Final Report

Development of a Sign Sheeting Sampling Protocol for the Determination of Service Life of Traffic Signs

Submitted by

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INTRODUCTION

Traffic signs provide important information to road users. To be effective, traffic sign visibility must be maintained during daytime and nighttime conditions. Sign visibility during nighttime conditions is achieved by the retroreflective properties of the traffic signs with the light emitted by the vehicles' headlights. Accordingly, standards indicating the minimum levels of retroreflectivity have been established for all roadway traffic signs and pavement markings. These standards are maintained in the Manual on Uniform Traffic Control Devices (MUTCD) published by the U.S. Department of Transportation and are applicable to all roads open to the public. The MUTCD's main audiences are: State, county and cities highway agencies responsible for traffic control devices in their respective jurisdictions [61] [84].

Retroreflectivity is "the efficiency of the material to redirect light back to its source", the formal definition is found in ASTM E808. Retroreflectivity standards for traffic signs are based on the type of sheeting material and the various applicable color combinations, including some special size conditions. The minimum retroreflectivity levels are in units of Candelas/lux/$meter^2$ at an observation angle of $0.2^o$and an entrance angle of -4.0^o. The measure of retroreflectivity is stated as the coefficient of retroreflection, R_A. Additionally, the MUTCD specifies a minimum sign contrast ratio between white and red retroreflectivity values. [61] [84]

New MUTCD Table 2A.3
Minimum Maintained Retroreflectivity Levels

Sign Color	Sheeting Type (ASTM D4956-04) ①				Additional Criteria
	Beaded Sheeting			Prismatic Sheeting	
	I	II	III	III, IV, VI, VII, VIII, IX, X	
White on Green	W* G ≥ 7	W* G ≥ 15	W* G ≥ 25	W ≥ 250; G ≥ 25	Overhead
White on Green	W* G ≥ 7	W ≥ 120; G ≥ 15			Ground-mounted
Black on Yellow or Black on Orange	Y*; O*	Y ≥ 50; O ≥ 50			②
Black on Yellow or Black on Orange	Y*; O*	Y ≥ 75; O ≥ 75			③
White on Red	W ≥ 35; R ≥ 7				④
Black on White	W ≥ 50				—

① The minimum maintained retroreflectivity levels shown in this table are in units of cd/lx/m^2 measured at an observation angle of 0.2° and an entrance angle of -4.0°.
②For text and fine symbol signs measuring at least 1200 mm (48 in) and for all sizes of bold symbol signs
③For text and fine symbol signs measuring less than 1200 mm (48 in)
④Minimum Sign Contrast Ratio ≥ 3:1 (white retroreflectivity ÷ red retroreflectivity)
* This sheeting type should not be used for this color for this application.

Figure 1 Retroreflection

The goal of the MUTCD retroreflectivity compliance requirements is to improve safety on roads. Approximately 42,000 people have been killed on U.S. roads each year for the last eight years. About half of traffic fatalities occur at night, although only about one quarter of travel occurs after dark. Nighttime driving is inherently hazardous because of decreased driver visibility. The nighttime fatality rate is approximately three times greater than that of the daytime. [11] [84]

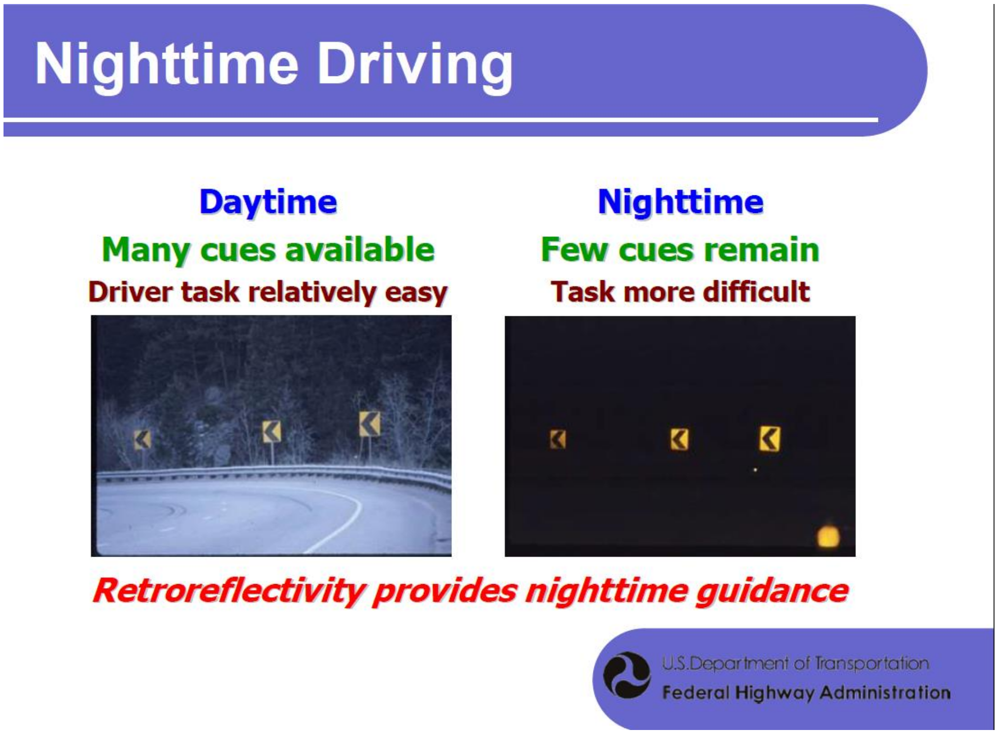

Figure 2 Nighttime Driving

Compliance with the retroreflectivity standards requires an assessment or management program for maintaining retroreflectivity at or above their corresponding minimum levels per MUTCD, Table 2A-3. [61] [84]

The **assessment methods** involve evaluating individual signs. They are:

- Visual Nighttime Inspection Method
  - Calibration Signs Procedure
  - Comparison Panels Procedure
  - Consistent Parameters Procedure
- Measured Sign Retroreflectivity Method

The **management methods** provide an agency with the ability to maintain sign retroreflectivity without having to physically inspect each individual sign. They are:

- Expected Sign Life Method
- Blanket Replacement Method

- Control Signs Method

<u>Other assessment or management methods</u> that are developed based on engineering studies can be used as long as they are designed to maintain the minimum levels as per MUTCD Table 2A-3.

There are some allowable exceptions from the retroreflectivity maintenance requirements, e.g., parking signs. Except for these exceptions, all minimum retroreflectivity levels need to be maintained using one of the assessment or management methods, or combinations thereof. [39][61][84]

There is no requirement for federal approval of an agency's method nor does it require agencies to submit documentation – annually or under any other timeframe. Agencies may choose to document their maintenance method and activities in managing sign retroreflectivity for their own purposes, such as scheduling, budgeting resources, defense against litigation, etc. [39][61][84]

Revisions to the MUTCD, published in 2012, extended the compliance date for maintaining sign retroreflectivity standards to June 14, 2014. The revision also refined the compliance date to apply only to regulatory and warnings signs. The compliance date has already passed. [39][61][84]

There is no compliance date for sign replacement. Nonetheless, signs identified through an agency's method as being below the minimum established retroreflectivity levels need to be replaced. Schedules for replacing the signs are based on resources and relative priorities [39] 84].

Retroreflectivity compliance has generated a number of studies on the expected service life of traffic signs as it plays a key role in some maintenance programs.

There are color standards identified in ASTM D4956-13, but there are no maintenance requirements in the MUTCD. Nonetheless, maintaining a certain level of color values is perhaps as important for daytime drivers as retroreflectivity is to nighttime drivers.

Color and retroreflectivity measurement instruments are expensive. For example, Tapco's GR3 retroreflectometer with remote control activation, extension pole and software costs approximately $10,000. And HunterLab's MiniScan EZ colorimeter with software also costs approximately $10,000. These prices are without sales tax and reflect university discounts.

Color specifications (x , y values) relate to the 1931 CIE Chromaticity Diagram. The Color Box shows the polygon formed by the x , y coordinates of the color specifications.

The dots in the Color Box reflect the x , y measurements observed. To be within ASTM specifications, the observed color measurements should be within the area of the polygon. At present, there is no standard software provided by the colorimeter instrument suppliers that renders the Color Box with the corresponding polygon and color values observed.

Table 1 Color Specification Limits (Daytime)

Color	1		2		3		4		5	
	x	y	x	y	x	y	x	y	x	y
White	0.303	0.300	0.368	0.366	0.340	0.393	0.274	0.329		
Yellow	0.498	0.412	0.557	0.442	0.479	0.520	0.438	0.472		
Orange	0.558	0.352	0.636	0.364	0.570	0.429	0.506	0.404		
Green[B]	0.026	0.399	0.166	0.364	0.286	0.446	0.207	0.771		
Red	0.648	0.351	0.735	0.265	0.629	0.281	0.565	0.346		
Blue[B]	0.140	0.035	0.244	0.210	0.190	0.255	0.065	0.216		
Brown	0.430	0.340	0.610	0.390	0.550	0.450	0.430	0.390		
Fluorescent Yellow-Green	0.387	0.610	0.369	0.546	0.428	0.496	0.460	0.540		
Fluorescent Yellow	0.479	0.520	0.446	0.483	0.512	0.421	0.557	0.442		
Fluorescent Orange	0.583	0.416	0.535	0.400	0.595	0.351	0.645	0.355		
Fluorescent Pink	0.600	0.340	0.450	0.332	0.430	0.275	0.536	0.230	0.644	0.290

[A] The four pairs (five pairs for fluorescent pink) of chromaticity coordinates determine the acceptable color in terms of the CIE 1931 Standard Colorimetric System measured with CIE Standard Illuminant D65.
[B] The saturation limit of green and blue may extend to the border of the CIE chromaticity locus for spectral colors.

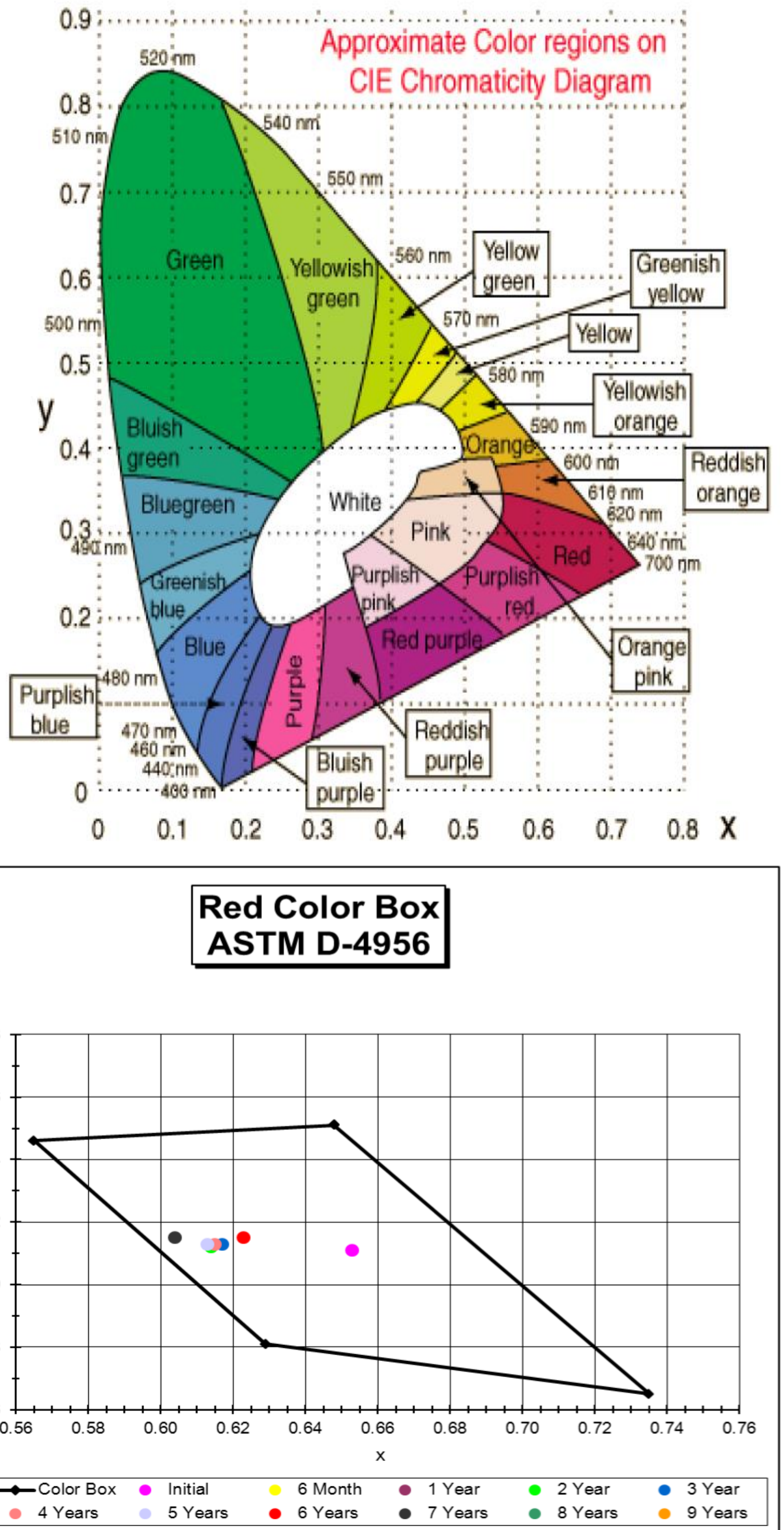

Figure 3 1931 CIE Chromaticity Diagram and Red Color Box

Literature Review

1. Previous studies pertaining to the service life of traffic signs

Studies on the service life of retroreflective traffic signs go back at least 25 years. [32]

In 1991, K.L. Black, et al., completed a study of the service life of retroreflective traffic signs throughout eight geographic zones covering the Continental U.S.A. These zones were developed for the data collection effort of the study. Based on this sample space, retroreflective data from 5,722 sign samples were analyzed using regression methods. The samples were selected from four State agencies, nine city agencies and four county agencies. [32]

The data collection addressed factors believed to contribute to the degradation of retroreflectivity. The data collected included: retroreflectivity, sign age, precipitation level, ground elevation, annual heating degree-days (a general climate measure), contrast ratio for red and white colors, orientation to the sun, ground elevation and area type (heavy industrial areas). However, few signs with date of installation older than 12 years were still in-service; and data from older high performance sheeting signs were difficult to find. Signs were washed before any readings were taken to determine the condition of the sign without the effect of dirt. [32]

The first criterion for selecting data collection locations was the availability of a computer based sign inventory system whose database contained information such as sign and sheeting type, color, date of installation, zones and geographic locations.

Nine regression models for the various sheeting color and type combinations were developed and tested for significance. These tests yielded four significant independent variables: age, heating degree-days, precipitation levels and ground elevation. Retroreflectivity was the dependent variable.

All nine models yielded poor prediction results as their adjusted coefficients of determination values, R^2, ranged between 0.129 and 0.479. The green color with high performance sheeting (Type III-A) showed the highest R^2 value of 0.479. And the red color with high performance sheeting showed the lowest adjusted R^2 value of 0.129. [32]

Although the models contained statistically significant independent variables, the low R^2 values indicate that much of the dependent variable (retroreflectivity) was left unexplained.

Age was the dominant independent variable and green sheeting was the least influenced by natural weathering. Most signs received little benefit from washing. [32]

Studies related to service life of traffic signs published after 1991 expanded the number of sheeting types. **They all used regression models and obtained similar results to K.L. Black, et al.**

One of the most recent publications published in June 2014 by Howard Preston, et al., was sponsored by the Minnesota Department of Transportation. The study primary goal was to provide objective data about sign life based on the degradation of retroreflectivity and color over time. [4]

Howard Preston, et al. reviewed eleven published articles ranging from 1992 to 2013. All used a regression model approach to determine the service life of the signs. The authors' state in their literature review conclusions that the most important lesson learned was "**None of the research continued collecting retroreflectivity readings long enough to observe failure from the perspective of actually watching retroreflectivity of a set of signs drop below the established thresholds in a controlled setting.**" Adding that "a number of the authors concluded that until that kind of research is conducted, any results regarding sign life will continue to be estimates as opposed to definitive values". Some of the additional lessons learned from the literature reviewed indicated that "sign orientation and weather did not play substantial roles in the deteriorating retroreflectivity", and "color fade may be as large of an issue or cause for failure as retroreflectivity degradation." And that "color degradation can result in an initial increase in retroreflectivity." [4]

Howard Preston, et al. research consisted of obtaining and analyzing in-service retroreflectivity data from approximately three hundred forty signs collected by local agencies throughout Minnesota. In addition, an outdoor test deck facility in Minnesota was established to obtain retroreflectivity information for the duration of the research. [4]

With a couple of exceptions, results from the in-service data collected in Minnesota show low R^2 values. And five out of the eleven models have trendlines with positive slopes, which could be due to color fading resulting in higher retroreflectivity.” [4]

Following are three examples depicting the results from the in-service data collected in Minnesota [4].

Figure 4 Type XI Yellow Trendline

Figure 5 Type XI Green Trendline

Figure 6 Type XI White Trendline

Note that the regression trendline with a positive slope (Type XI Green) is inconclusive. Regression trendlines with negative slopes have been extrapolated to calculate when, on average, the minimum required retroreflectivity levels would be met. **The extrapolation of the trendline and its intersection with the corresponding minimum established value of retroreflectivity should not be interpreted as the predictive average service life of the signs.**

Overall, the analysis from the in-service data was inconclusive. [4]

Additional conclusions from the study indicated that "none of the signs have been in-place long enough to observe failure and factors such as knock-downs, vandalism and sign sheeting misidentification make it difficult to collect reliable retroreflectivity data on the same signs over a period of time". [4]

Regarding the outdoor test deck facility study, the authors indicated that a longer range of sign life could be reevaluated as more data is collected from the outdoor test deck located in Minnesota. [4]

Figure 7 Outdoor test deck facility

The outdoor test deck layout "consisted of seven sign racks with different sheeting materials facing four cardinal directions. One of the south facing sign racks was palced at a 45 degree angle to simulate speeding the degradation process by approximately twice as much as a vertical sign." [4]

Data from the outdoor test deck was not collected for a long enough period of time to provide conclusive results by the time the study was completed. The study indicated that data from the outdoor test deck would continue to be collected over a period of multiple years to better determine an actual sign life for signs in the Minnesota climate. No additonal published data was found. [4]

Adam M. Pike and Paul Carlson's paper prepared for the 93rd Annual Meeting of the Transportation Research Board in 2014, studied data obtained from 525 in-service signs representing 783 different sign sheeting samples being measured, the majority were sheeting Types III and IV. Samples were taken from five districts in the state of Wyoming. Wyoming has varying terrain and weather conditions, and approximately 93% of its road miles are considered rural. The study identified that 21.5% of the signs had been shot, vandalized, damaged or notably dirty. [5]

Adam M. Pike and Paul Carlson's paper provided fourteen different regression models representing the combination of sheeting types, colors and sign orientation. **The R^2 values ranged from 0.0029 to 0.4436**. "The majority of the signs were installed within the last 13 years" [5].

See the following graphics representing examples of the results.

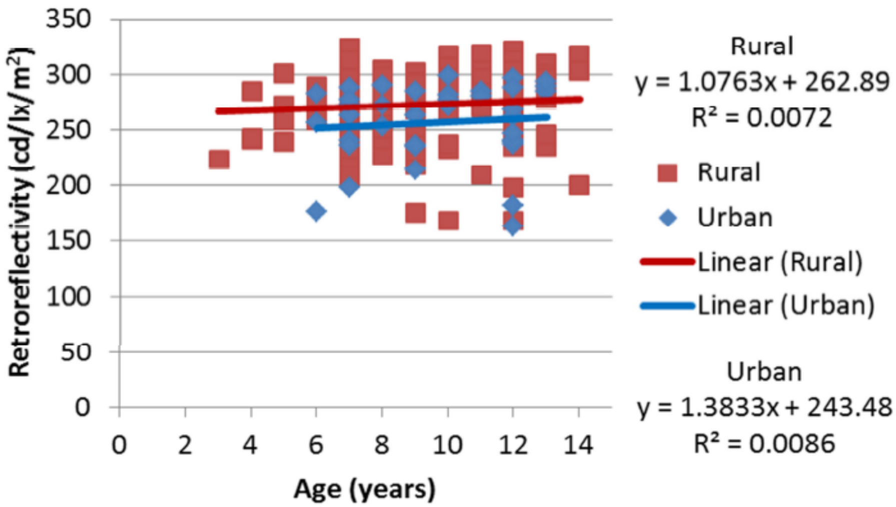

Figure 8 ASTM Type III white rural/urban

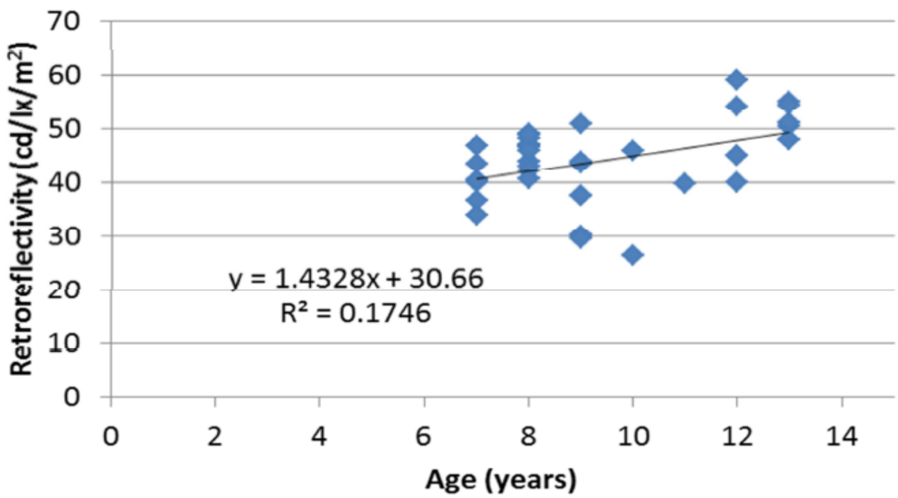

Figure 9 ASTM Type III Green

The positive trend lines could be due to "color fading, resulting in higher retroreflectivity as the sheeting ages" [5]

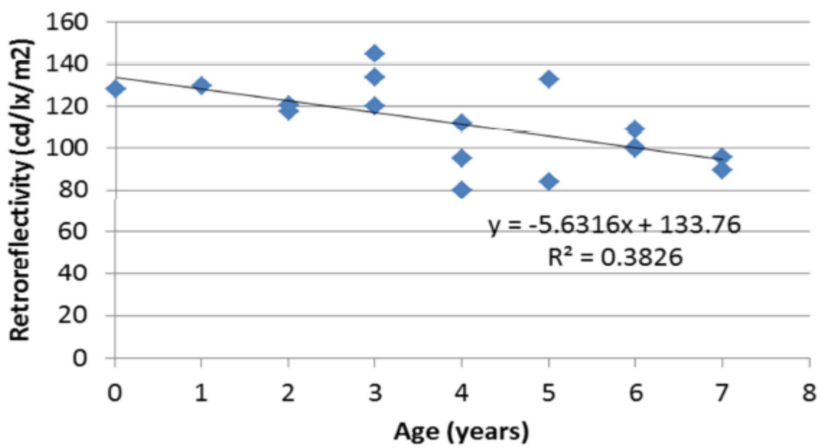

Figure 10 ASTM Type IV Green

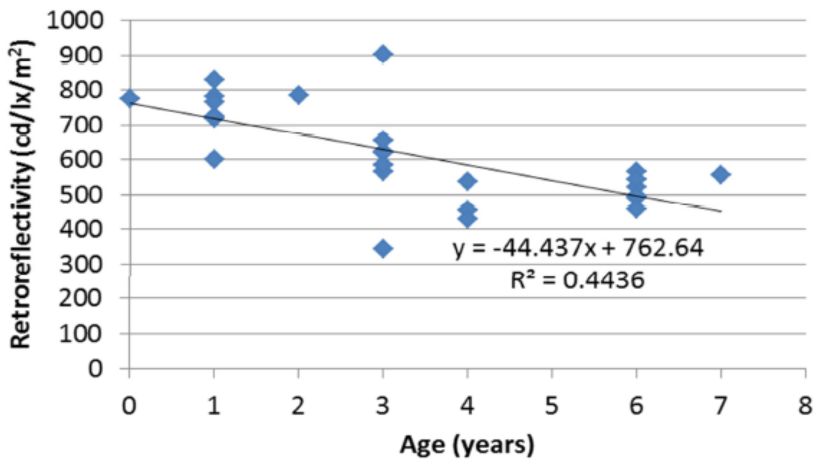

Figure 11 ASTM Type IV Yellow [5]

In the findings and recommendations section of the study, Adam M. Pike and Paul Carlson stated " that the white, yellow, green and red ASTM Type III material evaluated were each found to have at least 13 to 14 years of service life with no clear end of service life based on retroreflectivity." And for ASTM Type IV "the white material ranged from 17 to 143 years of service life … the yellow material ranged from 15 to 226 years of service life ... "the green material ranged from 19 years to no clear end of service life based on retroreflectivity … the red material ranged from 21 years to no clear end of service life based on retroreflectivity." [5]

Part of the reason for not seeing degradation in retroreflectivity, the authors indicated, may be due to "signs being replaced before their retroreflectivity actually begins to degrade … only leaving in place signs with good and similar retroreflectivity." The authors concluded that "based on the findings of this research it appears that the sign sheeting materials evaluated would not need to be replaced any sooner than on a 15 year cycle for retroreflectivity purposes in an environment like Wyoming's". [5]

N. Mike Jackson, et al. published a report on 2013 titled: Use of High Intensity Reflective Sheeting in lieu of External Lighting of Overhead Roadway Signs. The study was sponsored by the Florida Department of Transportation (FDOT) to investigate whether high intensity reflective sheeting (especially prismatic sheeting) can be used to replace overhead sign lighting. One of the tasks was to evaluate the impact that dirt and adverse weather conditions have on sign surfaces. For safety and costs considerations, shoulder-mounted guide signs were measured instead of overhead signs as their sheeting materials are the same. [6]

Based on the retroreflectivity readings of 52 guide signs taken along I-95, I-10 and I-75; and installed between 1995 and 2012. The authors determined that "dirt on average reduces sign retroreflectivity by about 10 percent; and that "signs in heavily shaded areas were notably dirtier than signs in open areas." [6]

Additional studies were performed to determine if retroreflectivity is affected by the sign direction (orientation), i.e., signs facing North and East versus South and West. Retroreflectivity measurements were taken between the two direction groups, before and after cleaning, and analyzed. There was a difference between the two direction groups; however the difference was not due to the sign direction, it was due to sheeting type. "… the random selection of signs resulted in having more signs made with prismatic sheeting material facing North and Esat (15 out of 34) compared to signs facing South and West (3 out of 18)". The authors stated that "based on the analysis of data collected in Florida and the sign study in Texas, direction is not a significant variable for sign retroreflectivity in Florida". [6]

To address the severity of adverse weather during nighttime conditions, climatic data were collected for Tallahassee, Jacksonville, Orlando, Tampa and Miami from 2009 to 2011. Findings showed that over 90 percent of the nighttime hours in Florida are clear and dry and no apparent difference amongst the five cities were apparent, except Jacksonville which showed a slightly more moisture/fog condition that the other four cities. [6]

To delevop the luminance computation model for visibility of overhead signs, the authors used the age degradation factor obtained from TTI's (Texas A&M Transportation Institue) long-term weathering tests on retroreflective sign sheeting products. And "as Texas and Florida have similar climatic conditions, the authors thought it reasonable to use the age degradation factor from signs in Texas for those in Florida. The weathering tests results from TTI's produced accelerated degradation rates of sheeting samples by placing samples in weathering racks facing south and oriented at a 45 degree angle. The testing lasted for over ten years, produceding a 20-plus year simulation. And "according to the TTI weathering rack data … the green prismatic materials maintained retroreflectivity levels above the MUTCD minimum threshold for at least 20 years". Four predictive models for sign sheeting degradation were presented for various sheeting Types, namely: Type I with an R^2 value of .97, Type II with an R^2 value of 0.90, Type III with an R^2 value of 0.53, and a group consiting of Types IV, VIII, and IX, all with an R^2 value of 0.49. Age was the only independent variable. By comparison, these were the best results found. [6]

Bradford K. Brimley and Paul J. Carlson presented in January 2013, at the Transportation Research Board 92nd Annual Meeting, a paper titled: "The Current State of Research on the Long-Term Deterioration of Traffic Signs". The paper is a compilation of eight studies on the subject, including the 1991 study by Black et al. previously reviewed in this document and thus not repeated here. The remaining seven studies reviewed are labeled as follows: Australia Study (1990), Purdue University Study (2002), Oregon Study (2001), Louisiana State University (LSU) Study (2002), North Carolina State University (NCSU) Study (2006-2008), Vermont Study (2009) and the Texas A&M Transportation Institute (TTI) Studies (2011). [8]

Australia Study (1990) was based on retroreflectivity data obtained from 2,144 in-service signs from all six Australian states covering sheeting Types I and III, found "no significant effect from sign orientation was discovered (north-facing signs, which face the sun in Australia were expected to deteriorate faster), through the researchers noted consistently higher deterioration rates in industrial areas) [8]". Three linear regression models for washed signs, with age as the only independent variable, predicted years to failure from 11.7 to 60.2, with an additional two models for washed signs indicated that years to failure were "Not Permitted" or "Never". No R^2 values were provided in the review. [8]

Purdue University Study (2002) "…measured retroreflectivity of 1341 in-service ASTM Type III red, white, and yellow signs in Indiana." The study focused on signs that were approximately 10 years old and retroreflectivity measurements were taken before and after wiping the sign face with a dry sponge. Separate linear regression models were developed for white, yellow and red colors with predictive years to failure of 236, 41.2 and 22.1, respectively. No R^2 values were provided in the review. [8]

Oregon Study (2001) "…measured retroreflectivity of 137 white, yellow, green, and red ASTM Type III in-service signs [8]. All five models used linear regression and their R^2 values were 0.0328, 0.0943, 0.0082, and 0.1034, respectively. No statistical test was performed to examine the effects of sign orientation; however, "**there was substantial variability in the retroreflectivity of south-facing red signs**". [8]

Louisiana State University (LSU) Study (2002) "…measured retroreflectivity of 237 in-service white, yellow, and green ASTM Types I and III … before and after washing the signs." Linear regression models, with age as the independent variable, showed Type I unwashed signs with 6.1 and 10.3 years to failure for white and green signs, respectively; and yellow signs showed years to failure as "not permitted". Type III unwashed signs with age as the independent variable showed 36.5, 17.4 and 55.2 years to failure for white, yellow and green signs, respectively. No R^2 values were provided in the review. [8]

North Carolina State University (NCSU) Study (2006-2008) " … measured retroreflectivity of 1,047 white, yellow, red and green ASTM Types I and III in-service signs in 2005. By the time follow up measurements were made in 2006, 192 signs (18 percent of the original sample) had been replaced. The most common replacement was a Type III sign replacing a Type I sign." The authors noted that only 6.0 percent of all signs had been replaced in 2005. Three linear regression deterioration models for Type I unwashed signs were generated with 13.4, 9.6 and 13.9 years to failure for white, red and green colors, respectively. Yellow Type I signs showed "not permitted" years to failure. Four deterioration regression models for unwashed Type III signs were developed with 298.0, 26.4, 19.8 and 8.9 years to failure for white, yellow, red and green colors, respectively. All used age as the only independent variable. It is worth noting that models for Type III yellow and green included age as first and second degree independent variables. No R^2 values were provided in the review. [8]

Vermont Study (2009) "… measured three hundred ninety eight white, yellow, green and red Type III in-service signs and 220 yellow and fluorescent yellow-green Type IX in-service signs for retroreflectivity." Mostly non-linear regression models were developed for unwashed signs Type III and IX. The Type III models showed 740.4, 25.4, 15.1 and 740.4 years to failure for white, yellow, red and green colors, respectively. Type IX models showed 74.0 and 77.7 years to failure for colors yellow and yellow-green, respectively. Authors noted that few signs were older than six years of age. [8]

Texas A & M Transportation Institute (TTI) Study (2011) used in-service and outdoor accelerated weathering methods. "… TTI measured retroreflectivity of 859 white, yellow, and red Type III in-service signs in seven regions of Texas …" The in-service study found " a 2 percent failure rate for sign age 10 to 12 years and 8 percent failure rate for sign age 12 to 15 years … and sign orientation did not have a strong correlation with retroreflectivity". Linear regression models for ASTM Type III unwashed signs, with age being the only independent variable, showed 34.7, 25.9 and 45.0 years to failure for white, yellow and red colors, respectively. [8]

TTI also used accelerated outdoor weathering tests on a variety of sign colors. And "although these studies were more controlled than the in-service evaluations, their conclusions are limited because the sample sizes were insufficient …and the true effects of accelerated weathering compared to regular weathering are not certain…" [8]

In the Current Study Limitations section of the study, Bradford K. Brimley and Paul J. Carlson highlight that practitioners have concerns with deterioration studies over a long time because " … products change within the time frame of the weathering, analysis, review and dissemination process … because the sheeting products are constantly evolving … there will be new products to evaluate by the time an original study concludes … additionally, the material composition of products meeting the ASTM D4956 (retroreflectivity) criteria may change over time ... " Noting the ages of the signs in the study, the authors showed a chart indicating that as the number of signs studied increased, the age of the studied signs decreased. The authors also stated "when signs that have deteriorated are replaced by new signs, it is impossible for the removed signs to be included in a study that only measures in-service signs. The predictive equations are thus applicable only to signs that have not failed in retroreflectivity, and cannot account for the signs that deteriorate and fail before and are replaced early. This is why some of the deterioration studies predict an unusually long lifespan for signs. If agencies rely on these results alone, they will invariably over-predict the service life of their signs." [8]

In the Research Needs section of the study, Bradford K. Brimley and Paul J. Carlson**,** referred to a 1983 article by Kenyon, et al., [47] where it states that "**to obtain an unbiased estimate of sheeting service life, it would be necessary to start with a sample of new signs and follow the history of each to failure**. However, even such an effort might be unproductive because of manufacturing changes that result in changes in the actual sheeting installed over time. Thus, by the time average sheeting life is reliably estimated, the material supplied may differ considerably from that tested." The authors also added the following three remarks: (1) "there was rarely a statistically significant contribution to deterioration from any factor other than age." (2) "… methods used have been insufficient for identifying trends that can be extrapolated to all signs, and (3) "it is clear that the data in an in-service study are not sufficient to identify the effect of sign orientation on deterioration rate." [8]

2. Statistical data driven approaches and their applications to infrastructure

Xiao-Sheng Si, et al., published in 2010 an article titled "Remaining useful life estimation – A review on the statistical data driven approaches". The remaining useful life (RUL) of an asset or system is defined as "the period (of time) during which an asset is expected to be usable for the purpose it was acquired." The authors' main interest was to investigate the literature on the modeling methods for RUL estimation given the condition of the asset. RUL estimation is one of the key factors in a condition based maintenance (CBM) program. [14]

To develop RUL predictions it is important to have "event data" (past recorded failure data) and "observed condition monitoring data" (monitored conditions). The following chart represents the taxonomy of statistical data driven approaches for the RUL estimation. [14]

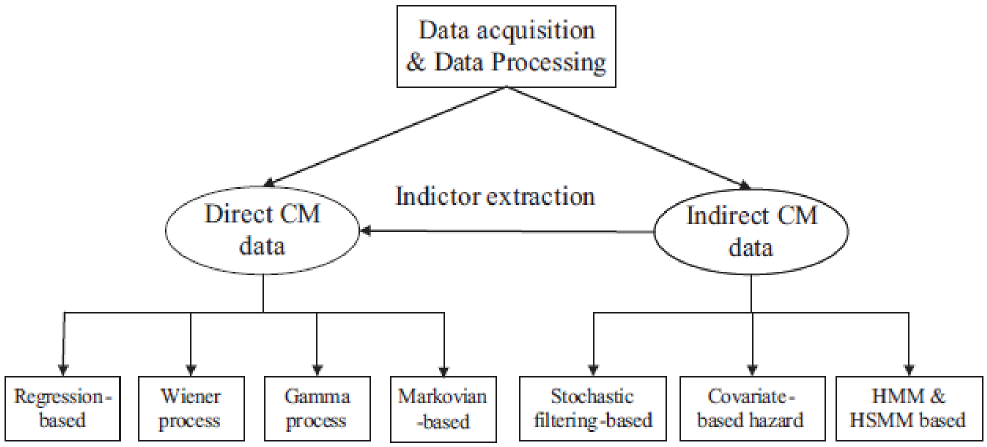

Figure 12 Taxonomy of statistical data driven approaches for the TUL estimation [14]

There are several published articles that applied non-regression based prediction models to non-signage infrastructure elements. The most applicable to sign retroreflectivity was the 2011 article by **Vishesh Karwas and Eric T. Donnell** titled Predicting Pavement Marking Retroreflectivity Using Artificial Neural Networks: Exploratory Analysis [52].

Artificial Neural Netwoks (ANN) are a form of artificial intelligence which mimic the learning process of the brain in order to extract patterns from historical data. [48]

The authors state that Artificial Neural Networks (ANN) were used to model the degradation pattern of PMR (pavement marking retroreflectivity) as a function of several input variables, including the initial PMR, age of the markings, traffic flow characteristics …"

" ANNs offer a flexible modeling framework to examine the data …" The exploratory study "found that thermoplastic pavement markings generally degrade in a nonlinear rate, and the rate of decay appears to differ among different pavement marking types. It was also found that the degradation process may differ by the geographic location of the markings as well as by the color of the marking …" Adding that "…for most of the pavement marking types, the variability in traffic volume did not appear to have a strong association with retroreflectivity degradation". [52]

The authors present predictive service life tables for four pavement makings types. The following three tables reflect the data collected, an example of the authors's predictive service life results and a graphic representing the service life for a particular pavement marking. [52]

Table 2 Pavement Marking Retroreflectivity Data

District	Route (county)	Length (mi)	Measured average initial retroreflectivity ($mcd/m^2/lux$)[a] White edgeline	White skipline	Yellow edgeline	Yellow centerline	Inspection intervals[b]
1	U.S.-13 (Bertie)	10.7	460	401	227	N/A	December 2001, June 2002, June 2003, June 2004
	U.S.-13 (Gates)	14.5	346	N/A	N/A	202	
	U.S.-158 (Northampton)	11.6	439	N/A	N/A	223	
	U.S.-64 (Washington)	9.4	430	N/A	N/A	206	
5	U.S.-15 (Durham)	3.0	512	450	348	N/A	December 2001, June 2002, June 2003, June 2004
	U.S.-158 (Person)	16.1	417	N/A	N/A	328	December 2001, April 2002, June 2002, June 2003, June 2004
	U.S.-158 (Vance)	11.1	429	N/A	N/A	304	
	I-85 (Warren)	9.6	353	352	241	N/A	October 2002, March 2003, June 2003, June 2004
	U.S.-158 (Vance)	11.0	405	N/A	N/A	302	December 2001, June 2002, June 2003, June 2004
12	I-40 (Catawba)	6.5	250	252	204	N/A	April 2002, June 2002, June 2003, June 2004
	I-40 (Iredell)	22.8	298	283	205	N/A	April 2002, June 2002, June 2003

Note: N/A = not applicable because roadway section was two-lane, undivided highway.

[a]Initial PMR levels were measured at the time when the markings were applied and values shown are the average over the entire length of roadway indicated.

[b]First inspection interval corresponds to a time period of approximately 6 months after the pavement markings were applied along the roadway section indicated.

Table 3 Predicted Service Life Limits for Yellow Centerlines

ADT (veh/day)			5,000		10,000		25,000	
Percent trucks			10	20	10	20	10	20
Division	Initial PMR	Threshold			[Lower limit, mean, upper limit]		(Months)	
1	300	150	[1,24,-]	[1,19,-]	[1,22,-]	[1,17,-]	[1,18,-]	[1,13,-]
		200	[1,9,16]	[1,5,18]	[1,8,21]	[1,3,10]	[1,3,12]	[1,1,8]
	400	150	[1,30,-]	[2,25,-]	[1,29,-]	[1,24,36]	[1,24,-]	[1,19,-]
		200	[1,16,-]	[1,11,21]	[1,14,-]	[1,9,17]	[1,10,27]	[1,5,17]
5	300	150	[1,32,-]	[1,27,-]	[1,30,-]	[2,26,-]	[1,26,-]	[1,21,-]
		200	[1,17,26]	[1,13,21]	[1,16,25]	[1,11,-]	[1,11,31]	[1,7,24]
	400	150	[1,38,-]	[1,33,-]	[16,37,-]	[1,32,-]	[13,32,-]	[1,27,-]
		200	[1,24,33]	[1,19,-]	[1,22,-]	[1,17,-]	[4,17,-]	[1,13,18]
12	300	150	[1,22,-]	[1,24,33]	[1,21,32]	[1,23,-]	[1,19,-]	[1,22,-]
		200	[1,8,23]	[1,7,22]	[1,7,17]	[1,6,12]	[1,4,5]	[1,3,19]
	400	150	[1,26,-]	[1,26,-]	[1,25,-]	[1,26,-]	[1,22,-]	[1,24,-]
		200	[1,12,34]	[1,11,-]	[1,11,-]	[1,10,27]	[1,8,12]	[1,7,15]

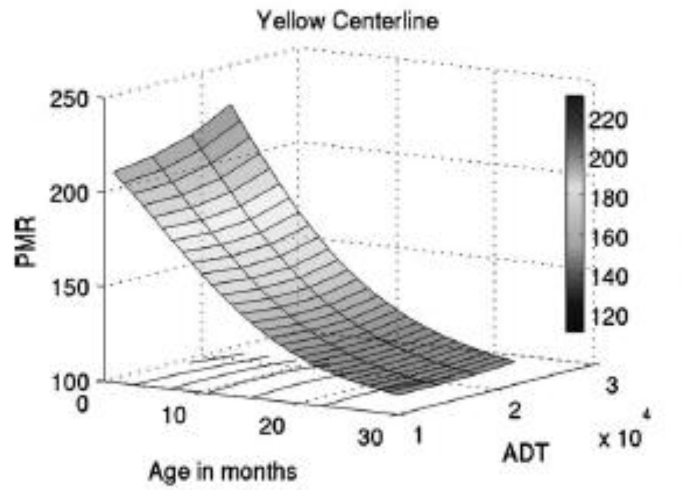

Figure 13 Pavement Marking Retroreflectivity (PMR) - Average Daily Traffic (ADT), in vehicles per hour x 10^4 [52]

Although the authors considered several key variables (initial PMR, age, geographic locations, traffic flow characteristics and marking type and color) in the ANN, there were some variables not included that deserve further examintion. These included pavement surface type and the application process used to install the pavement marking, e.g., speed, temperature, and pavement surface type [52].

The most recent publication on prediction modeling for infrastructure elements was a December 2015 Master of Science thesis by **Gini Arimbi** at Delft University of Technology, Netherlands. The thesis is titled Network-Level Pavement Performance Prediction Modelling with Markov Chains [44].

The main objective of the thesis was to develop a net-work level performance prediction model for raveling distress in open graded wearing courses for maintenance optimization based on Markov chains. Raveling is defined as "loose materials (usually aggregate) that "ravel" from the surface or edges of the pavement, resulting in depressions which may fill with moisture and loose aggregate. [44]

A Markov Chain is a statistical process that defines the state of a system at discrete points in time and predicts the probability of moving to the next state based only on the immediately preceding state. It is often referred to as a memoryless process since the probability of moving to the next state depends solely on the preceding state. The probabilities between stages are referred to as

Markov transition probabilities. The following graphic depicts the periodic maintenance process with a prediction of future deterioration. [44] [48]

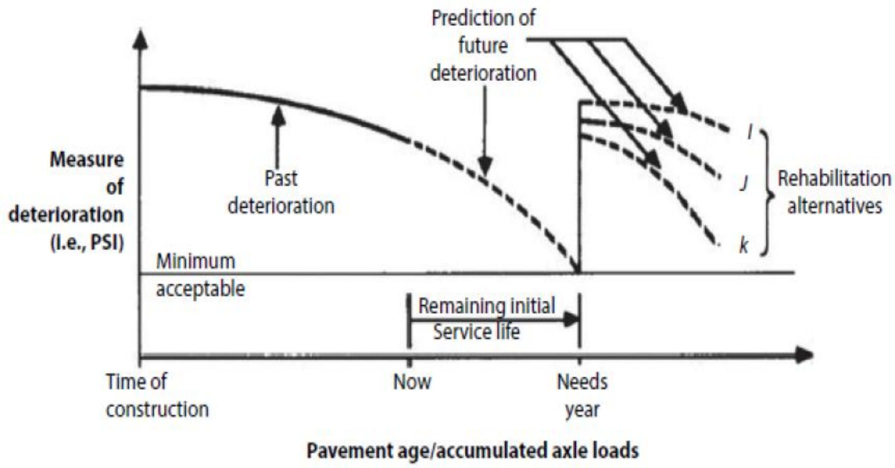

Figure 14 Pavement age/accumulated xle loads [44]

Gini Arimbi's thesis concluded that Markov chains offer good flexibility for the road agencies to create various performance prediction models; and road agencies can use it as a decision support to build a more reliable maintenance planning for asphalt wearing course preservation. [44]

Kiyoshi Kobayashi et al**.** published an article in 2010 titled Estimation of Markovian Transition Probabilities for Pavement Deterioration Forecasting. The authors' presented a methodology to forecast the deterioration of a pavement section using Markov transition probabilities based on an exponential hazard model. "The methodology proposed can be applied to forecast the deterioration not only of pavement sections but also to other engineering-works structures if the respective empirical research is accumulated." The paper concluded that the model (deterioration model) be expanded to include various other factors, e.g., environmental variables. [50]

G. Morcous's published an article in 2006 titled Performance Prediction of Bridge Deck Systems Using Markov Chains. The objective of the article was to investigate the validity of two Markov chains assumptions as they relate to the life-cycle assessment of highway bridges. The assumptions are (1) a constant inspection period and (2) the state independence assumption. The author concluded that (1) inspection periods must be constant, otherwise the "variation in the inspection period may result in a 22% error in estimating the service life of a bridge deck system." And (2) "…the state independence assumption is acceptable …" [53].

G. Morcous also states, and cites supportive references, for the main advantages of Markov Chain models. The advantages listed are: “(1) they are able to reflect the uncertainty from different sources … (2) they are incremental models that account for the present condition in predicting the future condition …and (3) they can manipulate networks with large number of facilities because of their computational efficiency and simplicity for use...” [53].

Manoj K. Jha and Jawad Abdullah published an article in 2006 titled A Markovian approach for optimizing highway life-cycle with genetic algorithms by considering maintenance of roadside appurtenances. As an illustrative example, the authors plotted the pavement deterioration characteristics and that of three non-perpetual roadside appurtenances, namely: guardrails (GR), signs (Signs) and luminaries (Lum). See the following two graphics. [28]

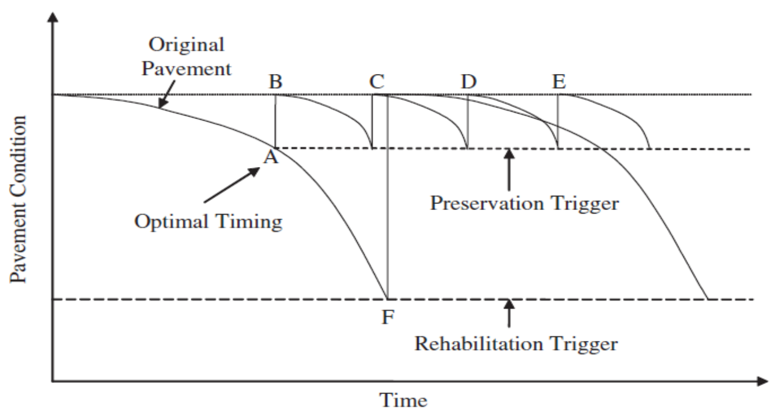

Figure 15 Pavement deterioration characteristics

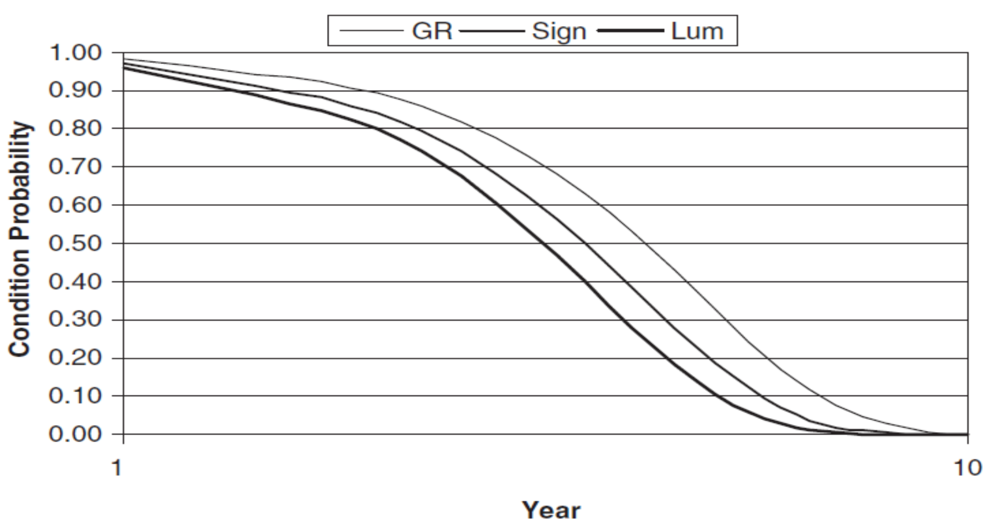

Figure 16 Roadside Appurtenances: Guard Rails (GR), Sign (Sign), Luminaries (Lum)

The pavement deterioration characteristics are based on empirical analysis and fitting actual data from pavement preservation analysis. It was assumed that roadside appurtenances deteriorate in a similar fashion exhibiting similar deterioration characteristics over time [28]. Notwithstanding this assumption, the authors conclude, "genetic algorithm seems to perform well and may be a better substitute for complex problems of a Markovian nature [28]."

In the case of sign retroreflectivity, the states of the Markov chain can be based on two or more ranges of retroreflectivity values, measured in equal time spans. The penultimate state provides the probability of the system moving to the last stage, i.e., the stage when retroreflectivity is less than the minimum standard for the given sign sheeting type and color. A periodical retroreflectivity measurement process would develop a deterioration rate model that would yield the probability the sign would fail at the last state, i.e., the failure state.

3. Other Methods and Applications

Hu Changhua et al., published an article in 2014 titled A Survey on life prediction of equipment. Although the authors present a variety of life prediction methods, the Remaining Useful Life (RUL) method based on direct monitoring of data is of most interest for maintaining signage retroreflectivity standards. For direct monitoring data, the RUL prediction usually includes autoregressive-moving average (ARMA) and the Artificial Neural Network (ANN) models. These models, however, cannot reflect the uncertainty of the RUL prediction effectively. For stochastic RUL prediction, the methods mentioned include the gamma process-based methods, the inverse Gaussian process-based methods, the Wiener process-based methods, and the Markov chain-based methods. [54]

The authors indicate that the RUL should be probabilistic. Adding that "… Markov chain is often used to describe the degradation process with continuous time and discrete state(s) … and have been used to describe wear degradation caused by an environmental load". [54]

Contrasting outdoor weathering versus indoor artificial weathering tests, and their viability for service life prediction, have been evaluated and considered by Q-Lab and Warren Ketola.

"Q-Lab Corporation is a global provider of material durability testing products since 1956. We design and manufacture standard test substrates as well as weathering, light stability, and corrosion testers. In addition, contract test services, which include accelerated laboratory testing, are available at Q-Lab Florida, Q-Lab Arizona, and Q-Lab Deutschland. Outdoor exposure testing for weathering, light fastness and corrosion are available at Q-Lab Florida and Q-Lab Arizona. [81]"

Q-lab Technical Bulletin LU-0833 addresses one of the most frequently asked questions about accelerated (artificial) weathering, namely: How Many hours in a Q-Sun Xenon Test Chamber or a QUV Weathering Tester equals a year of outdoor exposure? [82] Also see [87].

In answering this more general question, the bulletin states "… it is logically meaningless to talk about a conversion factor between hours of accelerated (artificial) weathering and months of outdoor exposure. One is constant, whereas the other is variable. Looking for a conversion factor requires pushing the data beyond the limits of its validity". "Nevertheless, you can still get excellent durability data from accelerated (artificial) weathering tests … but must realize that the data you get is Comparative data, not absolute data. The most you can ask from laboratory (artificial) weathering are reliable indications of the relative ranking of a material's durability compared to other materials". Comparative data is very powerful for quickly ranking performance between different materials. For example "… you might find that a slightly altered formulation of a material has over twice the durability of your current standard material." [82]

A search within the large volume of Q-Lab's Technical Bulletins did not yield accelerated (artificial) tests on retroreflectivity material. However, current sign suppliers, e.g., 3M, may have already performed accelerated (artificial) tests on retroreflective materials. **A telephone call to 3M on this matter produced no specific information due to the confidential nature of the subject.**

There are other studies comparing accelerated (artificial) testing versus outdoors testing of retroreflectivity on traffic signs.

Warren D. Ketola published two articles (1989 and 1999) on artificially accelerated tests versus outdoor exposure tests. Artificial accelerated exposures were conducted in the Weathering Services Laboratories of 3M. The outdoor exposure tests were conducted in Miami and Phoenix. [12] [13]

Ketola's article in 1989 concluded the following: (a) "artificial accelerated exposure tests are inadequate for assessing durability of retroreflective sheeting because they are poor replications of exterior exposure conditions and produce highly variable results for identical samples exposed in equivalent devices", (b) performance ranking of retroreflective sheetings exposed in standard artificial accelerated tests correlate poorly with those obtained in exterior tests" and (c) "performance of sheeting in one location is not necessarily a good predictor of performance in another environment" [13].

Ketola's article in 1999 concluded the following: (a) "materials that have excellent outdoor durability can fail the requirements of the laboratory-accelerated test, (b) Materials that have very poor durability can far exceed the requirements of specified laboratory-accelerated exposure tests, and (c) the variability in the laboratory-accelerated test most commonly used for retroreflective sheetings is greater than that for outdoor exposures" [12].

At the material level, however, efforts continue to better understand the correlation between accelerated and natural ageing.

Tocháček, Jiří, and Zlata Vrátníčková published an article in 2014 titled Polymer life-time prediction: The role of temperature in UV accelerated ageing of polypropylene and its copolymers. The authors concluded that "UV accelerated ageing carried out at different temperatures provided greatly varying results, thus not allowing unambiguous life-time prediction based purely on energy calculations. If temperature increased, less UV radiant energy is needed for polymer deterioration and vice versa." Adding that "despite life-time prediction being a complex problem and affected by many factors, simultaneous application and quantification of the most important ones – UV radiant and heat energies – may bring us much closer to the reliable prediction of polymer durability." [55]

Bram de Jonge, et al., article published in 2015, titled Optimum maintenance strategy under uncertainty in the lifetime distribution. The approach the authors followed was to assume a pre-defined distribution, e.g., Weibull distribution which is appropriate for modeling lifetimes of a wide variety units and systems, and to focus instead on a stochastic evaluation of the distribution's scale parameter. Another research avenue is to include the stochastic evaluation of Weibull's second parameter, the shape parameter. [56]

Rosmaini Ahmad and Shahrul Kamaruddin published an article in 2012 titled: An overview of time-based and condition-based maintenance in industrial application. The basic aim of time-based maintenance is to "statistically investigate the trend and characteristics of the set of failure times gathered." In contrast, the basic aim of condition-based maintenance is to "identify and evaluate equipment conditions based on current updated data. This process is also known as the deterioration modelling process". The authors conclude that although the application of condition-based monitoring (CBM) is more beneficial compared to time-based monitoring (TBM), there are opportunities pertaining to CBM, e.g., the development of built-in sensors to facilitate the monitoring process. [58]

W. Wang published an article in 2000 titled "A model to determine the optimal critical level and monitoring intervals in condition-based maintenance". A common practice in condition-base maintenance is to monitor the condition of the equipment at certain time intervals, and once the measurement of such condition information is higher or lower than a pre-specified critical level, item monitored is repaired or replaced by a new one". Wang's paper explores the relationship between the critical level, the monitoring intervals and the objective function of interest. The objective function can be the expected cost or downtime considered over an infinite or finite time horizon. [57]

Wang's methodology can be used to gain an understanding of the effect that various periodic monitoring cycles have on monitoring costs and unit reliability. [57]

There are articles that aim at simplifying the monitoring process and/or reducing the cost of the measuring instruments. The reflectometer unit cost is approximately $10,000 and proper use of the instrument requires some level of training.

David P. Orr and Geoffrey R. Scott published an article in 2015 titled Inexpensive Retroreflectivity Field Inspection Kit. The kit was patented [US Patent 8205994 B1, issued June 2012]. [1]

Orr and Scott commented that some New York agencies measuring retroreflectivity found the cost of the retroreflectometer a challenge, and that they were interested in a comparison panel that could be used in the field by crews without access to or training on the use of a retroreflectometer. [1]

"To help local agencies in New York State, Cornell Local Roads Program worked with three counties and several municipalities in New York State and developed a sign inspection field guide and an inexpensive sign inspection kit. The inexpensive sign inspection kit consists of (a) six 3 x 6 inch panels of colors: yellow, orange, green, fluorescent yellow-green, white and red, (b) two clamps to hold the panels to the sign, (c) a copy of the Traffic Sign Handbook, (d) and a flashlight. "Materials for these inexpensive kits were less than $50 each (panel)." [1]

The color panels were degraded to just above the corresponding minimum retroreflectivity levels that are to be maintained, and used as comparisons against visual nighttime in-service field inspections. The research team selected a degradation method requiring overhead transparency sheets. The degrading method consisted of continually placing clear transparent sheets of overhead transparencies on each panel until the retroreflectivity level dropped below the acceptable level identified in MUTCD Table 2A.3. Then, the last clear overhead transparency sheet was removed so that the retroreflectivity value on the panel is just above the MUTCD value. "The sign inspection kit can be used to confirm a safe level of retroreflectivity in the field." [1] Basically, the kit functions as a go-no-go gauge instrument.

The US Patent previously referenced describes the following inspection process in eight steps using the Inspection Kit: 1. Identify sign(s) for additional evaluation →2. Clean sign →3. Select comparison panel →4. Attach selected comparison panel to sign → 5. Radiate sign and comparison panel → 6. Compare radiated sign and comparison panel → 7. Determine whether sign needs to be replaced → 8. If required, schedule replacement. [1]

Figure 17 Inspection Kit

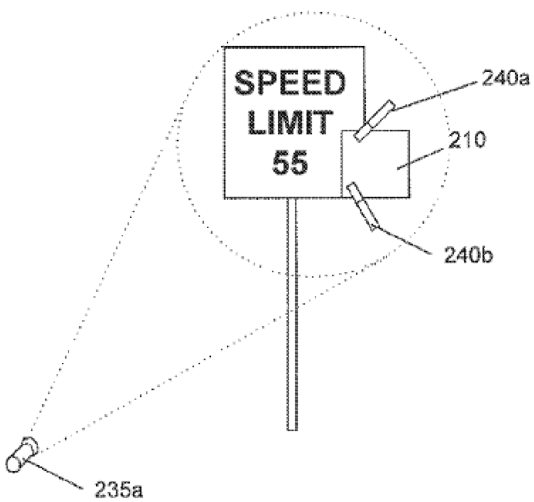

Figure 18 Sign Inspection Example

Sketch depicting the flashlight (235a), degraded color panel (210) and clamps to hold the degraded panel to the sign (240a & 240b). US Patent 8205994 B1, issued June 2012. [1]

Vahid Balali et. al, published an article in 2015 titled Image-based retro-reflectivity measurements of traffic signs in daytime. "Current (retroreflectivity) measurements techniques either (a) use vehicle mounted device during night, (e.g., SMARTS) or (b) use the manual handheld devices during the day. The former is expensive …the latter is time-consuming and unsafe." To address current limitations, the article presents a new technique for obtaining measurements remotely during daytime using hardware mounted on commonly used U.S. vehicles. A combination of computational photography and carefully tuned hardware is used to generate realistic photos of nighttime during daytime … and computer vision techniques are used to reconstruct nighttime images using images taken during the day. Then the reconstructed night images are used to measure retro-reflectivity..." [2]

The authors conclude that their technique "…shows promise in facilitating the current work flows by allowing inspection vehicles – widely used in the U.S. … to measure retro-reflectivity levels (remotely) during daytime … and also minimize the challenges associated with inspecting overhead and difficult-to-reach ground mounted signs." [2]

Chengbo Ai and Yichang James Tsai published an article in 2016 titled An automated sign retroreflectivity condition evaluation methodology using mobile LIDAR and computer vision. The authors indicated that traditional manual methods have become financially and/or practically not feasible; there is a need for an effective and efficient retroreflectivity evaluation method. The article "investigates the possibility and proposes a methodology for automatically evaluating traffic sign retroreflectivity condition using mobile light detection and ranging (LIDAR) and computer vision. The proposed methodology uses the traffic sign detection and color segmentation methods to evaluate the retroreflectivity of different traffic sign colors separately in an automated manner" [42].

Figure 19 Image of the Georgia Tech Sensing Vehicle – GTSV [42]

The authors concluded, "the proposed methodology provides more reliable and unbiased condition assessment results than the current handheld retroreflectometer measurement technology" [42]

4. Observations and suggestions for consideration

1. Studies focusing on predicting the life of in-service signs using regression analysis have been inconclusive.
    a. Data collected from in-service signs do not sufficiently capture the age of the sign at the time when the sign has degraded below its minimum required retroreflectivity level. This is partly due to signs that deteriorated and were replaced prior to data collection, thus the population from which the measurements were taken represented fewer older signs.

       The most significant statements were made in the Current Study Limitations section of Bradford K. Brimley and Paul J. Carlson's study in 2013 titled The Current State of Research on the Long-Term Deterioration of Traffic Signs.

       > "Because sheeting products are constantly evolving, with a general movement towards more efficient sheeting, there will be new products to evaluate by the time an original study concludes. Additionally, the material composition of products meeting ASTM D4956 criteria may change over time, even if the ASTM standard does not change. This leads to changes to the true estimated service life of a given type of sheeting."

    b. Regression models have not been able to sufficiently explain the variation of retroreflectivity based on age. Perhaps the yearly variability and cyclical pattern of solar irradiation is a factor that contributes to the unexplained variation in retroreflectivity. This solar irradiance affects all latitudes. See the following image. [83]

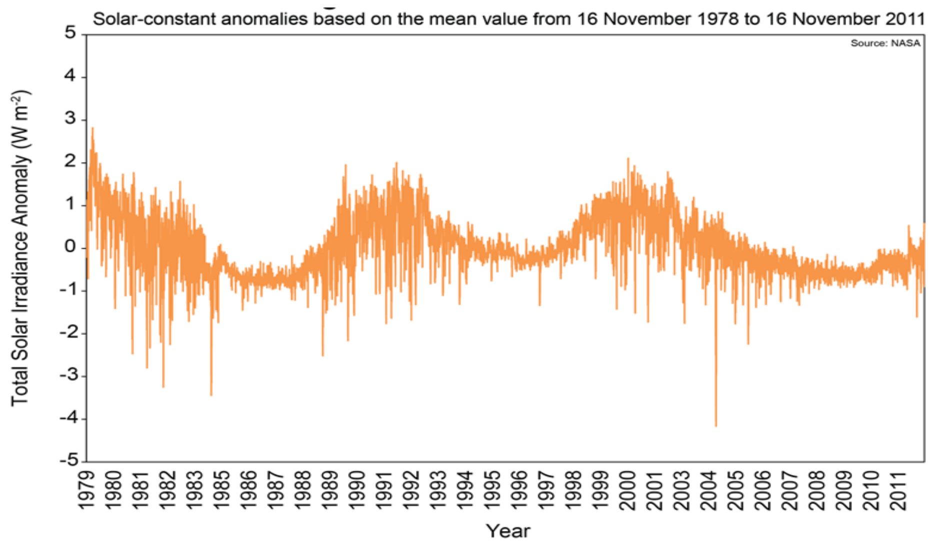

Figure 20 Changes in the Solar Constant

2. Studies focusing on predicting the life of signs using outdoor weathering tests have not been performed long enough to generate valid service life estimates. Additionally, outdoor tests do not appear to examine road traffic conditions.

3. The extrapolations of the trendline and its intersection with the corresponding minimum established value of retroreflectivity are not to be interpreted as the predictive average service life of the signs. It is incorrect to use regression analysis to predict the dependent variable (retroreflectivity) much beyond the range of the observed values; if so, you assume that the model has a constant linear function with the same slope.

4. Artificially accelerating the life of signs is appropriate for ranking comparisons but not for predicting the useful life of in-service signs. Control tests performed at a Laboratory may provide more clarity as to the behavior of the sign materials due to environmental conditions. [86]. This may be considered for further discussion.

5. There are Artificial Neural Network (ANN) and Markov chain models that have been used to predict deterioration in infrastructure, e.g. pavement and pavement markings. These methods should be considered in future work.

6. There is a need for a perpetual sign inventory system(s) that captures the sign characteristics needed for tracking and replacement decisions, e.g., installation date, location, orientation, sign type - with corresponding sheeting, color and supplier

information, maintenance dates – with observations and measurements documented. Without it, sampling plans for in-service data collection will be very inefficient; and maintenance strategies would be significantly difficult to execute.

7. Color fade may be as large of an issue as retroreflectivity degradation for some signs, e.g., regulatory STOP signs.

8. Vandalism and other physical damage to in-service signs have been found to be important factors in determining sign replacement. Where appropriate, consideration should be given to the use of drones to identify signs needing maintenance or replacement due to physical damage or color fading, especially for State and Inter-State roadways.

9. There are daytime color specification limits in ASTM D4956-13; however, there are no maintenance requirements in the MUTCD. Maintenance requirements, especially for selected sign types, e.g., STOP signs, should be further investigated.

10. Retroreflectivity and Color measurement instruments are expensive. Consider the Inexpensive Retroreflectivity Inspection Kit, or a variation of it, referenced in [1].

11. Investigate the viability of using sensors to monitor sign performance and/or to alert drivers in their vehicles of the oncoming sign and its message, i.e., "smart signage".

12. The objective of the prediction models is to determine, within a level of confidence, when to replace signs prior to their retroreflectivity and /or color failure. This objective requires capturing the deterioration of signs throughout a monitoring period and until failure is observed. This requirement is necessary regardless of what prediction model is used. Previous in-service sign studies have been inconclusive primarily due to the absence of failure data. Accelerated outdoor life tests have not been performed long enough to be conclusive. And artificial acceleration methods are not reliable predictors of in-service (real time) environments. Lastly, an in-service study capturing failure data will likely take longer than currently expected for the project.

Sign Sampling

1. Introduction

Florida is divided into seven districts and their geography is presented in Figure-1. Each district has its own sign inventory database. Florida Department of Transportation provided four out seven district sign inventory database. Remaining three districts do not currently hold a database to provide for a sampling study. Four districts that were able to provide inventory databases are Districts 1, 2, 4, and 7.

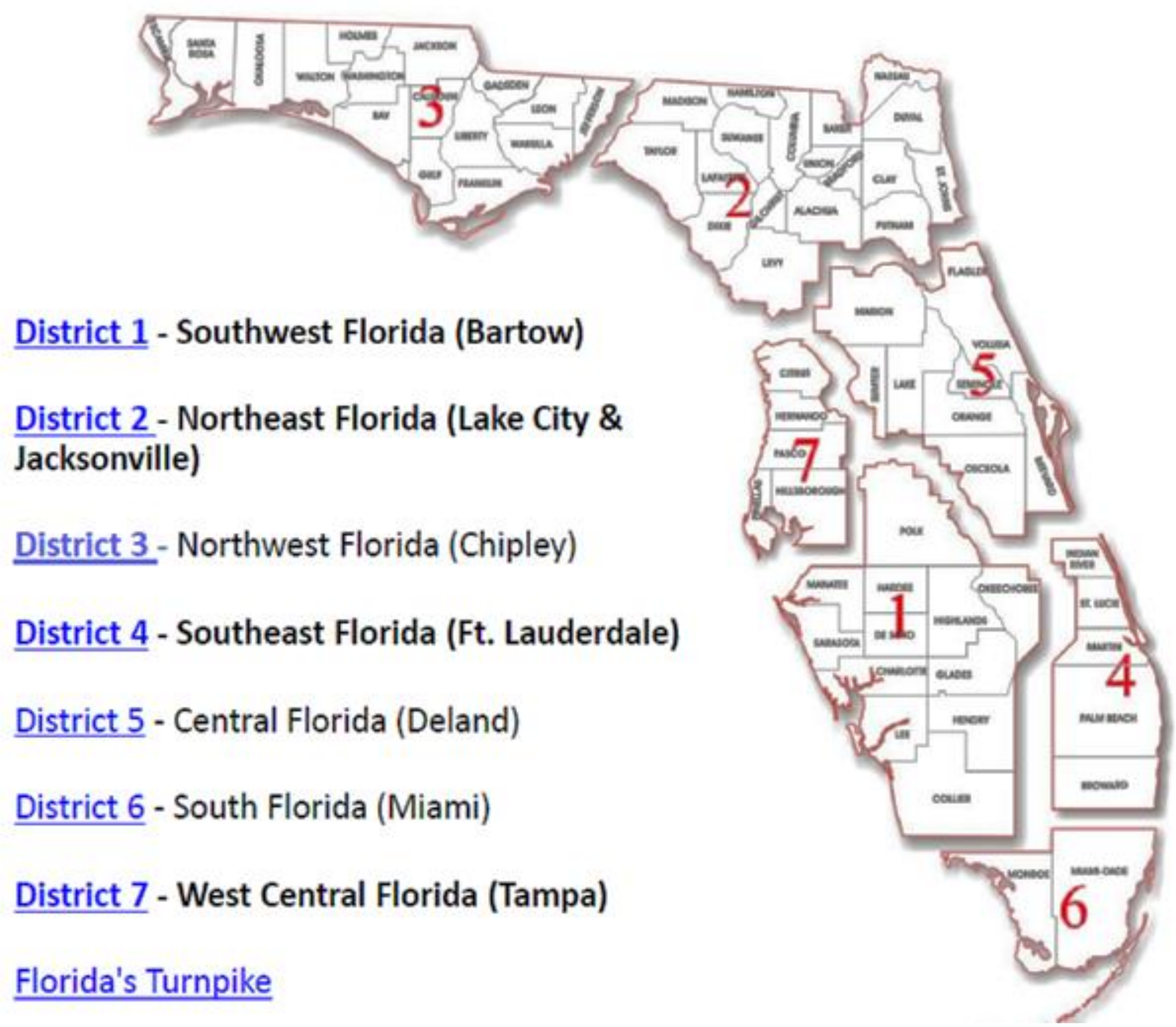

Figure 21 FDOT Districts

2. District Sign Inventory Databases

Sign inventory databases provided by FDOT districts are spatially plotted in the Florida map (see figure-2). There are four available district sign inventories which are as follows; District-1, 2, 4, and 7. The remaining districts (i.e. District 3, 5, and 6) have no sign inventory databases available. The format (i.e. types of attributes) of each district's dataset is unique. Therefore, each of them has different types and numbers of parameters. From the four district databases; only District 2 inventory database contained the installation date of the traffic signs which refers to the age of signs. Information about the age of signs is crucial to evaluate degradation rates of sign appearance.

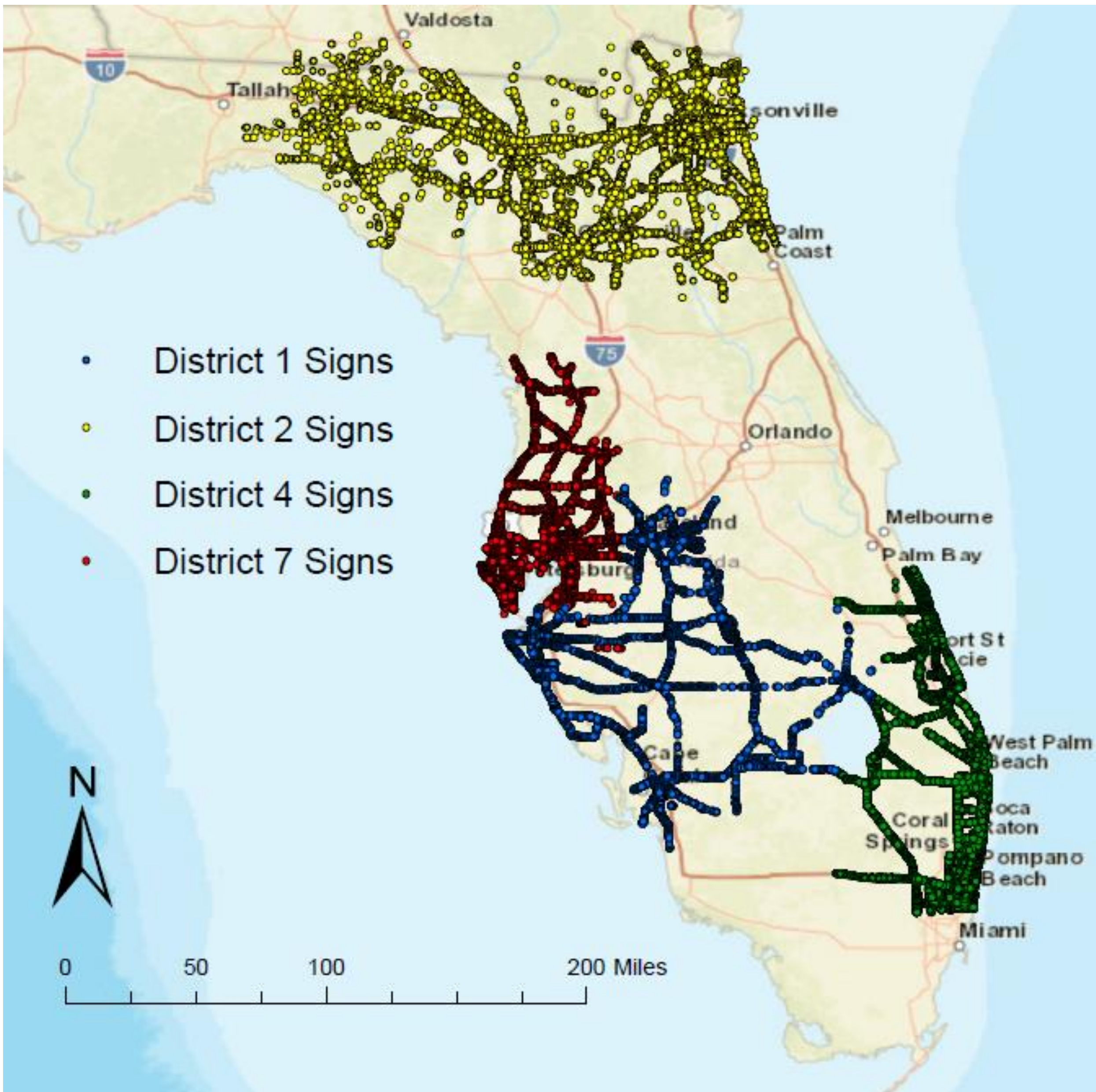

Figure 22 FDOT Traffic Sign Inventory Database Map

After examining the available datasets, it was found that Districts 1, 4, and 7 databases do not contain "Installation Dates" of the traffic signs. Having known that age of signs will be the main predictors of Retro-reflectivity measures of the signs, "age" should be considered in the assessment of sample population to increase the precision of key estimates. Data analytics performed for each district that were able to provide their sign inventory database are further discussed.

Factors that will be used in the modeling process are as follows;

- Manufacturer: Including but not limited to 3M, Avery, Dennison, and Nippon
- Sign Colors: White, Blue, Brown, Red, Green, Yellow, and Fluorescent Yellow-Green
- Sheeting Types: III, IV, VII, and XI
- Roadway Location Type: Urban or Rural
- Physical Geographic Location: Inland or Coastal
- Regional Locations: Overall, Northern Florida, Central Florida, and Southern Florida
- Cardinal Directions: North, South, East, and West

2.1. District 2

The only database that contains information regarding the current age of signs is District 2 sign inventory database. Table 1 provides the raw dataset fields and a brief description of the attributes of District 2 database.

Table 4 District 2 Inventory Database Fields

Fields	**Notes**
RouteNum	Route number
RouteName	Name of the route
Number	ID
SignCode	Sign Code
LogPoint	Log Point
Descriptio	Description of sign type
Width	Width of sign
Height	Height of sign
Side	Left/Right (Binary)
Direction	Direction (East, West, North, South)
SignType	Sign Type (categorical)
AssemblyNu	Assembly number
FaceMateri	Face material (Engineering, HI, 3M, Nippon Carbide) – (97% HI "Sheeting Type 3")
BlankMater	99.5% Aluminum, 0.5% Steel
Installation Date	Installed date of Sign
Latitude	Y coordinates
Longitude	X coordinates

LegendColo	Legend Color
BackgroundColo	Background Color

Sign inventory database was imported to GIS. Then, latitude and longitude information was displayed by implementing the appropriate coordinate system.

2.1.1. Data Cleansing Process

In order to detect and correct (or remove) corrupt or inaccurate records from the raw dataset of District 2, a data cleansing was performed with the following steps;

- Database files were imported to ArcGIS and exported as shapefiles.
- There were 6 operation areas in District 2 and each one has a database. These operation areas are; Jacksonville, Gainesville, Chiefland, Lake City, Perry, St. Augustine. Among these 6 areas, Chiefland's inventory does not contain the installation date. Therefore, the remaining 5 area files were merged.
- "Status" field provides the information of where the traffic sign is, thus, it tells if the sign is "trashed", "in warehouse", or "in field". Signs that were in field were kept.
- In the raw dataset; "Installation Date" field was not formatted in Date format. Rebuilding missing data was performed by conversion from text to date format.
- De-duplication was performed to eliminate duplicate copies of repeating data.

As a result, "24,222" traffic signs were considered as inaccurate records and thus removed from the dataset. Cleaned records are as follows;

- Chiefland region traffic signs were completely removed due to missing "installation date". Also, parts of other regions' signs were deleted due to the same issue.
- "Status" field from the data inventory provides the information of the traffic signs' current status such as; "In field", "In warehouse", or "Trashed". Traffic signs which were coded as "In warehouse" and "Trashed" were removed.
- Traffic signs which are missing latitude and longitude coordinates were deleted.
- Data inventory latitude and longitude information was plotted in Florida map by ArcGIS. The data points which found to be geo-coded incorrectly were removed.

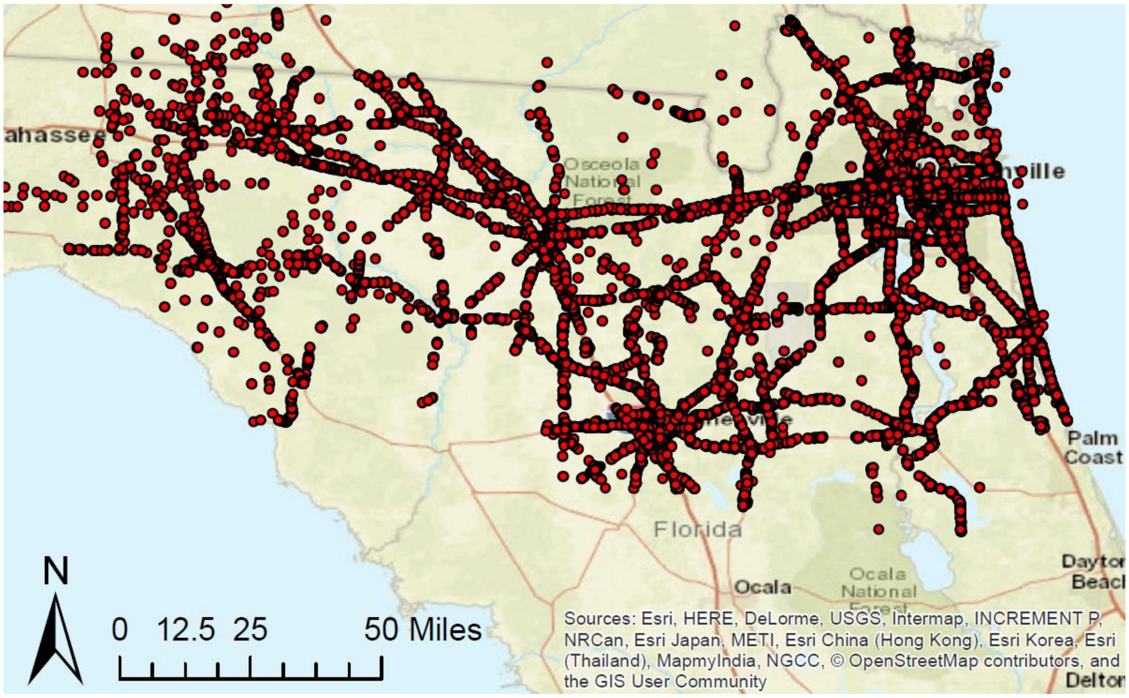

Figure 23 District-2 Traffic Signs Map

Finally, district 2 traffic signs GIS map is presented in Figure-3. Out of 65,550 records in District 2; 41,328 records left after data cleansing.

2.1.2. Joined Fields to District 2

In order to address the roadway location type and physical geographic location factors given above two binary variables were joined by using ArcGIS software features.

- Urban boundaries shapefile was downloaded from US Census Bureau website open database. [88]
- The assumption made for splitting the dataset by inland and coastal; Coastal signs are within 5 miles distance from coast.

Two fields were created as a categorization the age of signs for the simplicity of sampling. Age field was computed by using the installation date field (i.e. "Today's Date" – "Installation Date"). Ages of signs were categorized in six groups as described in Table 2.

Table 5 Age Categories

Age Groups	Description
(1)	1 to 3 years
(2)	4 to 6 years
(3)	7 to 9 years
(4)	10 to 12 years
(5)	13 to 16 years
(6)	17 to 20+ years

2.1.3. Data Clustering and Descriptive Statistics

- Roadway Location Type; Rural – Urban

Florida urban area boundary shapefiles were implemented and traffic signs located in urban and rural roadways were identified. Numbers of traffic signs found in rural and urban areas based on urban area boundaries of US Census Bureau are presented in Table 3.

Table 6 Descriptives of Rural/Urban

Roadway Location Type	Number of Records	Percentage
Rural	16,616	40.21%
Urban	24,712	59.79%

Geographic locations of traffic signs by roadway location type are displayed in Figure 4.

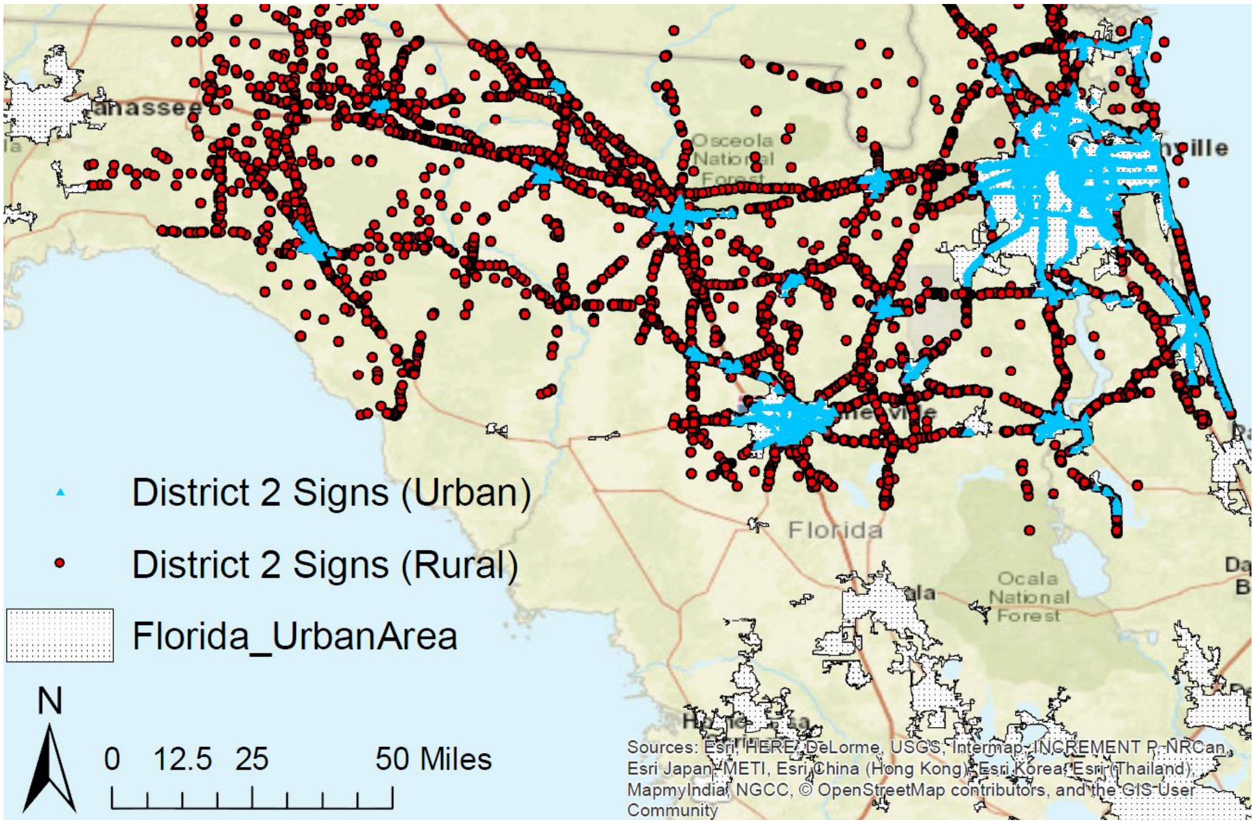

Figure 24 Roadway Location Type of District 2 Traffic Signs: Rural (Red circle) – Urban (Blue triangle)

- Physical Geographic Location; Inland – Coastal

As mentioned in section 4, coastal points were chosen within 5 miles of distance from the coast. Numbers of traffic signs found in inland and coastal areas are presented in Table 4.

Table 7 Descriptives of Inland/Coastal

Geographic Location Type	Number of Records	Percentage
Coastal	2,928	7.08%

Inland	38,400	92.92%

Geographic locations of traffic signs of Inland/Coastal areas are displayed in Figure 5.

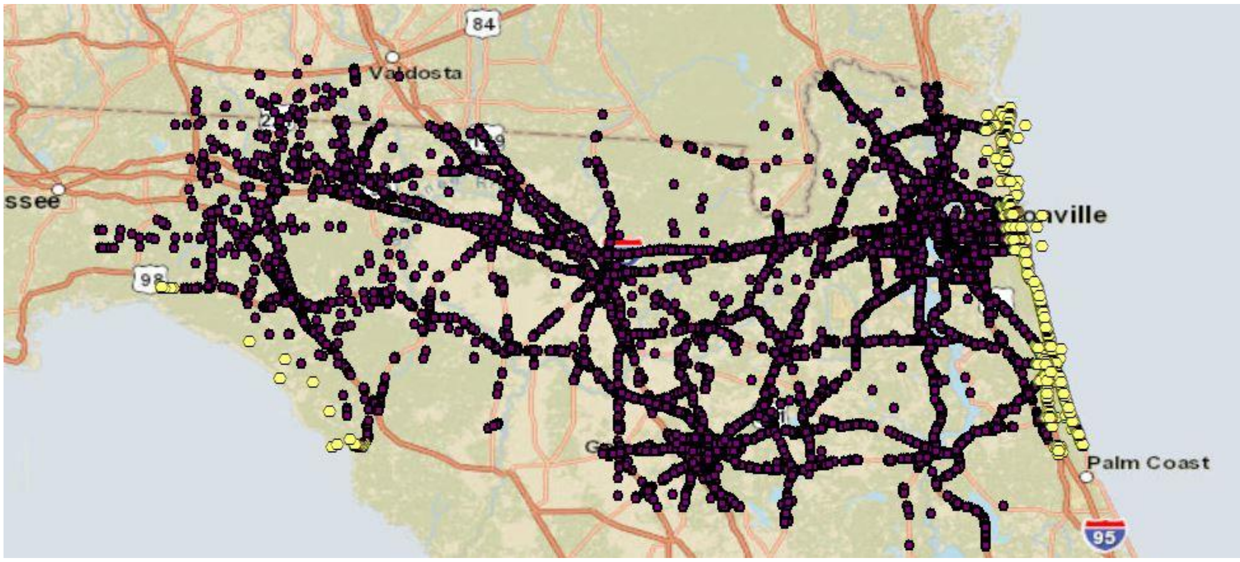

Figure 25 Geo-Locations of District 2 Traffic Signs by Inland/Coastal Area: Inland (Purple) - Coastal (Yellow)

- Cardinal Directions; North, South, West, East

Descriptive statistics of cardinal directions field are provided in Table 5.

Table 8 Descriptives of Cardinal Directions

Cardinal Direction	Number of Records	Percentage
North	12,061	29.18%
South	12,750	30.85%
East	8,214	19.87%
West	8,306	20.10%

Geographic locations of traffic signs by their cardinal directions are displayed in Figure 6 and Figure 7.

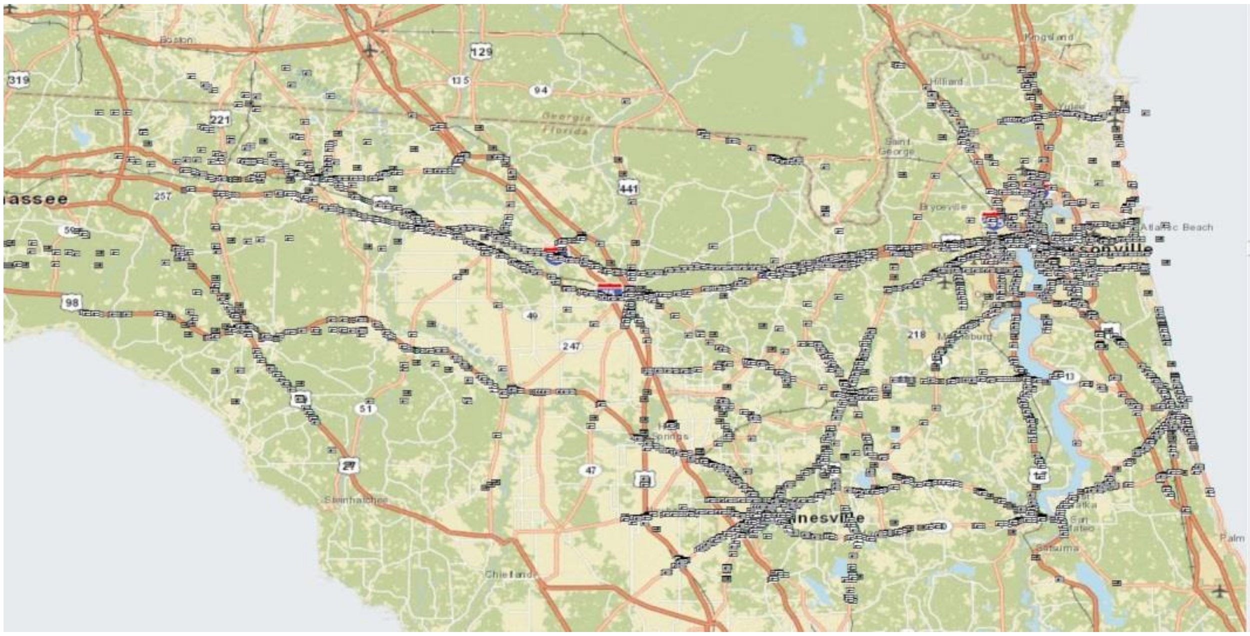

Figure 26 Cardinal Directions of District 2 Traffic Signs: East (White) - West (Grey)

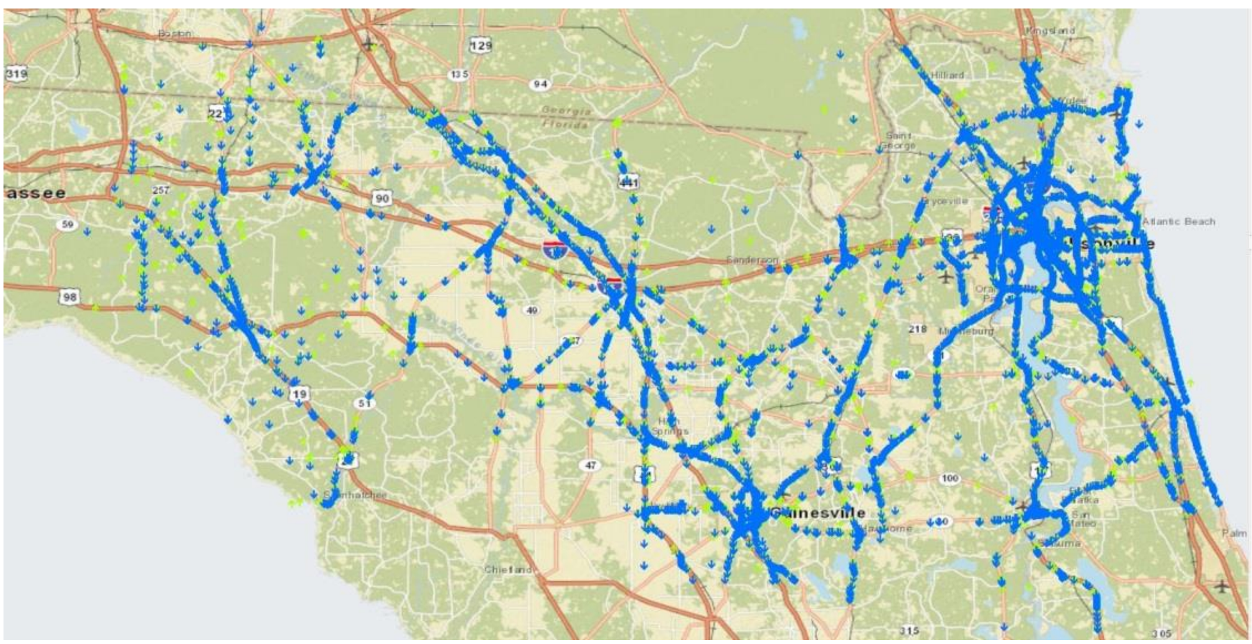

Figure 27 Cardinal Directions of District 2 Traffic Signs: North (Green) - South (Blue)

- Sign Colors; Blue, Brown, Red, Green, Yellow, and Fluorescent Yellow-Green

Table 6 provides the share of sign color type field in District 2.

Table 9 Descriptives of Sign Colors

Sign Color	Number of Records	Percentage
White	31,710	76.70%
Blue	3,594	8.70%
Brown	627	1.50%
Red	5,928	14.30 %
Green	4,151	10.00%
Yellow	8,417	20.40%
Flo. Yell. – Green	344	0.80%

There are two fields that indicate the color. First one is for the legend and second is for the background color. The color of the sign is chosen by a code that either one of the fields will count. Thus, if one of the fields are red, the will be considered as red. Due to this type of coding, there are duplicate signs for different colors, thus sum of percentages would be greater than 100%. Although, there are other colors provided in the inventory, only the colors from FDOT project agreement were chosen for clustering. Geographic locations of traffic signs by their background and/or legend colors are displayed in Figure 8.

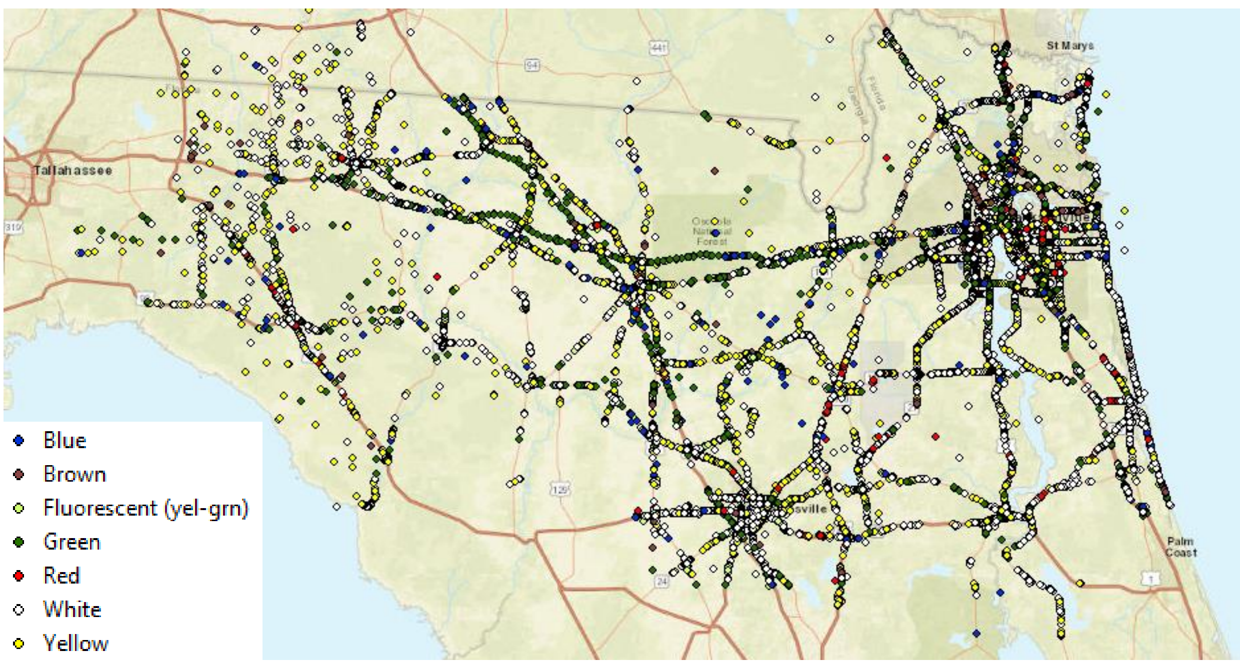

Figure 28 District 2 Traffic Signs Background Colors Map

- Age Group of signs;

Number and percentages of traffic signs in each group are presented in Table 7. Description and color legend for figure of each group are also provided in Table 7.

Table 10 Age Group Statistics

Age Groups	Description	Figure-10 Legend	Number of Records	Percentage
(1)	1 to 3 years	Green	4236	10.2 %
(2)	4 to 6 years	Light Green	5546	13.4 %
(3)	7 to 9 years	Light Yellow	6520	15.8 %
(4)	10 to 12 years	Yellow	8105	19.6 %
(5)	13 to 16 years	Orange	9392	22.7 %
(6)	17 to 20+ years	Red	7529	18.2 %

In Figure-9, geographic locations age groups of traffic signs are presented in district map.

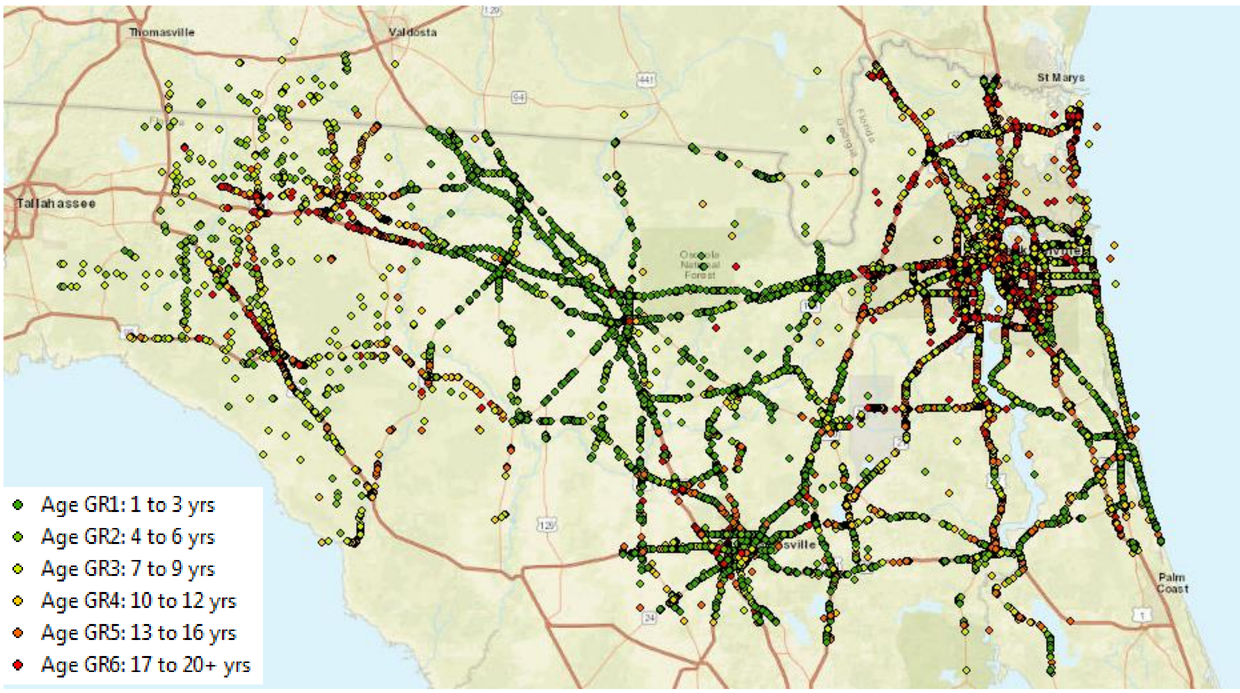

Figure 29 District 2 Traffic Signs Age Groups of Traffic Signs

2.2. District 1

District 1 sign inventory database consists of five regional datasets. These are; Glades-Hendry, Lee-Charlotte, Manatee-Sarasota, Desoto-Hardee-Highlands-Okeechobee, and Polk. These datasets were merged using GIS techniques and plotted in Figure 10. The attributes of the database are presented with some descriptions/notes from the examination in Table 8.

Roadway locations and geo-locational dataset were joined to district 1 database to identify traffic signs located at rural/urban and inland/coastal areas.

Table 11 District 1 Inventory Database Fields

<table>
<tr><th>Fields</th><th>Notes</th></tr>
<tr><td>OBJECTID</td><td>Unique ID number for each traffic sign.</td></tr>
<tr><td>KCAWO</td><td>Regional Code</td></tr>
<tr><td>MAINTUNIT</td><td>Maintenance Unit</td></tr>
<tr><td>SECTION</td><td>Section number</td></tr>
<tr><td>BEGINMP</td><td>Beginning milepost</td></tr>
<tr><td>ENDMP</td><td>End milepost</td></tr>
<tr><td>ROADNO</td><td>Road number</td></tr>
<tr><td>USROADNO</td><td>US Road number</td></tr>
<tr><td>DATEADD</td><td>Date of record added to the database.</td></tr>
<tr><td>SIGNMP</td><td>Sign milepost</td></tr>
<tr><td>SIGNLONG</td><td>Longitude (X)</td></tr>
<tr><td>SIGNLAT</td><td>Latitude (Y)</td></tr>
<tr><td>NOPANELS</td><td>Number of panels of the sign</td></tr>
<tr><td>NOPOSTS</td><td>Number of posts of the sign</td></tr>
<tr><td>MESSAGE</td><td>Message regarding some characteristics</td></tr>
<tr><td>ROADSIDE</td><td>Roadside or not (Binary)</td></tr>
<tr><td>COMMENT</td><td>All missing</td></tr>
<tr><td>PHOTOPAN</td><td rowspan="15">Photo database fields. Photos would have “installation dates”, “sheeting type” and “manufacturer name”, however they are not stored in a database. Thus, all photos need to be observed and manually recorded which was not found to be time efficient.</td></tr>
<tr><td>PHOTOPOS</td></tr>
<tr><td>PHOTOBAS</td></tr>
<tr><td>PHOTOB2</td></tr>
<tr><td>PHOTODOT</td></tr>
<tr><td>INSPECT</td></tr>
<tr><td>PACDIRT</td></tr>
<tr><td>PACSCRAT</td></tr>
<tr><td>PACBLIST</td></tr>
<tr><td>PACCRACK</td></tr>
<tr><td>PACPEEL</td></tr>
<tr><td>PACDENTS</td></tr>
<tr><td>PACBENT</td></tr>
<tr><td>PACBULLE</td></tr>
<tr><td>PAVTURN</td></tr>
</table>

In Figure 10, a GIS map of plotted merged traffic signs in District 1 is presented.

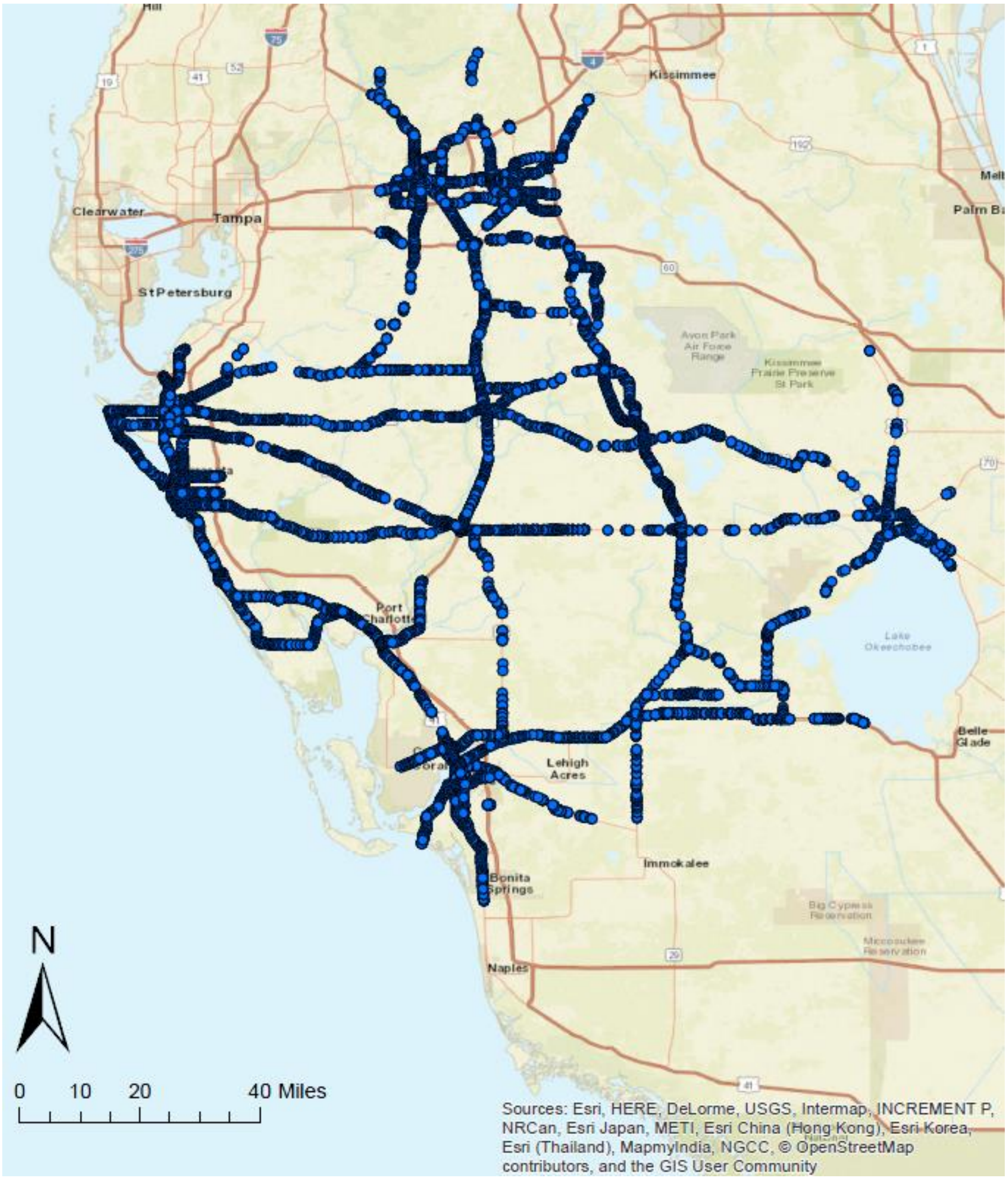

Figure 30 District 1 Traffic Signs

Florida urban area boundary shapefiles were implemented and traffic signs located in urban and rural roadways were identified. There were 18,842 traffic signs that were found in urban areas of District 1 out of 26,210 traffic signs (see Figure 11).

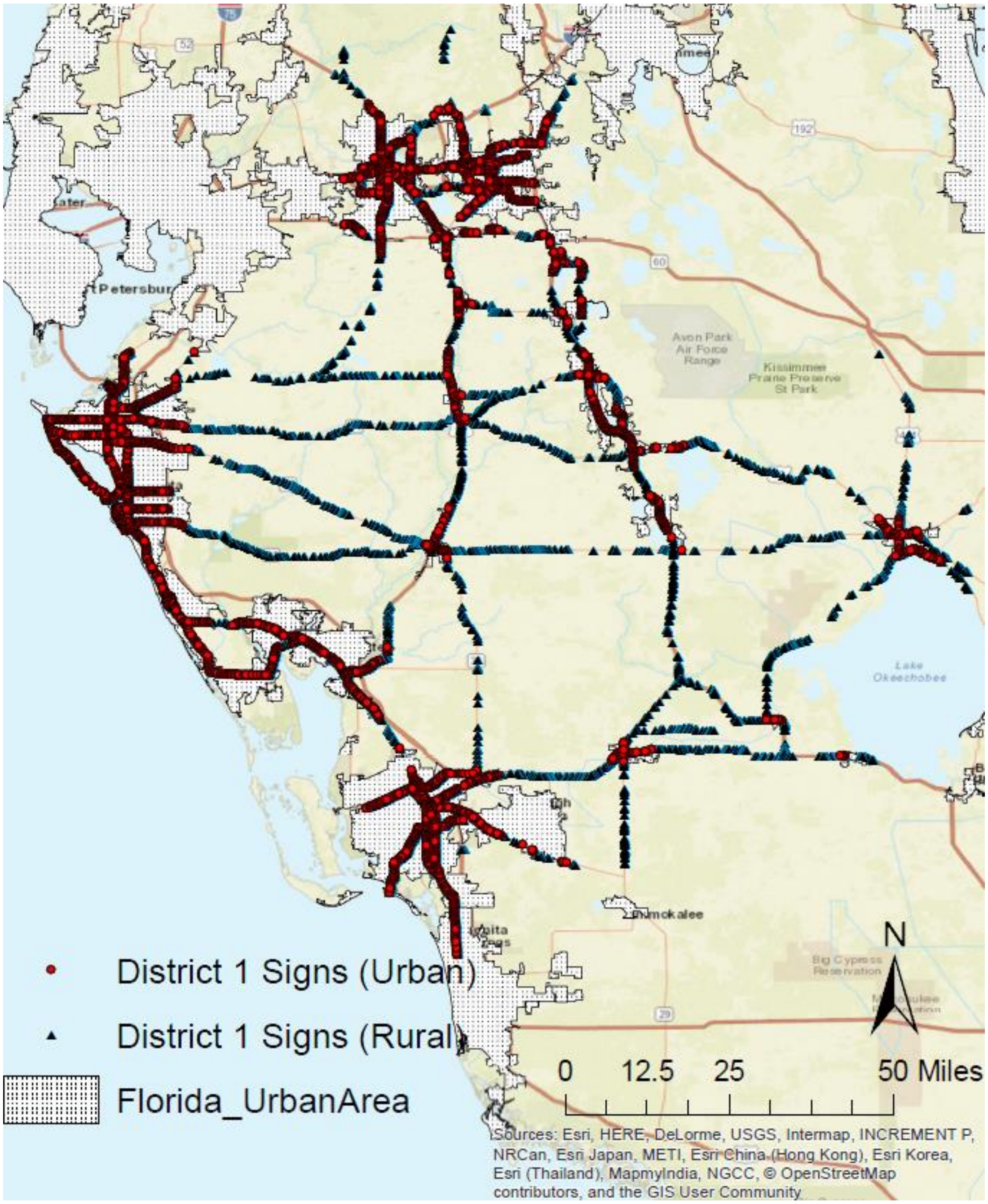

Figure 31 Roadway Location Type of District 1 Traffic Signs: Rural (Red circle) – Urban (Blue triangle)

2.3. District 4

Table 9 presents District 4 dataset fields/variables with some descriptions/notes from the analyses. As can be observed from the table; there are limited attributes compared to district 2 that will be used in sampling procedure.

Table 12 District 4 Inventory Database Fields

Fields	Notes
OBJECTID	Unique ID number for each traffic sign.
Easting	Longitude – Y
Northing	Latitude – X
MUT CD	MUTCD number
Type	Single post or not
State Rd	Road number
Visibility	Binary
Sheeting	Consist of 8 categories including; H. Intensity, Engineer, Diamond Gr etc
Global ID	ID number
Support ID	Support ID number
Shape	Shape description
Is Breakaway	Breakaway or not (binary)
Mounting Height	Height in fts.
Number of panels	Number of panels of the sign
Illumination	Mounted lighting or not (binary)
Sheeting Material	Mostly aluminum
Backing Material	Mostly aluminum
Size Height	Height
Size Width	Width
Sign Direction	Direction
Speed Zone	Posted speed limit

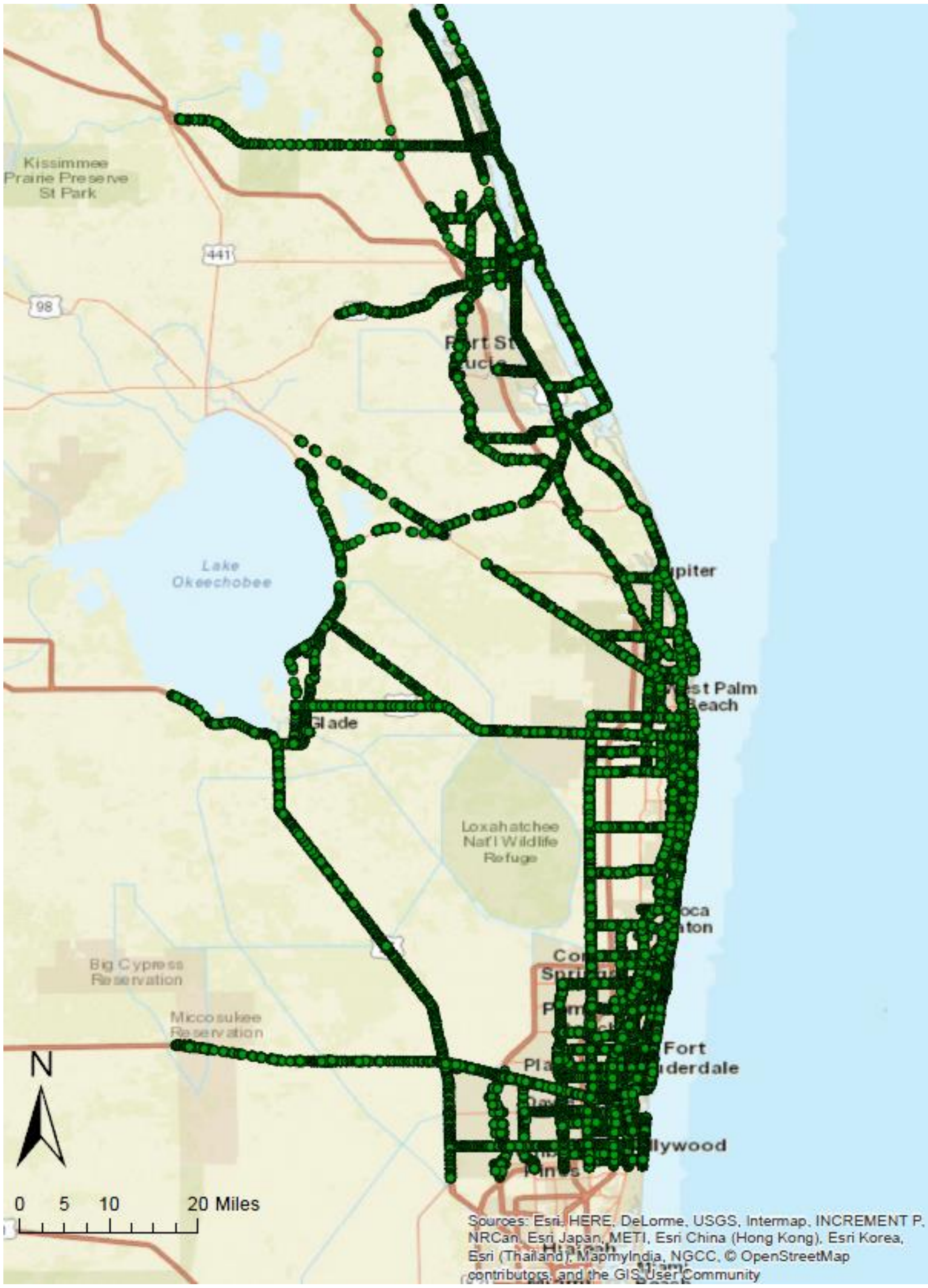

Figure 32 District 4 Traffic Signs

Florida urban area boundary shapefiles were implemented and traffic signs located in urban and rural roadways were identified. There were 59,425 traffic signs that were found in urban areas out of 74,188 traffic signs (see Figure 13).

Figure 33 Roadway Location Type of District 4 Traffic Signs: Rural (Red circle) – Urban (Blue triangle)

2.4. District 7

District 7 sign inventory geographic database consists of five separate county datasets. The counties are as follows; Citrus, Hernando, Hillsborough, Pasco, and Pinellas. The datasets were merged using GIS. In Table 10, District 7 dataset fields/variables with some descriptions/notes from the analyses are presented. This district sign inventory database also clearly lacking of important attributes for sampling procedure.

Table 13 District 7 Inventory Database Fields

Fields	Notes
County	Name of county
Mile post	Mile post of sign
X	Longitude
Y	Latitude
sign ID	Unique ID
Current Attachment ID	Unique ID
Pic. #	Picture ID to find the from the photo database
Support ID	Support type ID
MUTCD Code	MUTCD number
Sign Description	Sign type
Date of inspection	Inspected Date
Fails Bi-annual insp.	Binary (fail or not)
meets reflectivity	Binary (Yes/No)
Date of reflect. Check	Check date
Notes	Notes from check
Background	Background material
Position	Direction

Further, after joining geographical shapefiles, they are plotted in a GIS map (see Figure 14).

Figure 34 District 7 Traffic Signs

Florida urban area boundary shapefiles were implemented and traffic signs located in urban and rural roadways were identified. There were 28,842 traffic signs that were found in urban areas out of 33,978 traffic signs (see Figure 15).

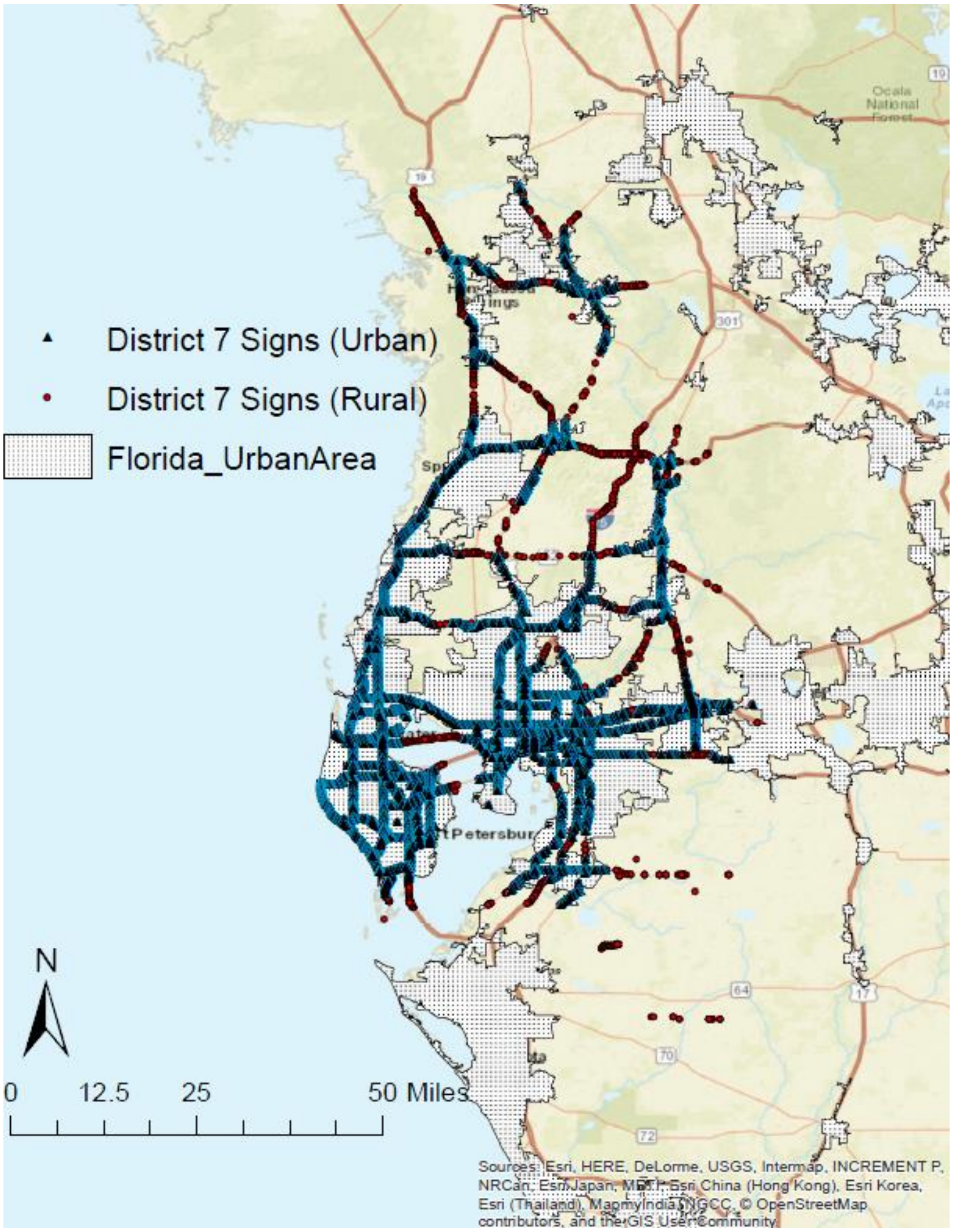

Figure 35 Roadway Location Type of District 7 Traffic Signs: Rural (Red circle) – Urban (Blue triangle)

3. Study Design and Sampling Process

In our study design, the aim is to analytically quantify the relationship between sign characteristics and Retro-reflectivity measure as well as design characteristics and chromaticity measure. According to FHWA, there are no plans for including a maintenance requirement for chromaticity value.

A multiple linear regression model design is proposed for Retro-reflectivity prediction. For chromaticity, measured values are not a continuous and needs to be tested if it falls in to the corresponding color area on the CIE Chromaticity Diagram (Figure 16) [98]. Based on this criteria, a binary variable (0: fail, 1: pass) will be created. Hence, a binary logit model is proposed for the chromaticity test.

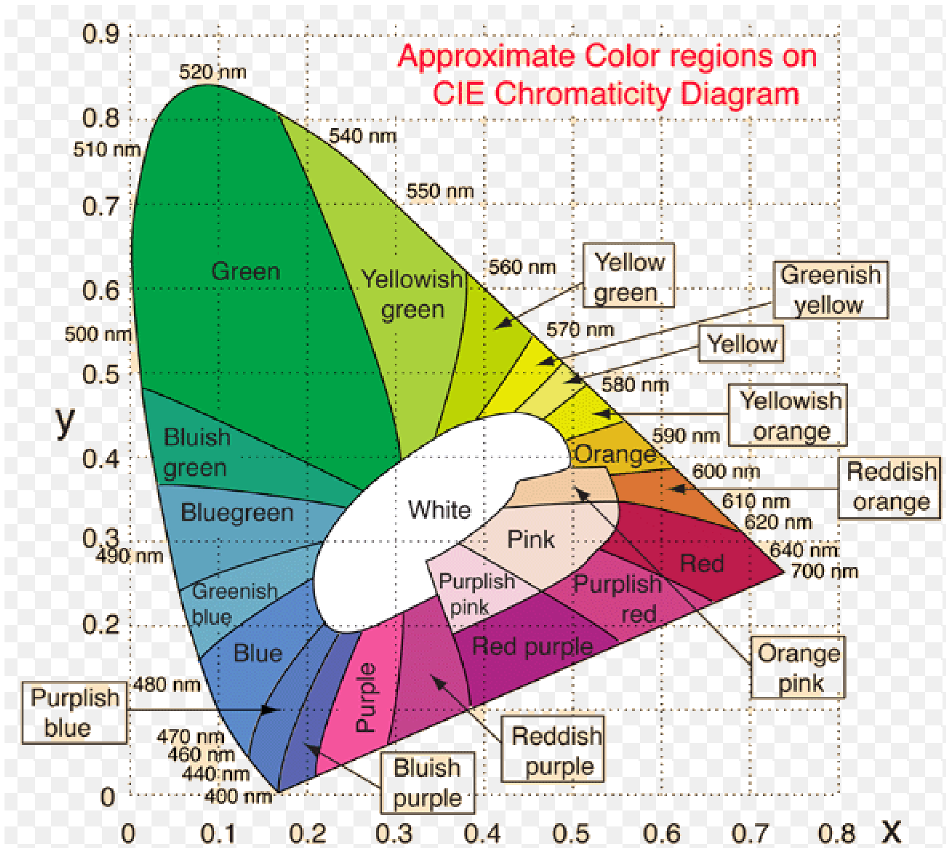

Figure 36 CIE Chromaticity Diagram

For this type of models, we will be using disproportionate stratified random sampling procedure. The outcomes of the study which is retro-reflectivity and chromaticity will be measured for the sample data. As mentioned earlier, after data cleansing; there are 41,328 data points in district 2, 26,210 in district 1, 74,188 in district 4, and 33,978 in district 7 databases. Sample size (n) estimation will be based on several rules. Sampling process was performed using ArcGIS, SPSS and Microsoft Excel computer software.

Aforementioned first relationship between sign characteristics and Retro-reflectivity will be modeled is a type of predictive analysis where the changes of a continuous dependent variable is explained by two or more independent variables. The purpose of the statistical approach is to predict retro-reflectivity measures of traffic signs. A multiple linear regression model design is shown below;

$$R_A = \beta_0 + \beta_1 X_{age}$$

Dependent variable: Retro-reflectivity, R_A

β_0: *Constant reflecting Sheeting Material Type III, Color Green, Manufacturer 3M, Regional Area North, Cardinal Orientation North, Roadway Location Urban, Geographic Location Inland.*

- Independent variables:
  - Continuous variables;

$$+ \beta_1 X_{age}$$

(Age in months)

  - Qualitative (Categorical) Variables;

$$+ \beta_2 X_{SIV} + \beta_3 X_{SVII} + \beta_4 X_{SXI}$$

(Qualitative Variables for Sheeting Materials types IV, VII, XI)

$$+ \beta_5 X_{CBn} + \beta_6 X_{CBe} + \beta_7 X_{CR} + \beta_8 X_{CW} + \beta_9 X_{CY} + \beta_{10} X_{CFY-G}$$

(Qualitative Variables for Brown, Blue, Red, White, Yellow, Fluorescent Yellow-Green)

$$+ \beta_{11} X_{Mad} + \beta_{12} X_{Mnc}$$

(Qualitative Variables for Manufactures: Avery Denninson, Nippon Carbide)

$$+ \beta_{13} X_{AC} + \beta_{14} X_{AS}$$

(Qualitative Variables for Regional Area: Central and South)

$$+ \beta_{15} X_{CoS} + \beta_{16} X_{CoE} + \beta_{17} X_{CoW}$$

(Qualitative Variables for Cardinal Orientation: South, East and West)

$$+ \beta_{18} X_{RwR}$$

(Qualitative variable for Roadway Location: Rural)

$$+ \beta_{19} X_{GeoC}$$

(Qualitative Variables for Geographic Locations: Coastal)

$$+ \varepsilon$$

(Error Term)

Binary logit model is a type of regression model for categorical dependent variable. As mentioned earlier, our outcome variable (chromaticity test results) is binary. In other words, a discrete choice modelling procedure will be implemented. Binary logistic regression procedure is used to estimate the probability of a binary response based on one or more predictor variables. Binary logit model design for chromaticity test is provided below;

$$C_T = \beta_0 + \beta_1 X_{age}$$

Dependent variable (binary): Chromaticity Test result, C_T

β_0: *Constant reflecting Sheeting Material Type III, Manufacturer 3M, Regional Area North, Cardinal Orientation North, Roadway Location Urban, Geographic Location Inland.*

- Independent variables:
  - Continuous variables;

$$+ \beta_1 X_{age}$$

(Age in months)

  - Qualitative (Categorical) Variables;

$$+ \beta_2 X_{SIV} + \beta_3 X_{SVII} + \beta_4 X_{SXI}$$

(Qualitative Variables for Sheeting Materials types IV, VII, XI)

$$+ \beta_5 X_{Mad} + \beta_6 X_{Mnc}$$

(Qualitative Variables for Manufactures: Avery Denninson, Nippon Carbide)

$$+ \beta_7 X_{AC} + \beta_8 X_{AS}$$

(Qualitative Variables for Regional Area: Central and South)

$$+ \beta_9 X_{CoS} + \beta_{10} X_{CoE} + \beta_{11} X_{CoW}$$

(Qualitative Variables for Cardinal Orientation: South, East and West)

$$+ \beta_{12} X_{RwR}$$

(Qualitative variable for Roadway Location: Rural)

$$+ \beta_{13} X_{GeoC}$$

(Qualitative Variables for Geographic Locations: Coastal)

$+ \varepsilon$

(Error Term)

<u>Sample Size Estimation;</u>

As a rule of thumb in priori minimum sample size estimation of multiple linear regression models; there should be at least a size of 10 samples for each independent variable. Multiple linear regression model for retro-reflectivity contains 19 independent variables which is higher than the number of binary logit model predictor variables. Therefore 19 was chosen for minimum sample size estimation; minimum sample size n=10*19=190.
For validation, we also use a priori sample size calculator for multiple regression;

Anticipated effect size (f^2): 0.1 (assumed correlation between R_A and independent variables),
Desired Statistical Power Level: 0.85 (sensitivity of the test correctly rejects null hypothesis),
Number of Predictors: 19 (independent variables).
Probability level (α): 0.01,
were chosen for the calculation; Computed sample size (n) = 320. [94], [95]

From 190 and 320, we choose 320 as our minimum sample size for the multiple linear regression model.
Assumptions for disproportionate stratified sampling;

- We know where the various signage factors combinations are located,
- No additional levels on the qualitative variables are required;

3.1. Disproportionate Stratified Random Sampling of District 2 Signs

Since district 2 sign inventory after data analysis is able to provide most of the attributes that will be used in our regression models beforehand, a disproportionate stratified sampling will be performed. The minimum sample size needed was determined as 320. In order to choose a representative sample of each known group from the traffic signs inventory dataset prior to data collection of the outcome variable, sample stratification will be performed for district 2 sign database. When some of the subgroups are small with proportionate stratification, disproportionate stratification can be used to increase frequencies of those strata. To obtain unbiased estimates for a disproportionate stratified sample, estimates will be weighted. In a disproportionate stratification, the population of sampling units is divided into strata and a random sample selected separately per stratum. Sampling fraction is not the same within all strata, in other words, some strata are over-sampled as compare to others. This type of stratification increases the precision of key estimates. Standard errors will also be reduced by disproportionate stratification if the population standard deviation for the subgroup variable is higher than average within the over-sampled strata. [90]
Strata were chosen based on three sign characteristic groups (i.e. age group, inland/coastal, and urban/rural) To prevent overlapping of strata, a combination of AGEGR (6) *

Geographic Location Type (2) * Roadway Location Type (2) = 24 subgroups (strata). The distribution of determined sample size of 336 is provided in Table 11. After grouping the population of 41,328 data points into 24 strata, a simple random sample selection of corresponding sample size for each stratum was performed. The distribution of sample size in strata was determined by the age group category. Sample sizes of older sign groups' proportions are larger than younger groups.

Table 11 provides the disproportionate stratification results with weights (fraction). Proportional sample sizes are also provided in Table 11. Disproportionate sample sizes are given in "sample" column. As can be seen in proportional sample sizes, there are strata which have very small sizes such as 0.29, 0.33, 0.59 etc. Therefore, disproportionate stratification is found to be more adequate for this case.

Table 14 Disproportionate Stratified Sampling Results

Strata	Inl/Coast	Rur/Urb	AgeGR	Records	Proportion	Sample	Prop. S. Size	Fraction
1	Coastal	Rural	(1)	62	0.15%	14	0.50	27.77
2	Inland	Rural	(1)	2306	5.58%	14	18.75	0.75
3	Coastal	Urban	(1)	358	0.87%	14	2.91	4.81
4	Inland	Urban	(1)	1510	3.65%	14	12.28	1.14
5	Coastal	Rural	(2)	36	0.09%	14	0.29	47.83
6	Inland	Rural	(2)	2313	5.60%	14	18.80	0.74
7	Coastal	Urban	(2)	393	0.95%	14	3.20	4.38
8	Inland	Urban	(2)	2804	6.78%	14	22.80	0.61
9	Coastal	Rural	(3)	73	0.18%	14	0.59	23.59
10	Inland	Rural	(3)	2837	6.86%	14	23.07	0.61
11	Coastal	Urban	(3)	223	0.54%	14	1.81	7.72
12	Inland	Urban	(3)	3387	8.20%	14	27.54	0.51
13	Coastal	Rural	(4)	171	0.41%	14	1.39	10.07
14	Inland	Rural	(4)	3165	7.66%	14	25.73	0.54
15	Coastal	Urban	(4)	356	0.86%	14	2.89	4.84
16	Inland	Urban	(4)	4413	10.68%	14	35.88	0.39
17	Coastal	Rural	(5)	147	0.36%	14	1.20	11.71
18	Inland	Rural	(5)	3708	8.97%	14	30.15	0.46
19	Coastal	Urban	(5)	635	1.54%	14	5.16	2.71
20	Inland	Urban	(5)	4902	11.86%	14	39.85	0.35
21	Coastal	Rural	(6)	40	0.10%	14	0.33	43.05
22	Inland	Rural	(6)	1758	4.25%	14	14.29	0.98
23	Coastal	Urban	(6)	434	1.05%	14	3.53	3.97
24	Inland	Urban	(6)	5297	12.82%	14	43.07	0.33
Total				41328	100%	336		

3.1.1. Cross-Checking with Other Factors' Proportions

In order to validate the representativeness of the sample with regards to remaining factors such as cardinal direction, face material, and sign type; Table 12 was provided as a comparison of proportions in population and sample.

Table 15 Proportions Cross-Check List

Cardinal Directions	Real Pop.	Sample Pop.	Background Color	Real Pop.	Sample Pop.	Sign Type	Real Pop.	Sample Pop.
East	19.9%	16.1%	**White**	54.8 %	56.8%	**Regulatory**	42.8%	48.5%
West	20.1%	16.7%	**Blue**	6.8%	5.4%	**Guide**	17%	16.4%
South	30.9%	32.7%	**Green**	9.8%	7.1%	**Rt. Marker**	18%	12.2%
North	29.2%	34.5%	**Yellow**	19.8 %	21.4%	**School**	2.9%	2.1%
			Red	4.6%	3.0%	**Warning**	15.8%	19.0%
			Flu. Yellow-Gr	0.8%	0.9%			

Figure 17 also illustrates the sign background color shares in both real population and sample population.

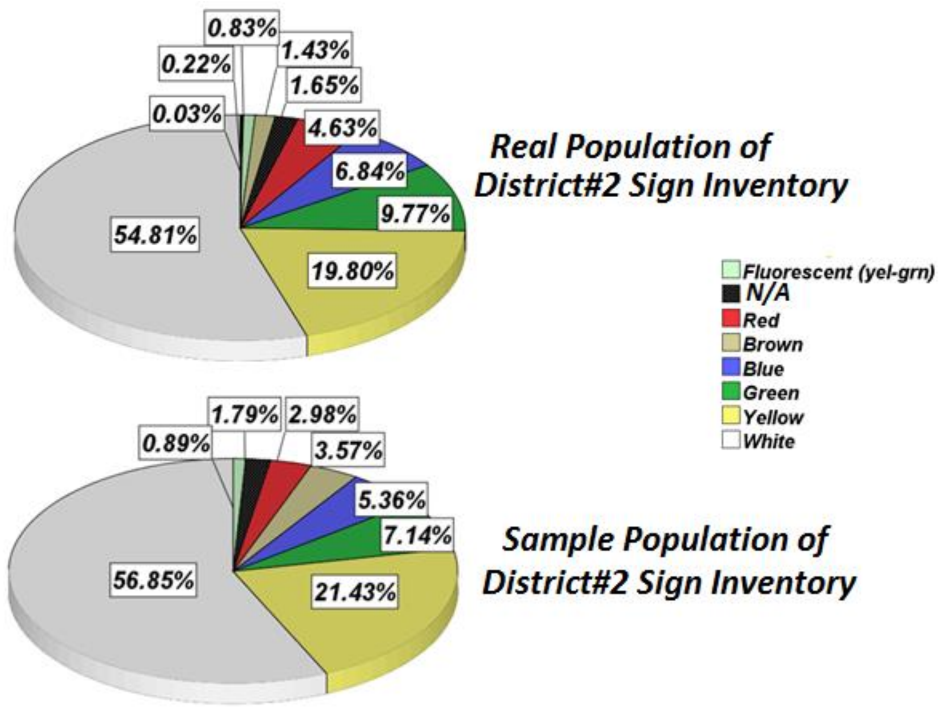

Figure 37 Sign Background Color Shares

3.1.2. Selected Traffic Signs for Data Collection in District 2

Locations of sample traffic signs selected are shown in District 2 map (Figure 18).

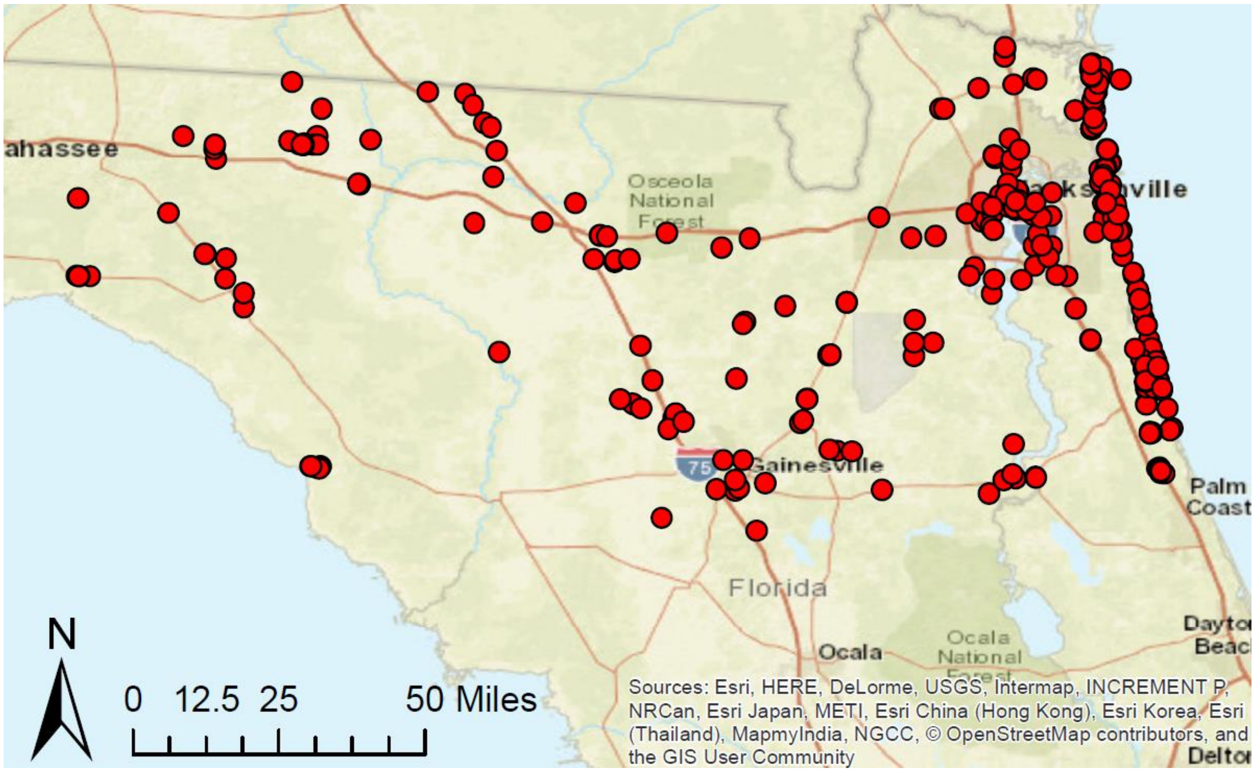

Figure 38 Sample Signs Geo-Locations

Sample of 320 traffic signs are listed in Table 12. Please see the attached excel sheets for the district 2 traffic signs list.

3.2. Zonal Ordinary Least Squares Sampling (OLS) Prediction Model

As mentioned in earlier chapters, the districts except district 2 lacks of information to perform stratified sampling. To overcome the issue and select appropriate samples from each of the remaining districts, a census tract (CT) aggregate level ordinary least squares (OLS) prediction model is generated using the existing signs (real population) and street centerline as the explanatory variables of the district 2 sample signs.

In order to build this prediction model, the sample signs and real population signs were aggregated at the census tract zone level. Thus, in district 2; 41,328 geo-located signs were spatially joined to 375 CT zone boundaries to find count data. Similarly, 336 sample signs of district 2 were also spatially joined to 375 CT zone boundaries and sample counts at CT level were computed. Additionally, the sum of street centerline lengths that falls into the CT zones were computed by implementing "intersect" and "spatial join" modules of ArcMap.

There are other variables that were considered as explanatory variables such as inland-coastal areas, rural-urban regions, etc. However, these variables were removed since they were used also in the disproportionate stratified sampling process of district 2. In other words, it would be a type of violation of one regression assumption, auto-correlation.

The prepared dataset including, sum of street centerline lengths, existing sign count, and sample sign count at CT level were used in the regression model estimated by applying OLS module of spatial statistics tools of ArcMap. This module performs global OLS linear regression to generate predictions or to model a dependent variable in terms of its relationships to a set of explanatory variables (see Figure 19).

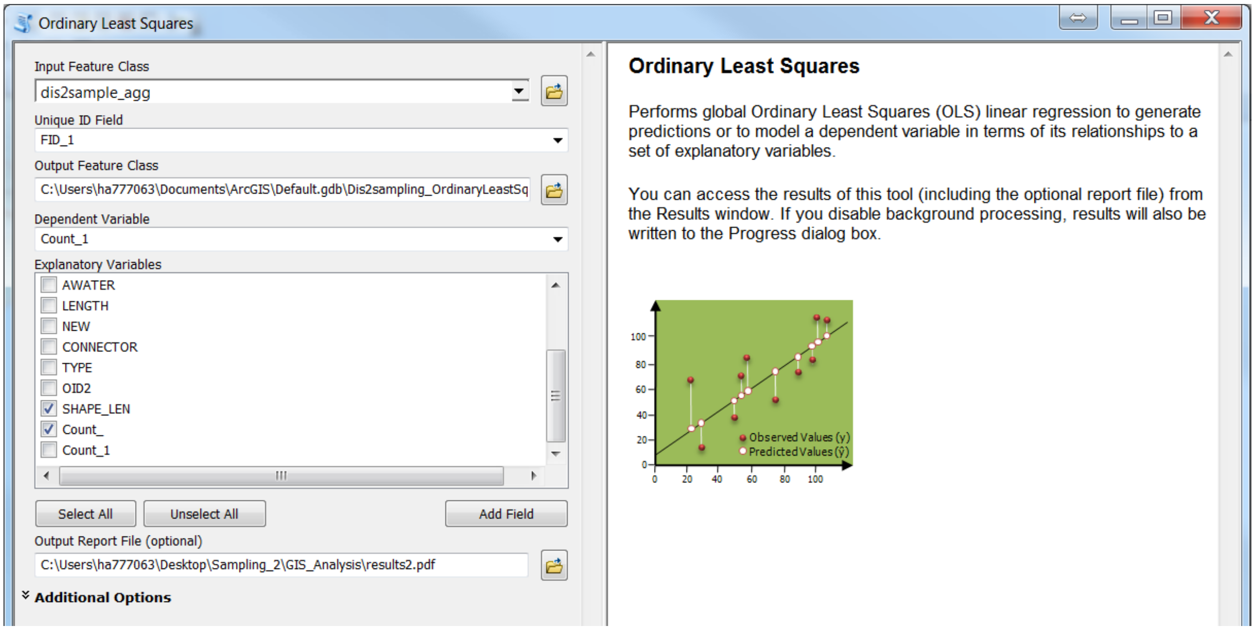

Figure 39 OLS Model Tool

The linear regression model formula is presented below;

$$S_A = \beta_0 + \beta_1 X_{street\ centerline} + \beta_2 X_{existing\ sign\ count}$$

where;

Dependent variable: Sample signs count, S_A

β_0: Constant value

β_1: Regression parameter of sum of street centerline lengths at CT level

β_2: Regression parameter of existing signs count at CT level

$X_{street\ centerline}$: Sum of street centerline lengths at CT level

$X_{existing\ sign\ count}$: Existing signs count at CT level

3.2.1. OLS Regression Model Results

The OLS module of ArcMap provides the map of OLS residuals by categorizing the CT zones according to their standard deviations. The hot spots and cold spots indicate the model over and under predicted zones.

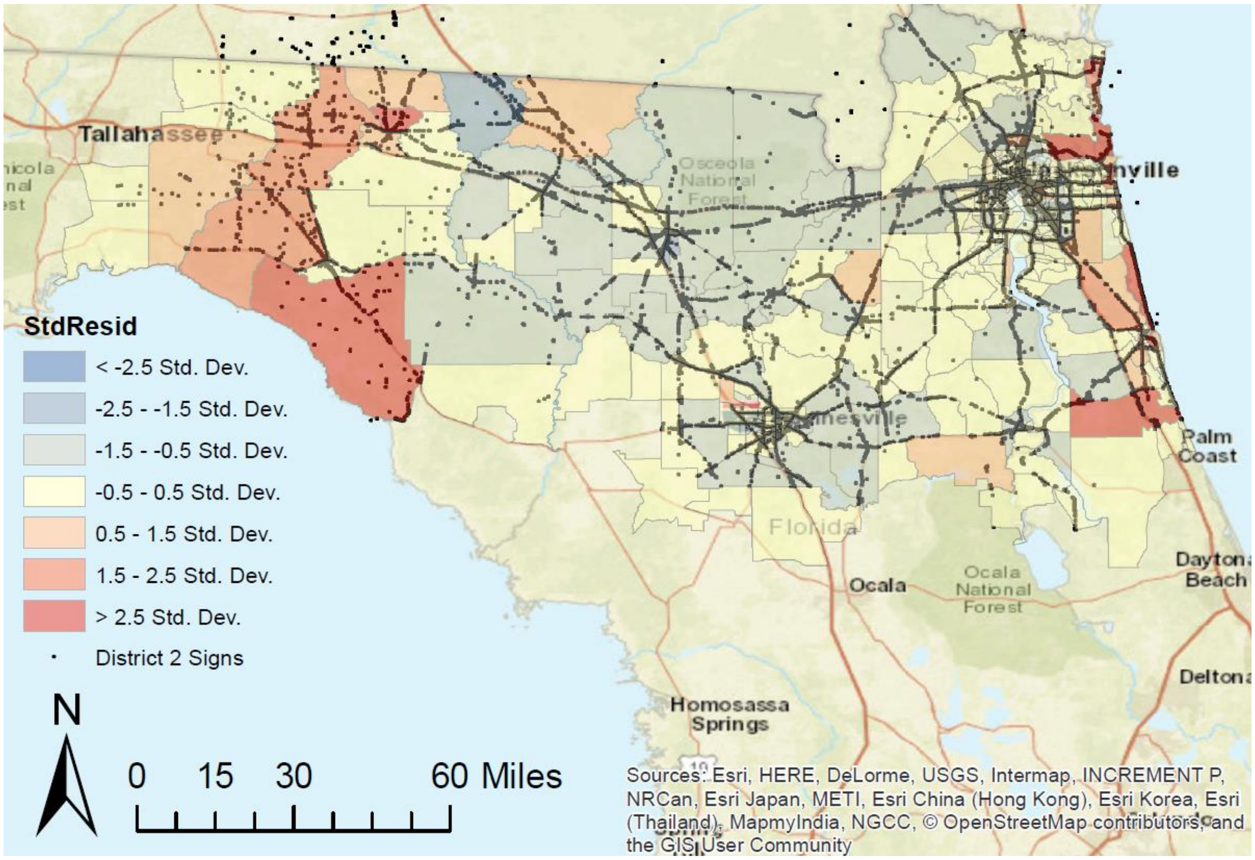

Figure 40 Prediction Model Results (Std. Deviations)

In the summary of OLS results presented in Table 13, regression coefficients and the intercept values can be seen. The t-statistics confirm both variables significance.

Table 16 Summary of OLS Results - Model Variables

Variable	Coef	StdError	t_Stat	Prob
Intercept	0.104501985	0.123736	0.844555	0.398889786
SHAPE_LEN (Street Centerline Length Sum)	-0.000000986	0.000272	-6.381896	0.000000000
COUNT_ (Existing Signs Count)	0.007275093	0.000943	7.712664	0.000000000

Input Features:	dis2sample_agg	Dependent Variable:	COUNT_1
Number of Observations:	375	Akaike's Information Criterion (AICc) [d]:	1492.521413
Multiple R-Squared [d]:	0.205628	Adjusted R-Squared [d]:	0.201357
Joint F-Statistic [e]:	48.147279	Prob(>F), (2,372) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	35.423785	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

* Statistically significant p-value ($p < 0.05$).

Figure 41 OLS Diagnostics

Notes on interpretation of Figure 20;

[a] Coefficient: Represents the strength and type of relationship between each explanatory variable and the dependent variable.

[b] Probability and Robust Probability (Robust_Pr): Asterisk (*) indicates a coefficient is statistically significant ($p < 0.05$); if the Koenker (BP) Statistic [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine coefficient significance.

[d] R-Squared and Akaike's Information Criterion (AICc): Measures of model fit/performance.

[e] Joint F and Wald Statistics: Asterisk (*) indicates overall model significance ($p < 0.05$); if the Koenker (BP) Statistic [f] is statistically significant, use the Wald Statistic to determine overall model significance.

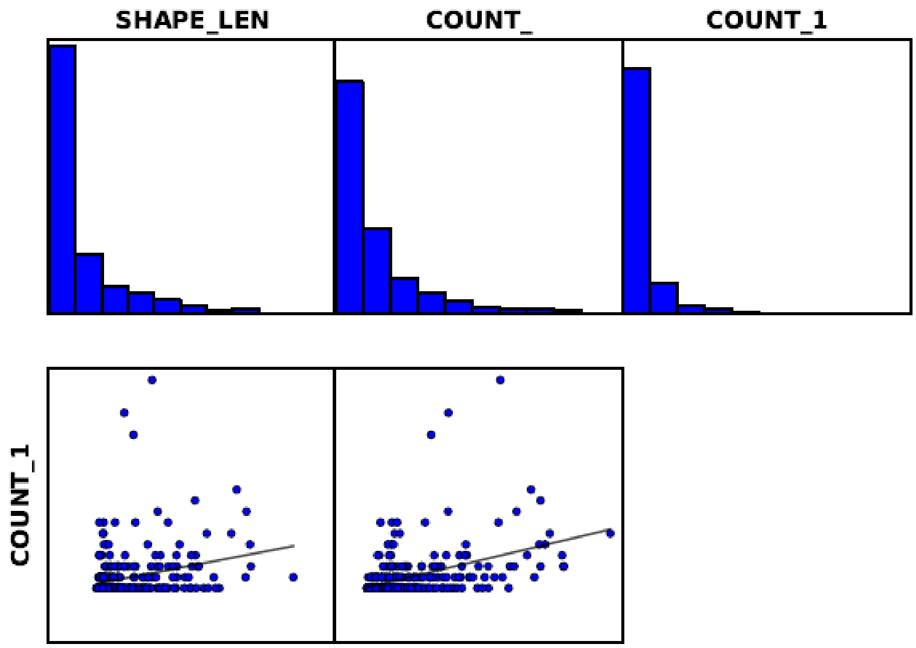

Figure 42 Variable Distributions and Relationships

The above graphs are Histograms and Scatterplots for each explanatory variable and the dependent variable. The histograms show how each variable is distributed. Each scatterplot depicts the relationship between an explanatory variable and the dependent variable. Strong relationships appear as diagonals and the direction of the slant indicates if the relationship is positive or negative.

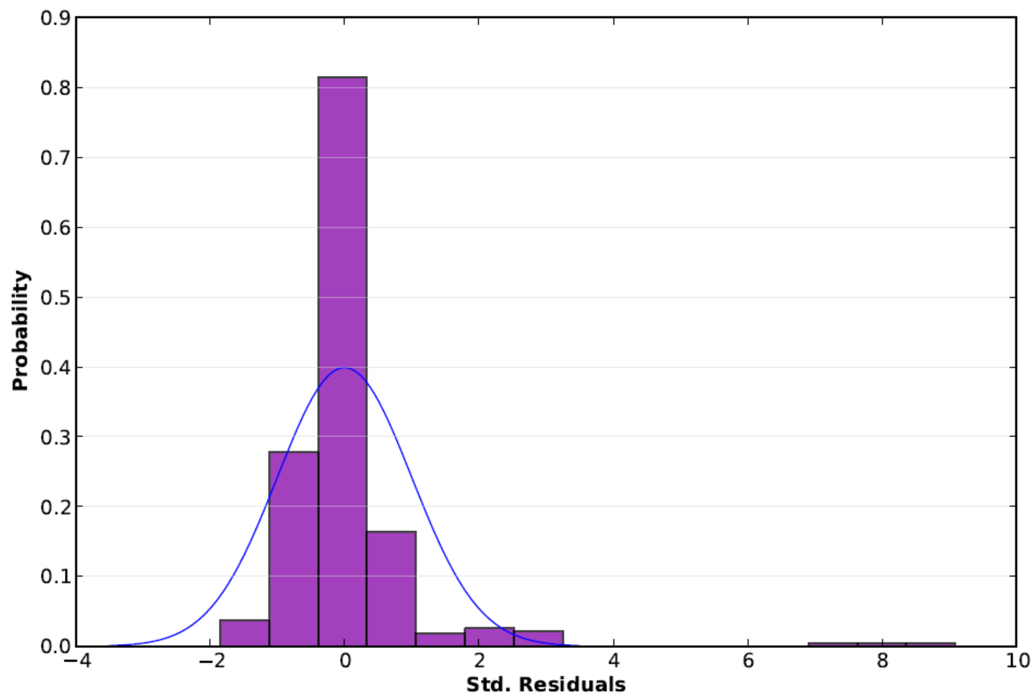

Figure 43 Histogram of Standardized Residuals

The histogram presented in Figure 22, provides the distribution of standardized residuals. Ideally, the histogram of the residuals would match the normal curve, indicated above in blue.

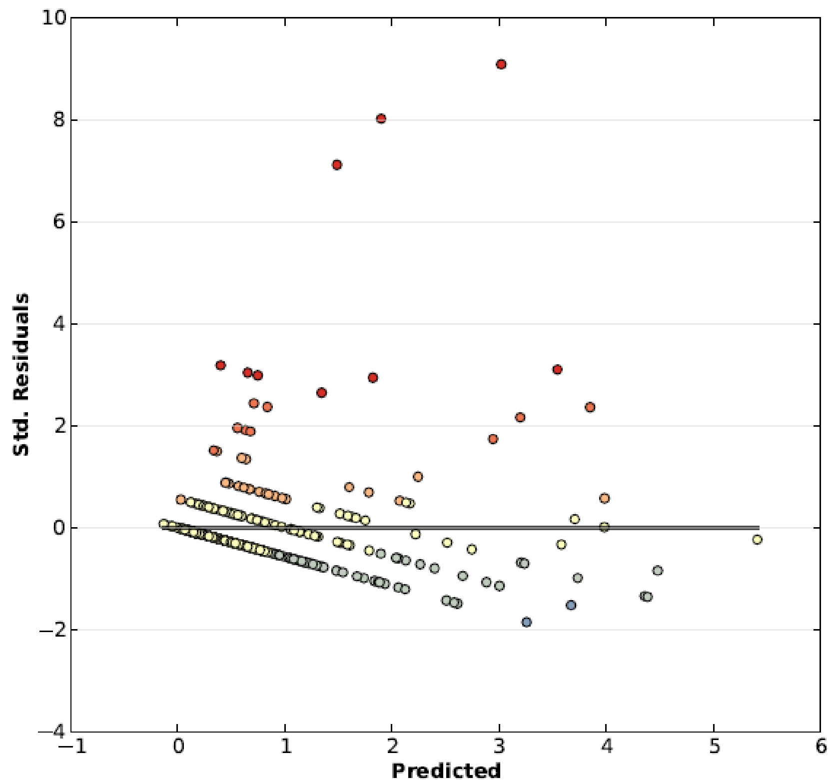

Figure 44 Residual vs. Predicted Plot

The residuals vs. predicted plot is presented in Figure 23. This illustrates a graph of residuals (model over and under predictions) in relation to predicted dependent variable values.

As a result, a regression model with an adjusted R-square of 0.2014 has been estimated to predict the samples of district 1, 4, and 7 as close as possible to district 2 sampling. The regression model will be applied to the remainder districts to predict the sample size in each of the CT zones. Then a simple random sampling will be performed in each CT zone.

3.3. District 1 Signs Sampling by District 2 Zonal Prediction Model

District 1 sign inventory database features were discussed earlier. In District 1; number of signs in the database is 26,210. The number of CT zones intersected with the District 1 boundaries is 447. Likewise the district 2 data preparation, in district 1; 26,210 geo-located signs were spatially joined to 447 CT zone boundaries to find count data. Similarly, the sum of street centerline lengths that falls into the CT zones were computed by implementing “intersect” and “spatial join” modules of ArcMap. The sample counts at CT zones are predicted by applying OLS model formula at the prepared dataset of district 1.

The descriptive statistics of the estimated counts at 447 CT zones are presented in Figure 24.

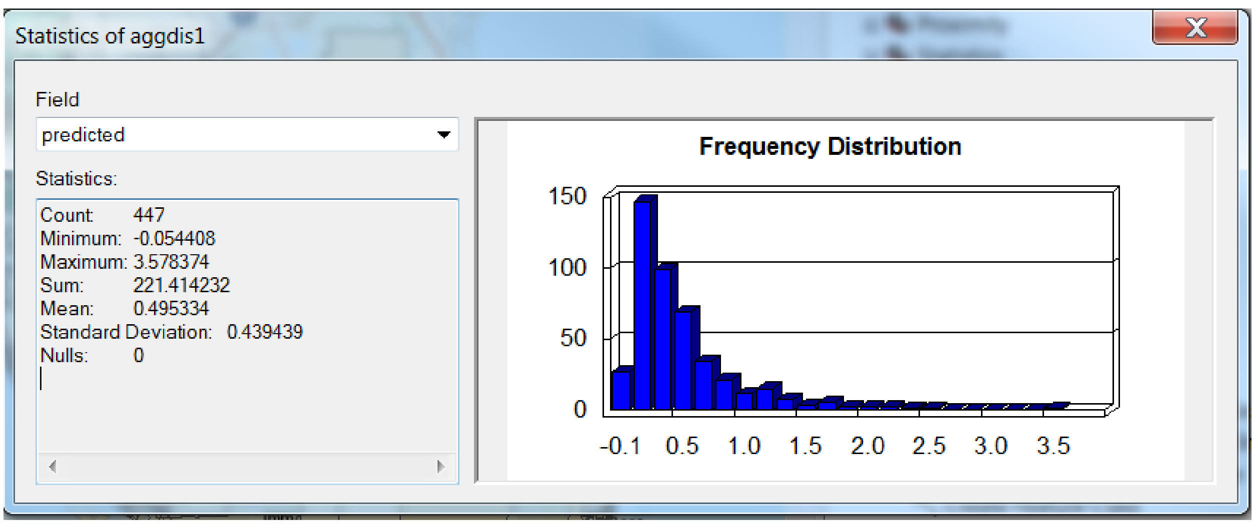

Figure 45 District 1 Estimated Counts Statistics

The predicted counts were rounded to the nearest integer and a random sample of signs was selected with the estimated sample size at the corresponding CT zone. Consequently, 190 sample signs were selected from district 1. Total sample size collected from the zones does not exactly match the sum of the counts presented in Figure 24 due to rounded up numbers. However, size of 190 sample signs is also consistent with the minimum sample size estimation for regression model of retro-reflectivity measures.

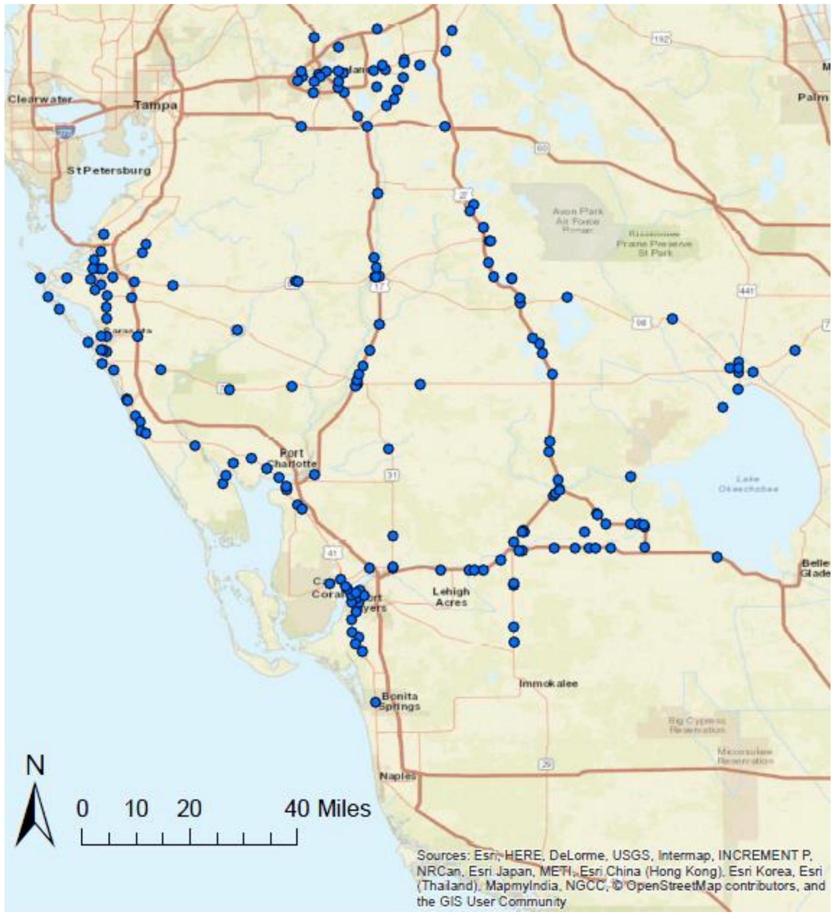

Figure 46 District 1 Sample Signs from Zonal Prediction Model

The sample signs collected by applying the zonal prediction model estimated with district 2 database are geo-located at Figure 25. Please refer to the attached excel sheets of zonal prediction model samples for the list of sample traffic signs.

3.4. District 1 Signs Sampling by Simple Random Sampling (SRS)

Minimum sample size was determined as 190 for multiple linear regression modeling. In District 1; number of signs in the database is 26,210. Since there is a lack of attributes in this inventory, simple random sampling procedure was applied to select a representative sample for both multiple linear regression and binary logit models. Simple random sample selection was made based on the spatial locations. ArcGIS, data management toolbox contains a ‘Create Random Points’ tool in feature classes. By using this tool, spatially randomized samples of 200 traffic signs were selected.

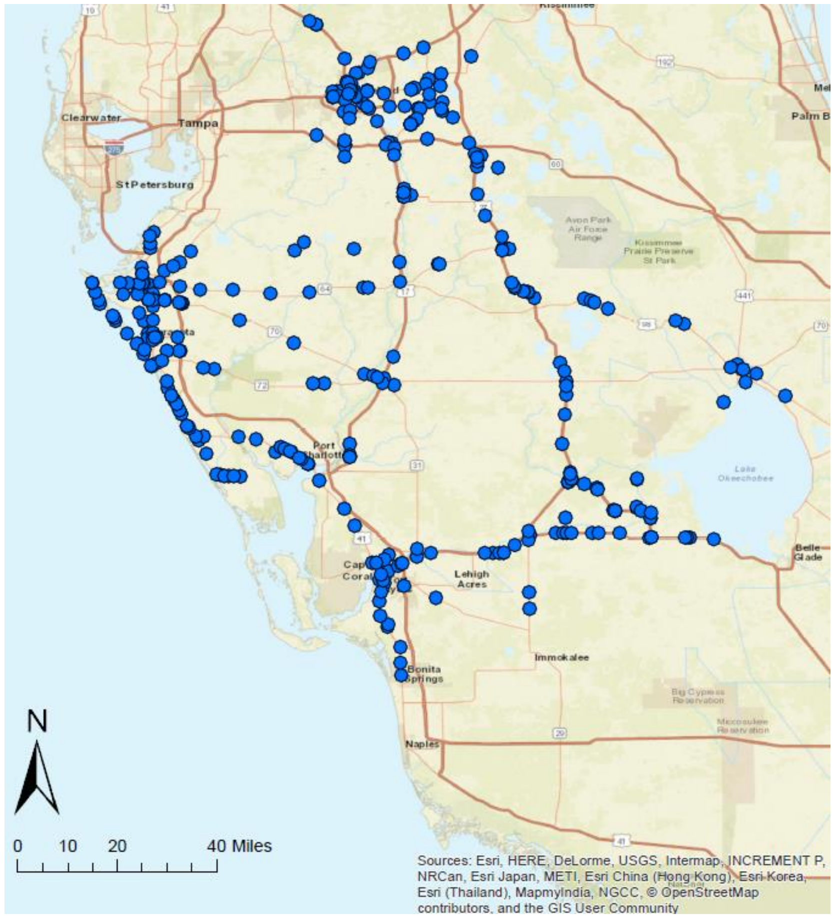

Figure 47 District 1 Sample Traffic Signs from SRS

District 1 SRS sampling results are illustrated by their geo-locations at a GIS map format. 350 spatially randomly selected traffic signs are presented in Figure 27. Please see the attached excel sheets of SRS samples for district 1 sample signs list.

3.4.1. Cross-Checking with Other Factors' Proportions

In this section, two examples of cross checks that were performed to compare real population versus the sample populations of traffic signs are presented.

First example is the roadway location type of the signs. In Table 14, the shares of rural and urban area traffic signs in district 1 populations are provided. It is clear that proportions are very close to each other. The zonal prediction model sample is slightly closer to the real population for this particular variable.

Table 17 District 1 Roadway Location Type Proportions

Roadway Location Type	Real Population	Sample (Zonal)	Sample (SRS)
Rural	28.12%	29.3%	26.3%
Urban	71.88%	70.7%	73.7%

Secondly, in table 15, another attribute that the database contained is evaluated by comparing the proportions of real population and random sample populations. Similarly, the real dataset results mostly match to the sample results. From this table, it is hard to tell which sample performs closer shares to the real population.

Table 18 District 1 Date of Inspection Proportions

Date of Inspection	Real Population	Sample (Zonal)	Sample (SRS)
MAY 2014	3.7 %	1.7 %	4.5 %
JUN 2014	5.7 %	3.1 %	7.7 %
JUL 2014	6.7 %	3.1 %	8.7 %
AUG 2014	6.5 %	6.3 %	6.5 %
SEP 2014	2.0 %	2.0 %	2.0 %
OCT 2014	7.0 %	7.4 %	5.0 %
NOV 2014	7.2 %	7.7 %	7.2 %
DEC 2014	11.0 %	11.4 %	10.0 %
MAY 2015	5.4 %	3.4 %	5.4 %
JUN 2015	15.4 %	10.9 %	17.8 %
JUL 2015	13.3 %	16.3 %	13.3 %
AUG 2015	4.7 %	5.4 %	5.7 %
SEP 2015	3.7 %	6.9 %	3.7 %
OCT 2015	1.4 %	2.9 %	0.4 %
NOV 2015	3.3 %	7.1 %	3.3 %
DEC 2015	2.2 %	4.3 %	1.2 %

3.5. District 4 Signs Sampling by District 2 Zonal Prediction Model

District 4 sign inventory database features were discussed earlier. In District 4; number of signs in the database is 74,188. The number of CT zones intersected with the District 4 boundaries is 658. Likewise the district 2 data preparation, in district 4; 74,188 geo-located signs were spatially joined to 658 CT zone boundaries to find count data. Similarly, the sum of street centerline lengths that falls into the CT zones were computed by implementing “intersect” and “spatial join” modules of ArcMap. The sample counts at CT zones are predicted by applying OLS model formula at the prepared dataset of district 4.

The descriptive statistics of the estimated counts at 658 CT zones are presented in Figure 28.

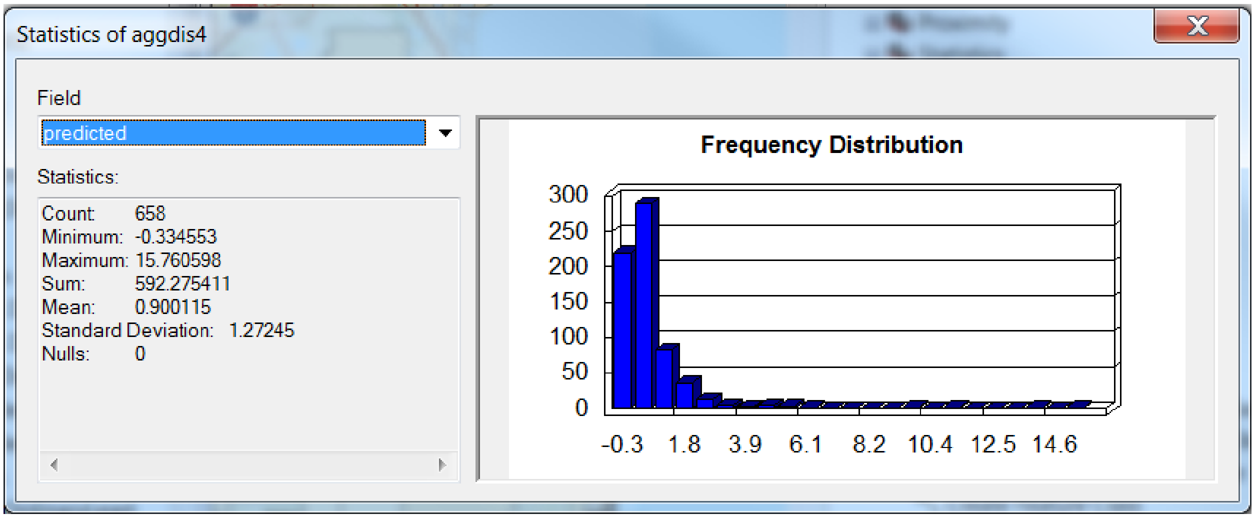

Figure 48 District 4 Estimated Counts Statistics

The predicted counts were rounded to the nearest integer and a random sample of signs was selected with the estimated sample size at the corresponding CT zone. Consequently, 547 sample signs were selected from district 4. Total sample size collected from the zones does not exactly match the sum of the counts presented in Figure 28 due to rounded up numbers. Accordingly, size of 547 sample signs is also consistent with the minimum sample size estimation for regression model of retro-reflectivity measures.

The sample signs collected at district 4 by applying the zonal prediction model estimated with district 2 inventory database are geo-located at Figure 29. Please refer to the attached excel sheets of zonal prediction model samples for the list of sample traffic signs.

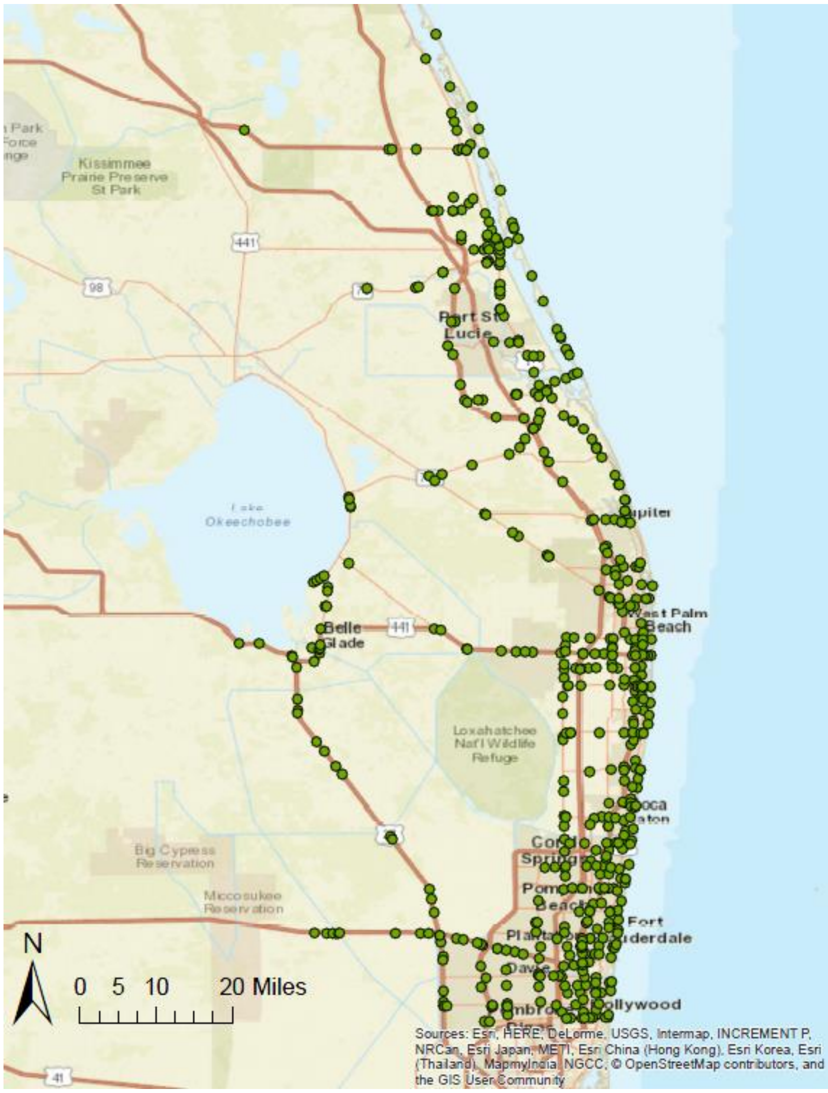

Figure 49 District 4 Sample Signs from Zonal Prediction Model

3.6. District 4 Signs Sampling by SRS

As mentioned earlier, minimum sample size was determined as 190 or 320. In District 4; number of signs in the database is 74,188. Since there is a lack of attributes in this inventory, simple random sampling procedure was applied to select a representative sample for both multiple linear regression and binary logit models. Simple random sample selection was made based on the spatial locations. ArcGIS, data management toolbox contains a 'Create Random Points' tool in feature classes. By using this tool, a spatially randomized sample was selected.

With many trials of cross checking the various attributes proportions with the real population; 200 traffic signs were selected as a representative sample. District 4 traffic sign samples are plotted the GIS map in Figure 30.

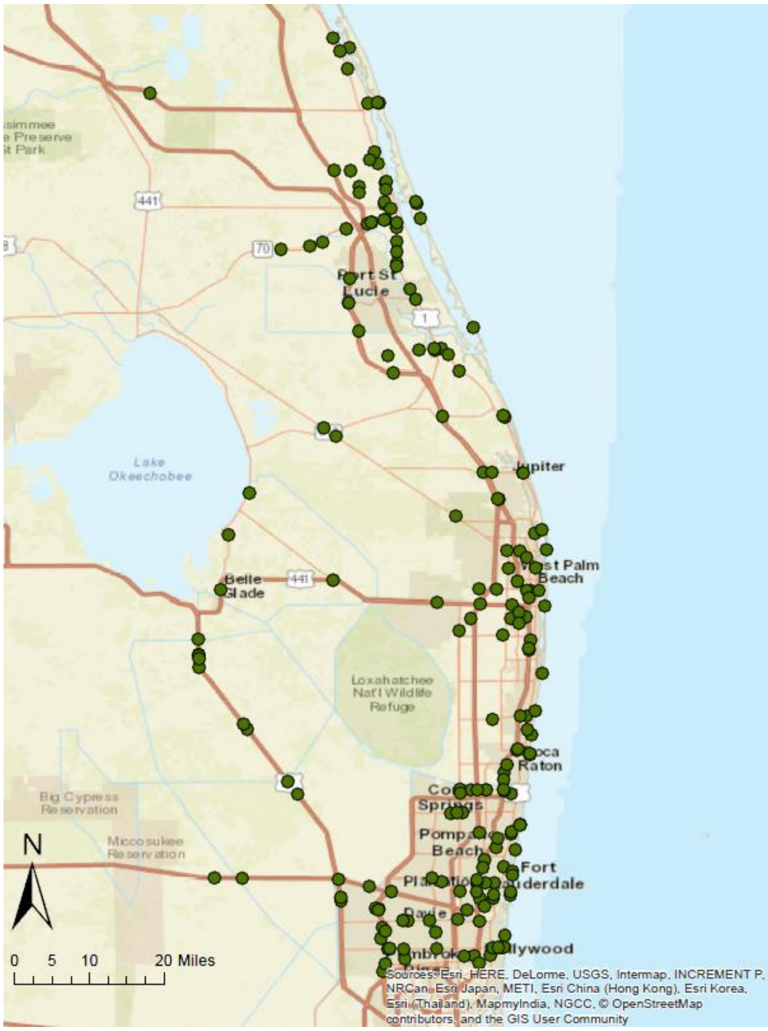

Figure 50 District 4 Sample Traffic Signs from SRS

District 4 SRS sampling results are illustrated by their geo-locations at a GIS map format. 200 spatially randomly selected traffic signs are presented in figure 30. Please see the attached excel sheets for district 4 sample signs list.

3.6.1. Cross-Checking with Other Factors' Proportions

In this section, three examples of cross checks that were performed to compare real population versus the sample populations of traffic signs are presented.

First example is the roadway location type of the signs. In Table 16, the shares of rural and urban area traffic signs in district 4 populations are provided. It is clear that proportions are very close to each other in at both sample proportions. Zonal prediction model sample slightly outperforms the SRS sample for this variable.

Table 19 District 4 Roadway Location Type Proportions

Roadway Location	Real Population	Sample (Zonal)	Sample (SRS)

Type			
Rural	19.89%	18.2%	22.3%
Urban	80.01%	81.8%	77.7%

Second example statistics are presented in Table 17 which is another attribute that the database contained which evaluated by comparing the proportions of real population and sample populations. Similarly, the real dataset results mostly match to the sample results for the year of sign inspections.

Table 20 District 4 Inspection Year Proportions

Inspection Year	Real Population	Sample (Zonal)	Sample (SRS)
2011	6.50 %	8.80%	7.10 %
2012	37.00 %	33.40%	32.00%
2013	50.50 %	53.50%	56.50%
2014	6.00 %	4.30%	4.40 %

Lastly, the sheeting type proportions are presented in Figure 31. It is clear from the pie chart comparisons that the sample successfully represents the real population. In zonal prediction model sample, the shares are as follows; diamond grade VIP %2.9 and high intensity grade 93.2%. Thus, zonal prediction model sample is closer to the real population than the SRS sample.

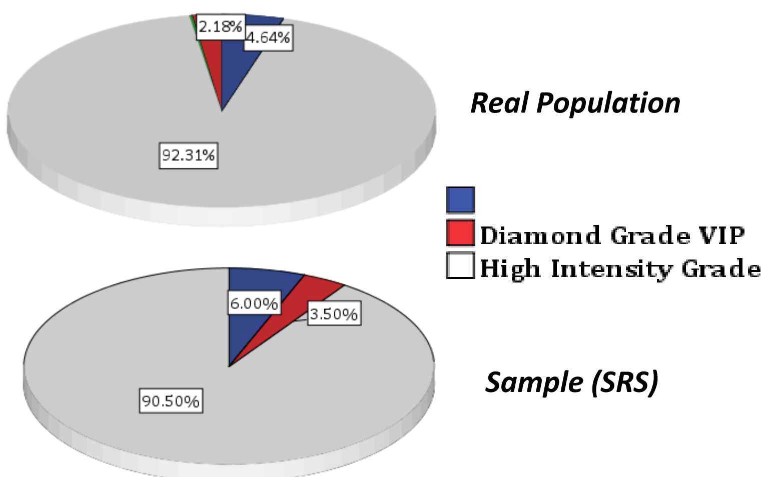

Figure 51 District 4 Sheeting Type Proportions

3.7. District 7 Signs Sampling by District 2 Zonal Prediction Model

District 7 sign inventory database features were discussed earlier. In District 7; number of signs in the database is 33,978. The number of CT zones intersected with the District 4 boundaries is 575. Likewise the district 2 data preparation, in district 7; 33,978 geo-located signs were spatially joined to 575 CT zone boundaries to find count data. Similarly, the sum of street centerline lengths that falls into the CT zones were computed by implementing "intersect" and "spatial join" modules of ArcMap. The sample counts at CT zones are predicted by applying OLS model formula at the prepared dataset of district 7.

The descriptive statistics of the estimated counts at 575 CT zones are presented in Figure 32.

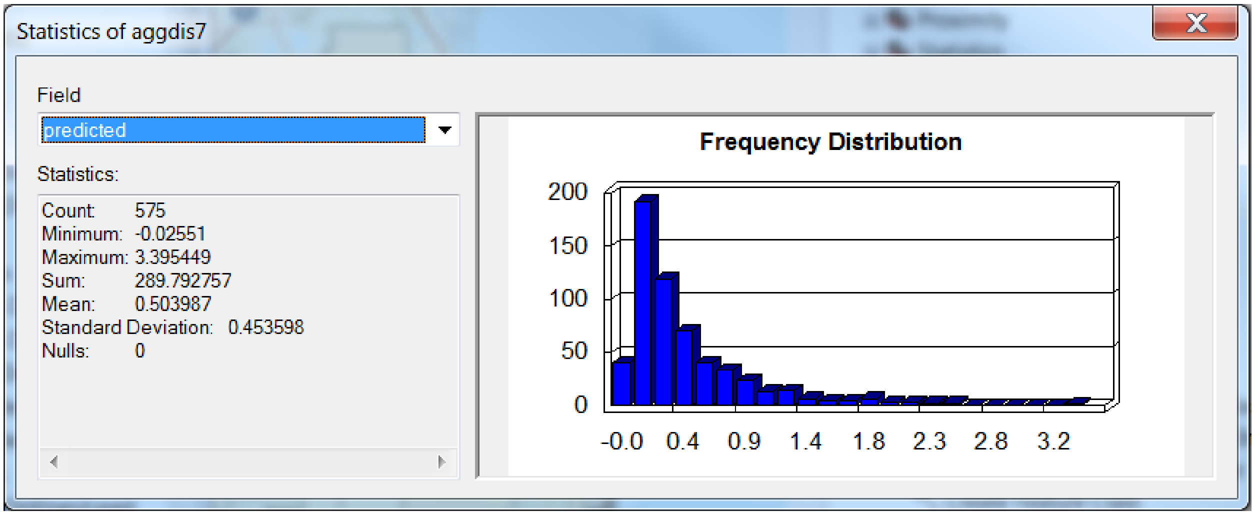

Figure 52 District 7 Estimated Counts Statistics

The predicted counts were rounded to the nearest integer and a random sample of signs was selected with the estimated sample size at the corresponding CT zone. Consequently, 221 sample signs were selected from district 7. Total sample size collected from the zones does not exactly match the sum of the counts presented in Figure 32 due to rounded up numbers. Accordingly, size of 221 sample signs is also consistent with the minimum sample size estimation for regression model of retro-reflectivity measures.

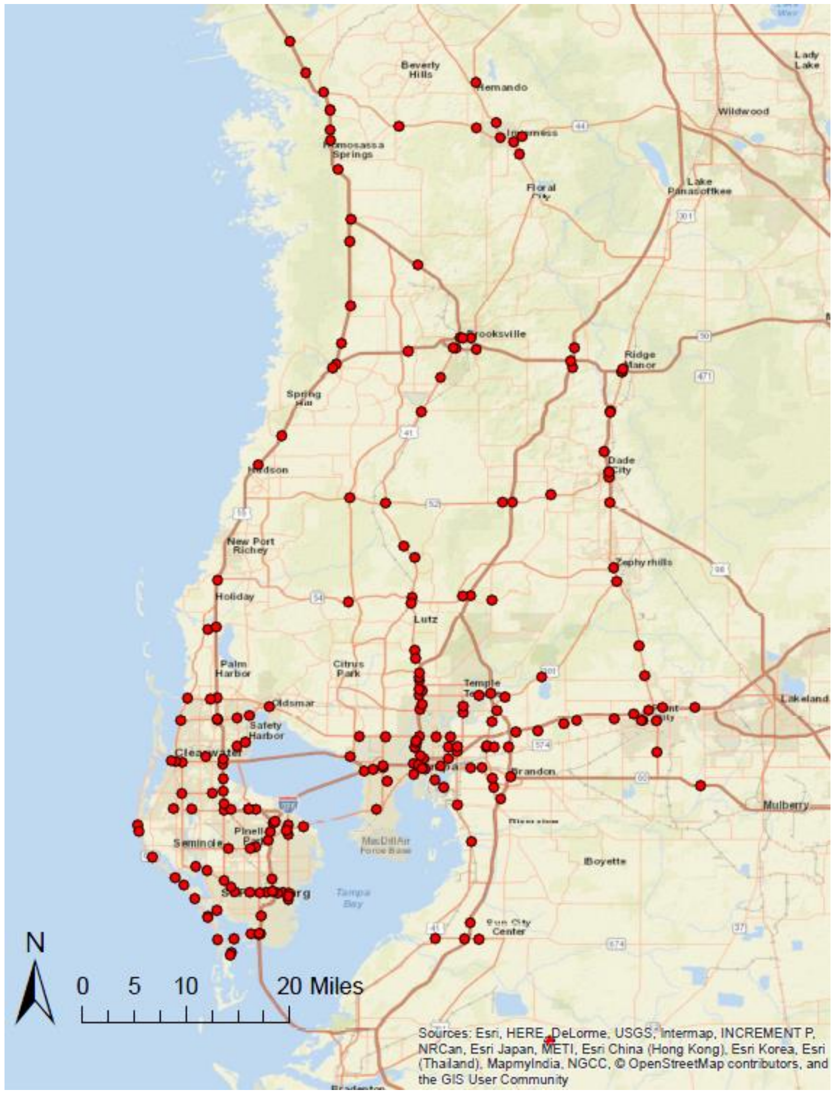

Figure 53 District 7 Sample Signs from Zonal Prediction Model

The sample signs collected at district 7 by applying the zonal prediction model estimated with district 2 inventory database are geo-located at Figure 33. Please refer to the attached excel sheets of zonal prediction model samples for the list of sample traffic signs.

3.8. District 7 Signs Sampling by SRS

As mentioned earlier, minimum sample size was determined as 190 or 320. In District 7; number of signs in the database is 33,978. Since there is a lack of attributes in this inventory, simple random sampling procedure was applied to select a representative sample for both multiple linear regression and binary logit models. Simple random sample selection was made based on the spatial locations. ArcGIS, data management toolbox contains a ‘Create Random Points’ tool in feature classes. By using this tool, a spatially randomized sample was selected.

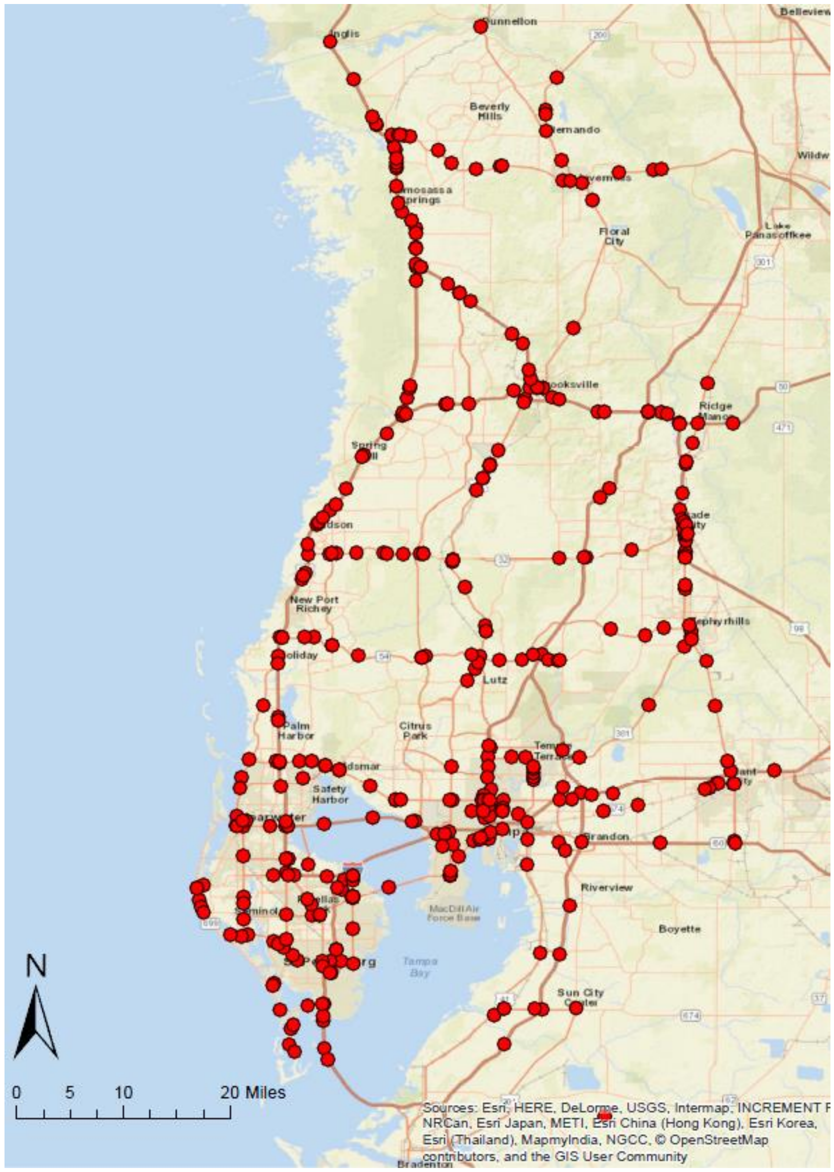

Figure 54 District 7 Sample Traffic Signs from SRS

District 7 SRS results are provided in this section. The 400 spatially randomly selected traffic signs are presented in figure 34. Please refer to the attached excel sheets for district 7 sample signs list.

3.8.1. Cross-Checking with Other Factors' Proportions

In this part, four examples of cross checks that were performed to compare real population versus the sample populations of traffic signs are presented.

First of all, the roadway location type of the signs. In table 18, the shares of rural and urban area traffic signs in district 7 populations are provided. It is clear that proportions are pretty close to each other when compared with real population.

Table 21 District 7 Roadway Location Type Proportions

Roadway Location Type	Real Population Percentage	Sample (Zonal)	Sample (SRS)
Rural	19.89%	25.4%	22.3%
Urban	80.01%	74.6%	77.7%

Secondly, inspection year statistics are presented in table 19 which is another attribute that the database contained which evaluated by comparing the proportions of real population and sample populations. Similarly, the real dataset results mostly match to both SRS and zonal prediction model sample results for the year of sign inspections.

Table 22 District 7 Inspection Year Proportions

Inspection Year	Real Population	Sample (Zonal)	Sample (SRS)
2011	6.5 %	8.30%	7.1 %
2012	37 %	29%	32%
2013	50.5 %	52.90%	56.5%
2014	6 %	9.40%	4.4 %

Thirdly, sheeting types proportions were evaluated and illustrated by a pie chart in figure 35, which is another attribute that the database contained which evaluated by comparing the proportions of real population and sample populations. Similarly, the real dataset results mostly match to the sample results for the year of sign inspections. Sheeting type shares found from zonal sample is as follows; 59% High intensity grade, 11% high intensity prismatic and 6% diamond grade high intensity.

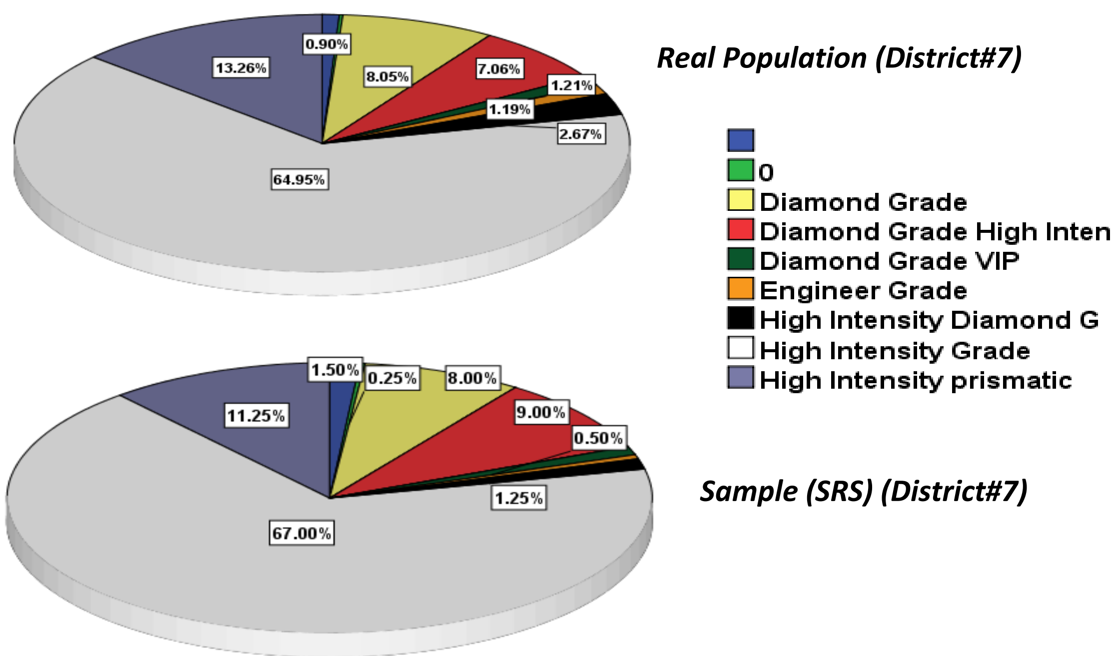

Figure 55 Sheeting Type Proportions of District 7

Last but not least, cardinal direction shares of the traffic signs in district 7 are presented in table 20. Both sample proportions are not as close to real population shares as they were in other attributes.

Table 23 District 7 Cardinal Direction Proportions

Cardinal Directions	Real Population	Sample (Zonal)	Sample (SRS)
North	27.5%	30.50%	29.3%
South	27.6%	25.20%	26.8%
East	22.4%	24.80%	22.5%
West	22.5%	19.50%	21.4%

4. Summary of Findings

In this report, sampling procedures were performed based on the availability of district sign inventory databases. In summary, four districts out of seven in Florida were evaluated. The remaining districts were not able to provide a geographic database of traffic signs. Therefore, districts 1, 2, 4, and 7 were only involved in sampling procedures based on the study design.

In total, there are 175,704 traffic signs in the district databases. For district 2, a disproportionate stratified sampling was performed and 336 sample traffic signs were selected based on the selected attributes, such as age of signs, geographic location of the signs etc. in order to make a similar sample selection, a framework methodology was developed. In this framework, first an OLS linear regression model was estimated to predict the sample sizes in each CT zone at district 2. The explanatory variables used in this statistical model were real population sign counts and street centerline lengths sum at CT zone level. Accordingly, the regression model formula was applied to the remaining districts to predict the sonal level sample sizes. Finally, random sampling was performed within each CT zone based on the estimated sample sizes. In addition, a simple random sampling procedure was performed as a baseline. The cross checking of proportions from both samples with the real population signs were presented.

Table 24 Summary of Sample Results

Number of Data Points	District 1	District 2	District 4	District 7	Total
Real Population	26,210	41,328	74,188	33,978	175,704
Sample (Zonal)	190	336	547	221	1,294
Sample (SRS)	350	336	200	400	1,286

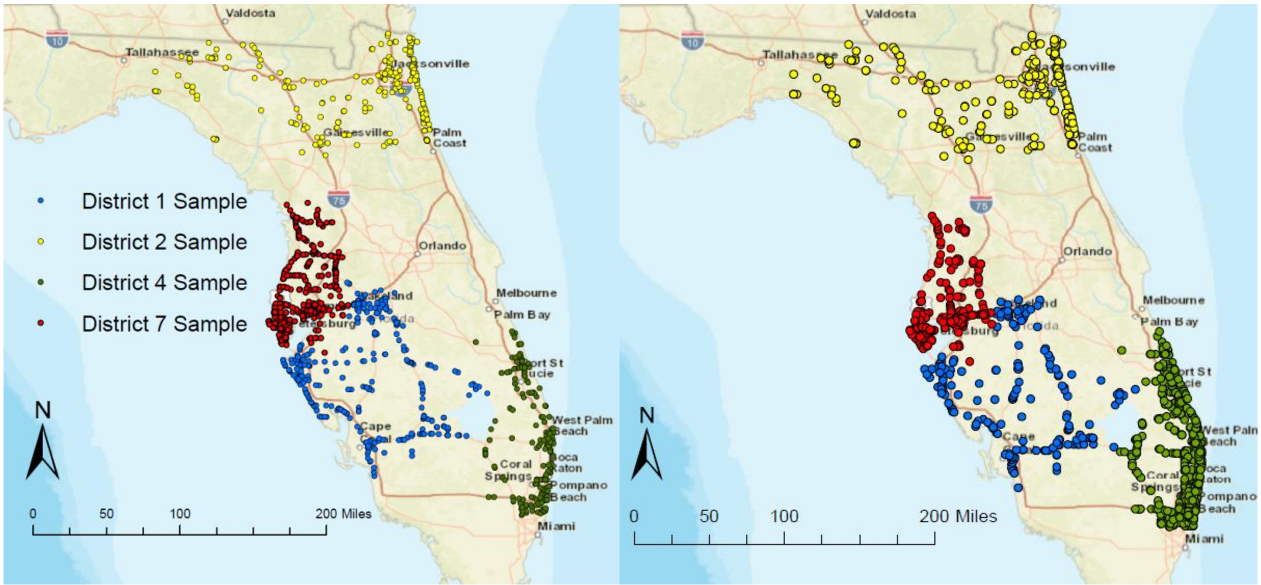

Figure 56 Sample Signs Selected for All Districts – SRS (Left) and Zonal (Right)

In conclusion, based on our study design that consists of two regression models with retro reflectivity and chromaticity as outcome variables; the stratified random sampling done for district 2 database as well as the two types of sampling procedures applied to districts 1, 4, and 7, the findings show that there is no enough evidence to prove the zonal prediction model sampling performs better than simple random sampling. Moreover, both samples are attached to the results in an excel format. 1,294 sample signs were selected by the zonal prediction model sampling while 1,286 sample signs were selected by simple random sampling for data collection (see table 21). The sample signs are spatially presented in figure 36.

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