistW2C8W2D

				0.9785 / /***/***

Best fit:
results282a1=lm(WaLDVMT~DistWare2Depot+DARoadDensity+DistWare2Cent,data=WaLDVMT)
> summary(results282a1)

```
Call:
lm(formula = WaLDVMT ~ DistWare2Depot + DARoadDensity + DistWare2Cent,
   data = WaLDVMT)

Residuals:
     Min       1Q    Median       3Q      Max
-0.133416 -0.032033 -0.004771  0.032631  0.152561

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    -0.7099548  0.0099497 -71.354  < 2e-16 ***
DistWare2Depot  0.0515729  0.0030590  16.860  < 2e-16 ***
DARoadDensity   0.0025952  0.0004312   6.018 2.01e-09 ***
DistWare2Cent   0.0098227  0.0030375   3.234  0.00124 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05295 on 2621 degrees of freedom
Multiple R-squared:  0.9785,    Adjusted R-squared:  0.9785
F-statistic: 3.981e+04 on 3 and 2621 DF,  p-value: < 2.2e-16
```

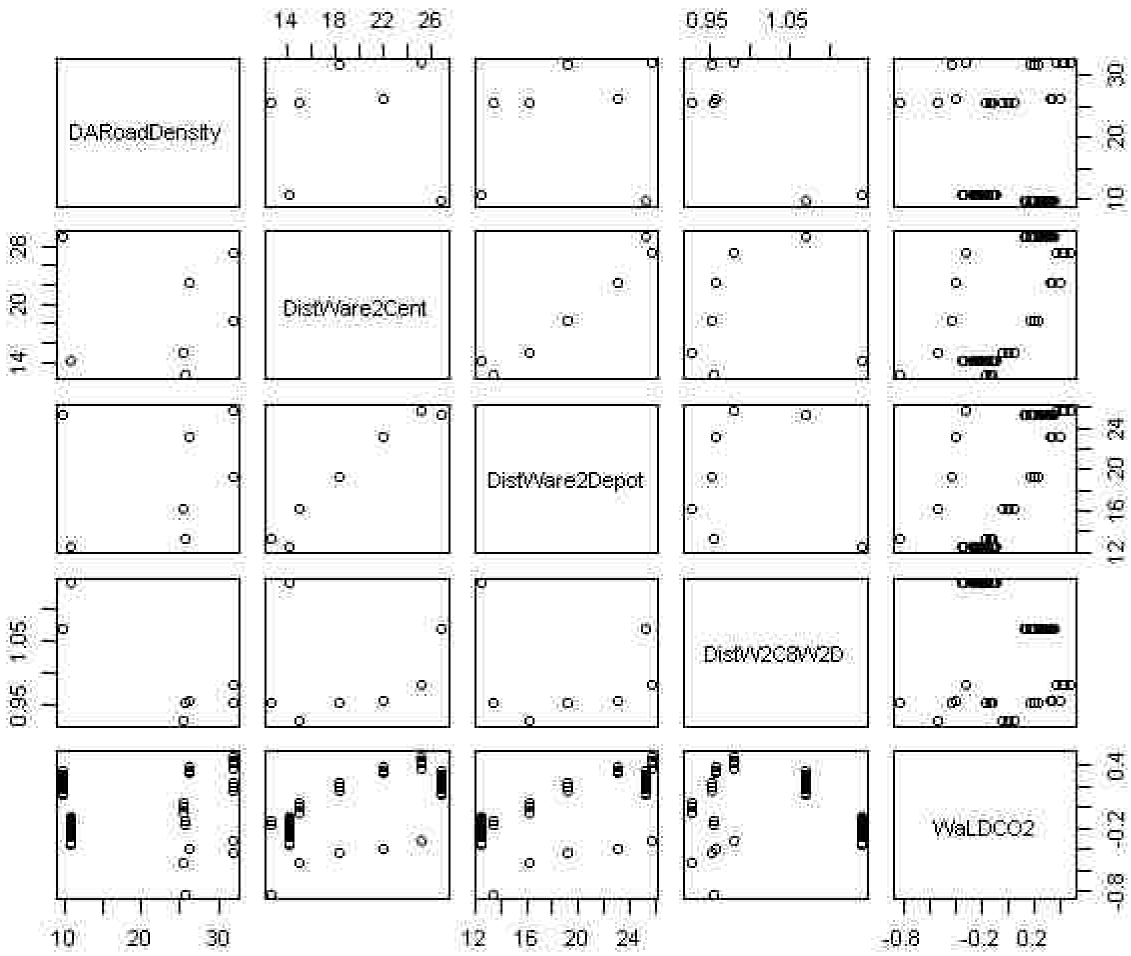
Parsimonious
DistWare2Depot
results282=lm(WaLDVMT~DistWare2Depot,data=WaLDVMT)
> summary(results282)

```
Call:
lm(formula = WaLDVMT ~ DistWare2Depot, data = WaLDVMT)

Residuals:
     Min       1Q    Median       3Q      Max
-0.142760 -0.036757 -0.001485  0.035749  0.143218

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    -0.6622719  0.0036326  -182.3   <2e-16 ***
DistWare2Depot  0.0615664  0.0001822   337.9   <2e-16 ***
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05413 on 2623 degrees of freedom
Multiple R-squared:  0.9775,    Adjusted R-squared:  0.9775
F-statistic: 1.142e+05 on 1 and 2623 DF,  p-value: < 2.2e-16
```

CO2

```
WaLDVars=c("DARoadDensity","DistWare2Cent","DistWare2Depot","DistW2C8W2D","WaLD
CO2")
WaLDCO2=Master35sRatios[WaLDVars]
WaLDCO2 [1:10,]
plot(WaLDCO2)
```




```
results290=lm(WaLDCO2~DARoadDensity,data=WaLDCO2)
summary(results290)
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WaLDCO2	DARoadDensity	**DistWare2Cent**	DistWare2Depot	DistW2C8W2D
R^2	0.001017	**0.6234*****	0.6424***	0.0547***
	DARoadDensity		DistWare2Depot	DistW2C8W2D
	0.6435*/*****		**0.6431***/***	0.6381***/***
			DistWare2Depot	DistW2C8W2D
			0.6437 /*/**	0.6437 /***/***

Best fit & parsimonious
results291a=lm(WaLDCO2~DistWare2Cent+DARoadDensity,data=WaLDCO2)
> summary(results291a)

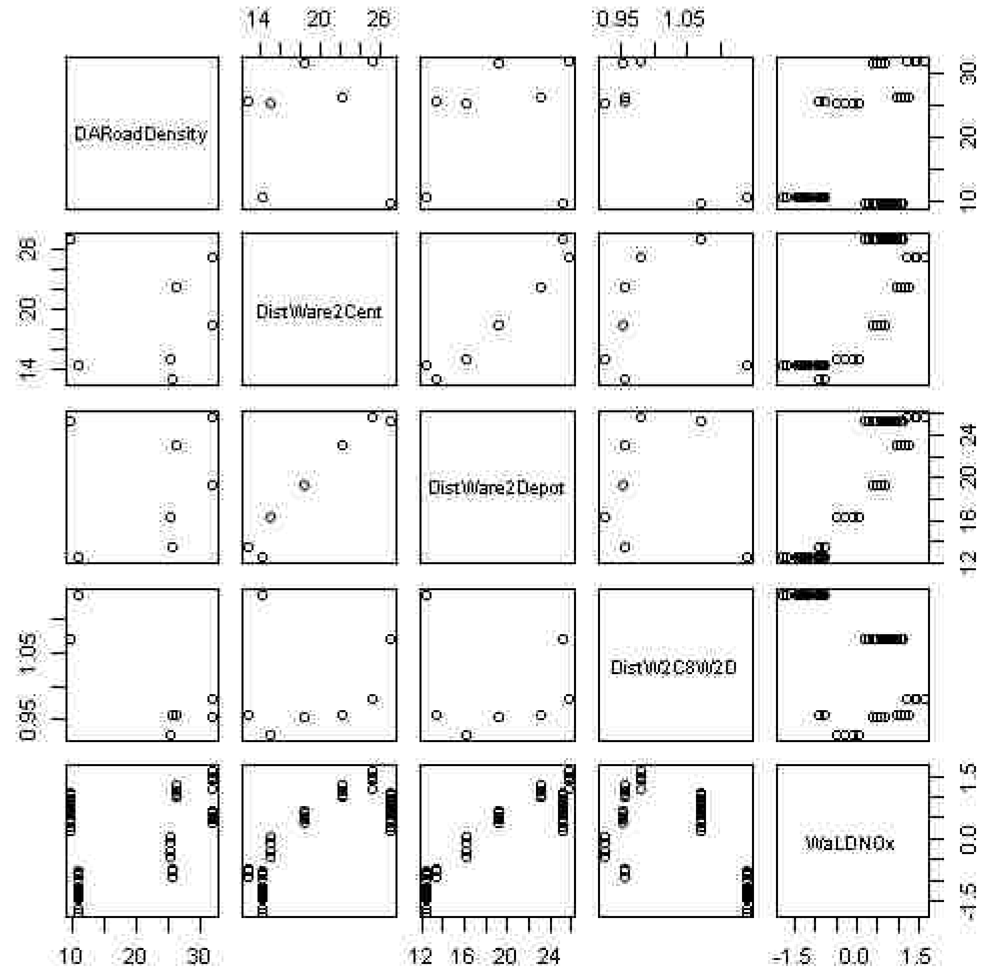
Call:
lm(formula = WaLDCO2 ~ DistWare2Cent + DARoadDensity, data = WaLDCO2)

Residuals:
```
    Min       1Q   Median       3Q      Max 
-0.62554 -0.03306  0.01883  0.09732  0.23708 
```

Coefficients:
```
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   -0.8128382  0.0138046  -58.88   <2e-16 ***
DistWare2Cent  0.0382341  0.0005562   68.74   <2e-16 ***
DARoadDensity  0.0046084  0.0003789   12.16   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.1661 on 2622 degrees of freedom
Multiple R-squared: 0.6435, Adjusted R-squared: 0.6432
F-statistic: 2366 on 2 and 2622 DF, p-value: < 2.2e-16

NOx
WaLDVars=c("DARoadDensity","DistWare2Cent","DistWare2Depot","DistW2C8W2D","WaLDNOx")
WaLDNOX=Master35sRatios[WaLDVars]
WaLDNOX [1:10,]
plot(WaLDNOX)



results300=lm(WaLDNOx~DARoadDensity,data=WaLDNOX)
summary(results300)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WaLDNOx	DARoadDensity	DistWare2Cent	**DistWare2Depot**	DistW2C8W2D
R^2	0.1031***	0.7468***	**0.8796*****	0.2854***
	DARoadDensity	DistWare2Cent		DistW2C8W2D
	0.9485***/***	0.9451***/***		0.9314***/***
		DistWare2Cent		**DistW2C8W2D**
		0.9487**/***/***		**0.9489*****/***/***
		DistWare2Cent		

		0.9531***/***/***/***		

Best fit

```
results302a2a=lm(WaLDNOx~DistWare2Depot+DARoadDensity+DistW2C8W2D+DistWare2Cent,data=WaLDNOX)
> summary(results302a2a)

Call:
lm(formula = WaLDNOx ~ DistWare2Depot + DARoadDensity + DistW2C8W2D +
    DistWare2Cent, data = WaLDNOX)

Residuals:
     Min       1Q   Median       3Q      Max
-0.55398 -0.12433 -0.02112  0.13855  0.44116

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    -7.937628   0.288384 -27.525  < 2e-16 ***
DistWare2Depot  0.581174   0.027308  21.282  < 2e-16 ***
DARoadDensity   0.009090   0.002034   4.469 8.19e-06 ***
DistW2C8W2D     4.469445   0.283954  15.740  < 2e-16 ***
DistWare2Cent  -0.403092   0.026202 -15.384  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2168 on 2620 degrees of freedom
Multiple R-squared:  0.9531,    Adjusted R-squared:  0.953
F-statistic: 1.331e+04 on 4 and 2620 DF,  p-value: < 2.2e-16
```

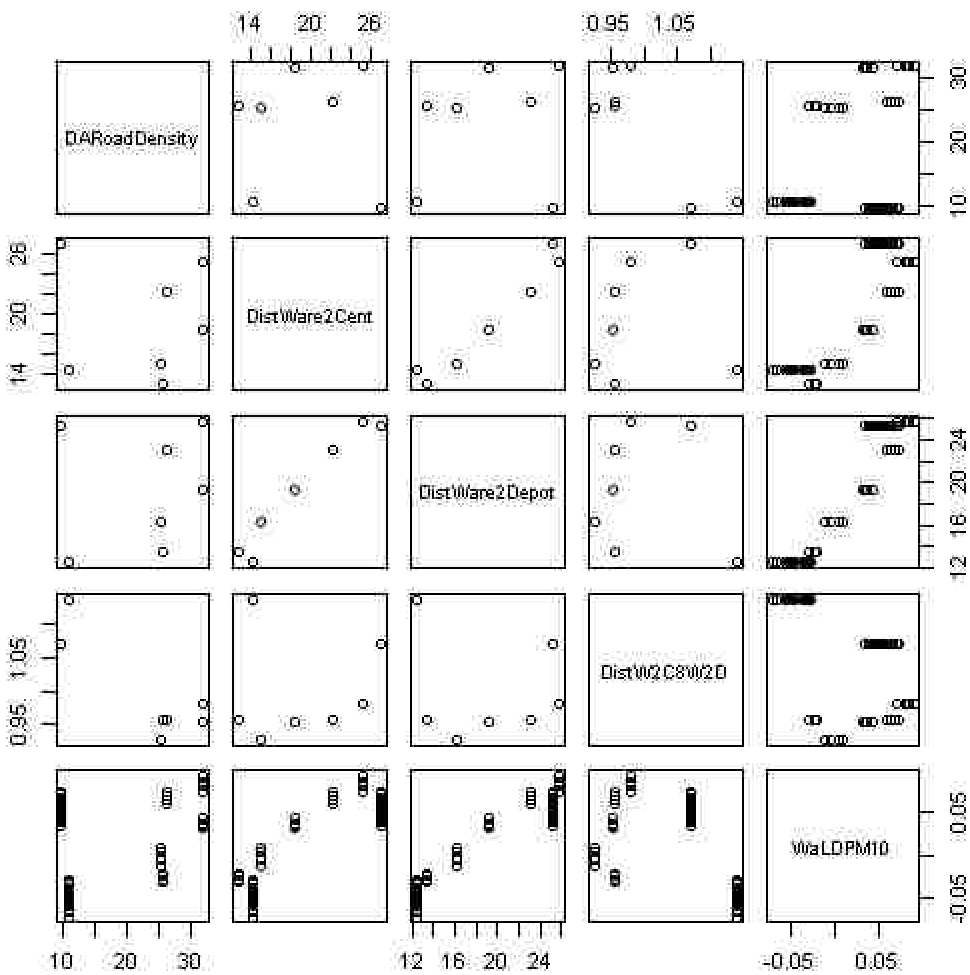
Parsimonious

```
results302a=lm(WaLDNOx~DistWare2Depot+DARoadDensity,data=WaLDNOX)
> summary(results302a)

Call:
lm(formula = WaLDNOx ~ DistWare2Depot + DARoadDensity, data = WaLDNOX)

Residuals:
     Min       1Q   Median       3Q      Max
-0.53410 -0.13358 -0.00877  0.14316  0.46743

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)    -3.5645111  0.0169633 -210.13   <2e-16 ***
DistWare2Depot  0.1589183  0.0007663  207.39   <2e-16 ***
DARoadDensity   0.0304410  0.0005144   59.18   <2e-16 ***
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2272 on 2622 degrees of freedom
Multiple R-squared: 0.9485, Adjusted R-squared: 0.9484
F-statistic: 2.413e+04 on 2 and 2622 DF, p-value: < 2.2e-16

PM10
WaLDVars=c("DARoadDensity","DistWare2Cent","DistWare2Depot","DistW2C8W2D","WaLD PM10")
WaLDPM10=Master35sRatios[WaLDVars]
WaLDPM10 [1:10,]
plot(WaLDPM10)



results310=lm(WaLDPM10~DARoadDensity,data=WaLDPM10)
summary(results310)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WaLDPM10	DARoadDensity	DistWare2Cent	**DistWare2Depot**	DistW2C8W2D
R^2	0.06934***	0.8076***	**0.9237*** **	0.2493***
	DARoadDensity	DistWare2Cent		DistW2C8W2D
	0.9649* ***/***	0.9634***/***		0.9569***/***
		DistWare2Cent		DistW2C8W2D
		0.9652* ***/***/***		0.9649 /***/***
				DistW2C8W2D
				0.9661* ***/***/***/***

Best fit
results312a1a=lm(WaLDPM10~DistWare2Depot+DARoadDensity+DistWare2Cent+DistW2C8W2D,data=WaLDPM10)

```
> summary(results312a1a)

Call:
lm(formula = WaLDPM10 ~ DistWare2Depot + DARoadDensity + DistWare2Cent +
    DistW2C8W2D, data = WaLDPM10)

Residuals:
      Min        1Q    Median        3Q       Max
-0.0239293 -0.0058721 -0.0004608  0.0053013  0.0190136

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    -2.651e-01  1.248e-02 -21.238  < 2e-16 ***
DistWare2Depot  1.967e-02  1.182e-03  16.642  < 2e-16 ***
DARoadDensity   5.159e-04  8.804e-05   5.860 5.22e-09 ***
DistWare2Cent  -1.088e-02  1.134e-03  -9.591  < 2e-16 ***
DistW2C8W2D     1.063e-01  1.229e-02   8.652  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.009386 on 2620 degrees of freedom
Multiple R-squared:  0.9661,    Adjusted R-squared:  0.9661
F-statistic: 1.868e+04 on 4 and 2620 DF,  p-value: < 2.2e-16
```

Parsimonious

results312a=lm(WaLDPM10~DistWare2Depot+DARoadDensity,data=WaLDPM10)

```
> summary(results312a)

Call:
lm(formula = WaLDPM10 ~ DistWare2Depot + DARoadDensity, data = WaLDPM10)

Residuals:
      Min        1Q    Median        3Q       Max
-0.0234829 -0.0061972 -0.0009972  0.0054727  0.0194599

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   -1.649e-01  7.128e-04 -231.38   <2e-16 ***
DistWare2Depot  8.332e-03  3.220e-05  258.76   <2e-16 ***
DARoadDensity   1.199e-03  2.162e-05   55.49   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.009546 on 2622 degrees of freedom
Multiple R-squared:  0.9649,    Adjusted R-squared:  0.9649
F-statistic: 3.607e+04 on 2 and 2622 DF,  p-value: < 2.2e-16
```