Final Report – Phase II

Viability of Vehicle Length in Estimating Vehicle Classification and Axle Factors

Transportation Pooled Fund Study TPF-5(340), led by Wisconsin Department of Transportation

Pooled Fund Partner State DOTs:
Georgia, Idaho, Illinois, Iowa, Kansas, Minnesota, New York, North Dakota, Ohio, Pennsylvania, Texas and Utah

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Executive Summary

Single-tube traffic counts are widely used because they are inexpensive and accurate enough to meet the needs of many travel monitoring applications. However, to convert single tube counts from an axle count to annual average daily traffic (AADT) volume, the axle count must be factored. The most common way to factor is to analyze axle-based classification data and determine the ratio of total vehicles to the axle count. Many agencies call this an "axle factor." Such axle-based vehicle classification sites have historically been significantly costlier and require more maintenance than length-based traffic detection methods. Non-intrusive sensors, such as sidefire radar sensors, can cost-effectively collect vehicle length data, which can then be used to determine axle factors.

The primary objectives of this project are to understand the accuracy of axle factors determined from vehicle length and to develop and evaluate methods for converting length data to axle-based classifications.

Phase I of project TPF 5(340) assessed alternative methods to estimate axle factors and vehicle class from length-based data. The two best performing methods (Method 1 and Method 5) were further evaluated using an additional dataset from the nationwide Long Term Pavement Performance Program (LTPP). Based on the results of the final round of evaluations, the performance of the two recommended methods was found within the expected limits of performance.

Phase II of this project develops and evaluates an implementation plan for Method 1 and Method 5. Since Method 1 is more straightforward with its methodology, its application is not as complicated to complete. Method 5, though, requires more complex mathematical applications, such as parametric functions and algorithm development, and the need for an automated application was identified. A data processing tool was developed to aid analysts in estimating axle factors and vehicle class using Method 5 techniques. The user inputs the raw traffic data inputs and the tool, with default "seed" data collected in Phase I of this project, estimates vehicle classes and axle factors for that site. The seed data used for the data processing tool is representative of the data inputted; therefore, consideration should be given to review and update the seed data, as needed. For example, seed data could be updated to reflect a specific region or highway characteristic so a more accurate representation of vehicle class can be applied to input data.

As a test of the data processing tool, traffic data from ten collocated test sites in Wisconsin were inputted into the data processing tool to evaluate the tool's ability to estimate FHWA vehicle classes from length-based data. The results are as follows:

- Traffic estimates for all sites were within one percent of actual observed counts, which is a good indicator that the data processing tool is not adding or removing vehicles to the data set.
- The data processing tool had difficulty replicating the vehicle class data that was gathered at each collocated site.

    - For lower-volume areas, such as the Adams County and Fond du Lac County sites, the data processing tool has a smaller "room for error" due to the low number of vehicles in each class.
    - The "cutoff" vehicle length measurement that separates vehicle classes may not be optimal for the data processing tool to estimate vehicle distributions. More specifically, the vehicle distribution the data processing tool uses for each vehicle class likely overlaps each other, causing over- and underestimation of several vehicle classes.
    - The calibration data used by the data processing tool uses both local and national distribution data. The data processing tool applies weights to each data set to incorporate both local and national data. These weights, or the national data, may produce results that are not entirely representative of the local site.
- A more detailed evaluation of the data processing tool and the most recent WisDOT data was performed by TTI and their results are provided below:
    - Calibrating the data processing tool with traffic data located within five or twenty miles from the test sites were found to have fewer misclassifications of traffic data and improved overall accuracy of the traffic estimates.
    - Calibrating the data processing tool with more localized traffic data did not provide a clear-cut improvement or decline when addressing misclassification of vehicle classes.
        - Vehicle classes with higher counts were found to improve with localized calibration data
        - Vehicle classes with lower counts or similar vehicle characteristics were estimated with more variance when compared to observed data.

Future updates to the data processing tool could explore improvements such as evaluating the impact of different seed data on the tool's accuracy. For example, seed data could be selected based on roadway classification, number of travel lanes, and/or vehicle distribution.

Introduction

Phase I of this project assessed alternative methods to estimate axle factors and vehicle class from length-based data. In the Phase I report, a set of eight methods was proposed and evaluated in an initial set of tests. This initial set of tests was carried out by comparing absolute errors in axle factors, and errors in the estimated proportion of vehicles per FHWA class. The two best performing methods (Method 1 and Method 5) were further evaluated using an additional dataset from the nationwide Long Term Pavement Performance Program (LTPP). Based on the results of the final round of evaluations, the performance of the two recommended methods was found within the expected limits of performance. The Phase I report recommends an implementation phase for both estimation methods.

Phase II of this project develops and evaluates the implementation plan for Method 1 and Method 5. Since Method 1 is more straightforward with its methodology, its application is not as complicated to complete. Method 5, though, requires more complex mathematical applications, such as parametric functions and algorithm development. Therefore, an automated application was identified.

Method 1 – Overview

Method 1 uses collected per vehicle axle class data to determine typical numbers of axles per length grouping ("band") and generate an axle factor. This method is performed through the development of "seed" data to represent axle and vehicle length characteristics for a particular area. Seed data is developed by collecting axle class and vehicle length data at representative sites to produce an estimate of the number of axles per length band. These estimates are then applied to locations that only collected vehicle length data to develop an estimated axle factor for that site. Figure 1 illustrates a flow chart to develop axle factor data using Method 1.

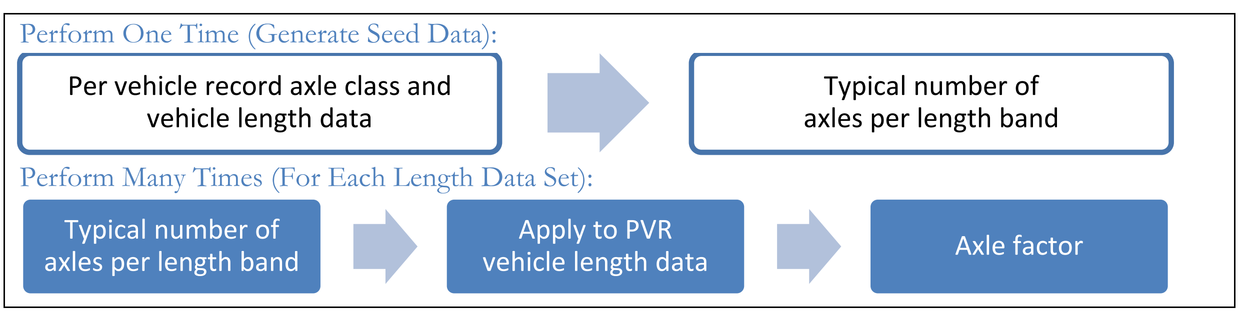

Figure 1. Method 1 Data Flow Chart

Method 5 – Overview

Method 5 uses per vehicle axle class data to classify the per vehicle length data into axle classes with a parameterized function. Similar to Method 1, seed data at representative sites is necessary to build the parameterized function. Once developed, the function can be applied to vehicle length data at local sites to estimate an axle class for that local site. Figure 2 illustrates a flow chart to develop axle class counts using Method 5.

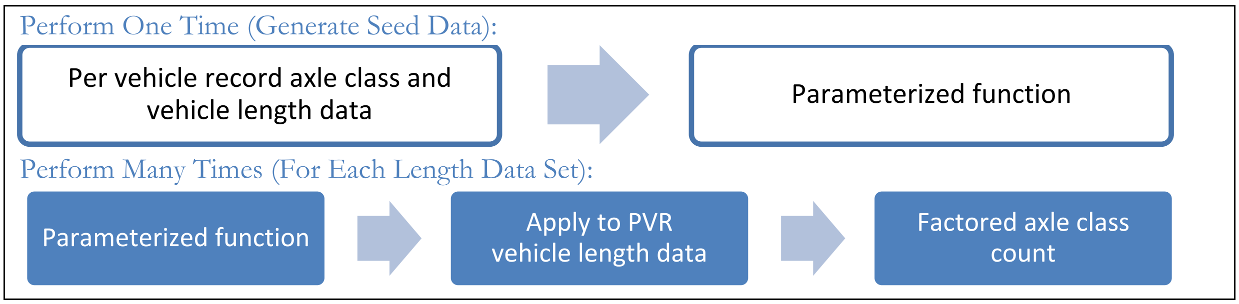

Figure 2. Method 5 Data Flow Chart

Method 5 – Data Processing Tool Development

The implementation of Method 1 and Method 5 involves the development of representative axle classes based on a vehicle length interval (seed data) and using those proportions for application of local collection sites. Implementing Method 1 is based on applying axle class proportions to local data. This process is straightforward and does not require powerful software or advanced mathematical experience to perform. Method 5, however, develops algorithms to build parameterized functions (seed data) and applies local data to generate local axle class information. This process is more complex and may not be user-friendly for analysts to use. Therefore, a data processing tool was developed to automate Method 5 methodologies. The data processing tool was designed for a user to enter locally gathered traffic data and provide axle class data based on the input data. The parameterized seed data could be user-developed or have default values based on evaluation of Method 5 performed in Phase I of this project.

The estimation tool can be accessed and run online, allowing for updates of the tool to be provided without sending software updates. Once loaded, an input screen is provided for the user to upload data to the estimation tool. A "help" hyperlink is provided throughout the input page for further guidance and instruction on information the software needs to function properly. Figure 3 illustrates the data processing tool home page.

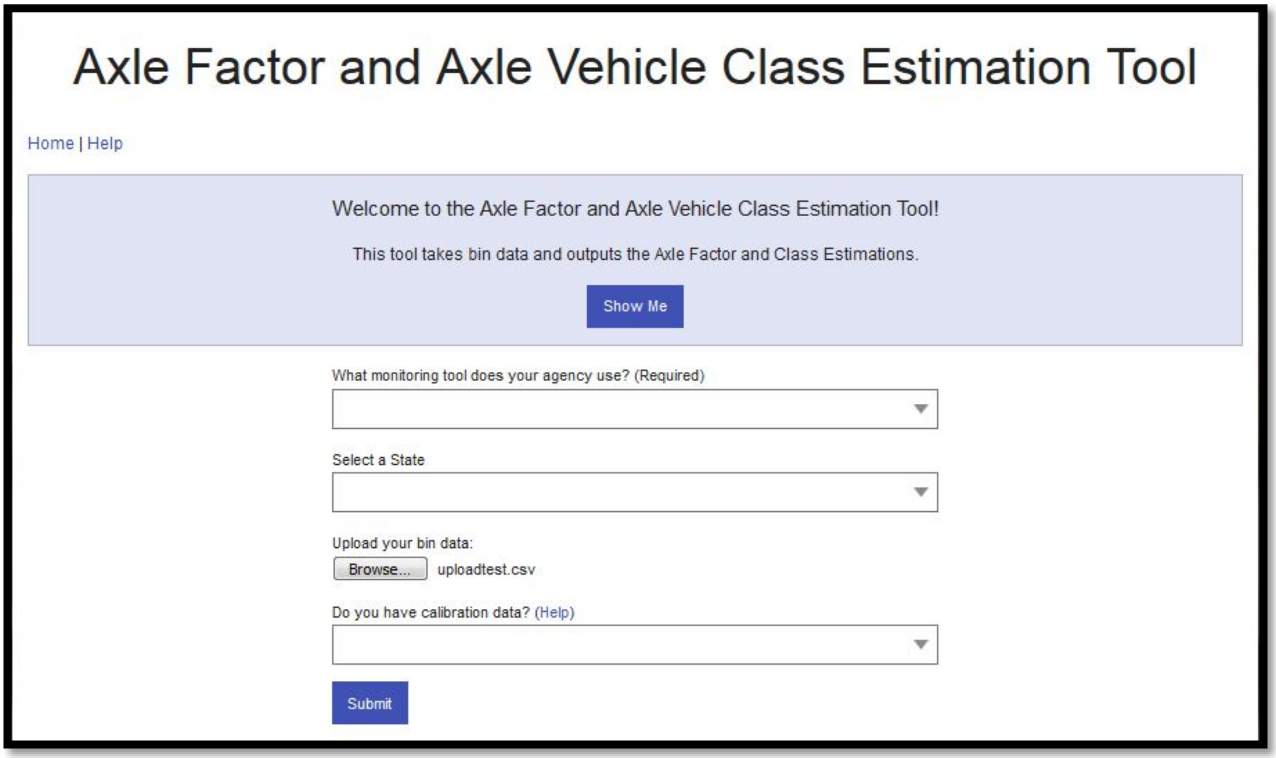

Figure 3. Data Processing Tool Home Page

Method 5 – Implementation Assistance

The data processing tool needs seed data to convert the local vehicle length data into an estimated axle class data. The seed data can be user-defined or can use default data developed from LTPP data. However, default seed data can, and should, be modified periodically to adjust for changing vehicle distribution trends along representative roadways.

The project team asked the sponsor states for additional data to aid in further refining the data processing tool. The rationale for this is listed below:

- Obtaining additional data further refines the data processing tool's default seed data by having more representative data to develop the associated algorithms and parameterized functions to estimate axle class information.
- Obtaining data from various state agencies allows the data processing tool to accommodate various data collection methods and file structures so minimal adjustments are needed by the user to input the local data into the data processing tool.

From this request, Ohio Department of Transportation (ODOT) provided vehicle length and axle class data at three sites in Ohio. Each site was unique in terms of location (rural/urban/suburban), roadway classification, and number of travel lanes. Traffic data was collected at each site for two days in May 2018 using loop detectors and Wavetronix out-of-roadway sensors.

Output files of the ODOT-collected traffic data was submitted to the project team to understand the formatting of the output files and how the data processing tool can obtain data from that particular file type and its formatting characteristics. In addition, the ODOT-collected traffic data, particularly the loop detector and piezoelectric sensor data, was incorporated into the default seed data for use by analysts and agencies that do not have local axle class and vehicle length data for analysis.

Method 5 – Tool Testing and Validation

Once sponsor states provided additional data to the project team, the data processing tool's seed data was further refined to include this data. The seed data was then tested to evaluate its performance in estimating axle data when compared to collocated sites.

Wisconsin DOT provided traffic data from ten sites statewide. These sites include urban, suburban, and rural roadways that include multilane freeways and expressways as well as two-lane arterial roadways. The duration of the counts ranged from approximately eight months (244 days) to approximately twenty months (612 days). Traffic data collected at each site included vehicle length data provided by Wavetronix radar-based sensors and axle class data provided by in-pavement inductive loops (i.e. each site was collocated). Fourteen vehicle classes (13 classes outlined by FHWA and 1 "unknown" class) were collected at each site. A check of traffic volumes collected at each site was performed to ensure that number of vehicles counted by inductive loops and by Wavetronix devices were comparable to each other. This check confirmed that the number of vehicles counted by the two data collection methods were similar. This check is important to the data processing task and its evaluation as the length-based data and axle classification data are shown to provide comparable traffic volume results. Any significant skew between the results of these methods may introduce bias or "bad data" into the analysis and evaluation processes.

Table 1 illustrates a comparative analysis of the raw axle class counts collected for all classes at each site versus the forecasted axle class counts produced from the data processing tool:

Table 1: Comparative Analysis of Axle Class Counts, All Vehicles

Roadway	County	Count days	Axle class count from site	Forecasted axle class count	Magnitude difference	Percent difference
I-39/90	Dane	459	97864	97991	127	0.13%
I-39/90/94	Columbia	584	59034	58912	-122	-0.21%
I-43	Waukesha	612	43257	43683	426	0.98%
I-94	Monroe	595	23623	23724	101	0.43%
US 10	Portage	500	13871	13933	62	0.45%
US 18/151	Iowa	519	16939	17077	138	0.82%
WIS 21	Winnebago	563	10706	10732	26	0.24%
WIS 21	Adams	244	3512	3547	35	0.98%
US 45	Fond du Lac	248	4393	4377	-16	-0.35%
WIS 100	Milwaukee	252	28054	28201	147	0.52%
Average	**10 sites**	**458**	**30125**	**30218**	**92**	**0.31%**

From Table 1, the percent difference between the raw axle class counts and the forecasted axle class counts for all vehicles are below one percent at each of the ten sites. This indicates that the seed data from the data collection tool provided an accurate forecast in determining axle class counts for the Wisconsin sites. Another check of this data was performed by creating axle factors from the length-based data and comparing to the axle factors determined from the axle classification data collected at each site. This check resulted in favorable results, reinforcing the validity of the data collected at the test sites.

Table 2 illustrates the magnitude difference between the raw axle class counts and the forecasted axle class counts based on the FHWA vehicle classes. Table 3 illustrates the magnitude difference shown in Table 2 in percent format.

Table 2: Raw Axle Count and Data Tool Estimate Comparison, Magnitude Difference

Site	Count Data	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14
I-39/90, Dane Cty	Raw Axle Class Count	182	68380	12630	709	2180	437	187	1355	10670	128	370	207	12	417
	Data Tool Estimate	324	58601	16870	1675	5077	1621	0	630	10884	17	5	143	57	2087
	Difference	-142	9779	-4240	-966	-2897	-1184	187	725	-214	111	365	64	-45	-1670
I-39/90/94, Columbia Cty	Raw Axle Class Count	90	37546	8063	449	1316	195	43	1019	9324	88	351	200	8	341
	Data Tool Estimate	9	33484	9577	730	2809	737	2	701	9368	147	86	163	18	1081
	Difference	81	4062	-1514	-281	-1493	-542	41	318	-44	-59	265	37	-10	-740
I-43, Waukesha Cty	Raw Axle Class Count	163	32828	6418	305	967	202	105	329	1760	37	41	11	2	87
	Data Tool Estimate	41	29788	8469	250	2165	531	7	2	1662	53	2	1	66	646
	Difference	122	3040	-2051	55	-1198	-329	98	327	98	-16	39	10	-64	-559
I-94, Monroe Cty	Raw Axle Class Count	31	12669	3040	187	564	107	41	534	5777	53	256	159	4	203
	Data Tool Estimate	140	11259	3394	314	1196	262	68	284	5841	14	16	161	61	714
	Difference	-109	1410	-354	-127	-632	-155	-27	250	-64	39	240	-2	-57	-511
US 10, Portage Cty	Raw Axle Class Count	40	9224	2418	119	358	66	38	216	1260	31	27	16	2	57
	Data Tool Estimate	166	8622	2452	210	689	218	1	62	1194	0	51	28	0	240
	Difference	-126	602	-34	-91	-331	-152	37	154	66	31	-24	-12	2	-183
US 18/151, Iowa Cty	Raw Axle Class Count	39	11961	2469	129	418	76	29	248	1453	23	11	3	3	75
	Data Tool Estimate	152	10812	3086	115	833	195	0	42	1458	0	2	39	0	343
	Difference	-113	1149	-617	14	-415	-119	29	206	-5	23	9	-36	3	-268
WIS 21, Winnebago Cty	Raw Axle Class Count	38	7555	2170	74	303	61	34	105	318	12	11	1	1	23
	Data Tool Estimate	176	7295	2051	96	516	143	0	2	252	46	0	10	1	144
	Difference	-138	260	119	-22	-213	-82	34	103	66	-34	11	-9	0	-121
WIS 21, Adams Cty	Raw Axle Class Count	11	1923	720	30	112	22	6	82	531	20	22	2	4	27
	Data Tool Estimate	97	1909	537	90	163	58	0	53	562	1	0	4	0	73
	Difference	-86	14	183	-60	-51	-36	6	29	-31	19	22	-2	4	-46
US 45, Fond du Lac Cty	Raw Axle Class Count	17	3328	847	21	99	16	11	21	28	1	0	0	0	4
	Data Tool Estimate	91	3117	870	1	200	27	0	0	9	0	0	0	0	62
	Difference	-74	211	-23	20	-101	-11	11	21	19	1	0	0	0	-58
WIS 100, Milwaukee Cty	Raw Axle Class Count	52	24111	3053	174	376	63	19	61	104	10	3	1	1	27
	Data Tool Estimate	0	21244	6121	0	651	0	0	0	101	11	41	31	1	0
	Difference	52	2867	-3068	174	-275	63	19	61	3	-1	-38	-30	0	27

Table 3: Raw Axle Count and Data Tool Estimate Comparison, Percent Difference

Site	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14
I-90/94, Dane Cty	78%	-14%	34%	136%	133%	271%	-100%	-54%	2%	-87%	-99%	-31%	380%	401%
I-39/90/94, Columbia Cty	-90%	-11%	19%	62%	113%	278%	-95%	-31%	0%	68%	-76%	-18%	128%	217%
I-43, Waukesha Cty	-75%	-9%	32%	-18%	124%	163%	-93%	-99%	-6%	45%	-95%	-91%	2650%	640%
I-94, Monroe Cty	351%	-11%	12%	68%	112%	145%	67%	-47%	1%	-74%	-94%	1%	1308%	252%
US 10, Portage Cty	317%	-7%	1%	77%	92%	232%	-97%	-71%	-5%	-100%	87%	79%	-100%	322%
US 18/151, Iowa Cty	293%	-10%	25%	-11%	99%	157%	-100%	-83%	0%	-100%	-82%	1140%	-100%	355%
WIS 21, Winnebago Cty	365%	-3%	-5%	30%	71%	134%	-100%	-98%	-21%	269%	-100%	782%	29%	524%
WIS 21, Adams Cty	747%	-1%	-25%	200%	46%	163%	-100%	-36%	6%	-95%	-100%	67%	-100%	168%
US 45, Fond du Lac Cty	422%	-6%	3%	-95%	102%	74%	-100%	-100%	-68%	-100%	-100%	-100%	-100%	1485%
WIS 100, Milwaukee Cty	-100%	-12%	101%	-100%	73%	-100%	-100%	-100%	-3%	13%	1335%	3990%	-1%	-100%

The results from tables 2 and 3 indicate the data processing tool has difficulty replicating the FHWA vehicle class counts at each study site. From Table 2 the data processing tool forecasts significantly differs from the raw count data in most of the FHWA classes, except for Class 2 and Class 9. Possible explanations for these results include:

- For lower-volume areas, such as the Adams County and Fond du Lac County sites, the data processing tool has a smaller "room for error" due to the low number of vehicles in each class.
- The "cutoff" vehicle length measurement that separates vehicle classes may not be optimal for the data processing tool to estimate vehicle distributions. More specifically, the vehicle distribution the data processing tool uses for each vehicle class likely overlaps each other, causing over- and underestimation of several vehicle classes.
- The calibration data used by the data processing tool uses both local and national distribution data. The data processing tool applies a weighting factor to each data set to incorporate both local and national data. These weighting factors, or the national data, may produce results that are not entirely representative of the local site.

Texas A&M Transportation Institute (TTI) performed a more detailed investigation of this dataset and how the data processing tool disseminated the traffic data. TTI developed a report describing these efforts, which is provided in Appendix A. The remainder of this section summarizes findings from their investigation.

Data Misclassification

In Phase I of the study, TTI estimated the data processing tool would generate approximately ten percent misclassified data across all axle classes. Misclassification occurs when the data processing tool incorrectly assigns a data point (i.e. vehicle) to a data bin. This condition, though, is a zero-sum procedure as the vehicle was counted, just placed in the incorrect data bin.

TTI evaluated the WisDOT data set for misclassifications and summed the results for each of the project sites (Table 4). This table indicates that eight of the ten sites have misclassification percentages below ten percent while the remaining two sites have percentages near twelve percent. With the large amount of data evaluated in this procedure, the number of misclassified vehicles seems reasonable.

Table 4: Misclassification Percentages by Site

Site	Misclassification Percentage
I-39/90, Dane County	12.0%
I-39/90/94, Columbia County	8.0%
I-43, Waukesha County	9.3%
I-94, Monroe County	8.4%
US 10, Portage County	6.7%
US 18/151, Iowa County	8.9%
WIS 21, Winnebago County	5.7%
WIS 21, Adams County	8.4%
US 45, Fond du Lac County	6.3%
WIS 100, Milwaukee County	11.9%

Calibration to Surrounding Sites

Phase I analysis involved evaluating traffic data at 61 sites throughout the State of Wisconsin. From these sites, ten were selected as test sites for this round of calibration. Figure 4 illustrates the location of the initial 61 sites (shown as red pins) and the ten test sites (shown as blue pins).

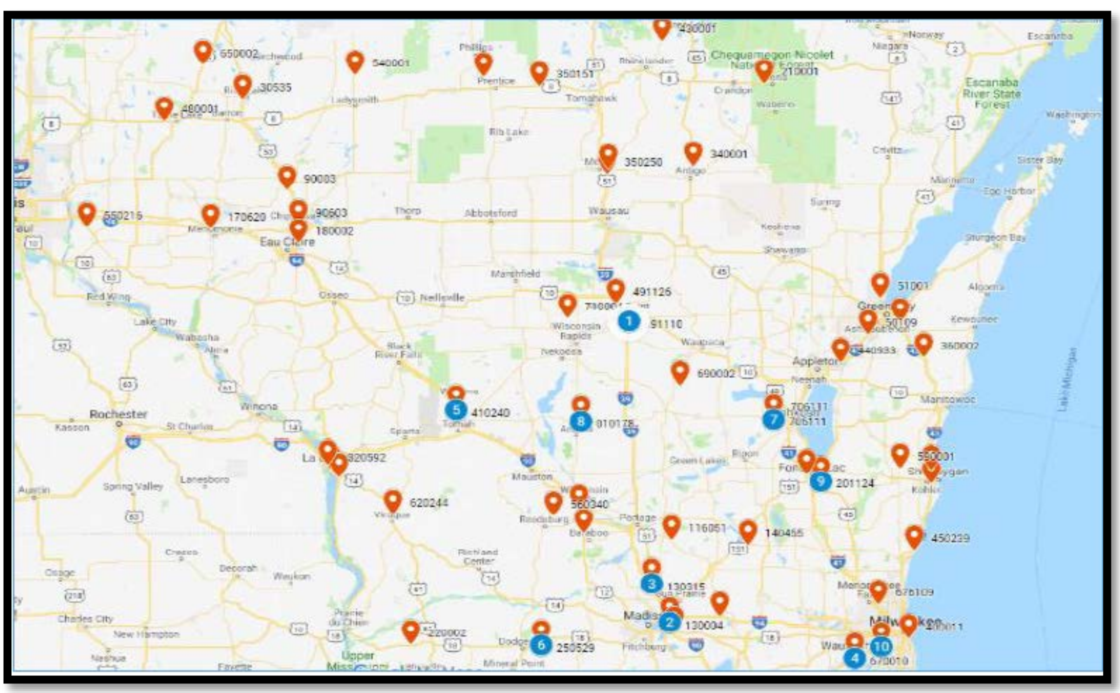

Figure 4. Wisconsin Count Locations

For the initial evaluation performed in this report, each site was calibrated to a statewide calibration distribution developed from all 61 count locations. From the results, it was deduced that using a statewide calibration distribution may be too generalized for each individual site. Therefore, additional analysis was performed that calibrated each test site to surrounding sites based on distance (5-mile, 20-mile, and 40-mile radii, respectively). Table 4 illustrates the percent misclassified vehicles based on each calibration level.

Table 5: Percent Misclassified Vehicles Based on Calibration Level

Site	Misclassification Percentage (percent)				
	No Calibration	5 miles	20 miles	40 miles	Full Calibration
I-39/90, Dane County	11.8	8.4	8.6	13.3	9.0
I-39/90/94, Columbia County	24.9	21.0	4.1	4.8	9.1
I-43, Waukesha County	18.1	2.2	15.9	21.3	3.1
I-94, Monroe County	7.6	4.2	4.2	5.7	13.1
US 10, Portage County	7.8	2.2	2.5	3.1	3.9
US 18/151, Iowa County	7.8	1.7	1.7	1.5	1.5
WIS 21, Winnebago County	4.3	3.0	5.0	9.1	5.5
WIS 21, Adams County	8.4	7.3	7.3	7.1	10.8
US 45, Fond du Lac County	5.8	3.7	3.7	3.4	3.4
WIS 100, Milwaukee County	11.9	23.6	7.0	10.1	8.5

To determine the significance of the various calibration levels, a mixed-effects model was applied to the data shown in Table 5. This analysis determined the effect of each calibration level based on accuracy and assigned a p-value to evaluate whether the observed difference is "random noise" in the traffic data. Figure 5 illustrates the results of this analysis. It should be noted that smaller p-values indicate a closer relationship between the site data (colored bar plots) and the calibration distribution (gray bar plot).

From Figure 5, the percent of misclassified vehicles for the ten sites went down for all calibration levels. Furthermore, three calibration levels have p-values that indicate statistical significance at the 95 percent confidence level (i.e. p-value <0.05) and two calibration levels having statistical significance near the 99 percent confidence level (5-mile and 20-mile). This indicates that calibration data located closer to the test sites have similar vehicle distribution patterns and fewer vehicle misclassifications.

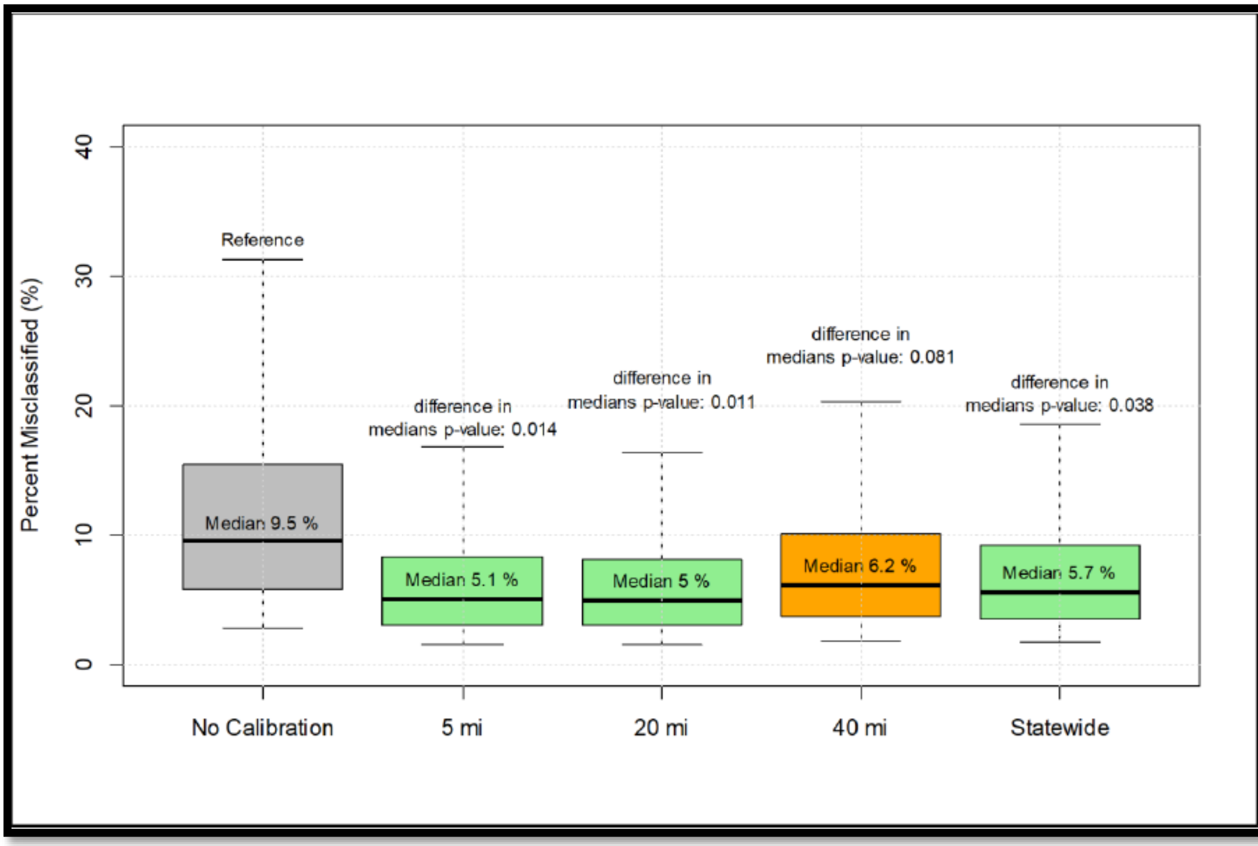

Figure 5. Misclassified Vehicles Based on Calibration Level

Analysis was also performed to evaluate how the varying calibration levels would affect the FHWA vehicle classes developed at each site. Figure 6 illustrates the results as plots of observed values versus estimated values, by FHWA vehicles class, at different calibrations levels. Each calibration level (5-mile, 20-mile, 40 mile) was plotted for evaluation. For many classes, the observed and estimated values mirrored each other as the number of vehicles counts for each class increases; however, a wider variance occurred with lower volumes (less than 100 vehicles) as the calibration model tended to achieve precision for certain vehicle classes at the cost of others. These classes that achieved lesser accuracy were ones with few data points and ones with little differentiation between the vehicle classes (e.g. FHWA classes 12, 13, and 14).

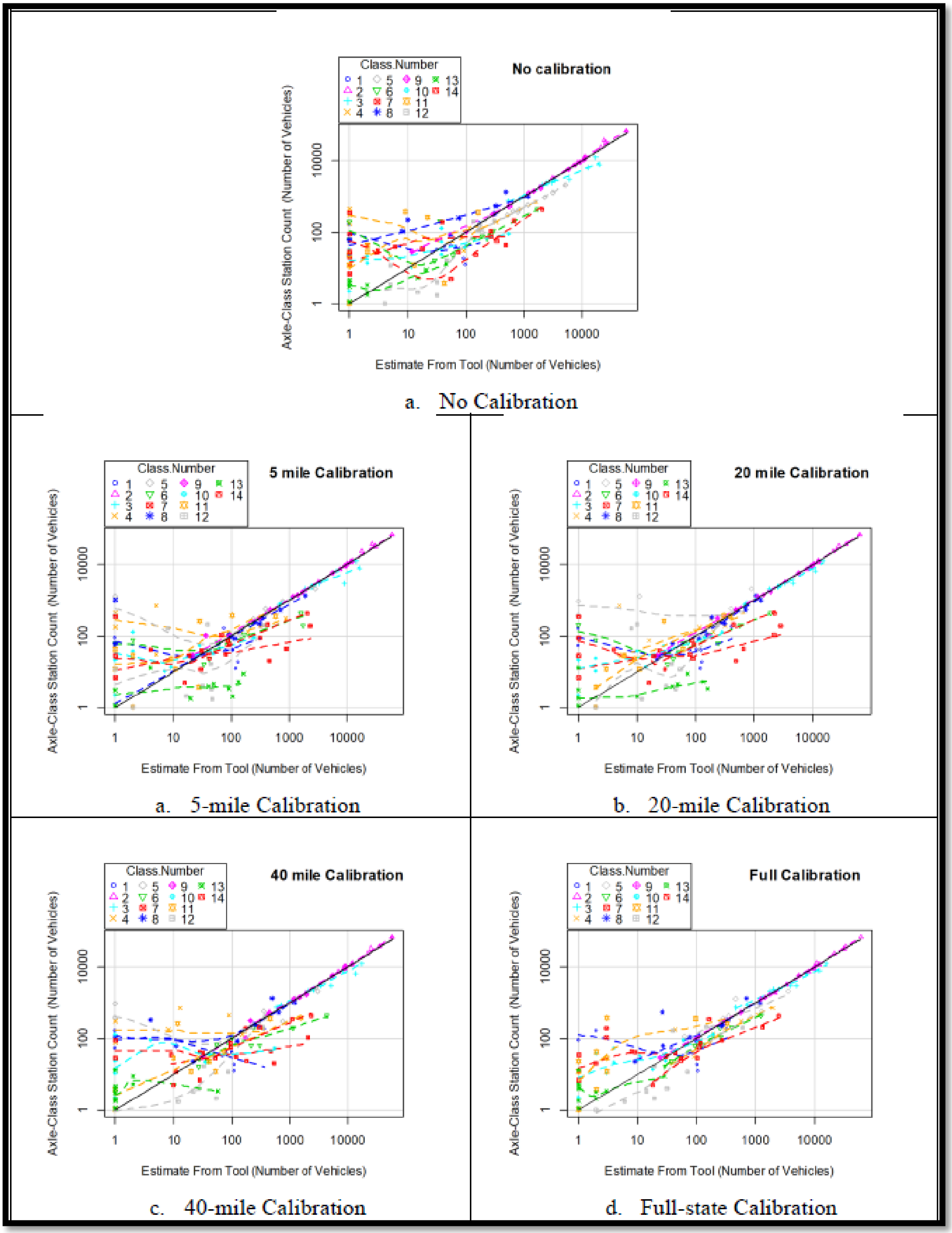

Figure 6. Misclassified Vehicles Based on Calibration Level

The misclassifications were then evaluated by absolute error for each vehicle class. This evaluation showed that classes with the highest counts had the best performance (i.e. smallest misclassification error) as their trend lines stayed near the zero-error axis. The average distribution of misclassified vehicles for each calibration level was tabulated to determine changes of misclassified vehicles per class due to calibration. This analysis indicated that while calibration reduced the number of misclassified vehicles, in general, some vehicle classes were benefited by calibration at the detriment of other classes having lesser accuracy.

This section evaluates the misclassifications between the data processing tool and each test site and suggests that misclassifications can be minimized by using seed data from nearby sites instead of regionwide or larger-area data sources. While the section concludes that using local seed data can reduce the number of misclassifications at a particular site, other factors that were not considered or evaluated in this study may also improve the amount of misclassifications in traffic data. For example, gathering and using seed data based on roadways with similar characteristics such as classification, number of travel lanes, and vehicle distribution (i.e. truck percentage) may result in improved accuracy of the data processing tool. While this study does not test these factors, future modification of the data processing tool should consider this as part of the update process.

Summary and Conclusions

This report summarizes the results of Phase II of project TPF 5(340), an evaluation of methods to estimate axle factors and vehicle class from length-based data. Phase II involved implementing Method 1 and Method 5 and evaluating their performance against field-observed data. A summary of key results of this implementation process follows:

- Method 1 uses collected per vehicle axle class data at a particular site and calibrated seed data at representative sites to develop axle factors for that site. This method is straightforward and does not require complex software or processes to complete.
- Method 5 uses collected per vehicle axle class data and distinguishes this data to length data using a parameterized function based on representative sites. This method is complex and cannot be easily processed without a processing algorithm/software.
- A data processing tool was developed to aid analysts in estimating axle factors and vehicle class using Method 5 techniques. The user inputs the raw traffic data inputs and the tool, with default seed data collected in Phase I of this project, estimates vehicle classes and axle factors for that site.
- The seed data used for the data processing tool is representative of the data inputted; therefore, consideration should be given to review and update the seed data, as needed. For example, seed data could be updated to reflect a specific region or highway characteristic so a more accurate representation of vehicle class can be applied to input data.
- Traffic data from ten collocated test sites in Wisconsin were inputted into the data processing tool to evaluate the tool's ability to estimate FHWA vehicle classes from length-based data. The results are as follows:

  - Traffic estimates for all sites were within one percent of actual observed counts, which is a good indicator that the data processing tool is not adding or removing vehicles to the data set.
  - The data processing tool had difficulty replicating the vehicle class data that was gathered at each collocated site.
    - For lower-volume areas, such as the Adams County and Fond du Lac County sites, the data processing tool has a smaller "room for error" due to the low number of vehicles in each class.
    - The "cutoff" vehicle length measurement that separates vehicle classes may not be optimal for the data processing tool to estimate vehicle distributions. More specifically, the vehicle distribution the data processing tool uses for each vehicle class likely overlaps each other, causing over- and underestimation of several vehicle classes.
    - The calibration data used by the data processing tool uses both local and national distribution data. The data processing tool applies weights to each data set to incorporate both local and national data. These weights, or the national data, may produce results that are not entirely representative of the local site.
  - A more detailed evaluation of the data processing tool and the most recent WisDOT data was performed by TTI. Key results from this process include the following.
  - Calibrating the data processing tool with traffic data located within five or twenty miles from the test sites were found to have fewer misclassifications of traffic data and improved overall accuracy of the traffic estimates.
    - Calibrating the data processing tool with more localized traffic data did not provide a clear-cut improvement or decline when addressing misclassification of vehicle classes.
      - Vehicle classes with higher counts were found to improve with localized calibration data.
      - Vehicle classes with lower counts or similar vehicle characteristics were estimated with more variance when compared to observed data.
- Future updates to the data processing tool should consider other parameters to test to improve the tool's accuracy, such as evaluating test sites to seed data based on roadway classification, number of travel lanes, and/or vehicle distribution.

As noted earlier, TTI's detailed investigation of how the data processing tool disseminated traffic data was captured in a separate report, which is provided in Appendix A.

Appendix A

Evaluation of the Effect of Calibration on Axle Factor and Axle Vehicle Class Estimation Tool

Validation of Performance and Quantitative Impact of Calibration

4/18/2019

Evaluation of the Effect of Calibration on Axle Factor and Axle Vehicle Class Estimation Tool

Validation of Performance and Quantitative Impact of Calibration

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Objective of this Analysis

In the context of research project TPF 5(340) led by SRF, TTI developed and deployed an online application tool that implements an axle class estimation procedure previously developed by TTI. The online tool's intent is to process length-based data from state members to the Transportation Pooled Fund study and to derive count estimates for each FHWA axle-class from said data.

Calibration to local data was originally recommended to ensure best performance of the tool, but its effects were not quantified. Therefore, the objective of this analysis is to assess the effect of calibration on the performance of the tool when performing the estimation.

Description of tool

The estimation tool takes available length data aggregated in bins and produces estimates of the axle factor and counts by axle class. This online tool can be accessed using the following URL: http://vehicleclassestimationtool.centralus.cloudapp.azure.com/tool.html.

In phase 1 of research effort TPF 5(340), the TTI team estimated the overall accuracy of the tool estimates at roughly a 10 percent average misclassification across all axle classes. This average rate of misclassification should be expected when analyzing a given site with the tool. The tool, however, allows the user to upload calibration data when available with the intent to adjust the algorithm using local data and thus producing improved axle-class estimates.

Calibration of the Tool

Some amount of data cleaning and wrangling is required while preparing the files for bin data and calibration data input. In general, the files should be consistent with the format described on the tool's website. For example, the numbers coding vehicle classes in the calibration data should range only from 1 to 14 (where 1-13 represent the 13 FHWA axle classes, and 14 represent the count of vehicles of unknown classes). Another important consideration is that any vehicles with a length value greater than 120ft should be coded as 999 ft.

Initial Validation of Tool Accuracy

To confirm the accuracy of the tool estimations, the Wisconsin DOT ran the analysis on 10 segments statewide which had co-located axle classification sites and Wavetronix sites. When comparing the estimates from the tool with the actual axle-class counts, the overall misclassification error was found to be about 10 percent for these ten sites. Table 1 provides the input data bins and the corresponding classification error from this exercise.

Table 1 Bin Data and Estimation Error

Site	Bin 1	Bin 2	Bin 3	Bin 4	Percent Misclassified (%)
Coldspring Road	100	27395	486	216	11.9
S. Fond Du Lac	100	4126	109	54	6.27
Preston	100	2594	182	672	8.37
Winnebago	100	9822	376	436	5.66
Dodgeville	100	14626	566	1785	8.87
Amherst Junction	100	11721	582	1530	6.65
Tomah	100	15840	987	6795	8.42
Crowbar Road	100	39870	1422	2287	9.25
Vienna	100	45231	2331	11143	8.04
Cottage Grove Road	500	79794	4395	13304	11.95

The TTI team was requested to perform calibration on these 10 site, assessing the extent to which such calibration step improves the performance of the tool. Such additional rounds of analysis, aimed at assessing the degree of improvement in the performance due to calibration of the tool, has been documented in the following sections.

Analyzing the Impact of Calibration on Tool Performance

The original vehicle classification data for 61 sites in Wisconsin (2015 and 2016) was used as the pool for calibrating the tool. The test set used to assess the impact of calibration were the additional ten sites provided by Wisconsin DOT and presented in Table 1. Figure 1 show the locations of the calibration pool (in red pins) and the locations of the test sites (in blue pins).

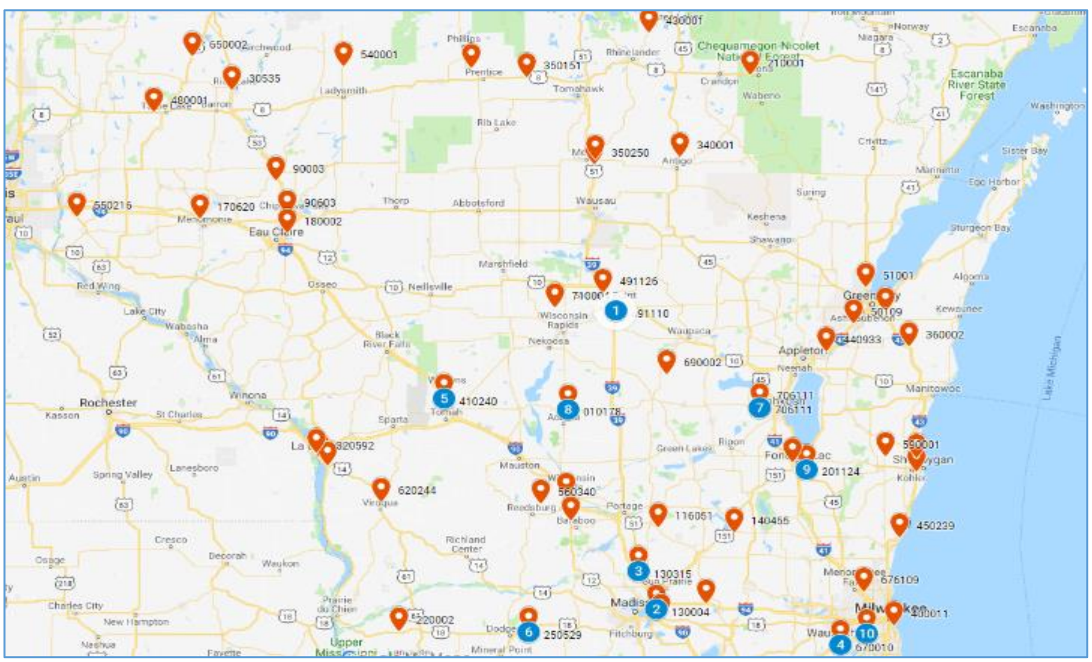

Figure 1 Test Sites and Calibration Sites - Wisconsin

The bin length thresholds used as input were:

L1: 0-7’: C1’s

L2: 7’-29’: C2’s - C3’s

L3: 29’-45’: C4’s - C7’s

L4: 45’ – 120’: C8’s and above.

Initially, some anomalies were observed at two test sites, but upon discussion with Wisconsin DOT, the issues were corrected and all 10 test sites could be used in this analysis. All sites were calibrated with the data from other sites (in the calibration pool) within 5 mile radius, 20 miles radius and 40 mile radius respectively. The results of these calibrations are shown in Table 2.

Table 2 Calibration Levels and Percent Misclassified

Site	Percent Misclassified (%)				
	No Calibration	**5 miles**	**20 miles**	**40 miles**	**Full Calibration**
Coldspring Road	11.9	23.6	7.0	10.1	8.5
S. Fond Du Lac	5.8	3.7	3.7	3.4	3.4
Preston	8.4	7.3	7.3	7.1	10.8
Winnebago	4.3	3.0	5.02	9.1	5.5
Dodgeville	7.8	1.7	1.7	1.5	1.5
Amherst Junction	7.8	2.2	2.5	3.1	3.9
Tomah	7.6	4.2	4.2	5.7	13.1
Crowbar Road	18.1	2.2	15.9	21.3	3.1
Vienna	24.9	21	4.1	4.8	9.1
Cottage Grove Road	11.8	8.4	8.6	13.3	9

To assess the significance of the impact of these calibration levels, a mixed-effects model was fitted to the results from the 10 test sites. This analysis determined the average effect of different calibration levels in terms of accuracy and assigned a p-value from the hypothesis that observed difference from random noise. The results comparing medians and misclassification spread resulting from the various calibration levels are shown below (Figure 2).

This report’s appendix shows the detailed axle-class-level results obtained for different levels of calibration. Smaller values of p in the figure indicate that the estimated difference between the given calibration level and the reference level (i.e., no calibration, plotted in gray) are more likely to be a clear systematic change in the performance of the algorithm due to the calibration performed.

It can be seen that the total percent of misclassified vehicles went down for all calibration schemes. The three boxes shown in light green correspond to statistically significant reductions at the 95 percent confidence level (p-value < 0.05). Only the calibration to a 40 mile radius shows a reduction with less confidence than the other calibration levels (p-value < 0.1, for a 90 percent confidence level).

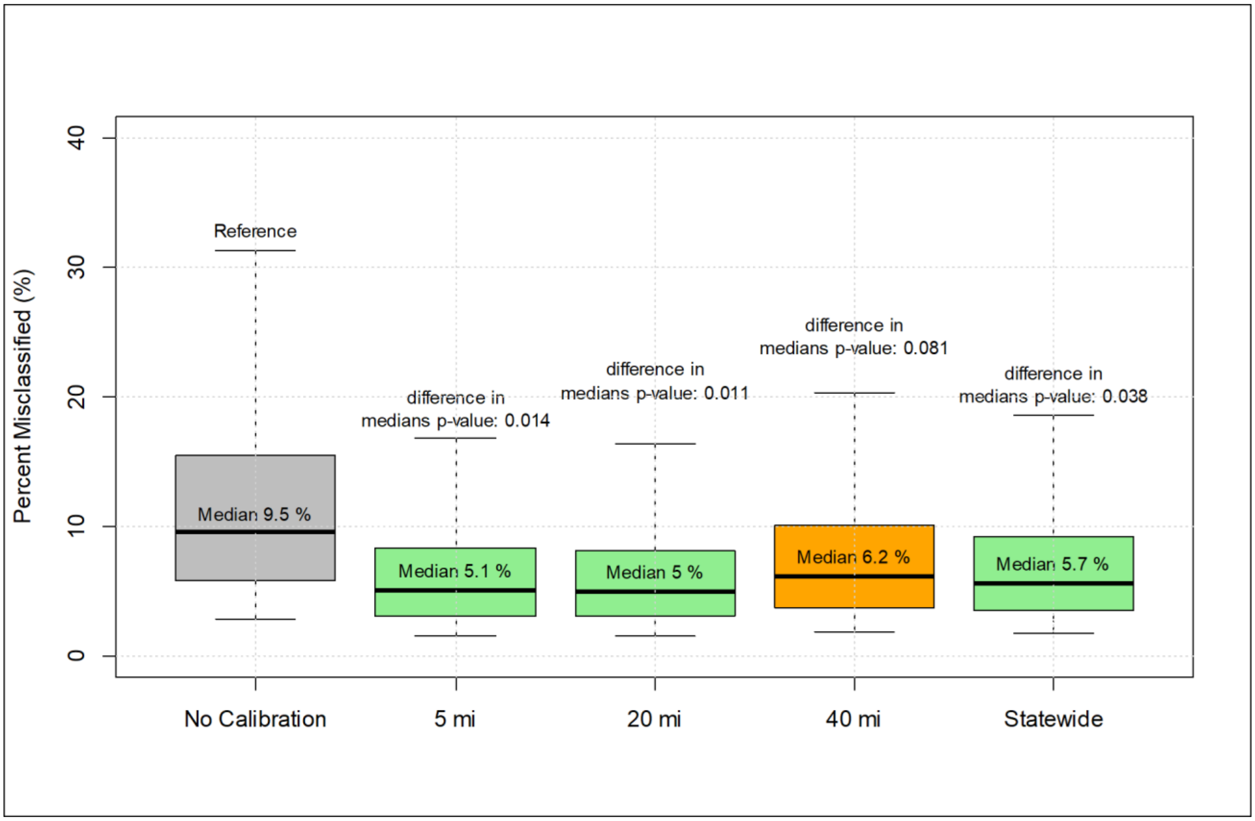

Figure 2 Calibration Levels and Percent Misclassification

It is clear from this exercise that the calibration levels improved the performance of the tool in terms of overall correct classification of vehicles. Moreover, all levels of calibration reduced the median misclassification rate approximately by half, compared to no calibration (median multiplicative factors ranging from 0.52 for 20 mi calibration to 0.65 for 40 mile calibration).Another round of analysis was conducted on these results to assess how the accuracy of vehicle count estimation changes for individual classes when calibration is performed.

Figure 3 shows the results as plots of true value versus estimated values of vehicle count, by class, at different levels of calibration.

A communality between calibration levels is the increased accuracy with increasing estimated number of vehicles. That is particularly clear for the both magenta trend lines, corresponding to classes 2 and 9, regardless of calibration threshold. These lines align nearly perfectly on the 1:1 diagonal in counts of 100 estimated vehicles up to close to 100,000 vehicles.

A closer look at the improved performance of 20-mile and 5-mile calibration compared to no calibration are shown in Figure 4 and Figure 5 respectively.

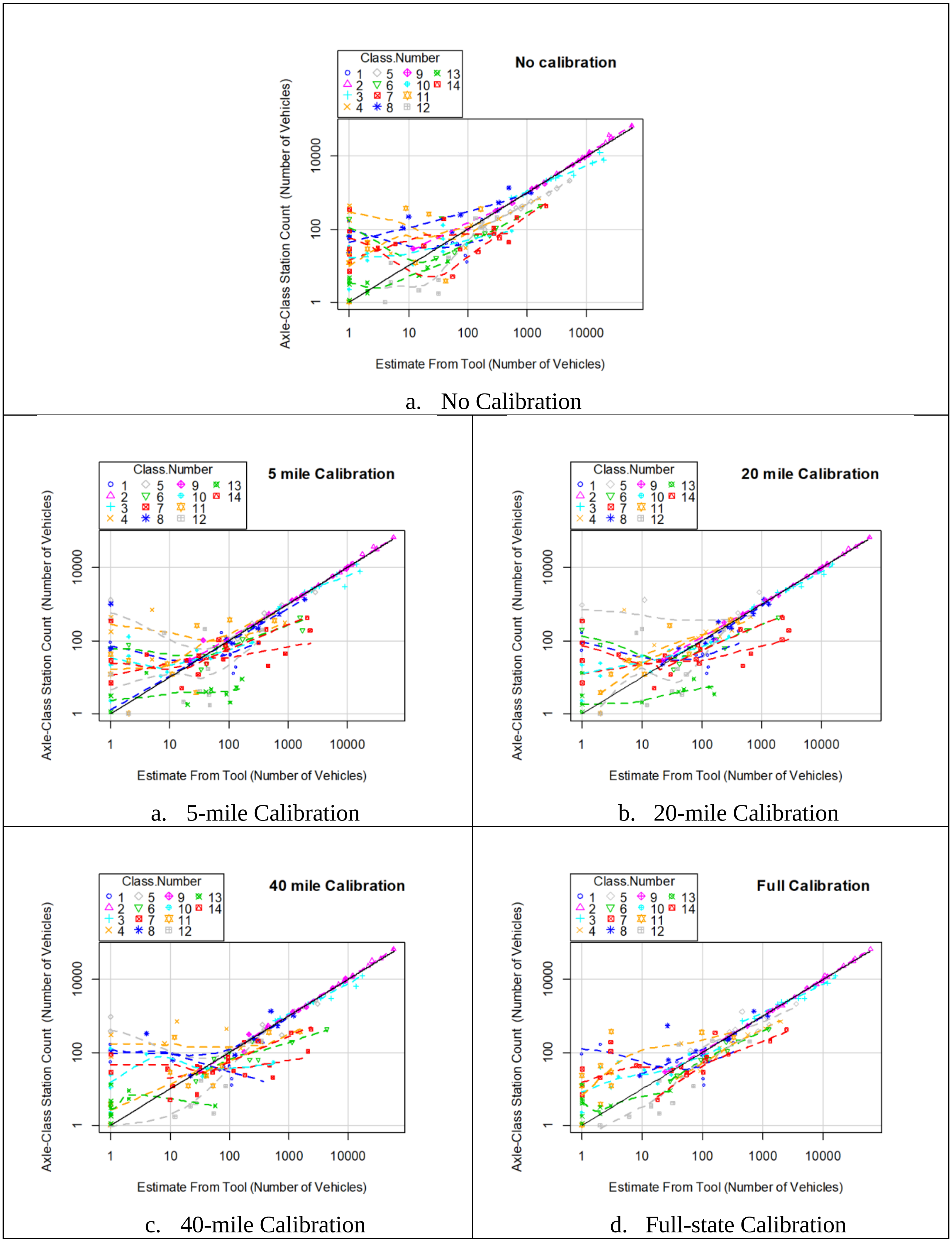

Figure 3 Accuracy of Prediction by Class and Calibration Level.

The benefit of calibrating at 20 miles is clearer on classes 4, 8, 10, and 11. The trend lines start aligning with the 1:1 diagonal between counts of 10 and 100 estimated vehicles and continue that alignment as the estimated number of vehicles increase. A detriment in estimating classes 5, 7, and 13 can be noticed, which tend to align less on the diagonal after the 20-mile calibration, with little to no effect observed for other classes. The following plots zoom at the range 10-1000 estimated vehicles to help appreciate these trend changes:

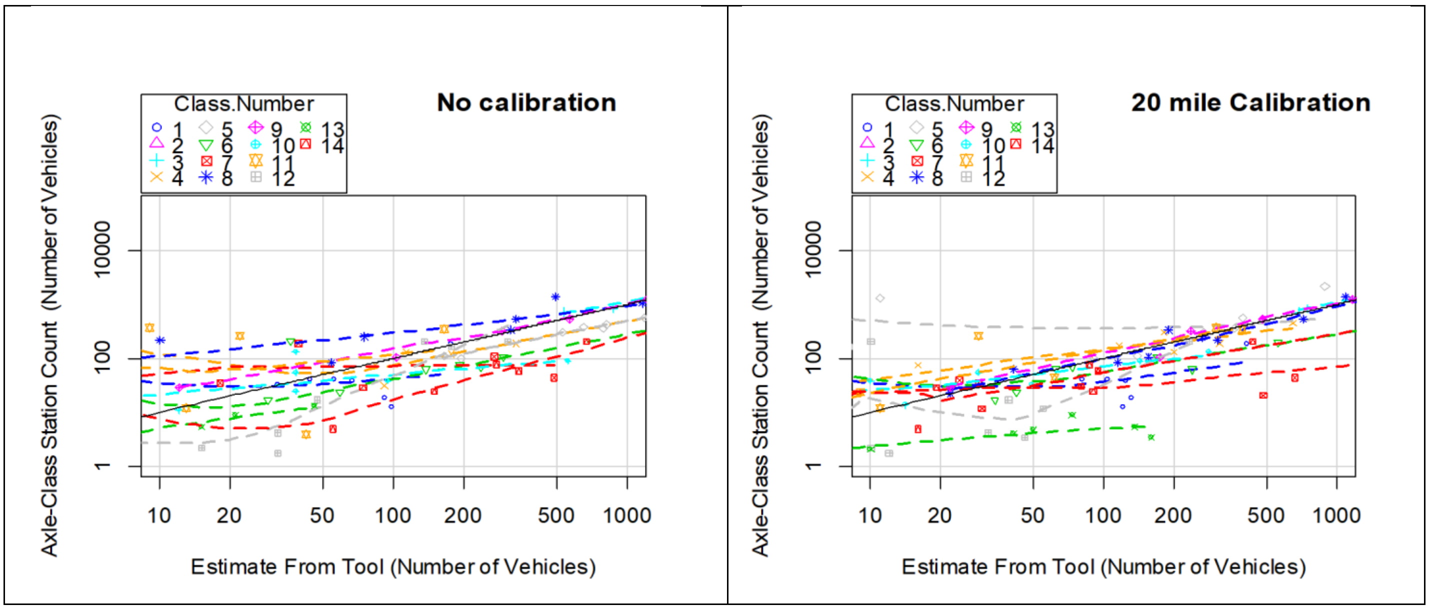

Figure 4 True Vehicle Count Value vs Predicted Value by Vehicle Class – No Calibration vs 20 mile Calibration

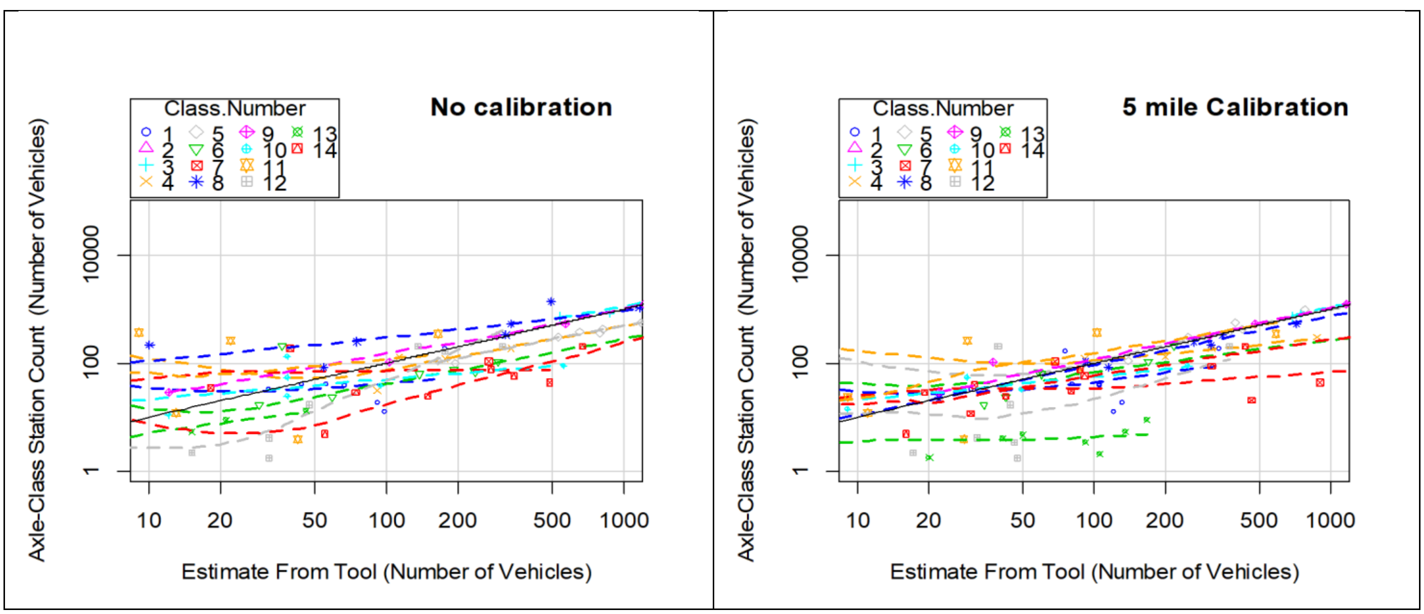

Figure 5 True Vehicle Count Value vs Predicted Value by Vehicle Class – No Calibration vs 5 mile Calibration

It is apparent from the above figures that the effect of calibration on the trends is to “whip” the trends of some key axle classes in line (such as classes 7 and 8) for counts as small as 20 to 50 vehicles. This improved alignment comes at the cost of loss in precision for some classes with fewer number of vehicles and for which less differentiation exists in the binning scheme (such as classes 12, 13 and 14).

Next, the differences are examined in terms of absolute classification error, by class, for the No-calibration vs the 20-mile calibration scenarios. The results are presented in Figure 6.

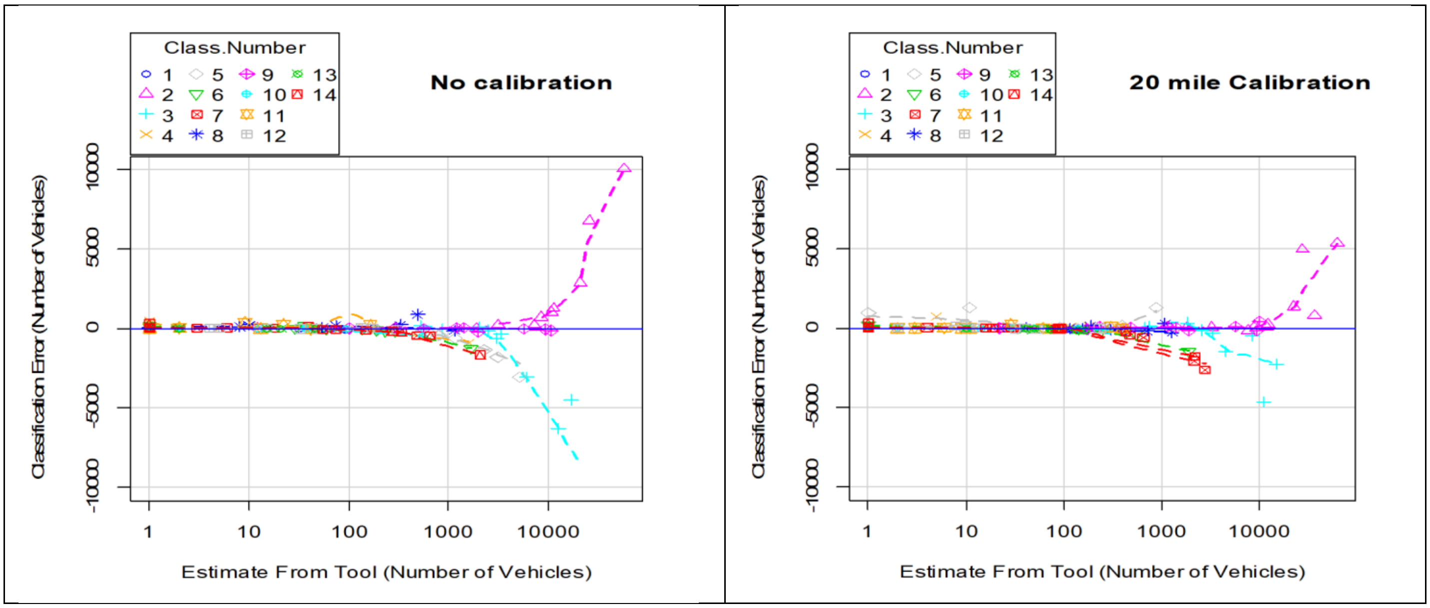

Figure 6 Absolute Difference in True and Predicted Vehicle Count Value by Vehicle Class – No Calibration vs 20 mile Calibration

From this comparison, it is evident that the reduction in overall classification error is also due to improved performance (i.e., reduced classification error) at the classes with highest counts. Lines for classes 2, 3, 8, and the rightmost side of Figure 6 are tighter around the zero error flat line for classes with large numbers of observed vehicles (i.e., in excess of 1000 vehicles). Again, worsening in the performance of counts in some classes can be observed, noticeably for classes 5 (leftmost side of both trends in the figure), and rightmost side of class 7. Finally, Figure 7 represents the average distributions of misclassified vehicles for each calibration level in order to identify average changes in number of misclassified vehicles per class due to calibration.

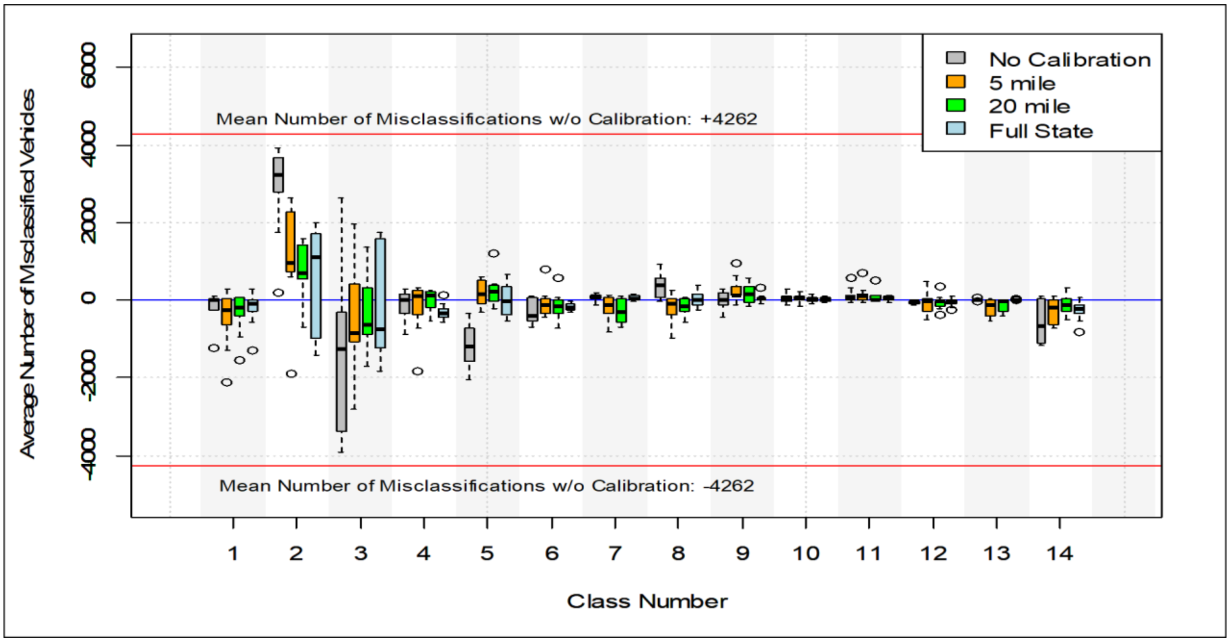

Figure 7 Effect of Calibration on Misclassification

The y-axis represents the average number of misclassified vehicles calculated across all 10 sites. As shown in Figure 7, calibration tended to reduce the number of misclassified vehicles in general, so it is expected that the number of average misclassifications for all the calibration schemes would remain within the limits of misclassifications observed without calibration (shown in red, average of 4,262 misclassifications without calibration).

In the plot above, we can see the positive effect of various calibration schemes on the number of misclassifications per axle class, and the negative effects in a few axle classes as well. Most relevant is the comparison of performances of No Calibration (in gray) scenario and the recommended calibration scheme (20 mile, in green). The significant overall improvement in performance identified earlier (median percent of misclassifications reduction from 9.5 percent to 5.0 percent) can be tracked to clear reductions in the number of misclassified vehicles for classes 2, 3, 4, 5, 8, 11, and 14 (i.e., the boxes for the 20-mile calibration are narrower and better centered around the zero-misclassified line for these classes, compared to no calibration). Although slightly worsened performance for classes 7, 9, and 13 is also evident, those shifts were clearly offset by the improvements in the other set of classes discussed above, as evidenced by the overall performance of the calibrations shown in Figure 2.

Conclusions and Recommendations

Based on the results on the percent of misclassified vehicles for different levels of calibration, it is recommended to calibrate the tool with any additional data available from sites that are within 5 mile or 20-mile radius of a site for which the axle-class distribution is subject to estimation. This process was found to improve the overall accuracy of the estimation by producing a reduction in percent misclassification of vehicles. This reduction was quantified as a decrease in median of misclassifications, from 9.5 percent with no calibration, to 5.1 percent or 5.0 percent respectively.

When considering misclassification of individual vehicle classes, calibration had mixed influence in the results. The positive effects on estimation accuracy of classes with higher counts was found to outweigh the negative effects on higher-number classes that tend to have smaller counts. It should be mentioned that 5-mile and full-state calibration provided comparable results to a 20-mile calibration (per Figure 2), so either of these levels is recommended to improve performance of the estimation tool.

Appendix A

The calibration results on estimated vehicle count for each vehicle class by test site.

Table A 1 Calibration Details for Cottage Grove Road

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	182	68380	12630	709	2180	437	187	1355	10670	128	370	207	12	417	97864
Without Calibration	175	58359	17106	1609	5241	1684	38	494	10804	37	8	307	45	2097	98004
Half Absolute Deviation	3.54	5010.63	2237.98	450.18	1530.74	623.25	74.58	430.69	66.95	45.31	181.15	50.17	16.56	840.08	11.8%
5-mi Calibration Estimates	340	61796	14489	4	2867	1590	2372	1926	10354	1	101	38	3	2123	98004
Half Absolute Deviation	78.96	3292.13	929.48	352.32	343.74	576.25	1092.42	285.31	158.05	63.31	134.65	84.33	4.44	853.08	8.4%
20-mi Calibration Estimates	411	63019	14877	4	888	1893	2802	1085	10232	281	301	9	0	2201	98003
Half Absolute Deviation	114.46	2680.63	1123.48	352.32	645.76	727.75	1307.42	135.19	219.05	76.69	34.65	98.83	5.94	892.08	8.6%
40-mi Calibration Estimates	376	58703	17405	12	3043	4396	174	499	9133	0	1537	345	0	2380	98003
Half Absolute Deviation	96.96	4838.63	2387.48	348.32	431.74	1979.25	6.58	428.19	768.55	63.81	583.35	69.17	5.94	981.58	13.3%
Statewide Calibration Estimates	324	61078	15828	1944	3600	1254	2	705	10472	190	2	143	0	2460	98002
Half Absolute Deviation	70.96	3651.13	1598.98	617.68	710.24	408.25	92.58	325.19	99.05	31.19	184.15	31.83	5.94	1021.58	9.0%

Table A 2 Calibration Details for Vienna

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	90	37546	8063	449	1316	195	43	1019	9324	88	351	200	8	341	59034
Without Calibration	0	24069	19718	0	3126	0	485	1159	9382	555	163	134	20	0	58811
Half Absolute Deviation	44.92	6738.33	5827.68	224.64	904.88	97.45	221.05	69.76	28.76	233.71	94.18	32.98	6.05	170.72	24.9%
5-mi Calibration Estimates	0	28226	16779	0	0	1759	903	0	9771	250	586	371	166	0	58811
Half Absolute Deviation	44.92	4659.83	4358.18	224.64	658.12	782.05	430.05	509.74	223.26	81.21	117.32	85.52	79.05	170.72	21.0%
20-mi Calibration Estimates	0	36740	8572	644	10	558	657	1293	9501	142	391	232	72	0	58812
Half Absolute Deviation	44.92	402.83	254.68	97.36	653.12	181.55	307.05	136.76	88.26	27.21	19.82	16.02	32.05	170.72	4.1%
40-mi Calibration Estimates	10	35740	8354	89	1241	1148	480	1193	8778	3	463	214	1	1097	58811
Half Absolute Deviation	39.92	902.83	145.68	180.14	37.62	476.55	218.55	86.76	273.24	42.29	55.82	7.02	3.45	377.78	4.8%
Statewide Calibration Estimates	0	33548	11869	1115	450	247	7	1199	9424	60	95	609	28	161	58812
Half Absolute Deviation	90	37546	8063	449	1316	195	43	1019	9324	88	351	200	8	341	59034

Table A 3 Calibration Details for Crowbar Road

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	163	32828	6418	305	967	202	105	329	1760	37	41	11	2	87	43257
Without Calibration	0	26060	12716	0	2313	35	268	317	1976	93	1	4	1	0	43784
Half Absolute Deviation	81.41	3384.01	3148.82	152.72	672.96	83.50	81.34	6.22	107.82	28.17	20.19	3.40	0.70	43.67	18.1%
5-mi Calibration Estimates	75	32515	6683	878	781	215	67	347	1717	1	0	0	91	313	43683
Half Absolute Deviation	43.91	156.51	132.32	286.28	93.04	6.50	19.16	8.78	21.68	17.83	20.69	5.40	44.30	112.83	2.2%
20-mi Calibration Estimates	0	27888	11039	180	0	0	2182	189	1923	9	60	54	159	0	43683
Half Absolute Deviation	81.41	2470.01	2310.32	62.72	483.54	101.00	1038.34	70.22	81.32	13.83	9.31	21.60	78.30	43.67	15.9%
40-mi Calibration Estimates	0	25667	13442	0	0	240	2097	3	1977	41	74	86	57	0	43684
Half Absolute Deviation	81.41	3580.51	3511.82	152.72	483.54	19.00	995.84	163.22	108.32	2.17	16.31	37.60	27.30	43.67	21.3%
Statewide Calibration Estimates	1	32042	7144	558	1117	389	2	339	1746	1	1	70	2	271	43683
Half Absolute Deviation	80.91	393.01	362.82	126.28	74.96	93.50	51.66	4.78	7.18	17.83	20.19	29.60	0.20	91.83	3.1%

Table A 4 Calibration Details for Tomah

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	40	9224	2418	119	358	66	38	216	1260	31	27	16	2	57	13871
Without Calibration	55	8518	2551	176	788	234	5	9	1210	0	1	46	0	342	13935
Half Absolute Deviation	7.61	352.86	66.54	28.54	214.96	84.17	16.44	103.52	24.81	15.72	13.12	15.18	1.05	142.56	7.8%
5-mi Calibration Estimates	104	9120	2506	90	368	57	30	312	1165	48	1	43	0	90	13934
Half Absolute Deviation	32.11	51.86	44.04	14.46	4.96	4.34	3.84	47.98	47.31	8.28	13.12	13.68	1.05	16.56	2.2%
20-mi Calibration Estimates	103	9073	2556	85	364	72	23	305	1168	48	5	38	0	93	13933
Half Absolute Deviation	31.61	75.36	69.04	16.96	2.96	3.17	7.44	44.48	45.81	8.28	11.12	11.18	1.05	18.06	2.5%
40-mi Calibration Estimates	101	8975	2654	91	375	54	31	292	1180	48	9	32	0	93	13935
Half Absolute Deviation	30.61	124.36	118.04	13.96	8.46	5.84	3.44	37.98	39.81	8.28	9.12	8.18	1.05	18.06	3.1%
Statewide Calibration Estimates	79	9469	2066	237	278	123	43	262	1236	10	2	18	1	110	13934
Half Absolute Deviation	19.61	122.64	175.96	59.04	40.04	28.67	2.56	22.98	11.81	10.72	12.62	1.18	0.55	26.56	3.9%

Table A 5 Calibration Details for Amherst Junction

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	31	12669	3040	187	564	107	41	534	5777	53	256	159	4	203	23623
Without Calibration	31	11410	3398	332	1183	295	1	332	5828	37	21	175	14	666	23723
Half Absolute Deviation	0.03	629.42	179.20	72.61	309.31	94.13	19.85	100.77	25.65	8.02	117.55	8.00	4.83	231.71	7.6%
5-mi Calibration Estimates	29	12428	3348	313	394	169	3	715	5695	28	28	7	134	433	23724
Half Absolute Deviation	1.03	120.42	154.20	63.11	85.19	31.13	18.85	90.73	40.85	12.52	114.05	76.00	64.83	115.21	4.2%
20-mi Calibration Estimates	29	12428	3348	313	394	169	3	715	5695	28	28	7	134	433	23724
Half Absolute Deviation	1.03	120.42	154.20	63.11	85.19	31.13	18.85	90.73	40.85	12.52	114.05	76.00	64.83	115.21	4.2%
40-mi Calibration Estimates	68	12151	3517	346	357	99	27	645	5485	552	11	164	1	302	23725
Half Absolute Deviation	18.47	258.92	238.70	79.61	103.69	3.87	6.85	55.73	145.85	249.48	122.55	2.50	1.67	49.71	5.7%
Statewide Calibration Estimates	59	10747	3984	292	1297	256	8	25	5365	3	329	39	0	1320	23724
Half Absolute Deviation	13.97	960.92	472.20	52.61	366.31	74.63	16.35	254.27	205.85	25.02	36.45	60.00	2.17	558.71	13.1%

Table A 6 Calibration Details for Dodgeville

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	39	11961	2469	129	418	76	29	248	1453	23	11	3	3	75	16939
Without Calibration	43	10942	3102	112	817	191	2	74	1439	37	12	31	0	275	17077
Half Absolute Deviation	2.17	509.72	316.39	8.71	199.28	57.55	13.69	86.77	7.06	6.98	0.46	13.93	1.48	99.78	7.8%
5-mi Calibration Estimates	80	11877	2571	199	422	1	79	262	1420	0	10	31	40	86	17079
Half Absolute Deviation	20.67	42.22	50.89	34.79	1.78	37.45	24.81	7.23	16.56	11.03	0.54	13.93	18.53	5.28	1.7%
20-mi Calibration Estimates	80	11877	2571	199	422	1	79	262	1420	0	10	31	40	86	17079
Half Absolute Deviation	20.67	42.22	50.89	34.79	1.78	37.45	24.81	7.23	16.56	11.03	0.54	13.93	18.53	5.28	1.7%
40-mi Calibration Estimates	80	11833	2537	152	388	84	118	254	1461	0	51	26	20	94	17078
Half Absolute Deviation	20.67	64.22	33.89	11.29	15.22	4.05	44.31	3.23	3.94	11.53	19.96	11.43	1.48	9.28	1.5%
Statewide Calibration Estimates	71	11866	2561	191	345	110	29	275	1454	29	2	31	0	115	17079
Half Absolute Deviation	16.17	47.72	45.89	30.79	36.72	17.05	0.19	13.73	0.44	2.98	4.54	13.93	1.48	19.78	1.5%

Table A 7 Calibration Details for Winnebago

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	38	7555	2170	74	303	61	34	105	318	12	11	1	1	23	10706
Without Calibration	66	7366	2081	82	525	137	17	7	290	1	0	14	1	148	10735
Half Absolute Deviation	14.08	94.26	44.37	3.95	111.20	37.91	8.55	49.14	14.07	5.74	5.52	6.43	0.11	62.46	4.3%
5-mi Calibration Estimates	105	7754	1962	86	248	59	40	91	305	8	0	16	19	41	10734
Half Absolute Deviation	33.58	99.74	103.87	5.95	27.30	1.09	2.95	7.14	6.57	2.24	5.52	7.43	9.11	8.96	3.0%
20-mi Calibration Estimates	123	7718	1840	15	268	239	28	155	234	13	2	9	0	89	10733
Half Absolute Deviation	42.58	81.74	164.87	29.55	17.30	88.91	3.05	24.86	42.07	0.26	4.52	3.93	0.39	32.96	5.02%
40-mi Calibration Estimates	101	6972	2125	0	762	303	8	0	209	0	19	53	0	183	10735
Half Absolute Deviation	31.58	291.26	22.37	37.05	229.70	120.91	13.05	52.64	54.57	6.24	3.98	25.93	0.39	79.96	9.1%
Statewide Calibration Estimates	85	7915	1738	168	259	106	0	77	297	17	0	18	0	53	10733
Half Absolute Deviation	23.58	180.24	215.87	46.95	21.80	22.41	17.05	14.14	10.57	2.26	5.52	8.43	0.39	14.96	5.5%

Table A 8 Calibration Details for Preston

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	17	3328	847	21	99	16	11	21	28	1	0	0	0	4	4393
Without Calibration	91	3139	866	4	193	28	0	0	11	0	0	3	0	54	4389
Half Absolute Deviation	36.79	94.47	9.68	8.44	47.01	6.25	5.36	10.69	8.45	0.59	0.01	1.50	0.06	25.04	5.8%
5-mi Calibration Estimates	130	3295	747	7	90	33	29	21	21	0	1	1	0	15	4390
Half Absolute Deviation	56.29	16.47	49.82	6.94	4.49	8.75	9.14	0.19	3.45	0.59	0.49	0.50	0.06	5.54	3.7%
20-mi Calibration Estimates	130	3295	747	7	90	33	29	21	21	0	1	1	0	15	4390
Half Absolute Deviation	56.29	16.47	49.82	6.94	4.49	8.75	9.14	0.19	3.45	0.59	0.49	0.50	0.06	5.54	3.7%
40-mi Calibration Estimates	109	3347	704	40	94	26	10	21	30	0	0	0	0	9	4390
Half Absolute Deviation	45.79	9.53	71.32	9.56	2.49	5.25	0.36	0.19	1.05	0.59	0.01	0.00	0.06	2.54	3.4%
Statewide Calibration Estimates	101	3316	734	36	115	28	0	8	23	0	0	1	0	17	4379
Half Absolute Deviation	41.79	5.97	56.32	7.56	8.01	6.25	5.36	6.69	2.45	0.59	0.01	0.50	0.06	6.54	3.4%

Table A 9 Calibration Details for S. Fon Du Lac

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	11	1923	720	30	112	22	6	82	531	20	522	2	4	27	3512
Without Calibration	97	1909	537	90	163	58	0	53	562	1	0	4	0	73	3547
Half Absolute Deviation	42.77	6.91	91.44	29.99	25.68	17.95	2.96	14.62	15.47	9.60	10.94	0.80	1.81	22.89	8.4%
5-mi Calibration Estimates	120	1852	684	4	138	41	0	114	477	0	8	45	49	18	3550
Half Absolute Deviation	54.27	35.41	17.94	13.01	13.18	9.45	2.96	15.88	27.03	10.10	6.94	21.30	22.69	4.61	7.3%
20-mi Calibration Estimates	120	1852	684	4	138	41	0	114	477	0	8	45	49	18	3550
Half Absolute Deviation	54.27	35.41	17.94	13.01	13.18	9.45	2.96	15.88	27.03	10.10	6.94	21.30	22.69	4.61	7.3%
40-mi Calibration Estimates	111	1939	586	26	101	37	27	123	451	34	40	21	0	51	3547
Half Absolute Deviation	49.77	8.09	66.94	2.01	5.32	7.45	10.54	20.38	40.03	6.90	9.06	9.30	1.81	11.89	7.1%
Statewide Calibration Estimates	105	2083	457	89	61	37	0	100	546	3	0	13	0	54	3548
Half Absolute Deviation	46.77	80.09	131.44	29.49	25.32	7.45	2.96	8.88	7.47	8.60	10.94	5.30	1.81	13.39	10.8%

Table A 10 Calibration Details for Coldspring Road

Wavetronix Data Tool Estimate	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	Class 14	Total / % Miscl.
Observed Counts by Axle Class	52	24111	3053	174	376	63	19	61	104	10	3	1	1	27	28054
Without Calibration	0	21244	6121	0	651	0	0	0	101	11	41	31	1	0	28201
Half Absolute Deviation	25.95	1433.57	1534.24	86.84	137.53	31.44	9.74	30.46	1.33	0.61	19.07	15.12	0.01	13.65	11.9%
5-mi Calibration Estimates	0	18385	9134	0	0	0	461	0	36	6	27	46	104	0	28199
Half Absolute Deviation	25.95	2863.07	3040.74	86.84	187.97	31.44	220.76	30.46	33.83	1.89	12.07	22.62	51.49	13.65	23.6%
20-mi Calibration Estimates	0	22755	4552	115	0	61	481	40	172	1	1	11	9	0	28198
Half Absolute Deviation	25.95	678.07	749.74	29.34	187.97	0.94	230.76	10.46	34.17	4.39	0.93	5.12	3.99	13.65	7.0%
40-mi Calibration Estimates	0	22024	5210	7	0	220	536	10	177	0	0	11	0	0	28195
Half Absolute Deviation	25.95	1043.57	1078.74	83.34	187.97	78.56	258.26	25.46	36.67	4.89	1.43	5.12	0.51	13.65	10.1%
Statewide Calibration Estimates	37	22019	4941	43	826	93	1	26	103	2	1	5	1	101	28199
Half Absolute Deviation	7.45	1046.07	944.24	65.34	225.03	15.06	9.24	17.46	0.33	3.89	0.93	2.12	0.01	36.85	8.5%