ANALYSIS OF VEHICLE CLASSIFICATION AND TRUCK WEIGHT DATA OF THE NEW ENGLAND STATES

FINAL REPORT

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EXECUTIVE SUMMARY

This report is about a statistical analysis of 1995-96 classification and weigh in motion (WIM) data from seventeen continuous traffic-monitoring sites in New England. It documents work performed by Oak Ridge National Laboratory in fulfilment of "Analysis of Vehicle Classification and Truck Weight Data of the New England States," a project for the Office of Highway Information Management. The purpose of the data analysis is basic research: policy recommendations are neither made nor implied.

The purpose of the data analysis is to study seasonality adjustments for classification and WIM data, and to infer strategies for using data from multiple states in a common resource data pool. Because data sharing means cross-state extrapolation, combined data should not be used without a proper statistical accounting for extrapolation error. Another major concern in implementing a data-sharing procedure is operational simplicity. Of particular interest are possible simplifications by combining vehicle classes (i.e., reducing the number of vehicle classes used in practice) and by combining roadway functional classes. These issues are considered from a statistical data perspective and not from the standpoint of equipment capability.

The data are considered, in particular, from the perspective of using long-term class and WIM data to adjust short term axle or class counts or short-term loads, to produce estimates of class-specific average annual daily traffic (AADT) or average annual daily load (AADL). In addition to the conversion of short-term class to AADT estimates, these schemes include (1) short-term class to AADL, (2) short-term WIM to AADL, and (3) short-term axle counts to AADL.

Initial data processing, screening and quality control (QC) procedures were a substantial effort, as there were about two gigabytes of raw data. Data screening and QC procedures were considered first on a coarse level for the purpose of deciding what data sets should be kept for analysis, and then on a finer level for deciding about individual data points that should be deleted or modified. The coarse screening procedures include analyses of ratios of vehicle Class 3 to Class 2 volumes, volumes over time, volumes by day-of-week, Class 9 weight distributions, and front axle weights. The finer-level screening procedures include many of the checks implemented in the *VTRIS* software and a cusum procedure from statistical quality control. The cusum procedure is designed to rapidly detect changes in data streams, and, potentially, could be used as traffic data is downloaded from data loggers to check for data quality problems. The QC analyses demonstrate the need for continuous data-quality monitoring.

Seasonal and day-of-week effects are demonstrated graphically and in statistical analyses. The adjustment factor (AF) method for seasonal and day-of-week adjustments in total traffic volumes, as prescribed in the *Traffic Monitoring Guide*, is extended to class-specific volumes, ESALs, and loads.

WIM data, which is initially stored on a by-truck basis, is reduced to frequency counts for axle combination and weight classes, defined in half-kip increments, for each site and day. In addition to effecting a considerable reduction in the data set size, this approach allows for estimation of ESALs for any underlying roadway characteristics (pavement type, thickness, etc.), not just the characteristics of the particular site. In this way WIM data at one site may be used to infer ESALs at a different site, having similar traffic but different roadway characteristics.

Limitations on the data structure, which is observational rather than designed-experiment, are discussed, which limit the scope of possible conclusions and necessitate making several assumptions about the statistical independence of sites, directions within sites, and time.

The approaches taken for the main statistical data analysis are analysis of variance (ANOVA) and propagation of errors. ANOVA provides a convenient tool for computing AFs (as arithmetic means) as well as additional statistics including standard errors of AFs and analyses (i.e., decompositions) of the variances into components for day-of-week, month, functional class, etc. Thus ANOVA measures the relative importance of these components. Propagation of error theory reveals the net effect of various sources of error (e.g., short term counting error, error in AFs), and thus answer questions about how accurate AADT and AADL estimates are, whether they are worth computing, and where resources might best be spent reducing their overall error.

Propagation of error theory shows that from the perspective of load estimation, there is little advantage to combining vehicle classes. ANOVAs of both the WIM and classification data suggests that differences among functional classes are sufficient to warrant against combining functional classes.

Even without simplifications in the vehicle or functional classifications, however, data sharing among states is a good idea. The ANOVA approach to computing AFs from multiple-site data is reasonably simple—the AFs are computed as simple arithmetic means—and can be done with an ordinary spreadsheet program. In addition to AF estimates, the ANOVA also provides an accounting for statistical error (i.e., standard errors of the AF estimates) and is thus a particularly appropriate tool for data sharing.

A map and general description of the data kept for analysis are on pages 2 and 3. Many other tables and figures were produced for the report. An interesting example is the following table (from Section 3) of truck statistic averages for the eleven WIM sites.

Site	Functional Class	Average trucks per day	Average load per day (kips)	Average load per truck (kips)
CT974	7	190	1,855	9.8
CT978	12	600	18,017	30.0
CT990	11	3,428	137,294	40.1
MA001	11	9,416	308,294	32.7
MA005	11	5,446	167,363	30.7
MA02N	11	212	3,463	16.3
RI350	12	1,768	73,711	41.7
VTD92	1	1,418	54,690	38.6
VTN01	1	858	35,683	41.6
VTR01	2	857	38,670	45.1
VTX73	1	1,525	65,601	43.0
All	–	2,321	82,207	35.4

1. INTRODUCTION

For many years the six New England States (U.S. DOT standard Region 1) have been collecting vehicle classification and truck weight data to meet programmatic needs of the state and Federal governments. Each state has a well-developed traffic monitoring system. In addition, a good working relationship exists among the states. This is evident from technology sharing meetings held several times a year, from regular exchanges of data, and from the states' desire and commitment to improve existing traffic monitoring programs, particularly for trucks. Currently, the Region 1 states are reviewing the cost-effectiveness of their data collection and analysis activities, and exploring possibilities of collaboration in their traffic data programs.

Although never formally demonstrated, it is reasonable to think that truck travel in each of these states is similar, because of geographic location, the small size of each state, continuity of major truck routes across the states, and similarity in economic activities. It is also reasonable to think that the six states may have other similarities and that by sharing their data they might significantly reduce the resource demand on each state. Unfortunately, available resources have limited detailed analyses of each state's data. These analyses are crucial to determine similarities in data and to establish effective ways of combining their traffic data.

The work described here is an analysis of classification and weigh-in-motion data from several of the Region 1 states. Details about data availability and decisions about what data was kept for further analysis are discussed in Section 2. The decisions were based on an analysis of missing data, and several preliminary data-quality checks. For the classification data, the checks were based on class frequency ratios, frequency changes, and three-standard-deviation control limits. For the WIM data, the checks were based on a graphical analysis of front-axle and gross-vehicle weights of five-axle single-trailer trucks (vehicle Class 9). Table 1.1 gives basic descriptive information about the sixteen classification sites and eleven continuous-monitoring WIM sites kept for further analysis. The total number of sites kept is seventeen—ten sites were kept for both their class and WIM data. Figure 1.1 shows the locations of the sites.

After deciding about basic selection of the data for analysis, several additional quality control checks were also performed. These are discussed in Section 3. A cusum (i.e., cumulative sum) statistic is considered there, which is designed to rapidly detect data (or instrument) problems and can be used with data streams as they are downloaded from data loggers.

Seasonal and day-of-week effects in traffic monitoring data are well known, and a well-developed methodology exists for computing adjustment factors (AFs) to account for seasonal effects in overall traffic volumes. This is described in the *Traffic Monitoring Guide* (TMG) [1] and in Appendix A. Seasonal and day-of-week effects in the Region 1 data are discussed in Section 4. One of the main objectives of this report is to explore extending these seasonal adjustment procedures to classification and WIM data.

Table 1.1. The Seventeen Classification/WIM Sites Kept for Classification Analysis

Site	Functional Class	Location (also see map)	Yrs.	Dir.	Avg. Ann. Daily Traffic[a]	Pct. in Class 4-13[a]	Avg. Daily Trks.[b]	Avg. GVW (kips)[b]
CT974	**Rural—Major Collector (7)**	**Rt. 117—.9 m N of Rt. 184**	**95**	**N**	4,802	4.61	190	9.8
CT978	**Urban—Principal Arterial Other Free/Expwy (12)**	**Rt. 2—2.5 m W of Rt. 83**	**95**	**W**	16,094	4.15	600	30.0
CT990	**Urban—Principal Arterial Interstate (11)**	**I-84—2 m W of Rt. 30**	**95**	**W**	42,681	8.59	3,430	40.1
CT991	**Urban—Principal Arterial Interstate (11)**	**I-84—.75 m W of Rt. 31**	**95**	**W**	33,009	10.09	Class Only	Class Only
MA001	**Urban—Principal Arterial Interstate (11)**	**I-93—N of Rt. 28**	**96**	**N, S**	93,070	5.64	9,420	32.7
MA002	**Urban—Principal Arterial Interstate (11)**	**I-391—N of I-90**	**96**	**N, S**	13,659	3.47	210	16.3
MA003	**Urban—Principal Arterial Other (14)**	**Rt. 27—S of Hospital Rd.**	**95, 96**	**N, S**	3,363	5.41	Class Only	Class Only
MA004	**Urban—Principal Arterial Interstate (11)**	**I-95—E of Acushnet River**	**96**	**E, W**	16,156	4.52	Class Only	Class Only
MA005	**Urban—Principal Arterial Interstate (11)**	**I-95—S of Rt. 38**	**95, 96**	**N, S**	85,172	5.69	5,450	30.7
RI350	**Urban—Principal Arterial Other Free/Expwy (12)**	**Rt. 146 at Mass. State Line**	**95, 96**	**N, S**	7,817	11.62	1,770	41.7
VT132	**Rural—Principal Arterial Other (2)**	**U.S. 7—Charlotte**	**95, 96**	**N, S**	5,131	8.09	Class Only	Class Only
VT249	**Rural—Principal Arterial Other (2)**	**VT 103, Rockingham**	**95**	**E, W**	2,512	11.35	Class Only	Class Only
VTa41	**Rural—Principal Arterial Other (2)**	**U.S. 7, New Haven**	**95, 96**	**N, S**	3,135	8.51	Class Only	Class Only
VTd92	**Rural—Principal Arterial Interstate (1)**	**I-91—Fairlee**	**95, 96**	**N, S**	WIM Only	WIM Only	1,420	38.6
VTn01	**Rural—Principal Arterial Interstate (1)**	**I-91—Fairlee**	**95**	**N, S**	3,893	11.55	860	41.6
VTr01	**Rural—Principal Arterial Other (2)**	**U.S. 4—New Haven**	**95, 96**	**E, W**	3,194	14.39	860	45.1
VTx73	**Rural—Principal Arterial Interstate (1)**	**I-91—Putney**	**96**	**N, S**	6,385	12.54	1,530	43.0
All	**1, 2, 7, 11, 12, 14**	**CT, MA, RI, VT**	**95, 96**	**N, S E,W**	18,865	6.66	2,320	35.4

[a]From the sixteen classification sites. [b]From the eleven WIM sites.

Figure 1.1. The Seventeen Classification/WIM Sites Kept for Analysis. *Classification analysis only; **WIM analysis only; other sites were used in both analyses.

In Section 5 ESALs are considered as data summarization statistics. Because of their importance in pavement design, ESALs are a powerful and convenient tool for summarizing traffic loads. But from the perspective of data sharing, they suffer from their dependence on roadway properties (pavement thickness, terminal serviceability, structural number). Highways having similar traffic characteristics may nevertheless differ in terms of ESALs, because of roadway differences alone. Therefore, in Section 5, a method is developed for reducing WIM data to counts for weight classes defined in half-kip increments. WIM data sets reduced this way are much smaller and more tractable than the original by-vehicle WIM data. Also in Section 5, a "standard" ESAL, computed from the reduced data, is defined, which is used in the rest of the report to summarize the data in a way that is not roadway-specific (i.e., is specific only to the standard). Graphs and tables summarizing loads in the Region 1 data are also discussed in Section 5.

1.1. SCHEMES FOR USING CLASSIFICATION AND WIM DATA

The purpose of the data analysis described here is to consider whether and how to combine classes from the statistical viewpoint of actual monitoring data. To do this it is necessary to understand how traffic data is ultimately used. In this report several schemes are considered for using WIM and classification data. Perhaps the most important in terms of its application in Region 1 is the computation of average annual daily load (AADL) estimates from short-term vehicle classification counts. The short-term class counts are first used together with long-term class counts to compute average annual daily traffic (AADT) estimates, which in turn are used together with long-term WIM data to estimate the AADL. (The long-term class data could be derived from the same long-term WIM data.) The AADT estimates here may be either overall or class-specific.[1] This scheme, call it Scheme 1, is illustrated in Figure 1.2.

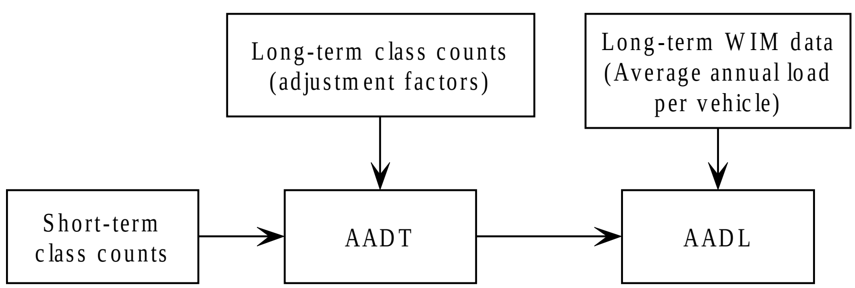

Figure 1.2. Scheme 1, for AADL estimation from short-term classification counts. The AADT here may be class-specific.

We will also consider a Scheme 2, for the direct conversion of short-term WIM data to AADL estimates. In Scheme 2, WIM-based seasonal and day-of-week AFs (AADL-to-average-daily load ratios) are used to convert short-term WIM data to AADL estimates. This is illustrated in Figure

[1] In this report, the term “AADT” will be used to refer to either overall or class-specific volumes or both, with the context denoted unless otherwise clear.

1.3. The logic in Scheme 2 parallels the procedure for adjusting short-term counts. Although problems with equipment accuracy and calibration have been a significant deterrent to short-term WIM monitoring, Scheme 2 may become more important as portable WIM technology becomes better and more economical.

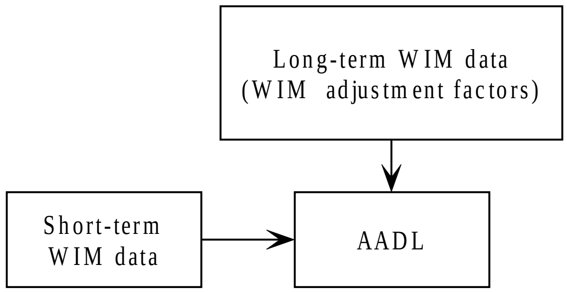

Figure 1.3. Scheme 2, for AADL estimation from short-term WIM data.

One other scheme is considered here, a Scheme 3, for converting short-term axle (tube) counts to average annual daily axle (AADA) estimates, and in turn to AADL estimates. This scheme, which is illustrated in Figure 1.4, would most likely be used when only short-term axle (rather than class or volume) counts are available.

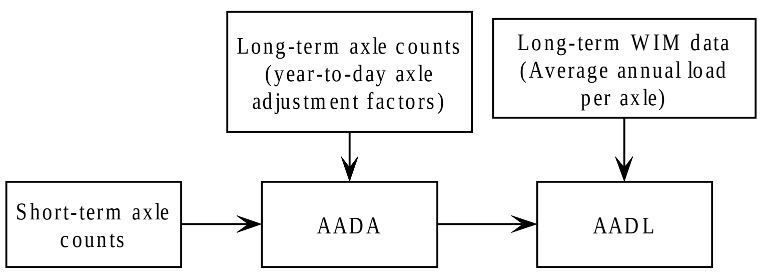

Figure 1.4. Scheme 3, for AADL estimation from short-term axle counts.

Further details about these Schemes will be presented in Sections 6 and 7; it is not necessary to understand all the details now. In Section 6, conversion and AFs are estimated from the long-term class and WIM data, for use with the various schemes. The schemes are then illustrated more completely in Section 7, where load estimates are computed from the conversion factors and classification, short-term WIM, or axle count data. Propagation-of-error theory is discussed for arriving at standard errors for the estimates, which indicate approximately how accurate the estimates are.

Of course other schemes are also possible. For example short-term axle counts could be converted to overall AADT estimates and then to AADL estimates. In that scheme, however, the WIM data itself would be used as in Scheme 1—to convert AADT to AADL. Schemes 1, 2, and 3 are considered here partly because they involve WIM data in different ways. In Scheme 1, to convert from AADT to AADL, WIM-based statistics like average vehicle weight or ESALs per vehicle are needed. In Scheme 2, WIM-based AFs are used. In Scheme 3, average weights or ESALs per **axle** are needed. Considering Schemes 1, 2, and 3 allows us to focus on these different statistics.

1.2. OBJECTIVES OF THE DATA ANALYSIS

The main data analyses in this report are discussed in Sections 6 and 7. The primary objectives of the data analyses are to cast light on the issues of (1) combining data across states, (2) combining vehicle classes, and (3) combining roadway functional classes—all in the context of how seasonal and day-of-week adjustments should be made.

Combining data across states means cross-site extrapolation beyond state borders. Cross-state extrapolations are subject to site-differences attributable not simply to differences in location but also to differences in weight-limit regulation. Therefore, it is especially important that any methodology for data-sharing across state boundaries should include measures of the extrapolation error, that is, standard errors of estimates based on extrapolating. Reasonable approximate standard errors allow for decisions about whether cross-site extrapolations are adequate. In addition, error analysis can identify where resources might best be spent in improving cross-site estimates (e.g., longer monitoring at short-term sites vs. more continuous sites).

The process of converting short- or long-term WIM data or axle or classification counts into estimates of loads and other useful statistics is deceptively complex. Thus, in addition to technical defensibility, a major concern in data-sharing methodology is simplicity of operation. Concerns about operational simplicity (and cost) have lead to the interest in combining vehicle classes or roadway functional classes, and these possible simplifications should be considered in decisions about methods for data-sharing.

A reason for investigating the possibility of combining vehicle classes is that because the traffic for some of the classes is low-frequency, statistical properties of estimates (particularly the relative error) for those classes tend to be poor. (Combining the vehicle classes might improve the relative error.) In addition, validation "ground-truthing" experiments [2] have indicated that FHWA vehicle Classes 2 and 3 might well be combined because of the incapability of classification equipment to differentiate those two classes. The same rationale about statistical properties applies to roadway functional classes, and, similarly, there is doubt that some of the functional classes are sufficiently different to warrant separate consideration. (See Appendix B for definitions of FHWA vehicle classes. Definitions of the roadway functional classes considered here are in Table 1.1.)

In pursuing these objectives, certain limitations on the data structure should be understood. Table 1.1 shows that in terms of functional classes, states, and years, **the Region 1 data is convolved**: comparisons among one of these are, for the most part, not easily separated from the others. For example, out of the eleven sites, the only comparisons of states that can be based on the data and that are free from differences due to functional class or year are (1) CT990 with MA005 and (2) CT978 with RI350. All other comparisons also involve year-to-year or functional class differences. This does not leave much statistical room for directly deciding about combining data across states. Regarding roadway functional classes, there are three different functional classes in CT (7,11, and 12; all 1995), and two different classes in VT (1 and 2 for 1995 and 1996). All MA sites are Class 11, and Rhode Island has only one site (Class 12). Again, statistically, there is little basis for direct conclusions about combining functional classes.

Therefore, some simplifying assumptions about the joint behavior of state-to-state, year-to-year, and functional class differences are made in the analysis of the Region 1 data considered here. These are discussed in Section 6. Although the data suggests that for certain schemes, certain functional class combinations may be reasonable, there are substantial differences among many of the classes. The conclusion is that for the purpose of Region 1 data sharing, there is neither sufficient evidence to support nor sufficient advantage to be gained from combining the functional class system.

The data analysis discussed in Section 6, which is analysis of variance (ANOVA), does suggest and provide a mechanism for cross-site extrapolation with a formal accounting for extrapolation error. It provides tests for differences between classes of sites, such as functional classes. It is simple enough to implement with an ordinary spreadsheet program such as Excel.

Propagation of errors is discussed in Section 7. Understanding error propagation is important because error estimates indicate the degree to which load or class frequency estimates should be trusted. Error analyses also show how resources might best be spent to improve the estimates (e.g., longer short-term counting or more long-term monitoring?). Error analysis leads to the conclusion that from the perspective of long-term load estimation, there does not seem to be much advantage to combining vehicle classes. The basic idea is that although load estimates for low-frequency vehicle classes may have high relative variability, because their contributions to overall loads (i.e., combined over all vehicle classes) are so small, and because errors in the various individual estimates tend to cancel, the high variability of the low-frequency classes does little harm.

The ANOVA and propagation of error methods together form a methodology that can be used for cross-state data sharing and extrapolation, a methodology that is reasonably simple and provides an accounting for statistical error incurred in cross-site extrapolations. From the standpoint of the statistical precision of load estimates, there is no advantage to combining vehicle classes. However, the utility of the thirteen class system for regulatory purposes, economic advantages to combining classes (e.g., through cheaper classifiers), and possible disadvantages in load estimation because of information loss—each, an important issue—are not considered here.

1.3. PRIMARY CONCLUSIONS

The main conclusions of this report are

- The seasonality adjustment procedures used for overall volume data (as in the TMG) extend to adjustments of classification and WIM data as well.

- From the perspective of the statistical precision of long-term load estimates, there is little advantage to combining vehicle classes. (There may, however, be advantages in equipment error and operational simplicity.)
- There is not sufficient evidence in the Region 1 data to support combining any of the roadway functional classes.
- Data-sharing among the New England States is reasonable, as long as there is a proper accounting for the statistical error of estimates based on the common data. ANOVA provides a method for that accounting.

2. DATA SELECTION

2.1. OBJECTIVE

The first task of the project was to perform a very general data-screening of the vehicle classification and truck weight data, to assess its general quality. The purpose was to exclude any data sets which are likely to be generally problematic in the data analysis. Finer data-screening of individual data points in the data sets kept for analysis in considered in the next chapter.

Programs for reading the data and computing basic data quality checks were developed in SAS[2] and carried out on the six states' vehicle classification and truck weight data. The next step was to develop descriptive profiles of the data collected at each site and to make recommendations about sites to be used for subsequent analysis. The descriptive profiles depict the geographic location (in terms of state, functional class, and route) and the number of days for which vehicle classification or truck weight data are available. Data availability was analyzed with respect to the day of week, the month of year, and traffic direction, to determine whether missing data patterns are temporally correlated (e.g., more missing data during a winter month than a summer month). Vehicle classification and truck weight data were analyzed separately in this manner. On the basis of these analyses, sites were either kept or rejected for subsequent analysis. The evaluation of which sites were included was based on both data availability and data quality. The data sets kept for analysis are listed in Table 1.1.

2.2. THE DATA

Vehicle classification and truck weight data are available in what is known as "4-card" and "7-card" formats. Because New Hampshire does not have permanent data-collection sites, this research is limited to data from the other five New England States. Table 2.1 summarizes the number of locations where vehicle classification and weigh-in-motion (WIM) data are available by state.

Vehicles were categorized into thirteen vehicle types by all states except Maine. Maine's data is grouped into the identical thirteen types plus two additional categories: "other" and "unclassified." Vehicles in the "other" category are those in which the classifier presumably recognizes the vehicle type, but is not one of the thirteen types. All counts in this "other" category are zero. Vehicles in the "unclassified" category are those which the classifier does not recognize the vehicle type.

The vehicle classification recorders have the flexibility of not recording motorcycles or recording passenger cars and 2-axle, 4-tire single units collectively. Our assessment indicates that motorcycles are counted, and passenger cars and 2-axle, 4-tire single units are counted separately.

Because of the great volume of hourly classification data, quality checks were implemented on counts that were condensed to a daily basis. The condensed file is between 5 percent and 10 percent

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[2] SAS is a registered trademark of SAS Institute Inc., Cary, NC, USA.

of the size of the hourly file. This is an important practical consideration for traffic data quality checking. The benefit of analyzing hourly data seems insignificant compared to the extra effort involved. As another way of reducing the volume of data, lane-specific data were combined to give estimates of total directional traffic flow.

Table 2.1. Number of Locations Where Vehicle Classification and Weigh-in-Motion Data are Available 1995 and 1996

State	1995		1996	
	Classification	WIM	Classification	WIM
Connecticut	4	4	0	0
Massachusetts	9	9	9	9
Maine	2	0	2	0
Rhode Island	1	1	4	4
Vermont	8	8	8	8
TOTAL	24	22	23	21

The decision about which sites to include in subsequent analysis is based on both data quantity and data quality. Data quantity is evaluated from the perspective of missing data. Patterns for missing data are analyzed graphically with respect to the day of the week and traffic direction. If classification data are collected for at least a single hour during a day, the day is considered "non-missing." A day is considered non-missing for WIM data as long as the weight of one truck is recorded during the day. Figure 2.1 is an example of a missing data plot.

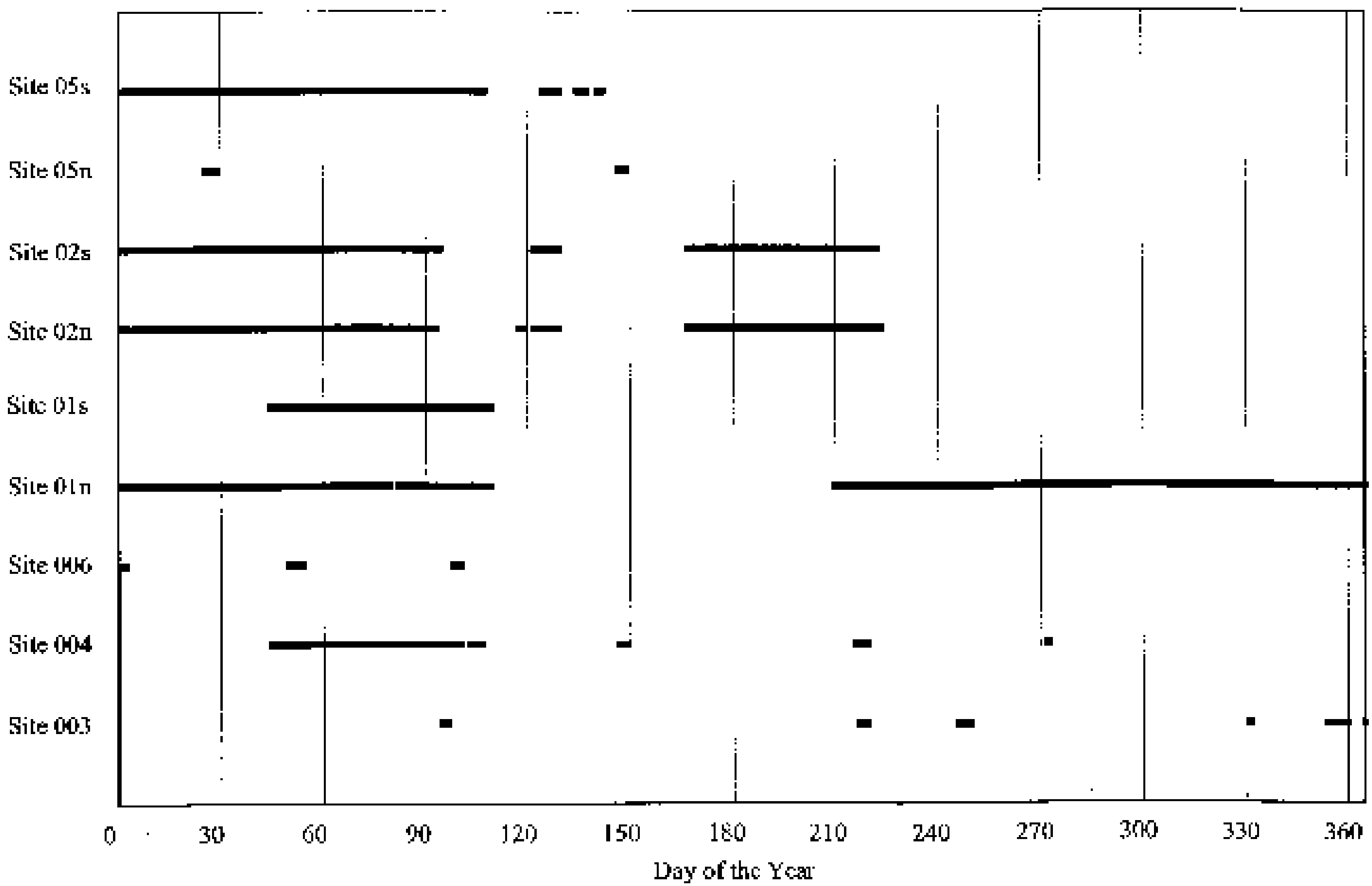
2.3. DATA QUALITY CHECKS

Based on recommendations published in *AASHTO Guidelines for Traffic Data Programs*, vehicle classification data were subjected to three different data-quality checks. The first check compares the daily volume of cars (Class 2) to that of 2-axle, 4-tire single units (Class 3). The rationale of this check is that if the number of 2-axle, 4-tire trucks is equal to or greater than the number of cars, then this may signal a number of equipment problems: (1) improper road tube spacing, (2) unmatched tube lengths, or (3) malfunctioning switches.

The second edit check puts the total traffic volume and vehicle classification distribution into a temporal context. The temporal context is checked by comparing the combined daily volume of cars (Class 2), 2-axle, 4-tire single units (Class 3) and 5-axle single trailers (Class 9) to historical

Figure 2.1. Example of missing data plots.

(Block Means Missing Day)



volumes. According to the AASHTO's guidelines, the combined volume of these three vehicle types should not vary by more than 15 percent when compared to historical data. With this 15 percent criterion, data for many of the days were "flagged" for further investigation. Consequently, ORNL developed a set of criteria that are location- and day-of-the-week specific.

First, the percent change between two consecutive days was calculated. Any daily change greater than 300 percent was considered an outlier and deleted from subsequent calculations. Next, the average daily change and the standard deviation were calculated for: (1) Friday to Saturday, (2) Saturday to Sunday, (3) Sunday to Monday, and (4) among weekdays. The reason for developing different criteria for specific days of the week is that a previous study has confirmed that the day of the week affects traffic volume. Days that record a percent change greater than the average percent change plus three standard deviations were thus "flagged" for further investigation. As an example, Table 2.2 shows the acceptable limits of percent daily change for Massachusetts Site 003 in 1995. For example, the combined volume of Classes 2, 3 and 9 was recorded at 3,526 on September 18, 1995 while the similar count for the previous day was 1,905, resulting in a percent daily change of 85 percent. Since September 17, 1995 was a Sunday and September 18 a Monday, the acceptable percent change is 77.7 percent (Table 2.2). Since 85 percent exceeds the acceptable level of 77.7 percent, September 17 and 18 were flagged for further checks.

Table 2.2. Acceptable Limits for the Percent Daily Change in Volume Classes 2, 3 and 9 for Massachusetts Site 003, 1995

Time Period	Acceptable Limit
Among weekdays	42.9%
Friday to Saturday	55.8%
Saturday to Sunday	56.4%
Sunday to Monday	77.7%

To assure temporal consistency with respect to traffic volume, the third data-quality check identifies days where total traffic volume by day of the week exceed three standard deviations from the mean. Daily traffic volumes were plotted by day of the week, and attention was focused on those days where total traffic volume is either too large or too small compared to those collected at the same day of the week. Again, using data from Massachusetts Site 003 as an example, Table 2.3 presents its lower and upper bounds by day of the week. Because the total volume in April 4, 1995 (Tuesday) was 2,099, which falls outside the acceptable range of 2,356 to 4,546, April 4, 1995 was flagged. Our subsequent investigation found that only 16 hours of data were collected on April 4.

WIM data were subjected to two different data-quality checks. The weight distribution of 5-axle semi-tractors is typically a bimodal distribution with one concentration between 28,000 to 32,000 pounds for unloaded vehicles and another between 70,000 and 80,000 pounds for loaded vehicles. For states allowing vehicles heavier than 80,000 pounds, a second concentration will be at 100,000 pounds which is the highest weight category (i.e., any vehicles heavier than 100,000 pounds are labeled ">100,000 pounds"). This knowledge is used to assess the quality of truck weight data. The reason for using five-axle single trailers for WIM data editing procedure is that this type of vehicle is considered to have the greatest impact on pavement deterioration. Sites where the distribution of 5-axle semi-tractors is not bi-modal were flagged for further investigation. Figure 2.2 shows an example of valid WIM data while Figure 2.3 shows a set of invalid WIM data.

Table 2.3. Lower and Upper Limits of Total Traffic Volume for Massachusetts Site 003, 1995

Day of Week	Lower Limit	Upper Limit
Sunday	1,754	2,733
Monday	2,543	4,229
Tuesday	2,356	4,546
Wednesday	3,054	4,275
Thursday	2,675	4,511
Friday	2,380	4,990
Saturday	1,663	3,970

When WIM data are collected for less than 2,500 5-axle single trailers, data for 2-axle, 6-tire single units (Class 5) are used. The typical distribution of these vehicles is unimodal with a mode around 8,000 pounds (or 8 kips). Figure 2.4 shows a set of valid Class 5 WIM data.

The second WIM data check for was based on the weight distribution of the front axles. The front axle weights are grouped into three categories:

Gross Vehicle Weight	Average Front Axle Weight
< 32,000	8,500
32,000 - 70,000	9,300
> 70,000	10,400

Figure 2.5 displays both valid and invalid data. Weeks 1–10 and 45–53 appear invalid due to their erratic pattern. The remaining weeks display relatively level points which indicate valid data.

Figure 2.2. Example of Valid Weigh-in-Motion Data
N = 7855

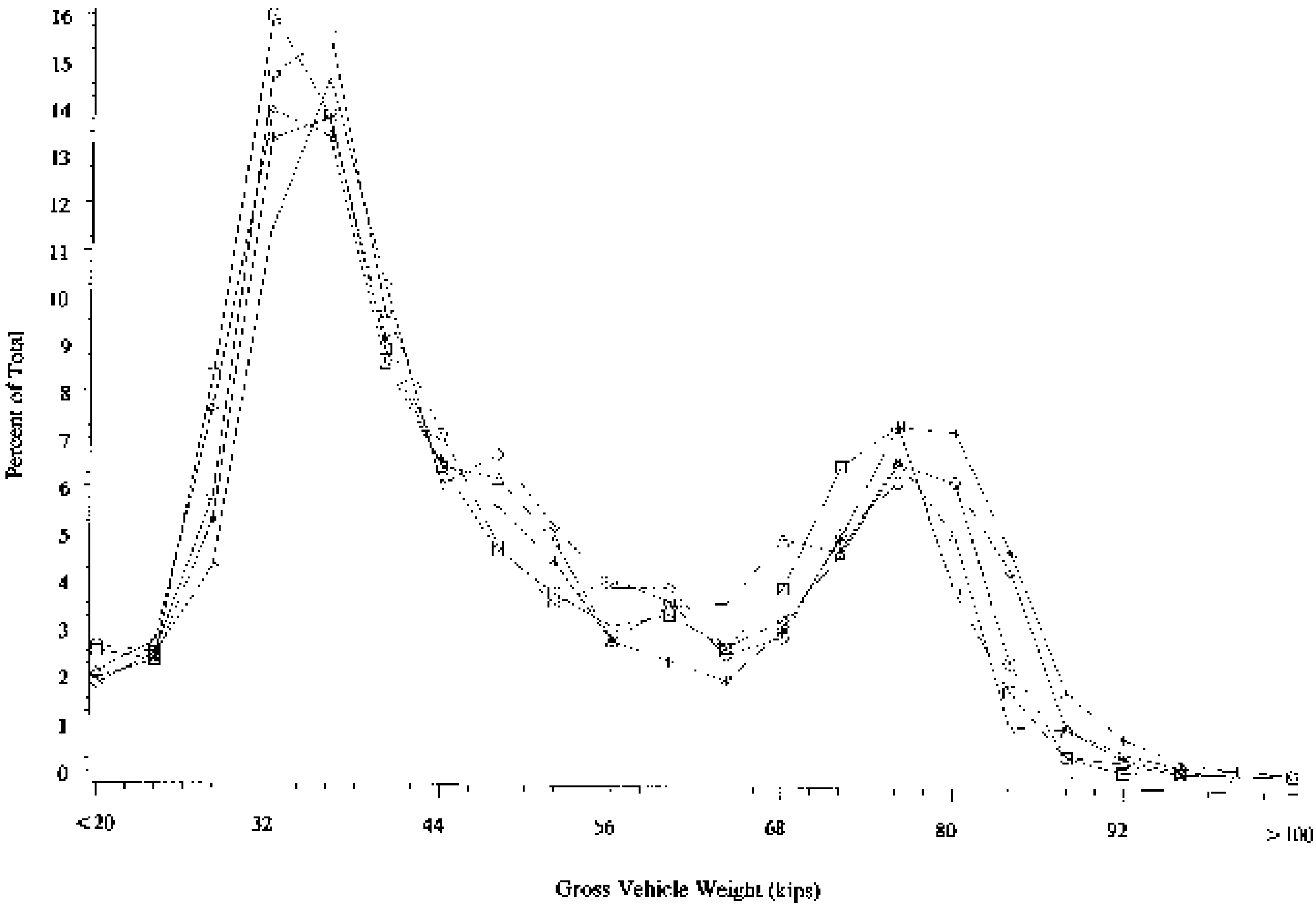


Figure 2.3. Example of Invalid Weigh-in-Motion Data
N=36697

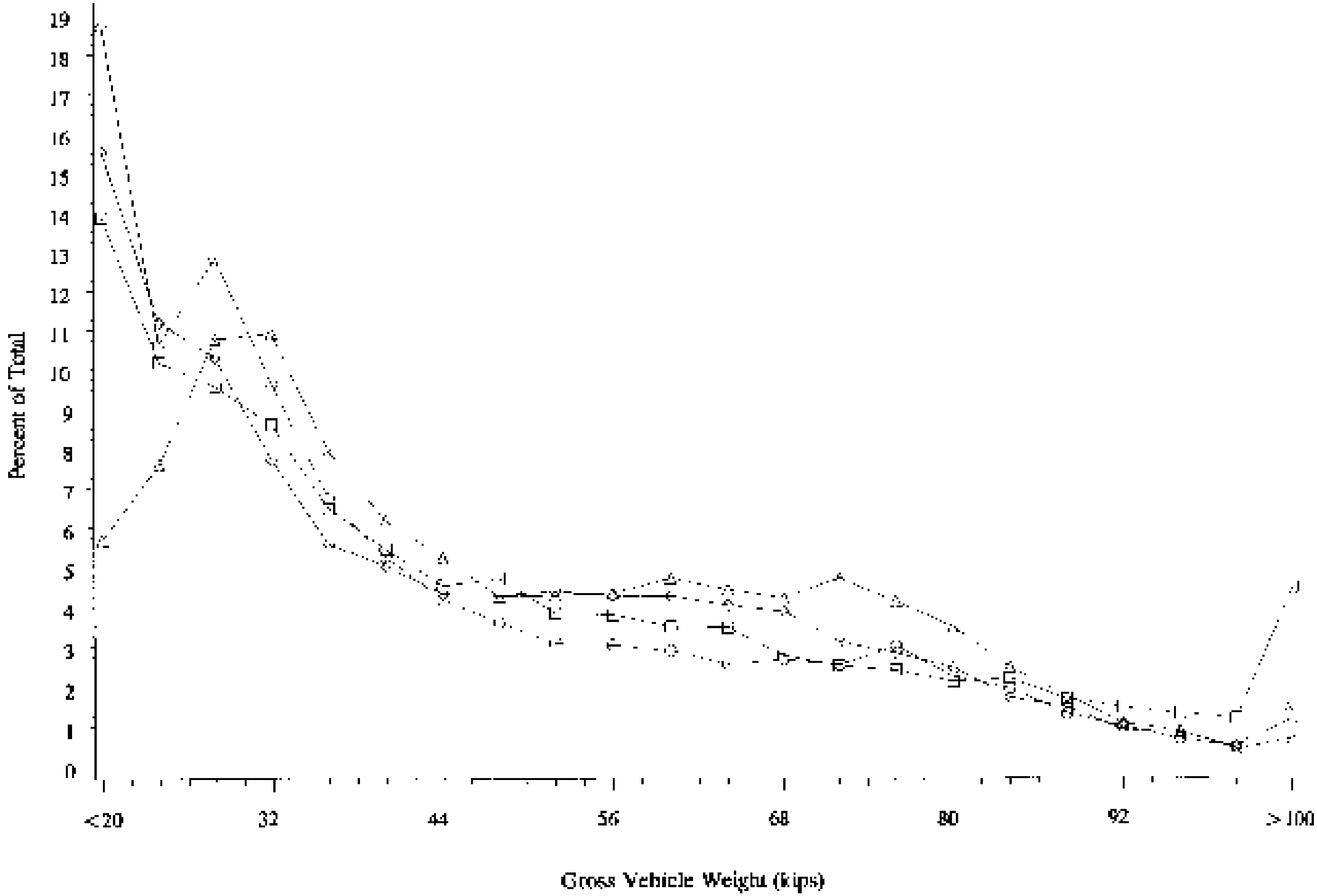


Figure 2.4. Example of Valid Class 5 Weigh-in-Motion Data
N=7510

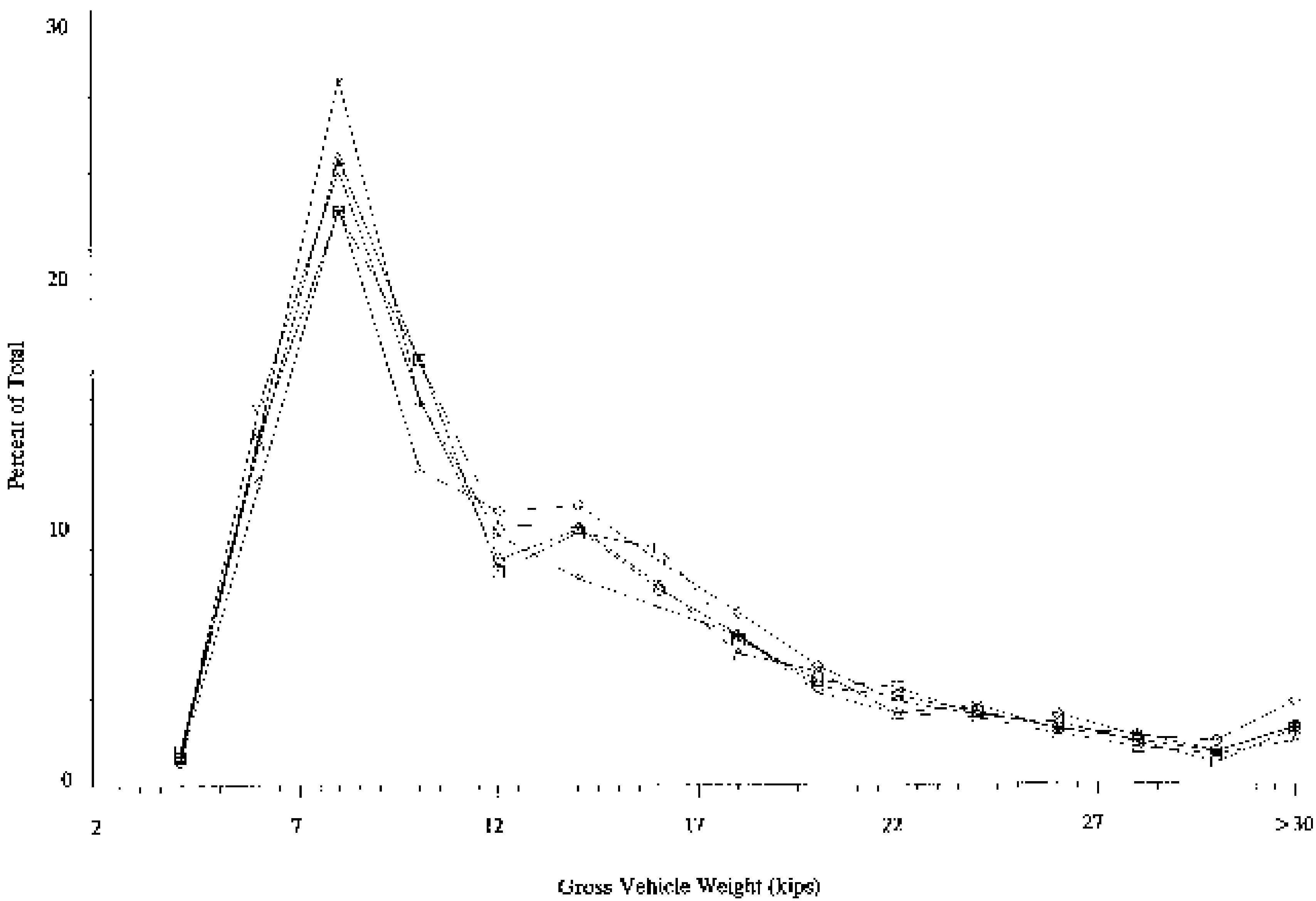
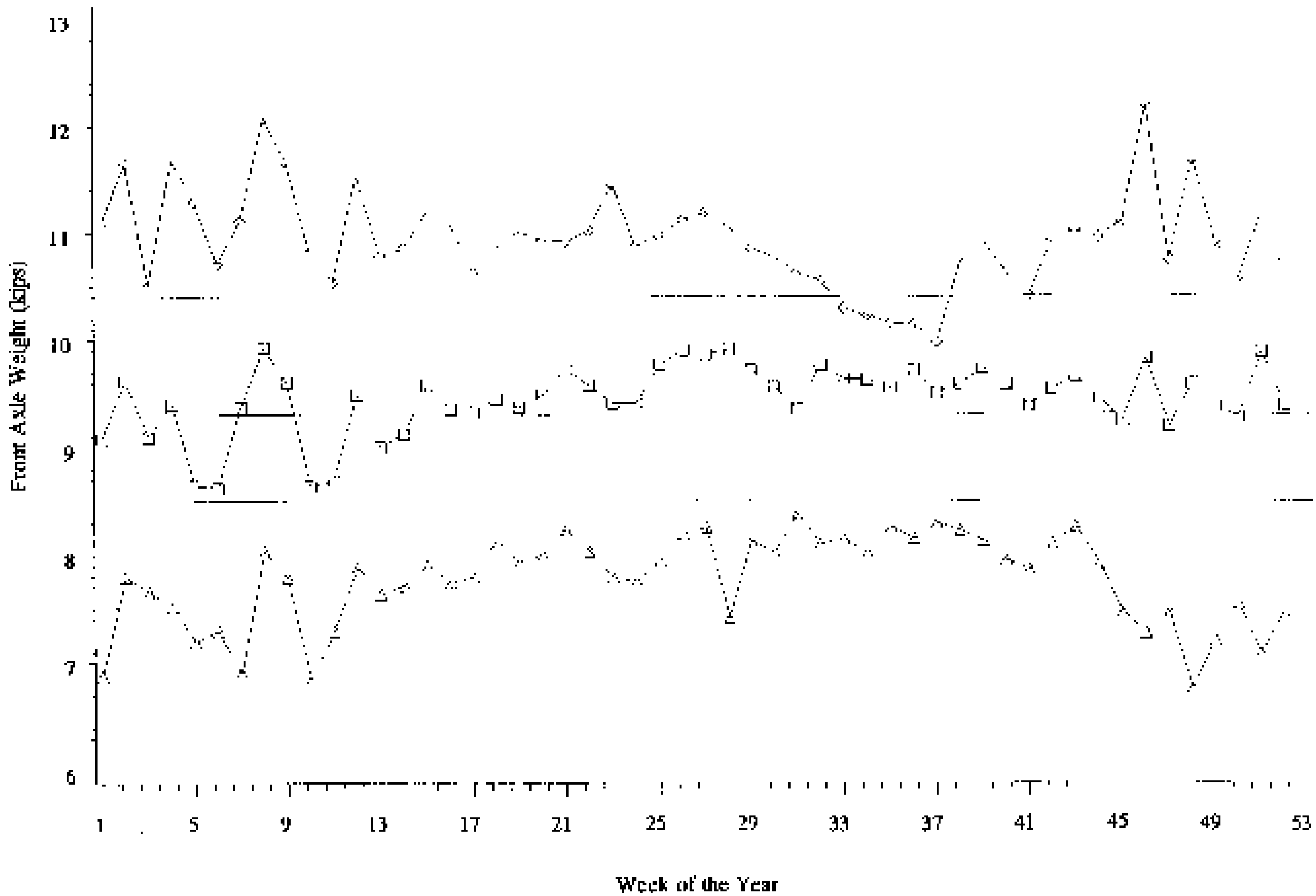


Figure 2.5. Example of Valid and Invalid Front Axle Weight



3. FURTHER DATA QUALITY CHECKS

The preliminary data checks discussed in Section 2 were more extensive and more formal for the classification data than for the WIM data. The checks for the classification data had explicitly defined rejection criteria, whereas the checks for the WIM data were graphical and more subjective. Therefore, although the preliminary checks for both the class and WIM data were used to decide whether to keep or exclude the class or WIM data for entire site-years, the same basic checks for the class data were also used as a basis for excluding smaller sections from the "kept" data. For the WIM data, a number of additional checks were made. The additional WIM data checking was done in two steps: (1) comparing data values to internal and external references checks, and (2) serial checks and graphical inspection.

3.1. CLASSIFICATION DATA

For the sixteen classification sites, an overall AADT estimate was computed for each site. First, results for all days were adjusted to a 24-hour basis (by dividing the counts by the number of hours and multiplying by 24). Second, the third classification check discussed in Section 2 was repeated on these modified data. This classification check flagged days which had total volume counts which were too high or too low. Any day whose count was more than three standard deviations away from the mean was further examined for a possible explanation (i.e., an increase or decrease in traffic volume due to a holiday). Data for days which could not be explained were generally set to missing. However, if there were only one or two such days, they were left in under the assumption that some days will fall outside of the "acceptable" range just by chance. Table 3.1 displays the days of data thus removed for each site.

3.2. WIM DATA

The truck WIM data for the sites listed in in Table 1.1, received from the states in FHWA’s “7-card” format [1], contains records for a total of 12,936,146 trucks:

State	Number of truck records
CT	1,264,845
MA	7,438,238
RI	1,276,305
VT	2,956,758
All	12,936,146

It consists of identification data (site, date, vehicle class, etc.), and axle spacings and weights in units of feet (in tenths) and pounds (in hundreds). Additional WIM data checks were performed in two steps: (1) comparing data values in internal and external references checks, and (2) serial checks and graphical inspection.

Table 3.1. Days for Which Classification Data Is Set to Missing

Site	Year	Days Set to Missing*	Site	Year	Days Set to Missing*
CT 974	1995	February 4	MA 05s	1996	April 26, April 27, April 28, April 29, April 30
CT 978	1995	February 4, March 15, March 16, March 17, March 18, March 19, March 20, March 21, March 30, March 31, April 1, April 2, April 3, April 7, April 8, July 17	RI 350	1995	February 4, June 16, December 9, December 20
CT 990	1995	January 12, February 4, November 22, December 11	RI 350	1996	January 3, January 8, June 11
CT 991	1995	February 4	VT 132	1995	
MA 003	1995	February 4, July 28, September 2	VT 132	1996	January 3, November 26
MA 003	1996	February 4, February 5, February 14, March 10, April 10, December 31	VT 249	1995	February 4 (E)
MA 004	1996	March 10	VT a41	1995	
MA 01n	1996	January 18	VT a41	1996	December 22, December 25, December 26
MA 01s	1996	April 23	VT n01	1995	July 27 (N), July 28 (N), July 29 (N), July 30 (N), July 31 (N), August 1 (N), August 2 (N), August 3 (N), August 4 (N), August 5 (N), August 6 (N), November 1 (S), November 2 (S)
MA 02n	1996	January 15, December 8, December 12, December 31	VT r01	1995	
MA 02s	1996	January 15, December 8	VT r01	1996	
MA 05n	1995	January 11, January 12, January 25, January 30, February 4, December 9, December 14, December 20	VT x73	1995	July 26
MA 05n	1996	March 7, December 31	VT x73	1996	
MA 05s	1995	April 18, November 29, December 9, December 14, December 20			

*A letter in parentheses following a date indicates the data were set to missing for that direction only.

Occasional anomalies **were** turned up here and there. The general policy taken, however, was to try to make as few changes to the WIM data as possible. Even if some of the anomalies are human artifacts, they reflect noise in the data collection process and therefore were not automatically discarded.

For the internal and external data checking, data checks were coded into a SAS program, along with calculations to determine axle-groupings (single, tandem, tridem, etc.) from axle spacings, and to determine the FHWA 13-class classification from a 6-digit class encoding used in the data. Axle groupings were computed by comparing axle spacings to the limits in Table 3.1. The conversion to the 13-class system was made by translating to SAS the algorithm used in the Office of Highway Information Management's VTRIS [4] software (as coded in the gm.pas Pascal program kindly provided by Ralph Gillman). A SAS macro for this conversion is in Appendix E. It happens that the six-digit class encoding for a particular truck actually implies the total number of axles the truck has. This provides one internal consistency check, because the number of axles is also a specific data entry.

The VTRIS software also performs several data checks: for minimum and maximum axle weights, minimum and maximum axle spacings, and total wheelbase. These checks were also done for the Region 1 data, using the VTRIS default limits, which are in Table 3.2. Axle weights recorded as zero were set to missing. (Zero-weight axles were common—see Table 3.2.) Of the almost 13 million vehicle records, 101 (.0007 percent) had no axles with positive weight. These records were deleted from the data, under the assumption that a proportion this small is not of practical importance.

Table 3.2. VTRIS Default Limits*

Minimum axle weight	.441 kips
Maximum axle weight	44.1 kips
Minimum axle spacing	1.64 feet
Maximum axle spacing	49.2 feet
Total wheelbase	98.4 feet
Axle spacing for tandem	8 feet
Axle spacing for tridem	8-10 feet
Axle spacing for quad	10-12.5 feet

*Values from VTRIS software [4], converted from metric equivalents (because pounds and feet are used in the input data for this report).

Positive axle weights above the 44.1 kip limit were set to 44.1, the rationale being that (1) there is no valid basis for excluding the axle data entirely, (2) replacing the high values with the VTRIS limits would bring them closer to the true axle weight, and (3) replacing the high values in this way (similar to statistical Winsorizing[3] [5]) allows them to be counted as "high," and yet prevents them from acting as outliers with undue influence on the overall calculations to be made in our data analysis. This is important, as heavy axles have tremendous impacts on pavements. Similarly, axle weights less than .441 kips (VTRIS default upper limit) were set to .441. In this case, including or excluding the low-weight axles is probably not critical, because of their minimal impacts on pavements. Similar changes were also made for the axle spacings, though the number of such changes was extremely small.

Internal consistency checks involved comparing: (1) the gross vehicle weight as a specific data entry, to gross vehicle weight computed by summing individual axle weights; (2) the total wheelbase specifically entered in the data, to the sum of individual axle-spacings; (3) the number-of-axles specifically entered in the data to the number of axles having positive weight and to the number of axles implied by the six-digit code.

With one exception, these quality checks turned up very few data problems, and the problems were scattered among all of the sites. An overall summary of these checks is in Table 3.3. The exception was for positive axle weights less than .441 kips. Of 38,843 of these, 8,131 occurred for CT site 974, which is on a two-lane road, and one of the smaller traffic-volume sites. This aspect of CT974 will be considered in the data analysis and interpretation discussed in Sections 4 and 5 of this report.

Of over 45 million axles with positive weight, 1,524 (.003 percent) appeared to be from a vehicle having only one axle. Because these likely represent real axles counted as separate from the rest of their corresponding vehicles (and should thus be counted as contributing to overall loads), and because their occurrence is very rare, these "singletons" were not thrown out.

Axle combinations were computed by comparing axle spacing sums to the default limits in Table 3.2: Starting with the front axle, spacings were added until the axle-spacing limit was exceeded for the corresponding number of axles. That axle number, less one, is the number in the combination.[4]

The second step in the WIM data quality checking, was to perform serial and graphical data checks: For each site, direction, and year, daily average GVWs were plotted over time, and marked, using a changepoint algorithm, wherever appreciable jumps or changepoints—possibly bad data—seemed to occur. The changepoint algorithm is based on the statistic:

$$T = 200 \times \left| \frac{\text{mean for two weeks post} - \text{mean for two weeks prior}}{\text{mean for two weeks post} + \text{mean for two weeks prior}} \right|,$$

[3]In Winsorizing, data values that exceed a certain percentile (e.g. the 95 percentile) or are less than a percentile (e.g., the 5 percentile) are set to the percentile value. Here, rather than a percentile, an a priori reasonable choice (e.g., 44.1 kips) is used for the threshold value.

[4]Combinations up to 6+ were computed using cutoff values of 16.67 (quad), 20.83 (quint), 25 (six+). No doubt some of the higher combinations are flukes, but there were extremely few of them. (See Figure 3.6.)

evaluated at each point in the data series. A change in the series is suggested at any point for which the mean for the last two weeks is appreciably different from the mean for the next two weeks. "Appreciably different" must be defined, of course, and should achieve a reasonable balance of false positives and false negatives. Here, after several trials, "appreciably different" was defined as "greater than 15 percent." It can be shown that the statistic T is actually a *cusum* (cumulative sum) statistic from statistical quality control theory [6].[5]

Table 3.3. Summary of Data Quality Checks

Records (trucks)	12,936,146
Records deleted (no axles or no weights)	101
Axle weights set from 0 to missing	20,234,829
Positive-weight axles	45,882,532
Axle weights > 44.1 kips	6,450
Axle weights < .441 kips	38,843
Axle spacings > 49.2 feet	40
Axle spacings < 1.64 feet	66
Axle combinations > 7	5
Number-of-axle discrepancies	3,336
Trucks with fewer than two axles	1,524
Wheelbase discrepancies	148
GVW discrepancies	417
Class 14 or 15 (unclassified in input data)	0

Two of these plots, for MA site 001 North, 1996, and MA site 02N (North), 1996[6] are in Figures 3.1 and 3.2. Appreciable changes are marked in red. There are no appreciable change points in the series for site MA001, but there is a change in the series for site 02N, near the beginning of

[5]Many variations on *T* have also been considered. For example, the denominator may be based on a standard deviation rather than an average, (prior+post)/2, as above.

[6]These series are actually for the periods March 1996 to March 1997.

November 1996. Other anomalous behavior at site 02N is revealed in some of the plots discussed below.

The change in the 02N series is evident from the data itself—the red marks are not really necessary in this case. Nevertheless, cusum markings can be a convenient way to draw attention to possible data problems, especially since it can be applied as data is downloaded from data loggers, even before careful graphical inspection would be possible.

The cusum plots for all twenty eight site-direction-years are in Appendix C. Because there is considerable variability in the GVW signals, the cusum-graphical approach occasionally points to changes that appear, upon graphical inspection, to be within the range of ordinary noise. Nevertheless, the approach does seem to point to similar data problems for sites CT974, MA005 North (1995 and 1996), VTr01 East (1996) and VTx73 South (1996). Again, this behavior will be considered in the data analysis and interpretation discussed later in this report. In view of the considerable variability in these series, however, occasional blips and anomalies may not be so anomalous after all. Therefore, it is important to account for this kind of variability in any statistical analysis of the data.

Several other plots were also made as data quality checks. These are in Figures 3.3, 4, 5, and 6. Figures 3.3 and 3.4 are plots of axle-weight and GVW percentiles at each site. For example, in Figure 3.3, the green dots indicate the median (50^{th} percentile) axle weight for each site-year. The red dots indicate percentiles less than the median (e.g., 10^{th}), and the blue dots indicate percentiles greater than the median (e.g. 90^{th}). (See figure legends.) Some of the dots may be coincident and hence not shown. The dots show the location and spread of axle weights and GVWs for each site and year, and thus allow for a comparison of site-years. The most substantial differences are at the two sites mentioned above, CT974 and MA02N.

Figures 3.5 and 3.6 are plots of percentages, rather than percentiles. Figure 3.5 is of vehicle class percentages at each site, and Figure 3.6 is of axle-combination percentages. In Figure 3.5, for example, the green dots show the percentages of Class 5 vehicles at each site. Figures 3.5 and 3.6 allow for two more ways to compare sites.

For Figure 3.5, the strongest indications of any anomaly are again at site CT974, and, particularly, MA02N. Table 3.4 shows that the average load per truck is much smaller at sites CT974 and MA02N than at the other sites. Figure 3.6 does not indicate any sites that are anomalous in terms of the percentages of each axle combination (single, tandem, etc.). The proportion of quints, and especially, 6+ combinations does seem anomalous, however, and is likely indicative of problems in spacings measurements or in our algorithm for defining high-order combinations. Fortunately, the five and 6+ combinations occur only about .001 percent of the time. They are assumed negligible for the purposes of this report.

Table 3.4. Truck Statistic Averages by Site

Site	Average trucks per day	Average load per day (kips)	Average load per truck (kips)
CT974	190	1,855	9.8
CT978	600	18,017	30.0
CT990	3,428	137,294	40.1
MA001	9,416	308,294	32.7
MA005	5,446	167,363	30.7
MA02N	212	3,463	16.3
RI350	1,768	73,711	41.7
VTD92	1,418	54,690	38.6
VTN01	858	35,683	41.6
VTR01	857	38,670	45.1
VTX73	1,525	65,601	43.0
All	2,321	82,207	35.4

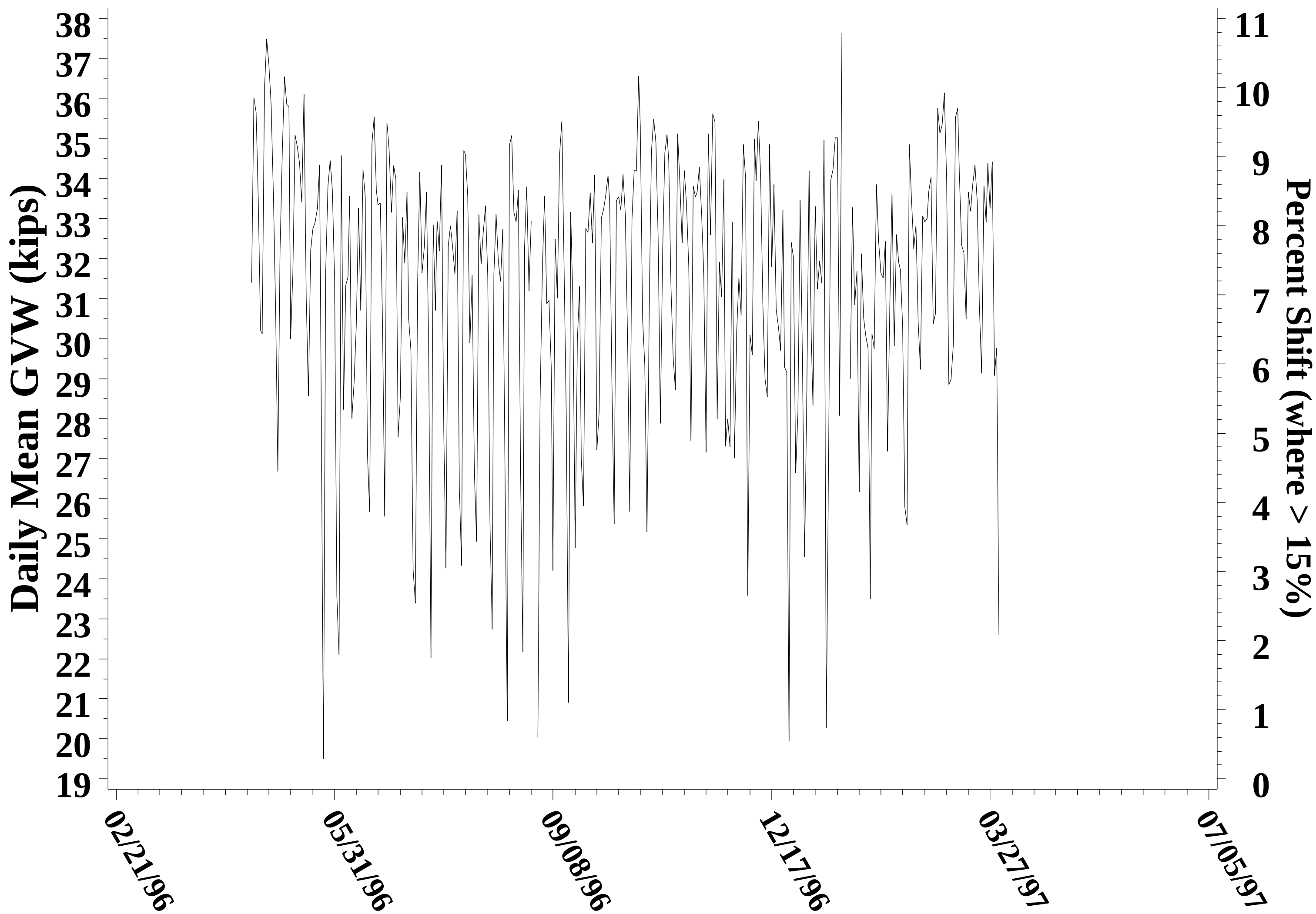


Figure 3.1. Daily mean GVWs for Massachusetts site 001 North (1996). There were no appreciable changepoints in this data.

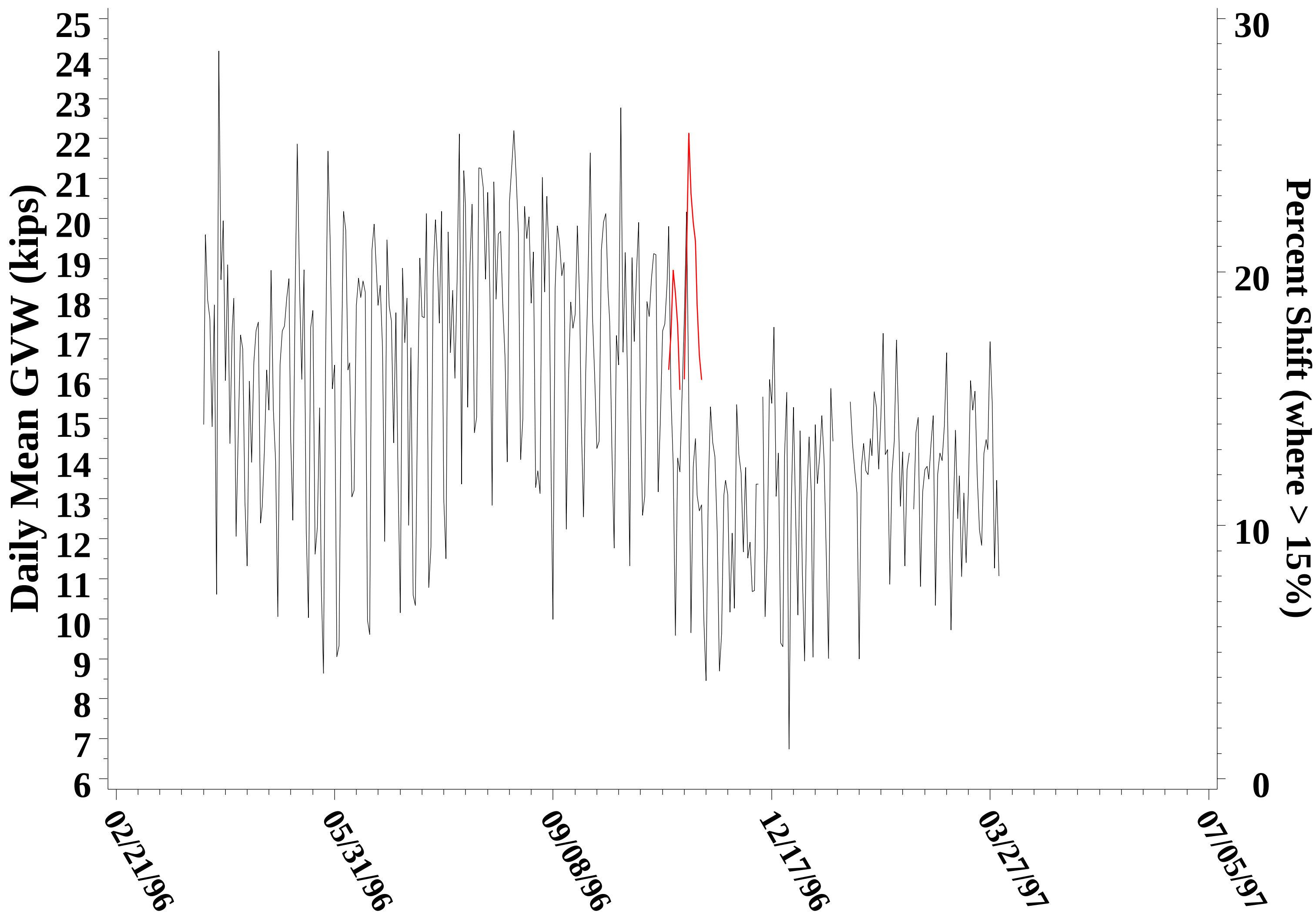


Figure 3.2. Daily mean GVWs for Massachusetts site 02N (1996). A likely changepoint is indicated in red.

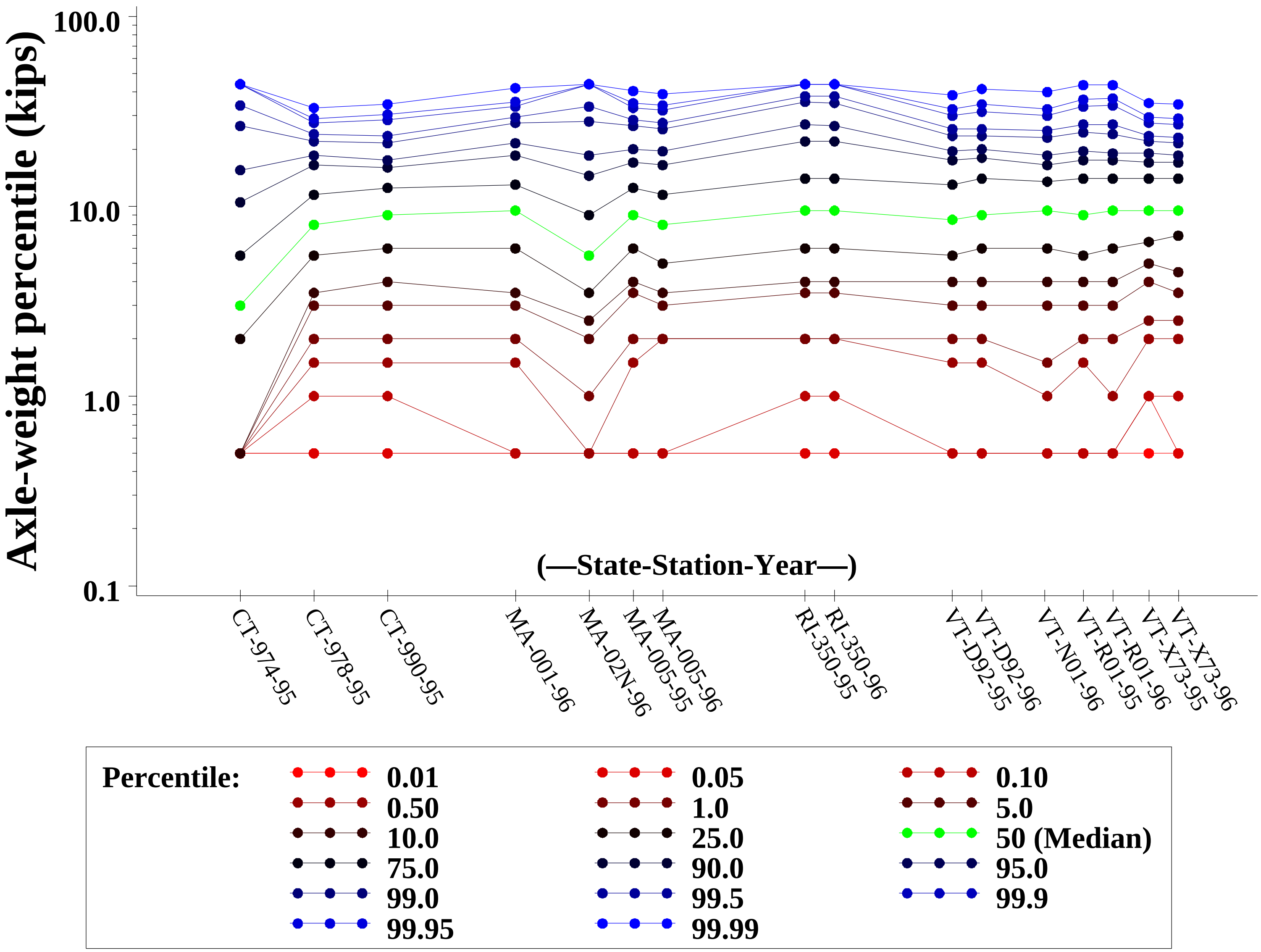


Figure 3.3. Axle weight percentiles by site and year. These are for individual axles, not combinations.

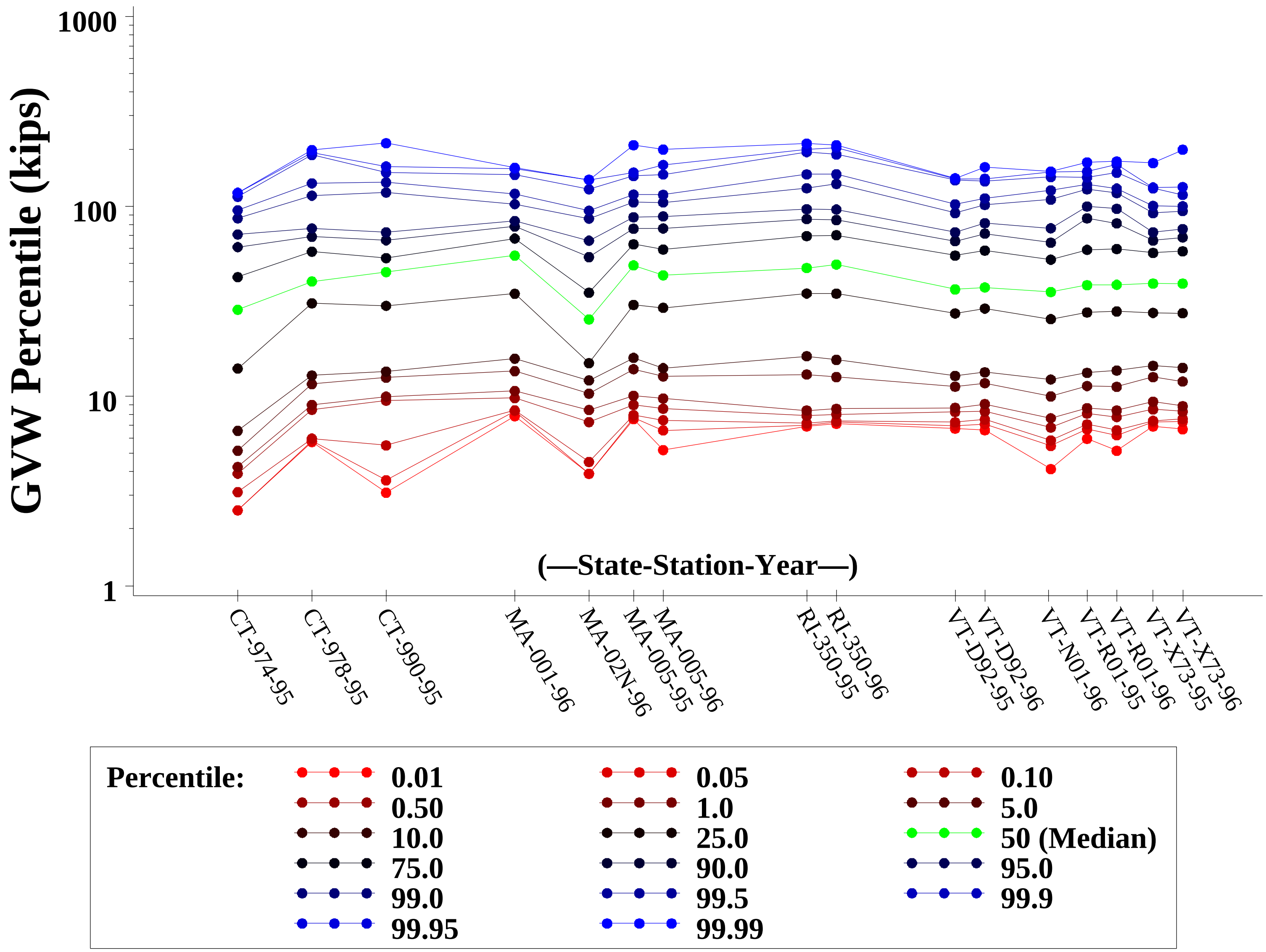


Figure 3.4. GVW percentiles by site and year.

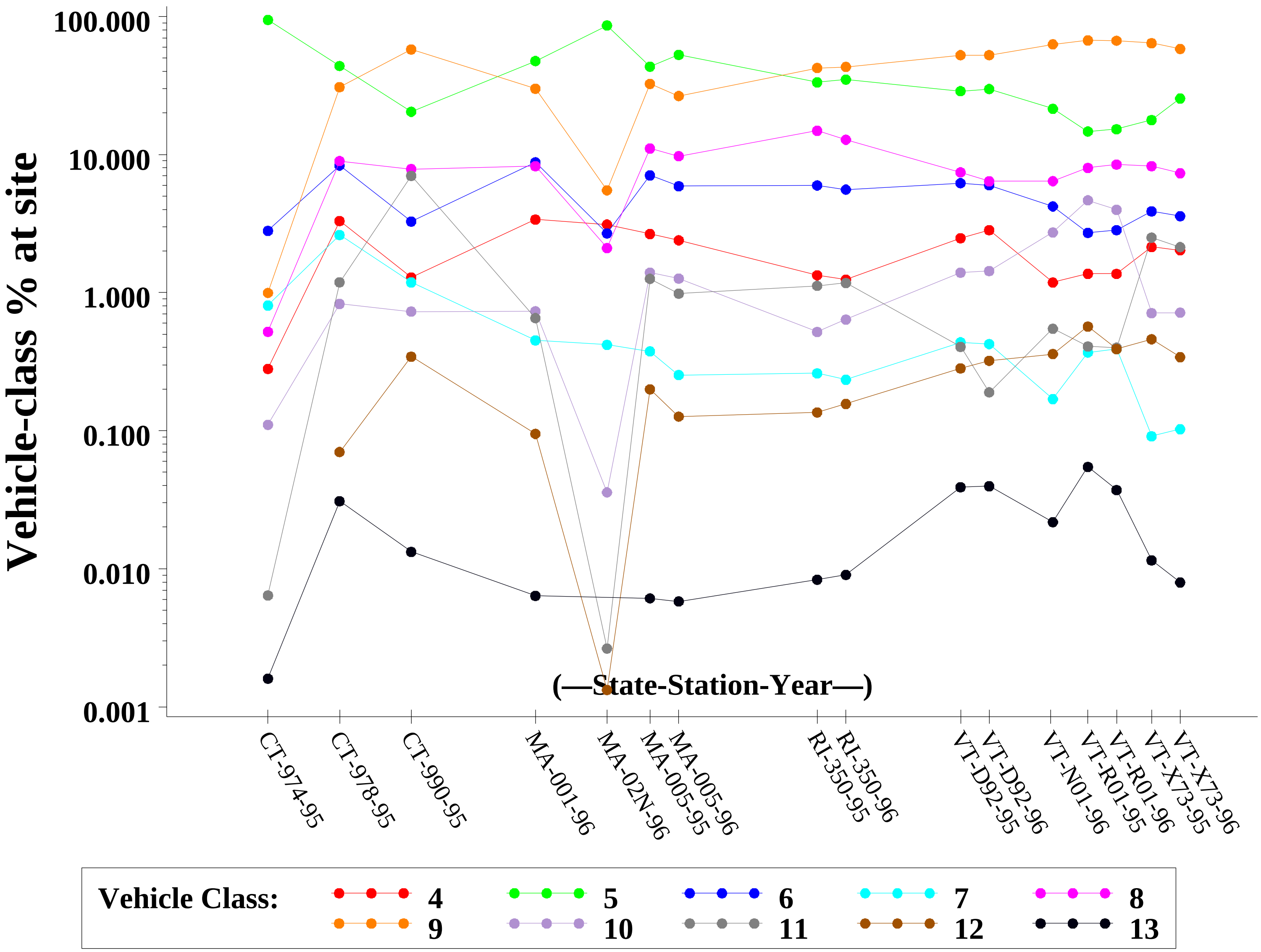


Figure 3.5. Vehicle class percentages by site and year.

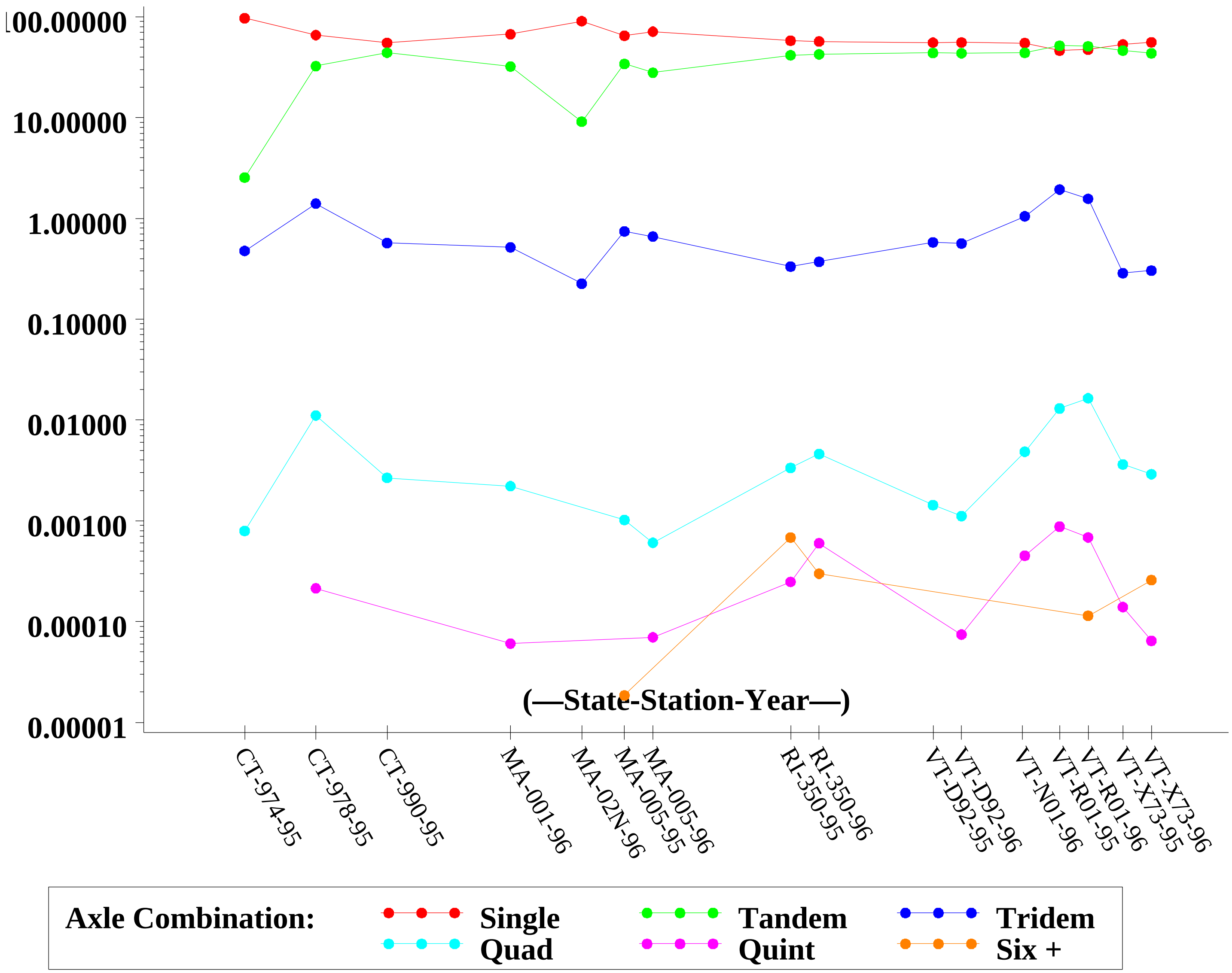


Figure 3.6. Axle combination percentages by site and year.

4. SEASONALITY ADJUSTMENTS FOR CLASS AND WIM DATA

This chapter is about seasonality and day-of-week adjustments for WIM and class-specific traffic volume data. Several plots illustrate important differences in overall and class-specific traffic volumes and the need to adjust for those differences. The approach to seasonal or day-of-week adjustments taken here is logically equivalent to the approach for overall traffic volumes, prescribed in the TMG and also discussed in Appendix A. The idea is to compute a ratio of average annual daily X (e.g., traffic volume) to the average daily X for a particular day or days. That ratio is the adjustment factor:

$$\text{AF} = \frac{\text{Average annual daily X}}{\text{Average daily X for particular day or days}}.$$

In theory, when the AF is multiplied by a new average daily X from a new site but for the same short-term period, the product is adjusted to an annual basis. The AF is unit free but can be interpreted as average annual daily units of X per average daily unit of X for the short-term period. Of course, the AF is computed from long-term data for which both average annual and individual daily values of X are available.

This same logic applies whether X is overall volume, class-specific volumes, ESALs, or loads. The "in theory" part of the adjustment is due to the extrapolation of long-term results to new, short-term sites. This part of the problem is more complex than the logic of seasonal or day-of-week adjustments once the appropriate long-term reference sites are established. The appropriate choice of reference sites, which entails appropriate definitions of roadway functional classes, is discussed in Sections 6 and 7.

The "particular day or days" could be a month, a month-by-day-of-week combination (e.g., June Tuesdays), or an individual day (e.g., June 1st). In this report periods are taken to be month-by-day-of-week combinations. This is consistent with the TMG (p 3-3-17). The average is simply the total divided by the number of days for the period (or year).

When AFs are computed from multiple sites, the "averages" in the AF definition require qualification for the AF is to be uniquely defined. (There is more than one way to define the average.) This is discussed in Appendix A. In this report, average AFs are the arithmetic means of AFs, computed as above for individual sites.

For example, consider Table 4.1 of average daily counts for August Wednesdays for vehicle Class 5 (2-axle, 6-tire SUTs) and sites in functional Class 12 (principal arterial other freeways/expressways).

Table 4.1. Average Daily Counts for August Wednesdays, Vehicle Class 5, Functional Class 12

Site	Direction	Year	August Wednesday Avgerage	Class 5 AADT	AF
CT978	W	95	379.80	278.81	0.7341
RI350	N	95	255.00	205.88	0.8074
RI350	N	96	294.00	250.07	0.8506
RI350	S	95	317.40	377.00	1.1878
RI350	S	96	495.33	410.10	0.8279

AFs are also given in the table, which are the ratios of the Class 5 August Wednesday Averages to the Class 5 AADTs. The overall average AF for functional Class 12, then is

$$\frac{.7341 + .8074 + .8506 + 1.1878 + .8279}{5} = .8816.$$

Analysis of variance, which is discussed in Section 6, is a convenient way of computing these arithmetic means as well as other useful output (e.g., standard errors).

Now suppose that at a new functional Class 12 site, on an August Wednesday, a single-day count is taken and turns out to be 285. To adjust that count to an annual basis, multiply by .8816: 285 $\times$.8816 = 227.5. Although this example is for vehicle Class 5, the above approach clearly applies as well to total volume counts. The overall volume AF for functional Class 12 was determined to be .8701.

If only axles are counted at a short-term site, it becomes necessary to convert the pulse count into a total traffic volume estimate. This is done with an axle correction factor:

$$CF = \frac{\text{total vehicle count for year}}{\text{total axle count for year}},$$

which is applied like an AF (see Appendix A). CFs can be computed from long-term axle counts, WIM data, or perhaps class data. In the last case, an approximation is needed, because five of the thirteen vehicle classes allow multiple axle counts. For example, Class 7 admits any single-unit truck with four or more axles. For these vehicle classes, the number of axles can be taken as in the following table.

Vehicle Classification	Actual Number of Axles	Number of Axles Used in Computing Total Axle Count
7	Four or More	4
8	Four or Less	4
10	Six or More	6
11	Five or Less	5
13	Seven or More	7

For example, suppose that at a short-term monitoring site, 20,000 pulses are observed in a 24 hour period. Using the above approach, it was determined that there are .470 axles per vehicle for functional Class 12 sites. Therefore, the 20,000 pulses translate to $.470 \times 20{,}000 = 9{,}400$ vehicles. Suppose the 24 hour period is an August Wednesday. Because the August monthly AF for functional Class 12 is .8701, the 9,400 vehicles translate to an overall AADT estimate of $9{,}400 \times .8701 = 8{,}179$ vehicles per day.

Figures 4.1 illustrates the pronounced effect of month on Class 2 (passenger car) volumes. Figure 4.2 illustrates the effect of day-of-week on truck Classes 5 and 9, for loads in this case, rather than volumes. Effects such as these, and the relatively straightforward nature of the seasonal and day-of-week adjustments suggests that these adjustments should be made as a matter of course, unless there is clear evidence to suggest the adjustments are not needed.

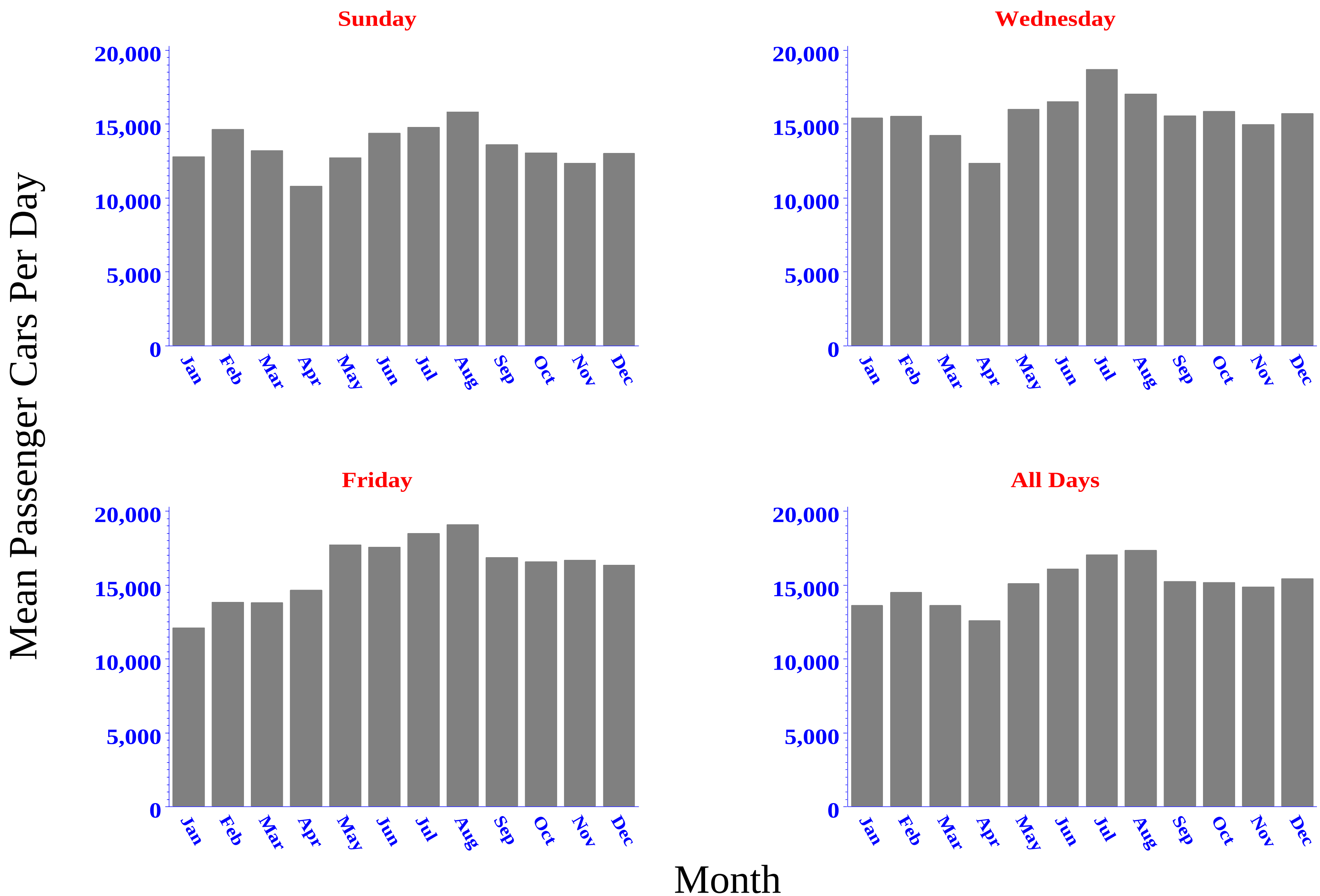


Figure 4.1. Effect of seasonality on passenger car volume for selected days-of-the-week, average for sixteen class sites.

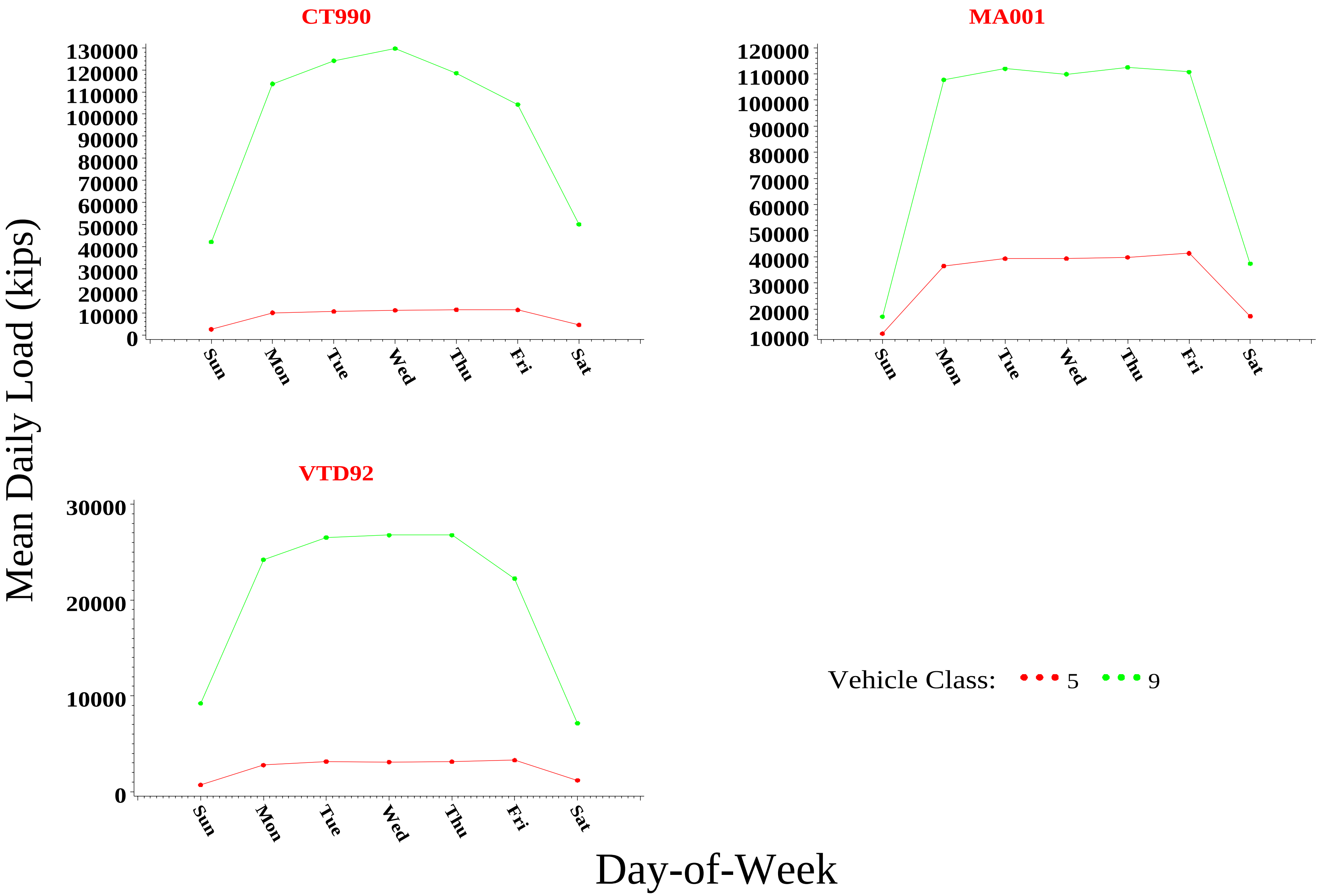


Figure 4.2. Effect of day-of-week, for selected WIM sites, on Class 5 and 9 truck loads.

5. ESALS AND LOAD

One of the main goals of this report is to address the question of how the New England states might best share WIM data. Because roadway wear and tear is a nonlinear function of axle-weight and axle combination, WIM data is stored as individual axle weights and spacings. Therefore continuous site WIM data sets are typically huge, and tractable methods of summarizing the data are essential—even more so when it comes to data sharing.

In Region 1 and elsewhere the most commonly used method for summarizing axle weights and spacings is by converting them, mathematically, to ESALs. All of the states compute ESALs to summarize WIM data, usually via formulas prescribed by AASHTO [7]. The calculations are often done with proprietary commercial software, but the VTRIS program from the OHIM also computes ESALs. Maine uses its own ESAL algorithm, which was inferred from load meter and WIM studies at their own sites.

ESALs are good for representing loads, because in addition to traffic characteristics, they also represent roadway properties such as pavement type and thickness. From the standpoint of data sharing, however, the dependence on roadway properties is inconvenient: the roadway properties are known; the issue is sharing the **traffic** properties and data. In practice ESALs are estimated at a site whose roadway properties are known, but whose traffic properties might be inferred from other sites.

Therefore, for this report, site-specific ESALs are not computed. Instead the WIM data is first reduced in a way that facilitates using it in ESAL calculations for any roadway. This reduction procedure is discussed next, in Section 5.1. Then, in Section 5.2, a "standard" ESAL is discussed, which will be used for making comparisons in this and subsequent sections of sites and HPMS classes, as well as months and days of the week. Several graphs and tables summarizing Region 1 loads, are discussed in Section 5.3.

5.1. REDUCTION OF DATA TO DAILY TOTALS

The procedure for reducing the WIM data from individual-vehicle data to daily totals is straightforward: (1) Round axle weights to five-hundred-pound (half-kip) increments. (2) For each day, compute a table of the axle counts for each axle combination and weight (ACW) class. A portion of such a table would look like Table 5.1 (from MA001).

In the AASHTO formulation, ESALs are computed from axle combinations and weights and from roadway properties expressed as parameters: terminal serviceablity, pavement type and thickness, and structural number. An ACW table for a site carries the traffic information necessary for computing ESALs according to the AASHTO formulation. That is, each ACW table cell represents one axle combination and weight, and therefore (for given roadway parameters) one ESAL value. Each cell's contribution to the total ESALs is the product of the cell's count and ESAL value, and the daily ESAL total is the sum of all such products.

Table 5.1. Axle combination and weight counts from MA001, 4/2/96 (partial table)

Axle Combination	Weight Class (kips)					
	...	**17.5**	**18**	**18.5**	**19**	**...**
Single	...	41	47	45	37	...
Tandem	...	133	126	106	118	...
Tridem	...	0	3	2	2	...
Quad	...	0	0	0	0	...

For example, suppose that in Table 5.1, a 17.5 kip single-axle is equivalent to .73 ESALs. Then the ESAL total for the single-axle 17.5 kip cell would be 41 × .73 = 29.9 ESALs. Repeating this calculation for all table cells and summing gives the daily ESAL total for the site.

From these ACW tables it is thus possible to compute daily ESALs for a site, as well as daily averages, monthly and yearly totals, etc. Also, ESAL estimates for any other site having the same statistical distribution of traffic counts, can reasonably be computed using the ACW for the first site, even if the roadway properties of the second site are different: the algorithm is the same, only the roadway parameters differ. So, for example, for a different roadway, a 17.5 kip single axle might translate to .90 ESALs, and for that roadway, the 17.5 kip cell in Table 5.1 would represent 41 × .90 = 37.1 ESALs. And other extrapolations, as in Schemes 1, 2, and 3 (Figures 1.2-4), can be applied when the traffic distribution matches partially, as when the combination counts have the same relative distribution, but the axle totals differ (Scheme 3).[7]

The data reduction incurred in the computation of the ACW tables is substantial. For example, for site VTn01, the 7-card data was reduced from 47.4 megabytes to a 6.9 megabyte SAS data set.[8] This kind of reduction puts data-sharing within a practical realm, even if continuous WIM data for a hundred sites is to be shared.

5.2. USE OF “STANDARD” ESALS

Despite their dependence on roadway parameters, ESALs are an extremely convenient and useful way of summarizing WIM data. Therefore some of the analyses in this report are done using ESALs. To do this, a “standard” ESAL was computed for flexible pavement with structural number SN=5 and

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[7]In this approach it is important to differentiate between axles and combinations (e.g., one tandem = two axles).

[8]The 7-card data is in ASCII format. The original and reduced data were not directly compared in ASCII format for this report.

terminal serviceability Pt=2.5.[9] Then, ESALs were calculated according to the AASHTO flexible pavement formula [7, Appendix MM].[10] The ESAL calculations, which are performed on the data for all eleven sites, thus represent what would be expected if all sites had these particular standard pavement characteristics. The calculations could easily be repeated for other roadway properties. This approach allows us to compare sites, months, days-of-the-week, etc. in terms of ESALs, although the comparisons are specific to the particular parameters selected.

One other feature about ESALs should be noted: ESALs increase exponentially in axle weight. This is seen in the following table of the standard ESALs for single axles with weights ranging from 10 to 100 kips.

Weight of single axle (kips)	Proportion of 18 kips	"Standard" ESAL (AASHTO, flexible pavement, Pt=2.5, SN=5)
10	0.56	0.09
20	1.11	1.51
30	1.67	6.97
40	2.22	21.08
50	2.78	52.88
60	3.33	116.73
70	3.89	233.03
80	4.44	429.08
90	5.00	739.99
100	5.56	1209.56

Because of this exponential behavior, ESALs have a potential for bad statistical outlier problems. Moderate axle-weight outliers can translate to gross outliers when converted to ESALs. This could affect statistics such as sample means and statistical analyses based on means (e.g., ANOVA) in ways

[9] Use of default values for ESALs was suggested by Mike Sprague, Rhode Island DOT, and Ralph Gillman, FHWA.

[10] We used this formula for all combinations up to quads. For the very few and possibly spurious combinations of order higher than quad, we used the quad formula. (It is beyond the scope of this report to decide about how ESAL calculations should be performed or extended to combinations such as tridems or quads.)

well known to be excessive and sometimes ruinous [8]. For this report, however, individual axle weights are truncated at 44.1 kips (effectively 88.2 for tandem, 132.3 for tridem), which is below the range where ESALs become extremely sensitive to axle weight. ESALs are still more variable, however. Their statistical behavior is not as good, a feature that will be noted again in this report.

5.3. LOAD SUMMARIES

In the remainder of this section several graphs of load statistics for the Region 1 sites are presented. More formal analyses (ANOVAs) are presented in the next section. The graphs serve to compare ESALs and loads—the two behave quite similarly, though ESALs tend to be more variable. As is often the case with graphs, they also say more than their primary intended purpose. They also illustrate that the Region 1 sites are similar in many respects, except for sites CT974 and MA02N, which tend to be anomalous. The graphs also illustrate, in more detail and for all vehicle classes, seasonal and day-of-week effects, which were illustrated in Figures 4.1 and 4.2 (for Class 2 and Classes 5 and 9 only).

Figure 5.1 is a chart of the distribution by site of daily loads in kips, and Figure 5.2 is the same chart for standard ESALs. These charts show the percentages of days in categories defined by equally-spaced, log-scale increments of total load (kips or ESALs). The site contributions due to the thirteen vehicle classes are differentiated by color. For example, for CT974, 10% of days are in the 1000 kip category, and nearly all of that is due to vehicle Class 5. At CT990, about 6% of vehicles are in the 100,000 kip category, all in Class 9.

Figures 5.1 and 5.2 are log-scale charts because of the wide range of daily loads. In view of the wide range, the plots suggest that outliers are not a bad problem for either daily totals weights or ESALs. Rather, the data is highly variable. Appendix D contains tables of summary statistics: vehicle counts, loads in kips and ESALs and coefficients of variation for each site and day-of-the-week (Table D.1) and each site and month (Table D.2). The coefficients of variation are considerably higher for the standard ESALs than the weights. In addition to the variability associated with the upper tail of the ESAL distribution, this may also reflect the lower tail, as ESALs also decrease rapidly as axle combination weights decrease.

Figures 5.3 and 5.4 are plots, for each site, of daily loads (weight and ESALs) versus day-of-week. For site CT974, for example, there the average daily load for Class 5 vehicles (green curve) is just under 1000 kips per day during weekends, and about 1100 kips per day during the week. There are separate graphs for each vehicle class. Again CT974 and MA02N are different from the other sites, with more Class 5 vehicles than Class 9. The effect of day-of-week on daily load is clear from Figure 5.3 and 5.4. This is primarily a reflection of reduced truck volumes on weekends: changes in mean loads per vehicle are not nearly so great (see Section 4). Again the behavior of weight and ESALs are generally similar, except that ESALs are more variable. This is true for most of the analyses discussed in this report, and so, for the remainder of the report, more attention will be paid to weights than ESALs.

Figure 5.5 is like Figure 5.3, except month plays the role of day-of-week. Again CT974 and MA02N are different from the other sites. In general, the effect of month is evidently much smaller than the effect of day-of-week. Hallenbeck [9] also observed that seasonal load differences are small relative to within-site and site-to-site variability. The analog of Figure 5.5 for ESALs is similar, but is not shown here. Additional plots, particularly with respect to functional classes, will be presented in the next section, which is about an analysis of the effects of month and day-of-week, as well as site-to-site differences.

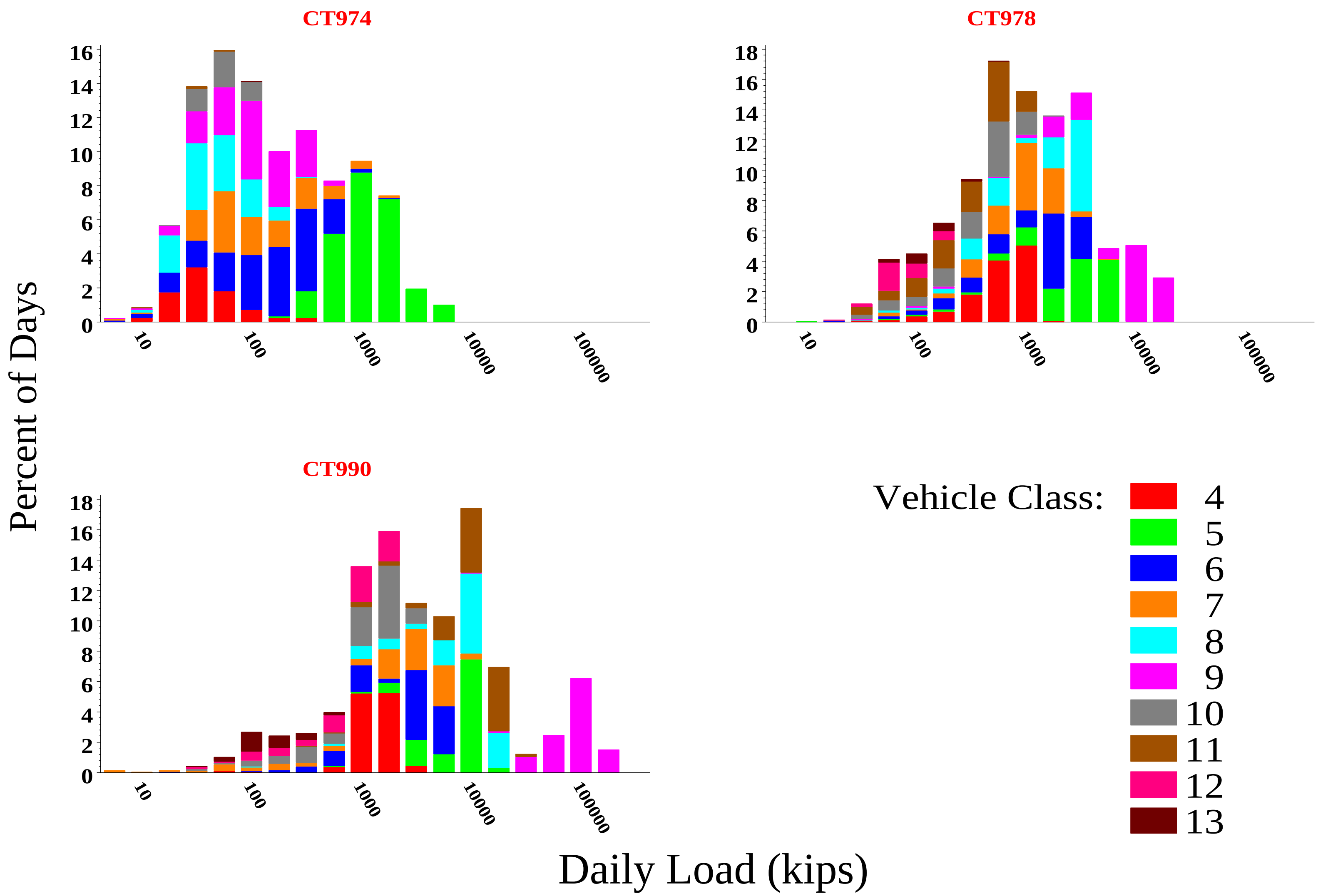

Figure 5.1. Distribution (percent of days) of daily load in kips by site, with vehicle-class subtotals.

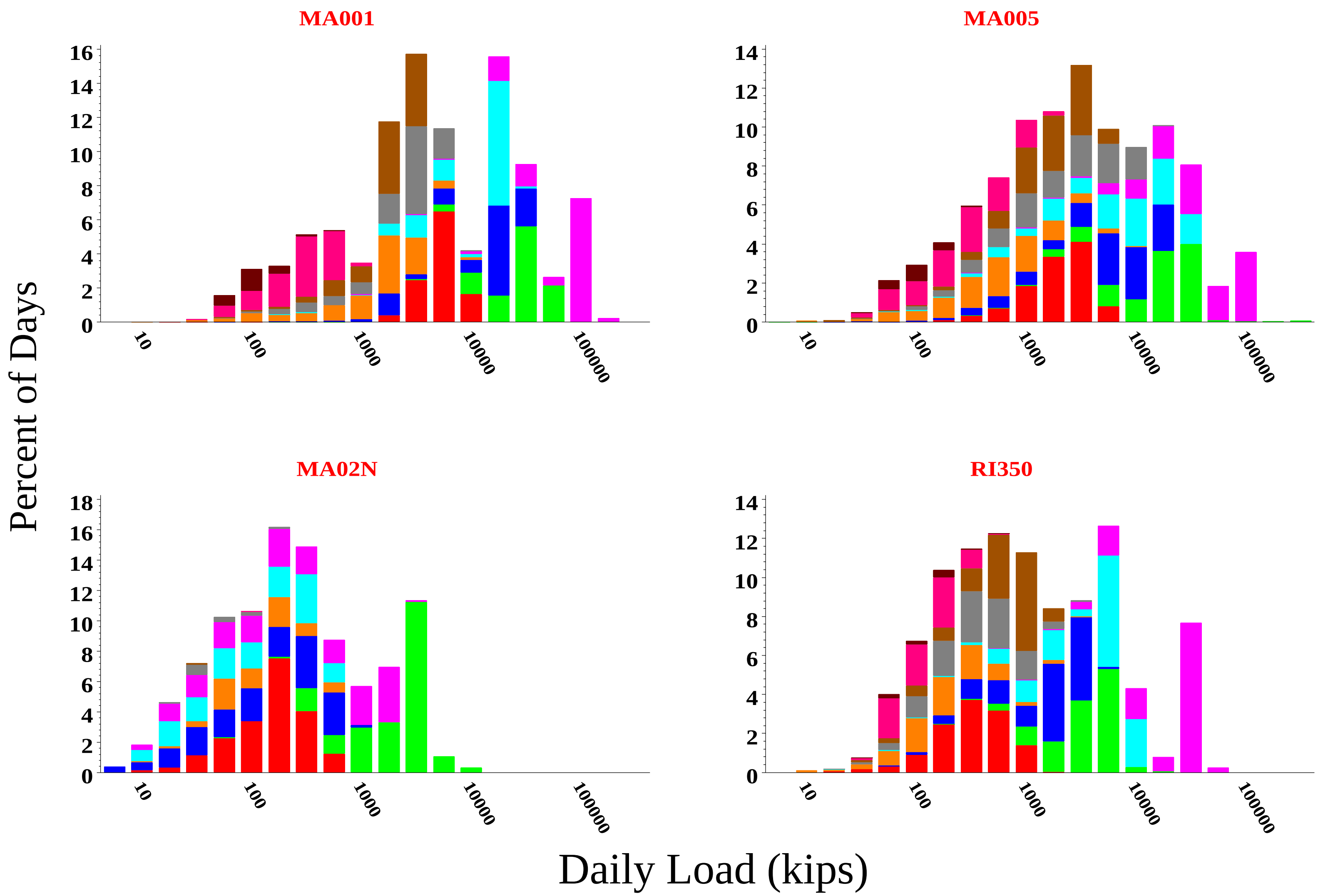

Figure 5.1 (cont'd). Distribution (percent of days) of daily load in kips by site, with vehicle-class subtotals. (Legend at beginning.)

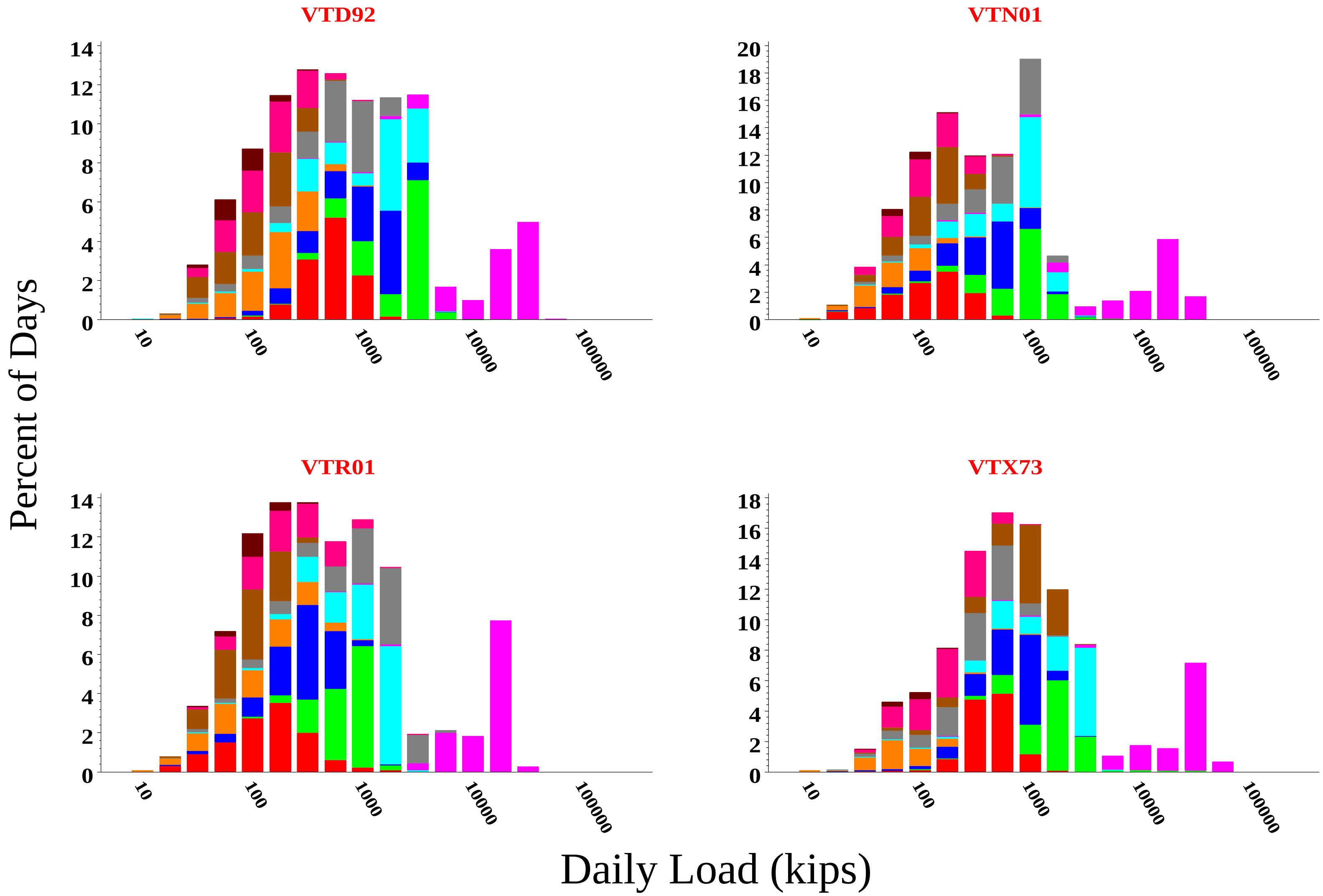

Figure 5.1 (cont'd). Distribution (percent of days) of daily load in kips by site, with vehicle-class subtotals. (Legend at beginning.)

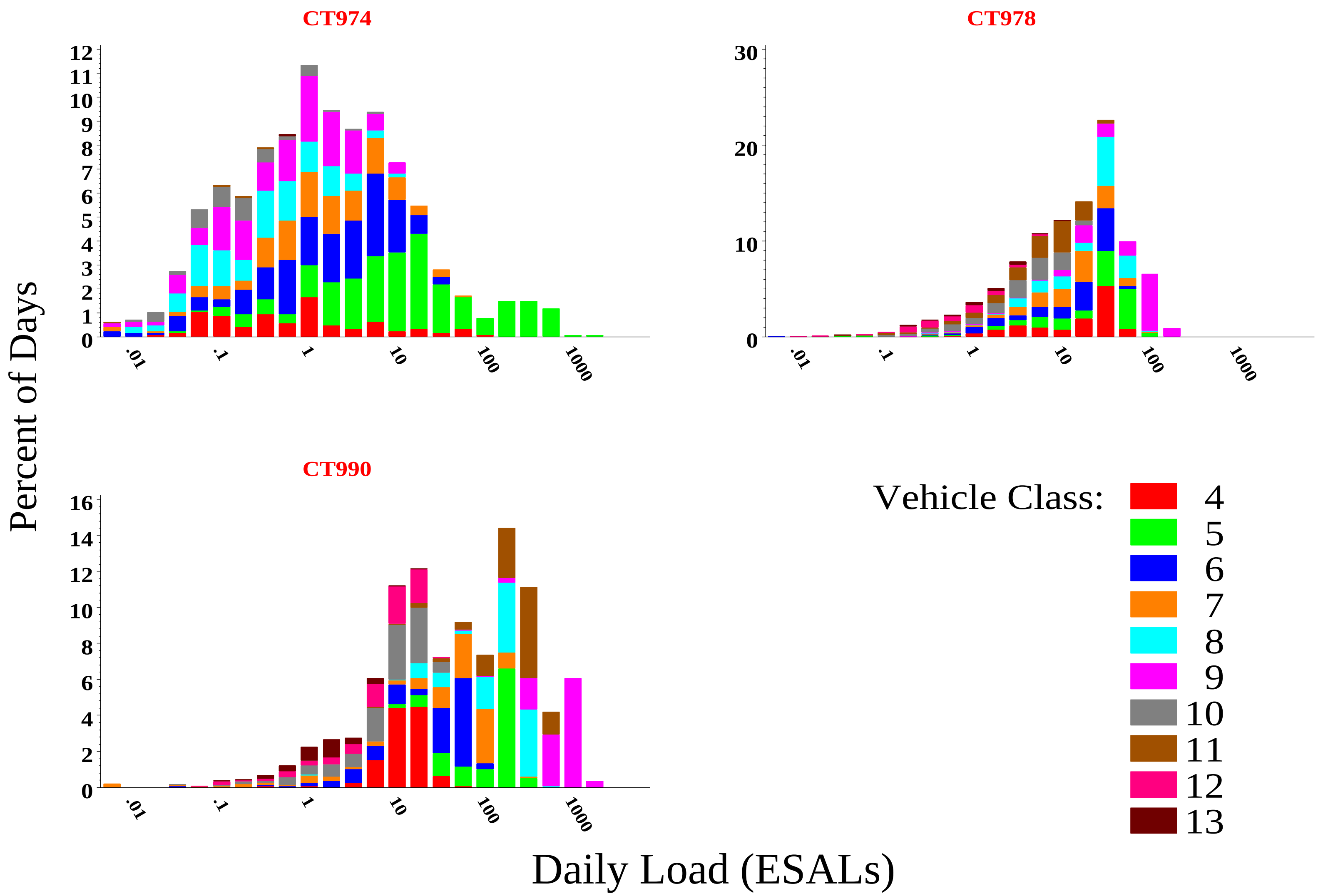

Figure 5.2. Distribution (percent of days) of daily load in ESALs by site, with vehicle-class subtotals.

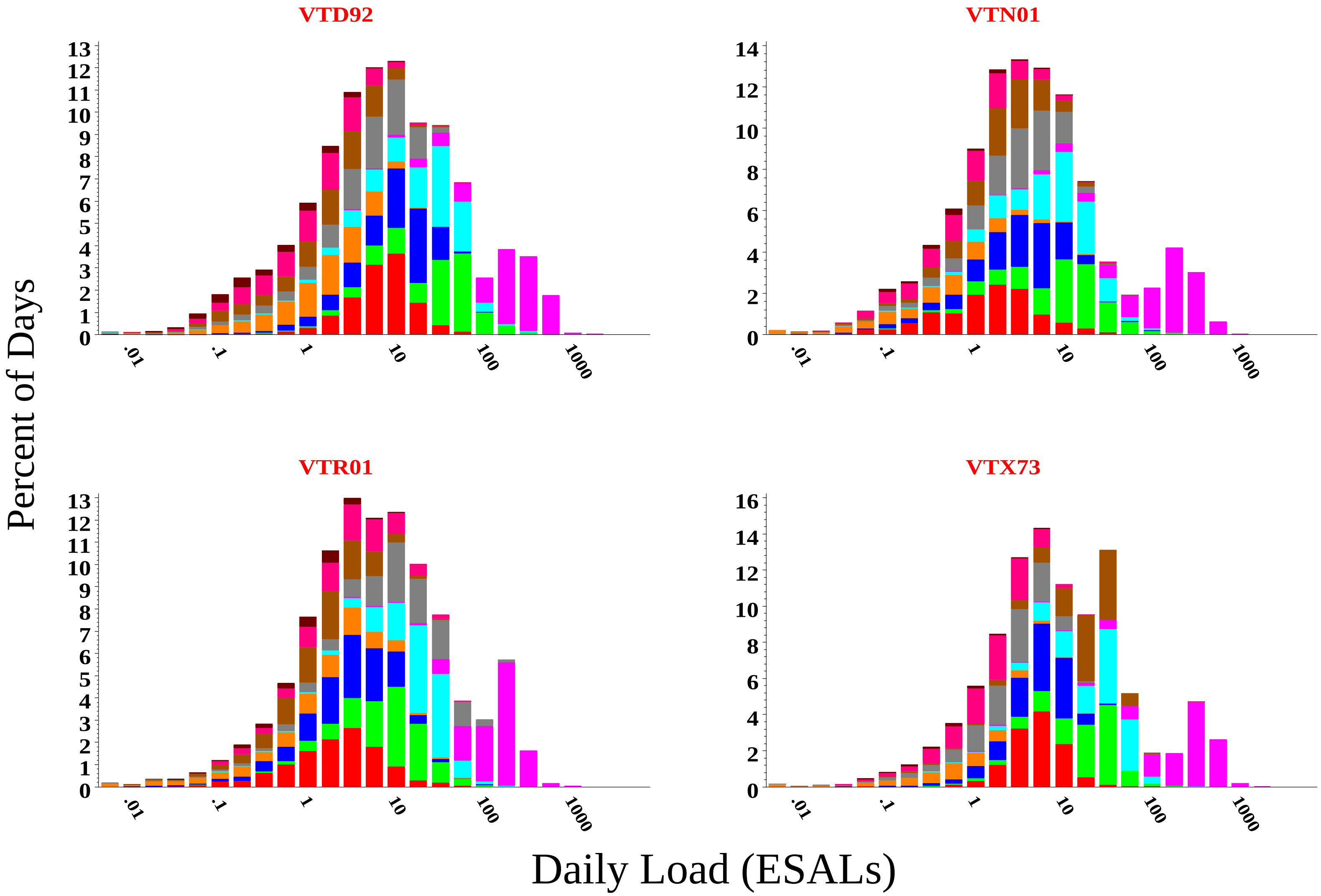

Figure 5.2 (cont'd). Distribution (percent of days) of daily load in ESALs by site, with vehicle-class subtotals. (Legend at beginning.)

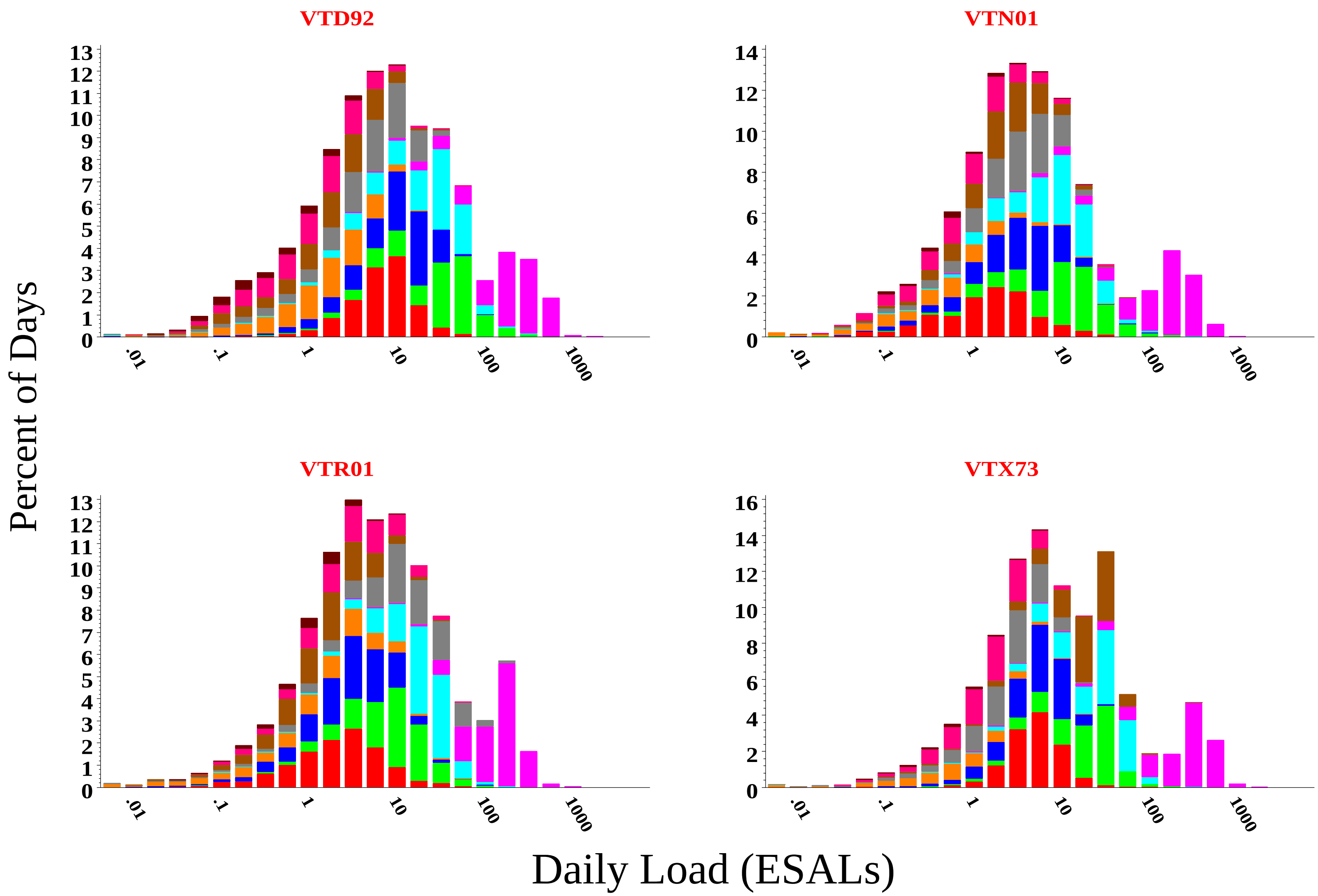

Figure 5.2 (cont'd). Distribution (percent of days) of daily load in ESALs by site, with vehicle-class subtotals. (Legend at beginning.)

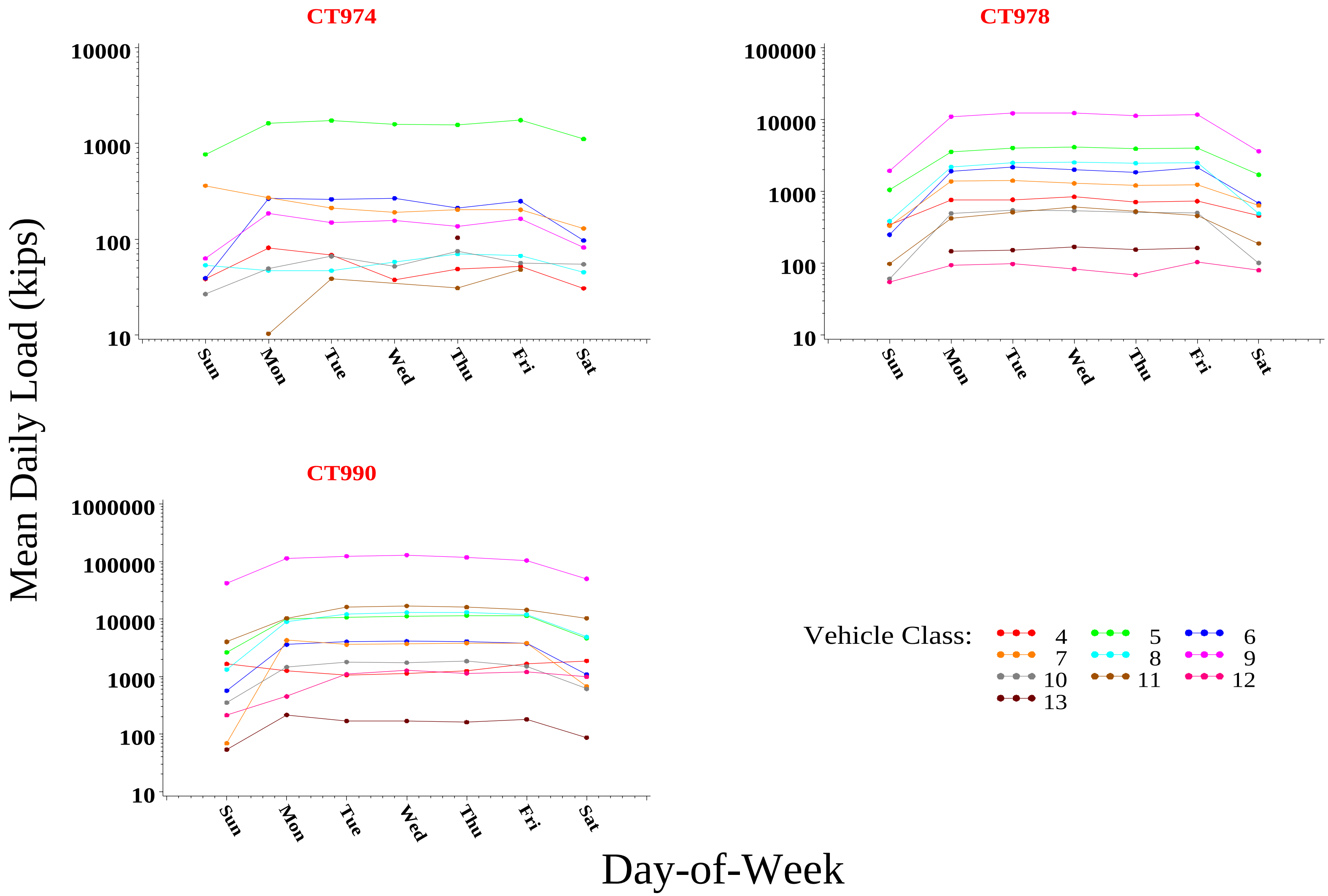

Figure 5.3. Effect of day-of-week on average daily load (kips), by site and vehicle class.

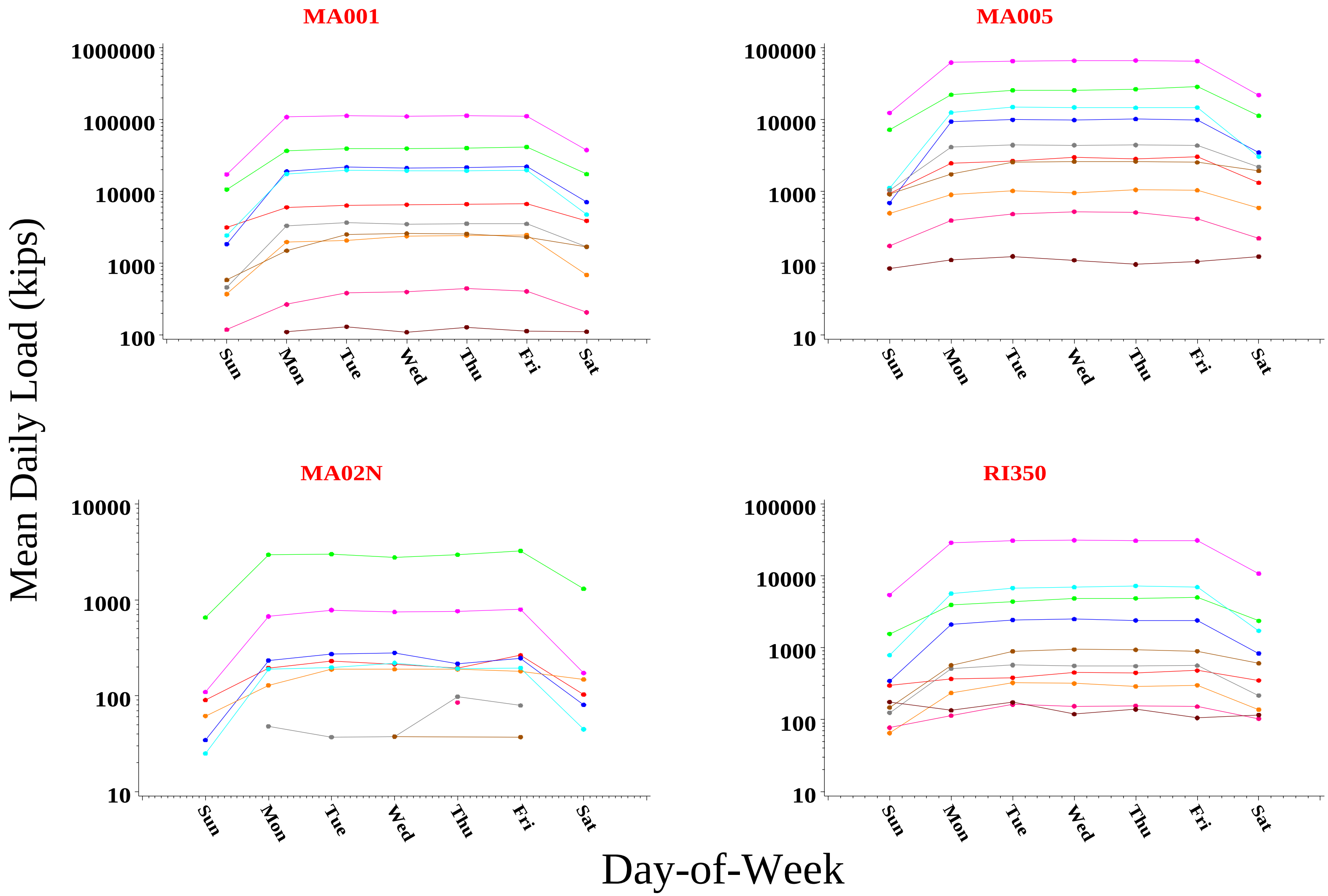

Figure 5.3 (cont'd). Effect of day-of-week on average daily load (kips), by site and vehicle class. (Legend at beginning.)

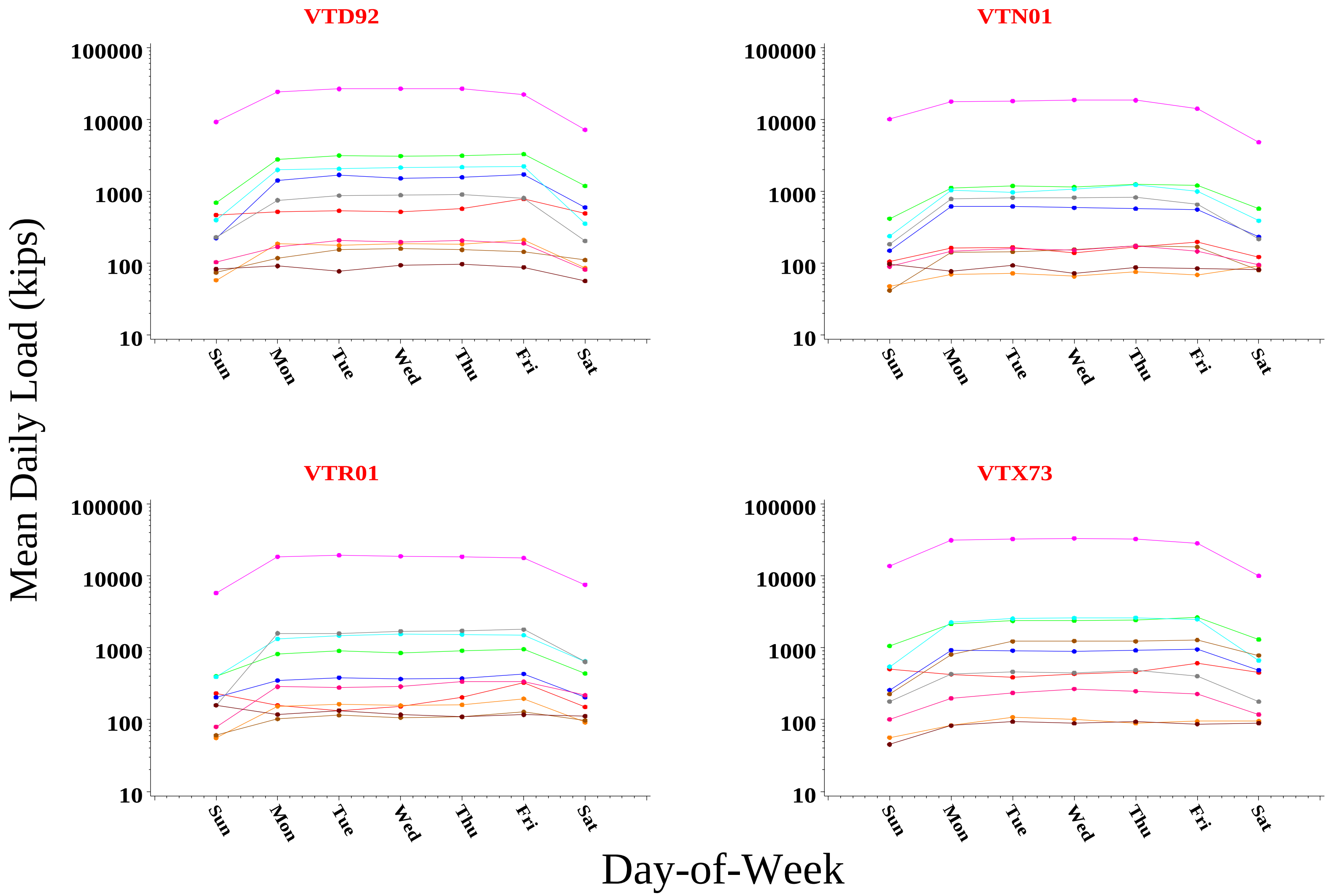

Figure 5.3 (cont'd). Effect of day-of-week on average daily load (kips), by site and vehicle class. (Legend at beginning.)

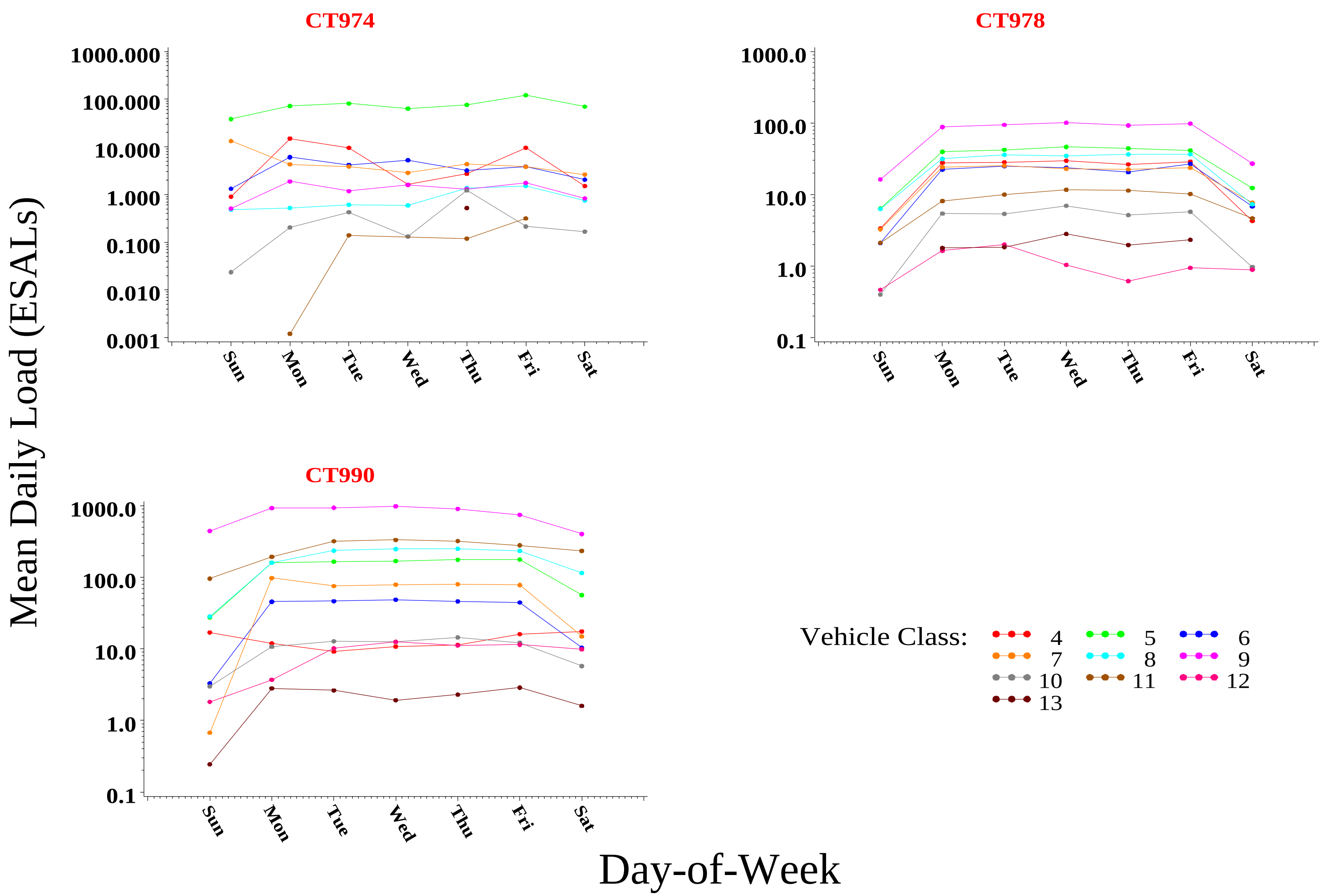

Figure 5.4. Effect of day-of-week on average daily load (ESALs), by site and vehicle class.

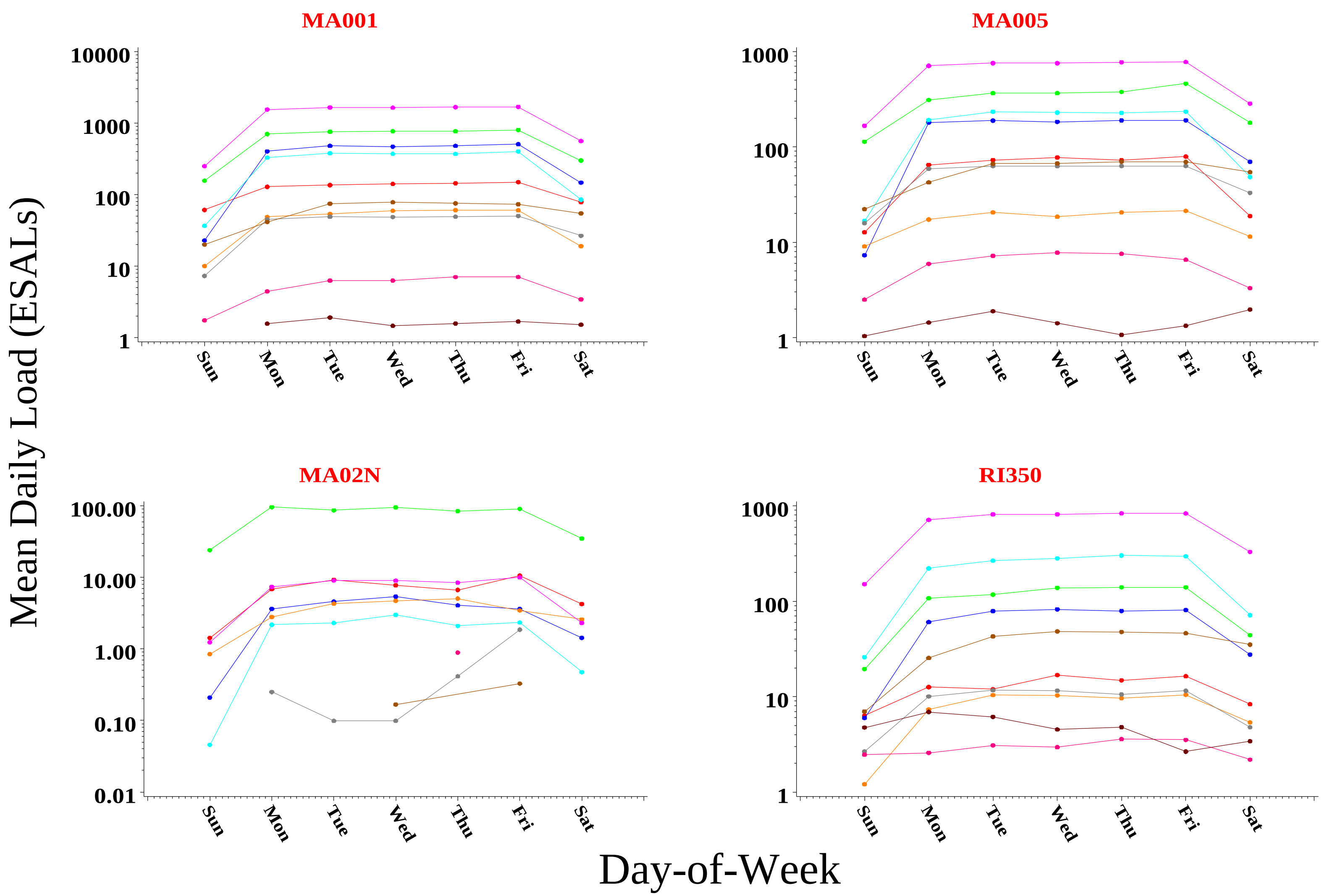

Figure 5.4 (cont'd). Effect of day-of-week on average daily load (ESALs), by site and vehicle class. (Legend at beginning.)

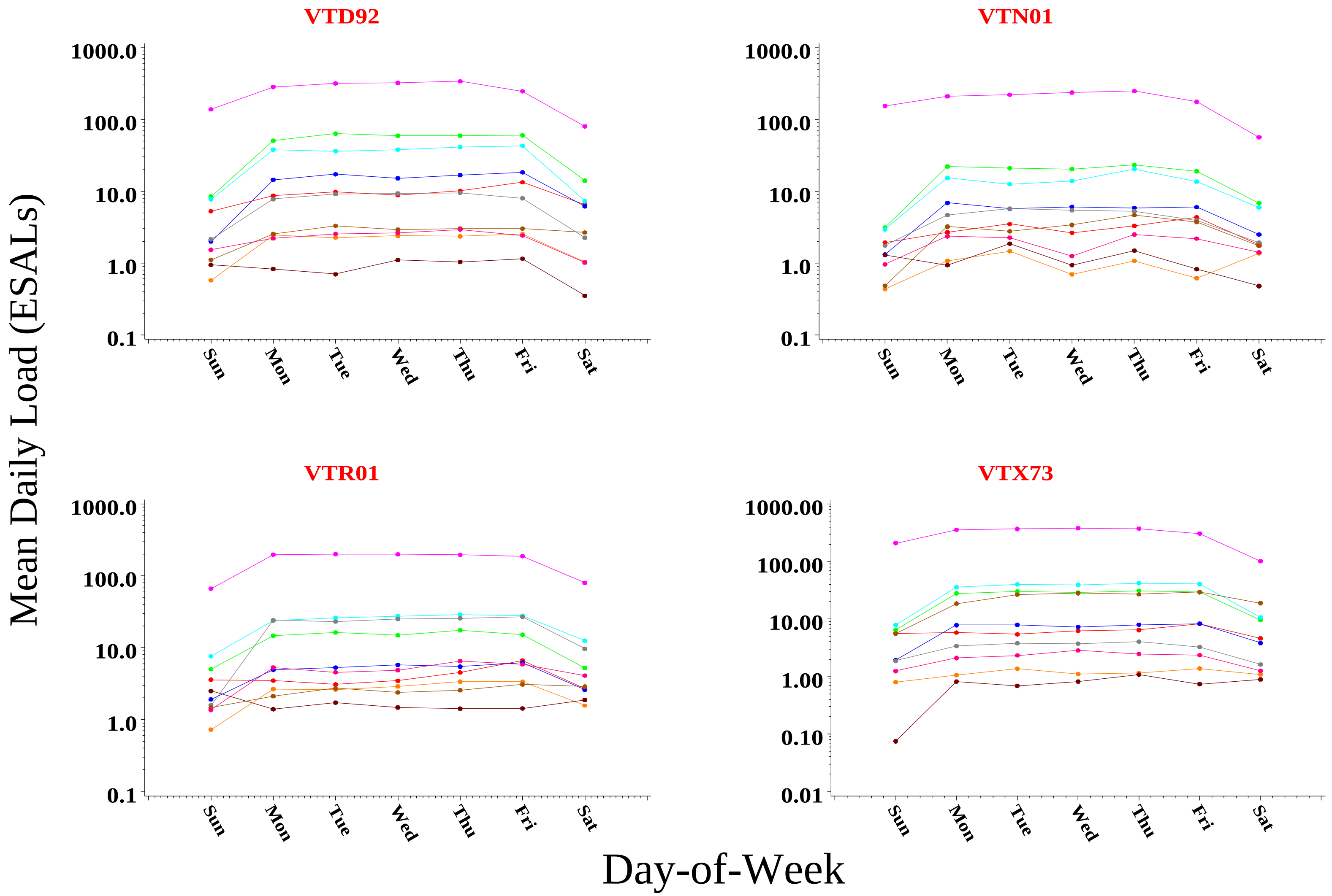

Figure 5.4 (cont'd). Effect of day-of-week on average daily load (ESALs), by site and vehicle class. (Legend at beginning.)

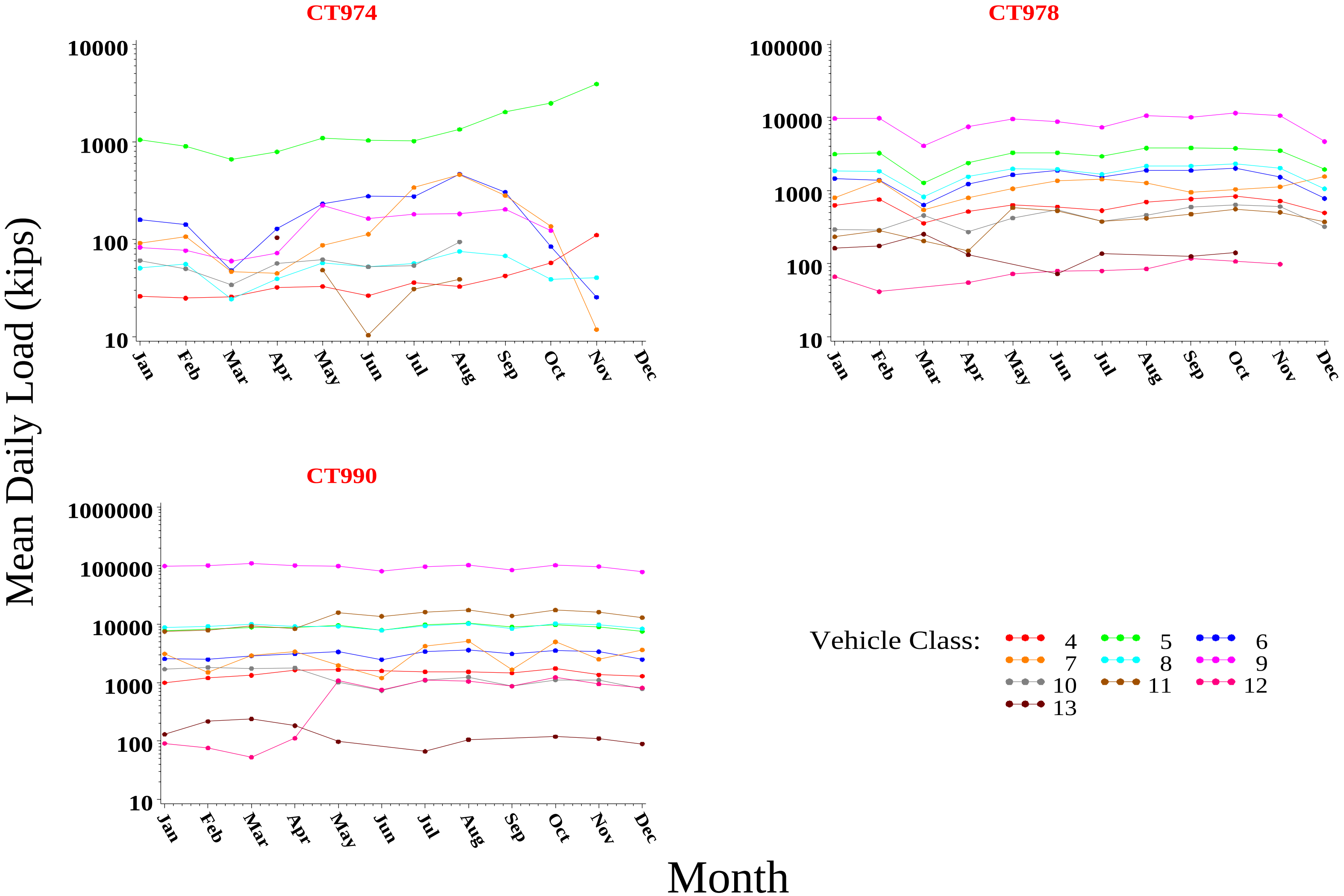

Figure 5.5. Effect of month on average daily load (kips), by site and vehicle class.

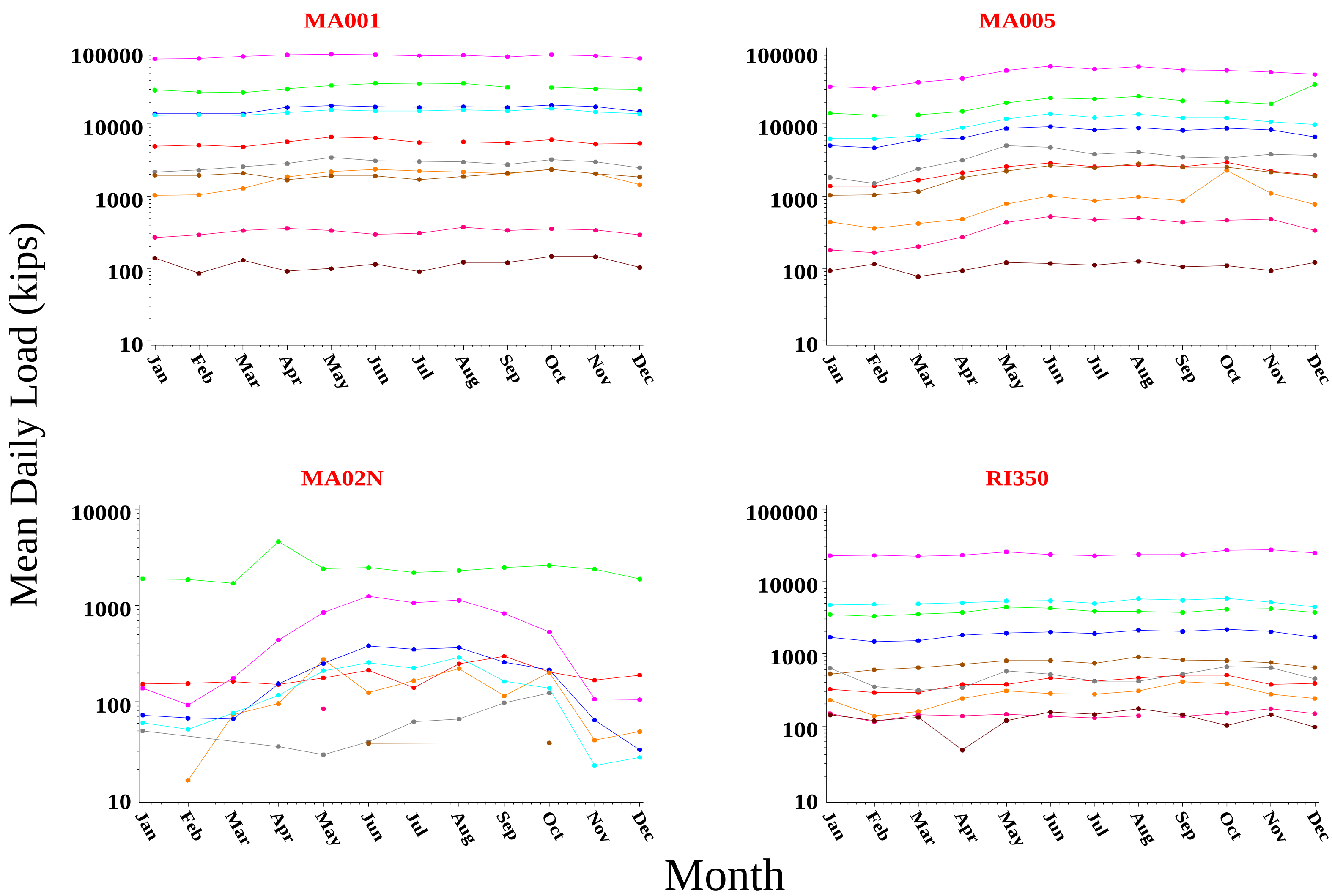

Figure 5.5 (cont'd). Effect of month on average daily load (kips), by site and vehicle class. (Legend at beginning.)

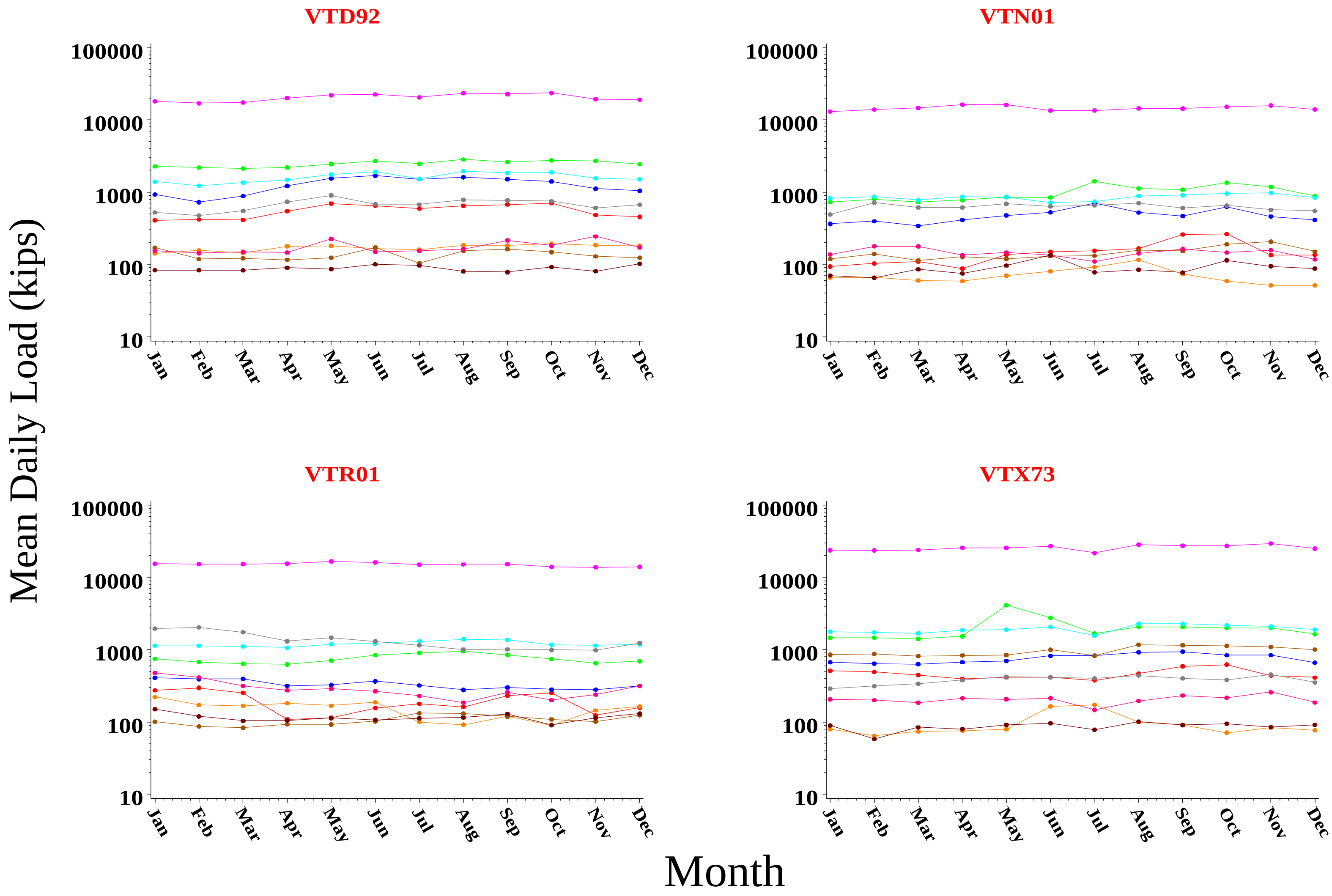

Figure 5.5 (cont'd). Effect of month on average daily load (kips), by site and vehicle class. (Legend at beginning.)

6. ANOVAs

This section is about several statistical analyses of the Region 1 data. The goals of these analyses are to decide about whether roadway functional classes might be combined and, more generally, to demonstrate a statistical approach to using data from multiple sites. In Section 6.1 we consider analysis of multiple site AFs computed from classification counts. Schemes 1, 2, and 3 (Figures 1.2-1.4) are considered in Sections 6.2, 6.3, and 6.4 respectively. Although the endpoint in each of Schemes 1, 2, and 3 is an AADL estimate, each scheme involves different intermediate statistics (e.g., ESALs per vehicle or ESALs per axle). All of the analyses are done using ANOVAs to compute the arithmetic means as well as other statistics such as standard errors. The Scheme 2 analysis is very similar to the class-count AF analysis, with loads playing the role of counts. Because Scheme 1 is prevalent in current practice in Region 1, it is discussed first and in more detail than the other schemes.

Although the ultimate endpoint for each of Schemes 1, 2, and 3 is an (overall) AADL estimate, the estimation in this section, other than for Scheme 3, is vehicle class-specific. (The input to Scheme 3 is axle counts; no class counts.) The issue of whether vehicle classes should be combined is considered in Section 7. Examples of AADL estimation under each of the schemes are also given in Section 7.

Certain limitations on the structure of the Region 1 data (see Table 1.1) were mentioned in Section 1. For example, there are eleven WIM sites in four states. Eight sites have 1995 data, eight have 1996 data, and they are in five different functional classes. Thus the data is convolved: generally only a few comparisons can be made of levels of any one of these factors (state, year, functional class) that do not also involve at least one of the other factors. For example, the only comparisons of states that can be made that do not also involve differences due to functional class or year are for sites CT990 with MA005 and CT978 with RI350. Similar restrictions hold for the class data.

Hallenbeck [10] confronted a similar situation in working with data from 99 sites from 19 states and functional classes 1, 6, 7, 11, 12, and 14. Siting a continuum (rather than clustering) of day-of-week patterns, and differences between automobile and truck day-of-week patterns as primary reasons for the difficulty in developing roadway factor groups, Hallenbeck concluded (p 11) "there is insufficient data in the LTPP database at this time to support the creation of these [factor] groups." The difficulty with sparsity is similar in the Region 1 data discussed here, though here the focus is only on one region.

Therefore, several simplifying assumptions about the joint effects of state, year, and functional class differences will be made in the data analyses discussed here. Conclusions should be tempered with understanding of these assumptions. The first assumption is that for either the classification or WIM data, the selection of Region 1 sites emulates a simple random sample. That is, the selection of one site is assumed to be statistically independent of the selection of other sites. This is clearly an approximation. Because permanent WIM sites are expensive, selection of their locations is usually purposive rather than random. Nevertheless, the sites **are** approximately randomly scattered over a subset of the total New England area.

The second simplifying assumption is that results (counts, loads, load means, etc.) for separate directions and years are also statistically independent. The rationale for this assumption is that because the Region 1 data is sparse and uneven, it would be too complicated to account for year-to-year and direction-within-site differences while simultaneously measuring the effect of functional class differences. The assumption is also clearly an approximation. Traffic at the same site but different directions tends to be similar (though it can be quite different—as it is for example at site VTr01). Traffic at the same site in different years is also similar. To some extent, however, the consequence of departures from independence is limited in that there are at most two years and two directions for any given site.

The two independence assumptions imply that results (averages, totals, etc.) for different site-direction-years are statistically independent. Therefore departures of results for different site-direction-years from their functional class means are also statistically independent. This is a requirement for a valid one-way ANOVA, which is the statistical method used in Sections 6.1-4 to investigate functional class differences. ANOVA provides a method for both computing adjustment or correction factor estimates and for accounting for errors in those estimates. The AF estimates and short-term counts can then be combined to estimate AADLs (or overall AADTs). The combined error in AADL estimates—from short-term counts, AF estimates, and estimates of load per vehicle or axle—is discussed in Section 7.

One-way ANOVA is discussed in [11] and in many other introductory statistical texts. One-way ANOVA is the simplest variety of ANOVA. Although the ANOVA calculations discussed here were done with SAS, they could also be done using an ordinary spreadsheet program such as Excel.

For both the class count and Scheme 2 analyses, seasonal and day-of-week variation of loads are considered in addition to variation with functional class. This lets us see the extent of site-to-site and functional class differences in the context of monthly and day-of-week differences. The class count AF and Scheme 2 procedures for adjusting short-term loads are parallel: Adjustment factors computed for each day-of-week and month combination are used to adjust short-term class or WIM totals by multiplying the total for any particular day by the AF for the corresponding day-of-week and month.

As in Schemes 1 and 3, extrapolations in the class-count or Scheme 2 analyses are across sites: AFs computed from long-term sites are used to adjust class or WIM data from different, short-term sites. To account for site-to-site differences, separate AFs are computed for each functional class. This is done for each of the 7×12=84 day-of-week and month combinations and for each vehicle class. Thus 84 × 13 = 1092 AFs are computed for each functional class.[11] This may seem like an overwhelming number of AFs, but is of course very tractable in the context of computer data processing. ANOVAs are used to compute the AF estimates (arithmetic means) for each functional class, in addition to standard errors, variance analyses, etc.

[11] If the number of vehicle classes were reduced to say three, the number of ANOVAs would still be 84 × 3 = 252, which from a practical perspective, is not really any more tractable than 1092. Using 84 month-by-day-of-week combinations is as prescribed in the TMG.

However, the task here is also to decide about data-sharing and combining functional classes. Eighty four separate analyses for the months and days-of-the-week (for each vehicle class) do not let us assess the **relative** importance of day-of-week, month, and site-to-site or functional class differences. Understanding how big functional class differences are relative to day-of-week and month differences helps to put the issue of cross-site extrapolation and data sharing in perspective. Therefore, for the class count and Scheme 2 analyses, bigger, "three-way" ANOVA, in the factors day-of-week, month, and functional class together, were also computed to provide a decomposition of overall variance into separate components for day-of-week, month, and functional class, and thus an assessment of the relative importance of day-of-week, month, and functional class as determinants of counts or loads. These higher order ANOVAs, joint in day-of-week, month, and functional class, are discussed in Sections 6.1 and 4.6.

6.1. ANOVA OF CLASS-COUNT AFs

Figure 6.1 illustrates "raw" AFs for vehicle Class 5, for August Wednesdays (arbitrary choice). Recall that Table 4.1 contains raw AFs for vehicle Class 5 and sites in functional Class 12. The raw AFs are simply the Class 5 AADTs divided by the Class 5 average daily traffic for August Wednesdays, for each classification site, direction, and year. The AFs for all functional classes were entered into one-way ANOVAs. As in Table 6.1, the ANOVAs produce the means for each functional class, which are the ANOVA AF estimates, standard errors for the means, and standard errors for new predicted values. The ANOVA AF estimates are just arithmetic means of the raw AFs. As an example, the AF estimate for functional Class 12 is the same as the estimate obtained in Section 4 by simple averaging.

Table 6.1. Class-Count AF Estimates and Standard Errors for August Wednesdays, Vehicle Class 5 (2-axle, 6-tire, single-unit trucks)

Functional Class	AF Estimate	Std. Err. Individual	Std. Err. Mean
1	0.830	0.198	0.075
2	0.781	0.189	0.049
7	1.467	0.259	0.183
11	0.804	0.191	0.053
12	0.882	0.201	0.082
14	1.338	0.205	0.092

Table 6.1 also contains standard errors for the AF estimates (i.e., standard errors of the mean), and standard errors for new predicted individual values. Both kinds of standard errors are useful products of the ANOVA. The new prediction standard errors are larger than the mean standard

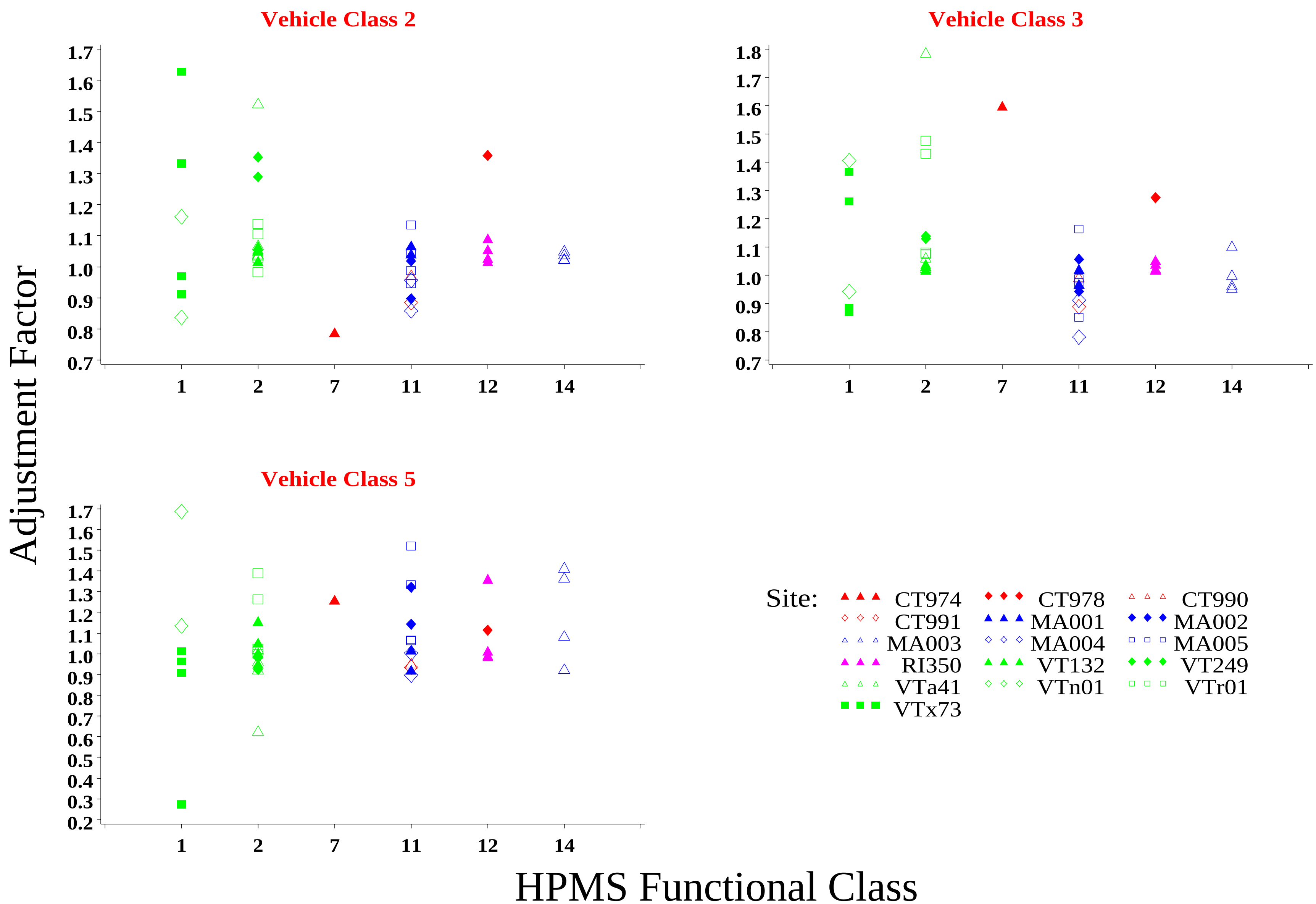

Figure 6.1. Example “raw” adjustment factors—for August Wednesdays—for input into a one-way ANOVA.

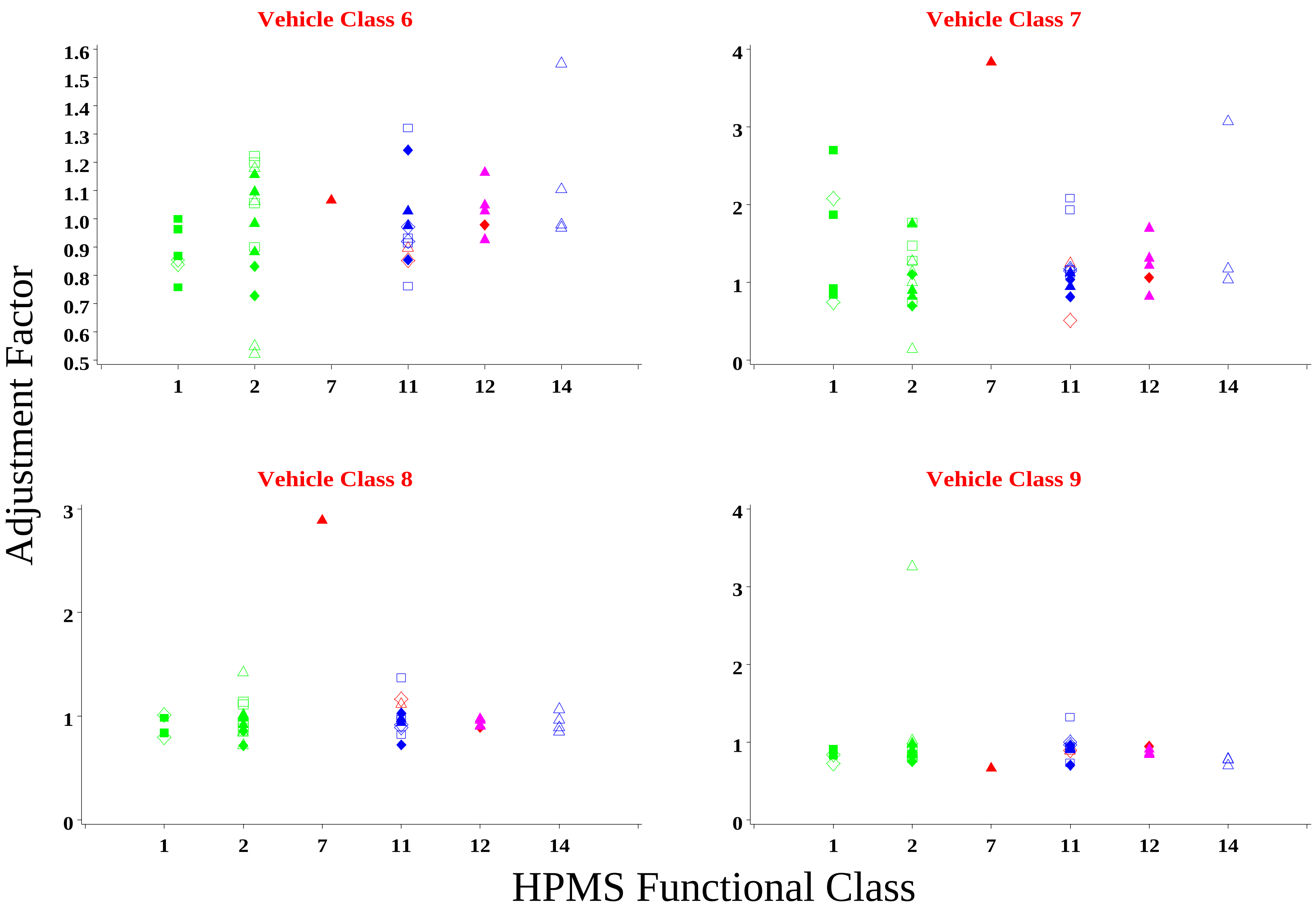

Figure 6.1 (cont'd). Example "raw" adjustment factors—for August Wednesdays—for input into a one-way ANOVA.

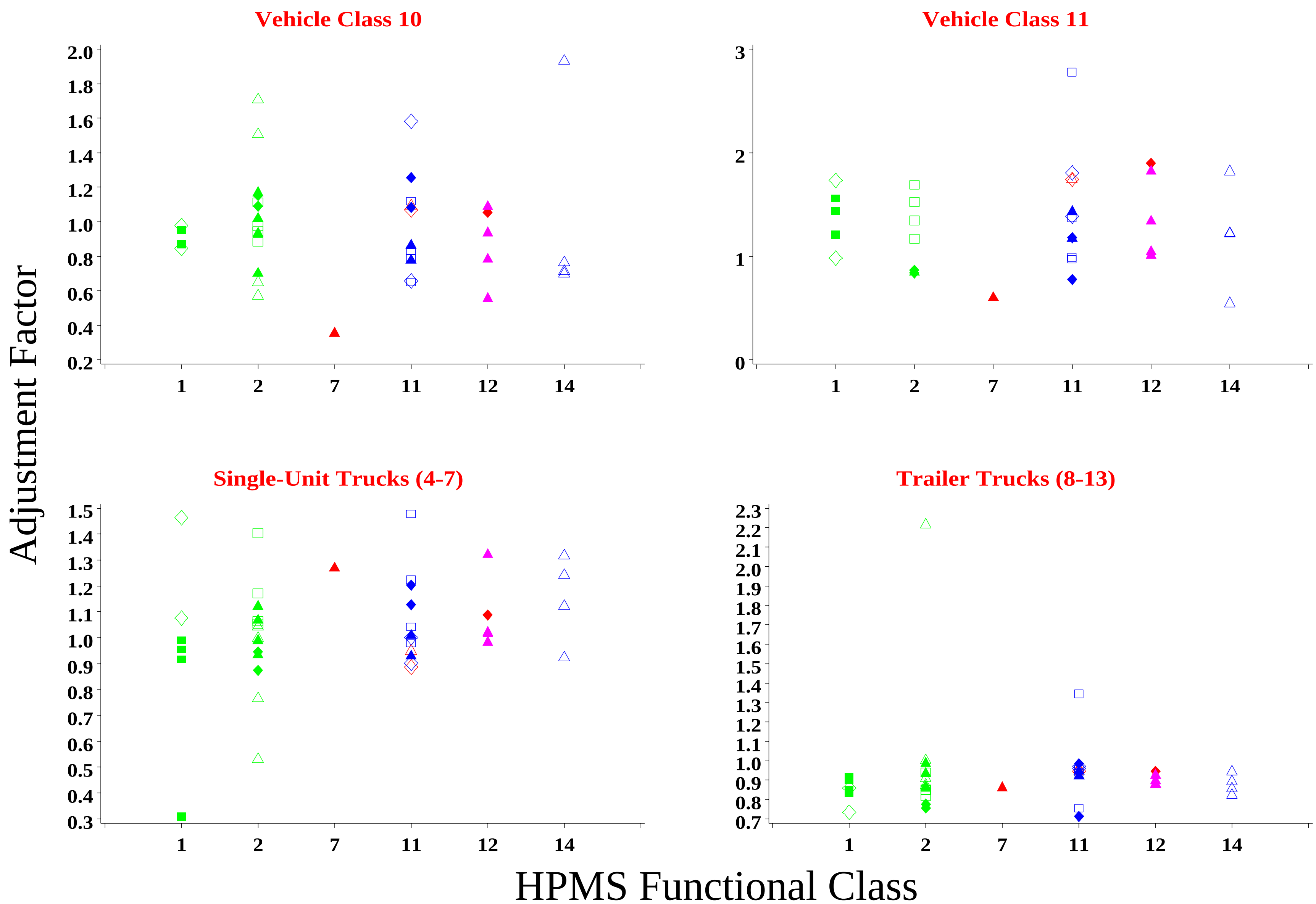

Figure 6.1 (cont'd). Example "raw" adjustment factors—for August Wednesdays—for input into a one-way ANOVA.

errors, because they reflect the error in the mean estimates plus the error in the data itself. (The mean standard error depends on not just the data error, but also the number of observations that go into each mean estimate.) The prediction standard errors can be entered into propagation of error formulas to yield overall standard errors for class-specific AADT or AADL estimates computed from short-term monitoring data. This is illustrated in the next section.

Table 6.1 represents only one of 84 possible day-of-week and month combination and only one vehicle class, but the table is not atypical in the sense of exhibiting substantial differences between functional classes. In Table 6.1, functional Classes 1, 2, and 11 appear similar, but the other functional classes are all different. A more thorough examination of data for the other months, days-of-the-week, and vehicle classes, demonstrates many other AF differences that are big enough to be of practical importance (e.g., greater than 10 percent), and are also statistically significant (as indicated by a t-test based on the ANOVA standard error of difference of means). For example, in the following table for passenger cars (Vehicle Class 2), functional Class 11 is substantially different from functional Classes 1 and 2.

AF Estimates and Standard Errors for April Sundays, Vehicle Class 2 (Passenger Cars)

Functional Class	AF Estimate	Std. Err. Individual	Std. Err. Mean
1	0.988	0.193	0.073
2	1.011	0.185	0.048
7	1.148	0.253	0.179
11	1.240	0.186	0.052
12	1.111	0.196	0.080
14	1.384	0.200	0.089

WIM data differences between functional classes are illustrated in the next subsections. In general we found that functional Classes 7, 11, 12, and 14 are all different and different from Classes 1 and 2. Classes 7, 11, 12, and 14 should be kept separate. Classes 1 and 2 tend to be similar (though there are exceptions). However, all of the functional Class 1 and 2 data considered here is from Vermont. Therefore, we feel the data is inadequate to support a recommendation to combine Classes 1 and 2.

To get an idea about the importance of functional class differences relative to to day-of-week and monthly differences, an ANOVA higher than one-way is needed. A feature of ANOVA that has not yet been exploited here is a decomposition—an analysis—of variances into components for individual contributing causes. A contributing cause could be due to an overall effect of one variable (Month, Day-of-Week, functional class), or the joint effect of several variables (e.g., Month×Day-of-Week interaction). Each contributing cause is measured with a sum of squared differences between the ANOVA estimates made with and without terms for that cause. The sums of squares themselves add to a total sum of squared differences from the simple overall mean of the class AF. From the sums of squares, root mean squares (square root of sum of squares divided by number of observations) can be also be calculated, which measure (in the sense of root mean square) the average magnitudes of the differences.

One-way ANOVAs have only one contributing cause. However, an ANOVA that is joint in month, day-of-week, and functional class produces an analysis showing the relative importance of these three contributing factors to the overall variance. Table 6.2 contains such an analysis for vehicle Class 2. The table shows that 45 percent of the total variation is unexplained by the factors in the ANOVA model (month, day-of-week, functional class). That leaves 55 percent explained, which is the value of R^2, expressed as a percent. The table shows that overall, monthly (seasonal) differences are greater than daily differences,[12] and that functional class differences are at least as important as day-of-week and seasonal differences.[13]

Table 6.2. Analysis of Variance of AFs for Vehicle Class 2 (Passenger Cars)

Cause	**Sum of Squares**	**Percent of Total**	**Root Mean Square**
Month	28.9	17.6	.092
Day-of-week	11.5	7.0	.058
Month×Day-of-week	3.6	2.2	.033
Functional Class×All	46.2	28.1	.117
Functional Class	1.0	0.6	.017
Month×Functional Class	10.0	6.1	.055
Day-of-Week×Functional Class	27.3	16.7	.090
Month×Day-of-Week×Functional Class	7.8	4.8	.048
Error (unexplained by above)	73.8	45.0	.148
Total (for 2298 observations)	**5607.0**	**100.0**	**1.56**

[12]The Region 1 data generally indicates seasonal differences are more pronounced for cars than trucks.

[13]The substantial effect of functional class here is in part reflects the functional classes being kept separate rather than combined into more general groupings.

6.2. SCHEME 1 (AADT to AADL)

Scheme 1 entails converting vehicle counts to AADL estimates (see Figure 1.2). Long-term WIM data is used to compute load per vehicle estimates, which are multiplied by class-specific AADT estimates to estimate AADLs. In this section, only the load per vehicle estimates are considered; using the load per vehicle estimates to compute final AADL estimates is considered in Section 5.

The Scheme 1 approach could be taken for total traffic, for combinations of vehicle classes, or separately for each vehicle class. Class-specific AADL estimates can be summed to estimate overall AADL. The class-specific approach is taken in this section and in Section 5. Motivation for the class-specific approach is discussed in Section 5.

To compute load per vehicle estimates, an ANOVA was performed on raw load per vehicle estimates computed for each year. The raw estimates are computed by summing, for each vehicle class, the daily loads and truck frequencies—up to the level of year, site, and direction—and then by computing the average annual load per truck. The average loads (in kips) per vehicle are plotted in Figure 6.2. Though not huge in relation to the overall scatter, differences among the functional classes are clear. There do seem to be differences between the functional classes, not just in average daily load, but in average load **per truck**. For most of the vehicle classes, GVW increases with functional class.

For each of the thirteen vehicle classes, the average loads per truck were entered into an ANOVA in functional classes. The outputs of the thirteen ANOVAs include various measures of differences between functional classes, and predicted values and standard errors for the average load per vehicle at a new site, given the new site's functional class. In view of the plots in Figure 6.2, it is not surprising that the functional class differences are statistically significant in the ANOVAs. Table 6.3 shows R^2 (squared correlation coefficient) values and significance levels for the ANOVAs for each vehicle class.

Table 6.2 shows that the differences among functional classes are statistically significant; the next question is Are they big enough to be of practical importance? Table 6.4, which contains mean load estimates (in kips and standard ESALs) and standard errors for each vehicle class and functional class, shows that many of them are. For many of the vehicle classes, including Class 9 (five-axle single-trailer trucks), the mean load per vehicle for functional Class 12 (urban other freeways and expressways) is more than 10 percent higher than for the other functional classes. Functional Class 7 (rural major collector) stands below the other functional classes for mean vehicle load in kips or ESALs in vehicle Classes 8-11.[14] Functional Classes 1, 2, and 11 tend to be much more similar for most vehicle classes (exceptions: Classes 6 and 2). In terms of mean load per vehicle, it might be

[14]Recall that the only data for functional Class 7 is from site CT974, which exhibits behavior different from the other sites. For vehicle Class 4, the kip average for this functional class is not large compared to the other functional classes, but the ESAL average is largest! An explanation is suggested in Figure 3.6, which shows markedly more single-axle and markedly fewer tandem vehicles at CT974 than at the other site (even MA02N). This is also true for vehicle Class 4 (buses).

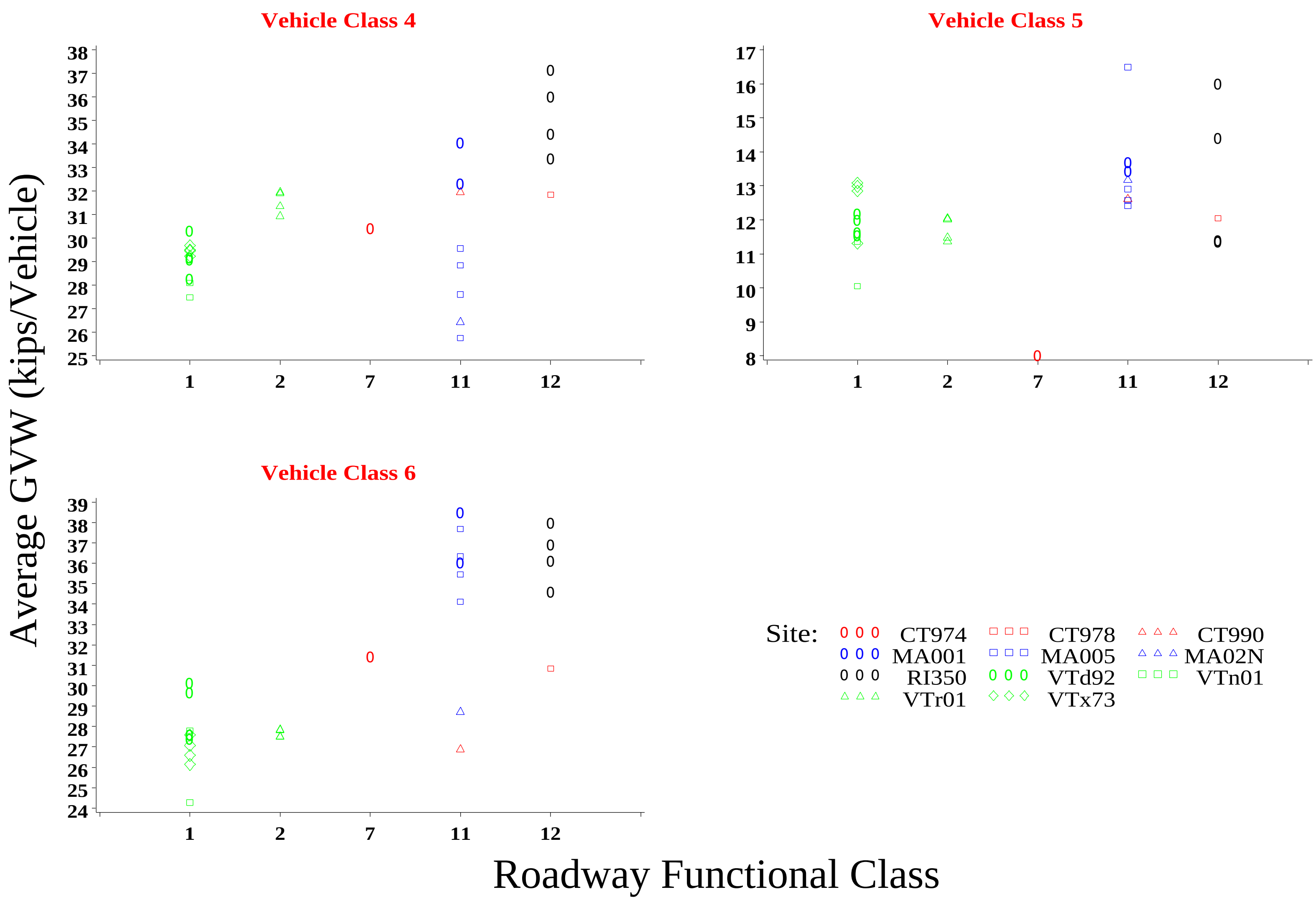

Figure 6.2. Average weights (kips) per vehicle—input to Scheme 1 ANOVA.

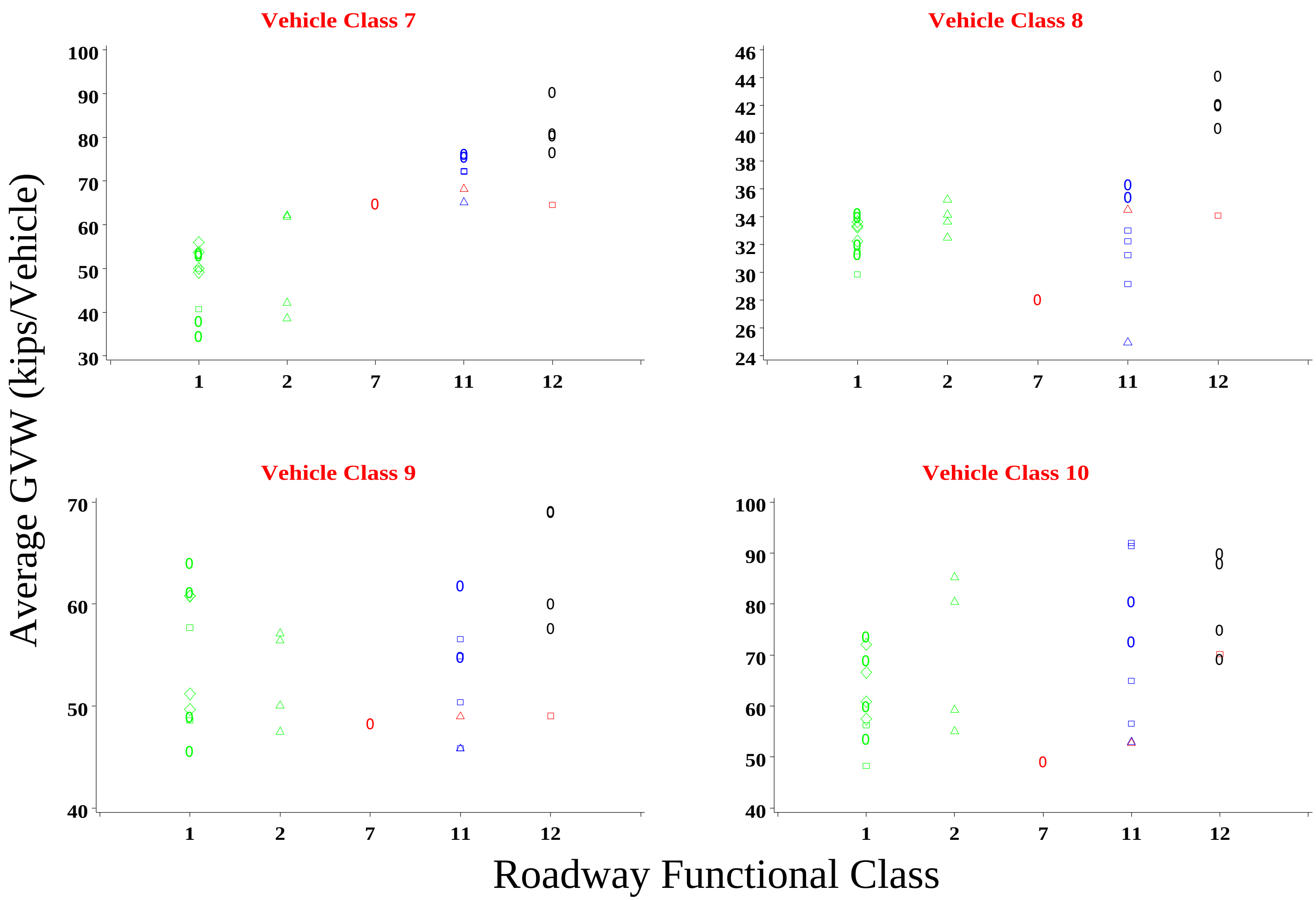

Figure 6.2 (cont'd). Average weights (kips) per vehicle—input to Scheme 1 ANOVA. (Legend at beginning.)

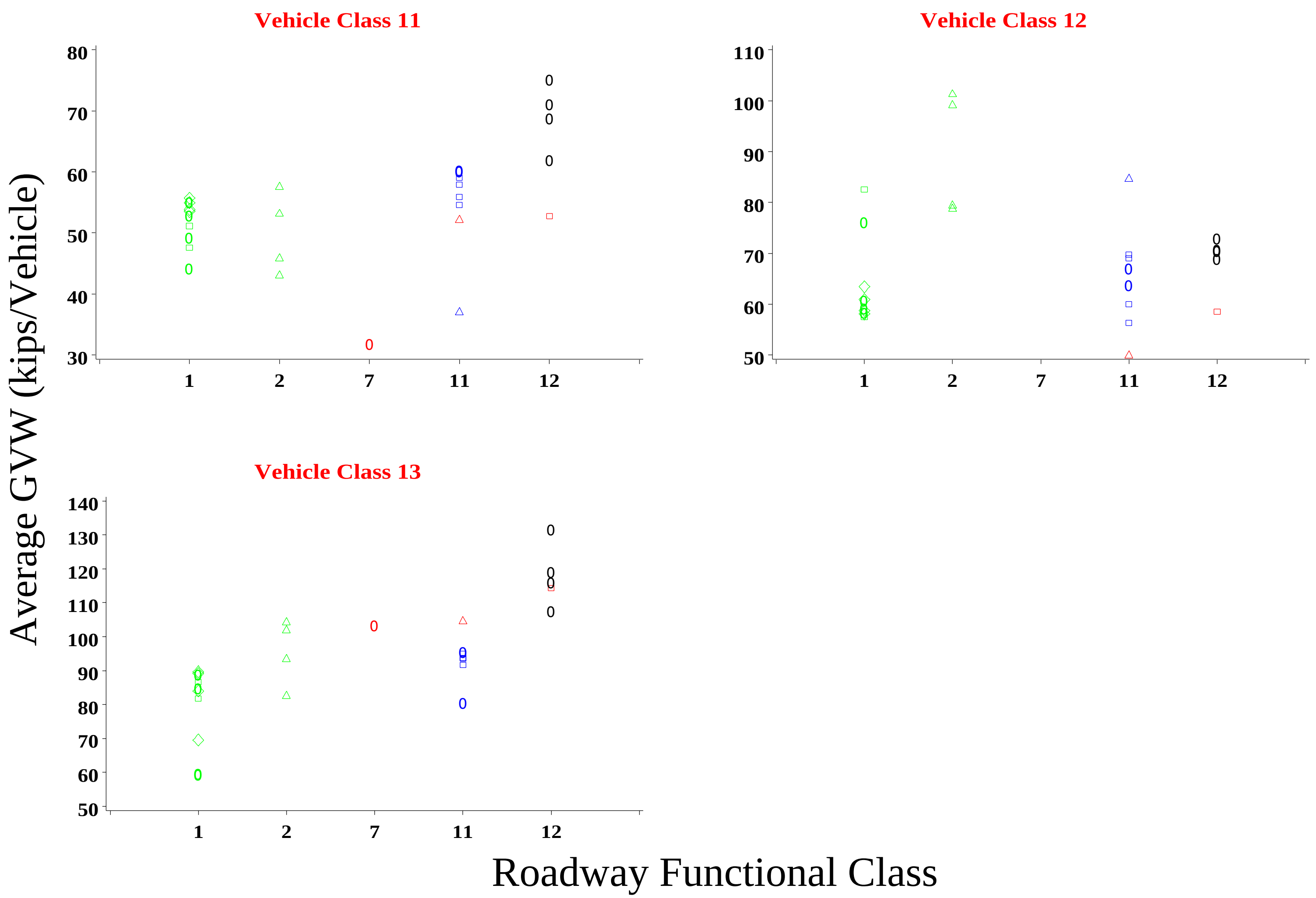

Figure 6.2 (cont'd). Average weights (kips) per vehicle—input to Scheme 1 ANOVA. (Legend at beginning.)

reasonable to combine these functional classes (at least for vehicle classes other than 6 or 12). As we will see in Section 4.2, this does not imply that the seasonal or day-of-week behaviors in these classes are the same, however. For vehicle Class 9, for example, functional Class 11 has substantially different day-of-week and month AFs than Classes 1 or 2. Also, because all of the functional Class 1 and 2 sites considered here are from Vermont, there is not a sufficient basis for recommending general combination of those functional classes. Therefore, neither Classes 1, 2, and 11 nor any other functional classes will be combined here.

Table 6.3. R^2 values and Significance Levels for Scheme 1 ANOVA of Loads per Vehicle

Vehicle Class	Load Units	R^2	Significance Level
4	kips	0.71	0.0000
	ESALs	0.57	0.0005
5	kips	0.94	0.0000
	ESALs	0.47	0.0041
6	kips	0.34	0.0385
	ESALs	0.66	0.0000
7	kips	0.69	0.0000
	ESALs	0.77	0.0000
8	kips	0.78	0.0000
	ESALs	0.63	0.0001
9	kips	0.65	0.0001
	ESALs	0.23	0.1764
10	kips	0.46	0.0053
	ESALs	0.28	0.0991
11	kips	0.44	0.0074
	ESALs	0.58	0.0004
12	kips	0.53	0.0011
	ESALs	0.52	0.0007
13	kips	0.38	0.0109
	ESALs	0.70	0.0000

Table 6.4, also contains standard errors for predicted loads per vehicle for a new site. The standard errors are part of the ANOVA computer output. The load-per-vehicle prediction standard errors in

Table 6.4. Means and Standard Errors From Scheme 1 ANOVA

Vehicle Class	Functional Class	Mean kips per Vehicle	Std. Err. Mean kips	Std. Err. Predicted kips	Mean ESALs per Vehicle	Std. Err. Mean ESALs	Std. Err. Predicted ESALs
4	1	29.05	0.62	2.05	0.45	0.05	0.16
	2	31.59	0.97	2.18	0.67	0.08	0.18
	7	30.46	1.95	2.76	3.55	0.16	0.22
	11	29.59	0.69	2.07	0.69	0.06	0.17
	12	34.60	0.87	2.14	1.11	0.07	0.17
5	1	11.91	0.40	1.34	0.18	0.03	0.09
	2	11.76	0.64	1.43	0.20	0.04	0.10
	7	8.04	1.28	1.81	0.41	0.09	0.13
	11	13.43	0.45	1.36	0.24	0.03	0.09
	12	13.06	0.57	1.40	0.32	0.04	0.10
6	1	27.45	0.88	2.93	0.26	0.06	0.21
	2	27.73	1.40	3.13	0.38	0.10	0.22
	7	31.46	2.80	3.95	0.58	0.20	0.28
	11	34.24	0.99	2.96	0.65	0.07	0.21
	12	35.33	1.25	3.06	1.00	0.09	0.22
7	1	47.93	2.49	8.25	0.64	0.12	0.40
	2	51.49	3.93	8.79	0.87	0.19	0.43
	7	65.06	7.86	11.12	1.23	0.38	0.54
	11	72.34	2.78	8.34	1.59	0.13	0.40
	12	78.70	3.52	8.61	2.39	0.17	0.42
8	1	32.57	0.88	2.91	0.55	0.09	0.30
	2	33.98	1.39	3.10	0.63	0.14	0.32
	7	28.15	2.77	3.92	0.44	0.28	0.40
	11	32.15	0.98	2.94	0.53	0.10	0.30
	12	40.59	1.24	3.04	1.47	0.13	0.31

Table 6.4 (cont'd). Means and Standard Errors From Scheme 1 ANOVA

Vehicle Class	Functional Class	Mean kips per Vehicle	Std. Err. Mean kips	Std. Err. Predicted kips	Mean ESALs per Vehicle	Std. Err. Mean ESALs	Std. Err. Predicted ESALs
9	1	54.88	2.06	6.83	0.66	0.12	0.40
	2	52.89	3.26	7.29	0.56	0.19	0.42
	7	48.36	6.52	9.22	0.47	0.38	0.54
	11	52.45	2.30	6.91	0.63	0.13	0.40
	12	61.04	2.91	7.14	1.44	0.17	0.42
10	1	61.83	3.92	13.01	0.55	0.13	0.44
	2	70.27	6.20	13.87	1.05	0.21	0.47
	7	49.38	12.41	17.55	0.32	0.42	0.59
	11	70.58	4.39	13.16	0.92	0.15	0.44
	12	78.60	5.55	13.59	1.45	0.19	0.46
11	1	51.85	2.06	6.82	1.12	0.24	0.79
	2	50.09	3.25	7.27	1.23	0.38	0.84
	7	31.98	6.50	9.19	0.14	0.75	1.07
	11	54.70	2.30	6.90	1.36	0.27	0.80
	12	66.00	2.91	7.12	3.00	0.34	0.83
12	1	63.61	2.96	9.81	0.81	0.12	0.41
	2	89.85	4.67	10.45	1.52	0.20	0.44
	11	65.15	3.31	9.92	0.89	0.14	0.42
	12	68.39	4.18	10.24	1.36	0.18	0.43
13	1	79.41	3.15	10.44	0.88	0.22	0.72
	2	95.84	4.98	11.13	1.24	0.34	0.77
	7	103.50	9.95	14.07	0.52	0.69	0.97
	11	93.61	3.76	10.64	1.29	0.26	0.73
	12	117.84	4.45	10.90	3.53	0.31	0.75

Table 6.4 are about 10 percent of the predictions, with several exceptions, particularly for functional Class 7. The standard errors for a new predicted value differ from standard errors of the mean in that they account not just for variability in the mean estimates, but also for variability in the underlying population from which a new site is selected. Thus the standard errors of the predicted values are bigger.

The means (i.e., predicted values) and standard errors of the predicted values are an end product, which can be used in practice, of this Scheme 1 ANOVA. The predicted loads per vehicle can be multiplied by class AADT estimates from a new site to give AADL estimates for the new site. As will be discussed in Section 7, the standard errors can be combined with standard errors of the AADT estimates to yield an overall standard error of the AADL estimate. This shows that combining functional classes is not necessary for a reasonable shared-data approach to Scheme 1 AADL estimation.

These standard errors are one of the advantages of an ANOVA approach. Although the ANOVA predicted values are actually just ordinary arithmetic means, the standard errors differ from ordinary standard errors. The standard errors are pooled across functional classes. Because the sample sizes (number of site-direction-years) for each functional class are fairly small, standard errors computed for individual functional classes tend to be unstable. Under the assumption that the variance is about the same for all functional classes, the ANOVA provides an overall variance estimate, pooled over functional classes, and prediction standard errors that tend to be better than estimates based on individual class data.[15] Also, for functional classes for which data is available for one site only, standard errors are inferred from the other sites. Several other advantages of ANOVA over simply computing ordinary arithmetic means will be mentioned in the following sections.

6.3. SCHEME 2 (SHORT-TERM WIM TO AADL)

The logic in Scheme 2 for converting short-term (e.g., daily) load data to AADLs (see Figure 1.3) parallels the logic for converting short-term counts to AADTs: Permanent WIM site data can be used to compute load AFs—average-annual-daily-to-average-daily load ratios—which can be used to adjust short-term loads from new sites. This can be done on a vehicle-class-specific basis, and the overall loads estimated by addition over vehicle classes. Thus, the role of the WIM input in Scheme 2 depends not only on site-to-site differences, as in Scheme 1, but also on day-of-week and monthly differences.

The data-reduction procedure for Scheme 2 is as follows. For each vehicle class,

(1) For each site-direction-year compute, the AADL.
(2) For each site-direction-year and month-day-of-week combination, compute the average daily load.
(3) Compute raw AFs, that is, the ratios of the values from (1) to the values from (2).

[15] The equality-of-variance assumption can be checked by inspecting Figure 3.1. The assumption seems reasonable here.

(4) For each month and day-of-week combination, enter the raw AFs into a one-way ANOVA in functional class.

The ANOVA then produces class-specific AF estimates for each functional class, and standard errors for the estimates. These AF estimates can be used as predictions of the true AF that should be used at a new site. (The estimates **are** AFs.) A table, analogous to Table 6.4 for Scheme 1, of AF estimates, standard errors, and prediction standard errors, is produced by the ANOVA. The independence assumptions made for Scheme 1 apply as well to the raw AFs for individual day-of-week and month combinations.[16]

Although they are averaged over days within day-of-week and month combinations, some of the individual raw AFs can be unstable. This can be due to low count frequencies for certain vehicle classes, but can also be due to other data-quality problems. Here raw AFs greater than 10 were set to 10. This reduces their impact in the ANOVA. Of 20,649 raw AF averages, 255 (1 percent) had weight AFs (i.e., weight load ratios) greater than 10, and 1070 (5 percent) had standard ESAL AFs greater than 10. The truncation value 10 was selected as an initial guess and should not be viewed as a final recommendation.[17] Nevertheless, the percentages are small enough that the choice of truncation point is unlikely to be critical (i.e., other reasonable choices would lead to nearly the same final AF estimates.)

A table, analogous to Table 6.4, of AF estimates, standard errors, and prediction standard errors for the Region 1 data for each vehicle class, month, day-of-week, and functional class is too big to reproduce here. Nevertheless, examination of such a table for vehicle Class 9 and for its analogs for the other vehicle classes, reveals that the prediction standard errors are big relative to the corresponding AF estimates, occasionally as big as 100 percent. For vehicle Class 9 (3S2's), this cannot be due to infrequency of traffic in the vehicle class. Thus, combining Class 9 with another class would not help. The ANOVA done here was also done in logs of AFs rather than simple AFs, which helped reduce the prediction standard errors a little, but the within-functional-class variance remains substantial. The situation might be improved by subdividing functional classes, but that is beyond the scope this report. Fortunately, because of cancellation of errors, the relative error improves a lot when short-term WIM totals for each vehicle class are multiplied by the AFs and summed to produce an overall load estimate. Even though standard errors for individual class estimates are relatively large, the standard error for the overall load estimate (root sum of squares—see Section 7) is much smaller. This is illustrated in Section 7 (Example 7.2).

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[16]The raw AFs from Steps 1-3 can be computed using ordinary arithmetic means. They can also be computed using ANOVA. The ANOVA approach is also useful when all data for a particular day-of-week and month combination is missing, as ANOVA then provides a convenient framework for modeling the missing values. This extension of ANOVA, however, will not be considered further in this report.

[17]The choice of "10" was made for the purpose of illustrating the approach. Nevertheless, the choice of truncation threshold is not likely to be critical, as long as only a small percentage of values are truncated. A **lower** truncation threshold of .1 was also considered here, but no weight AFs and only 7 ESAL AFs were below it.

A three-way ANOVA analagous to the ANOVA for counts in Section 6.1 can be used to assess functional class differences under Scheme 2. Table 6.5 contains results of such an analysis for vehicle Class 9. The table shows that 38.9 percent of the total variation is unexplained by the factors in the ANOVA model (month, day-of-week, functional class). That leaves 61.1 percent explained, which is the value of R^2, expressed as a percent. The table shows that day-of-week is clearly the dominant model effect. This is true not just for Class 9, but for all of the vehicle classes except Class 13 (7+ axle multi-trailer) and Class 4 (buses). That day-of-week has more influence than month on loads is also illustrated in Figures 5.4 and 5.5.

Table 6.5. Analysis of Variance of AFs for Vehicle Class 9

Cause	**Sum of Squares**	**Percent of Total**	**Root Mean Square**
Month	83.4	1.5	.19
Day-of-week	2793.0	49.8	1.10
Month×Day-of-week	53.4	1.0	.15
Functional Class×All	498.6	8.9	.47
Functional Class	93.8	1.7	.20
Month×Functional Class	119.0	2.1	.23
Day-of-Week×Functional Class	177.3	3.2	.28
Month×Day-of-Week×Functional Class	108.5	1.9	.22
Error (unexplained by above)	2178.5	38.9	.95
Total (for 2298 observations)	**5607.0**	**100.0**	**1.56**

The Functional Class×All row in Table 6.5 measures how much AFs differ with functional class. Because AFs at any one site are about 1 on the average, the effect of functional class individually would be expected to be small.[18] But the interactions of functional class with month and day-of-week can be large. Here the combined effects of functional class, which are summarized in the "Functional Class×All" row of Table 6.5, account for about 9 percent of the total variation. The average departure for the combined functional class effects is .47 (root mean square), which is certainly

[18] Because the distributions of AFs are skewed, their means actually tend to be greater than 1 even though their medians are much closer to 1. Thus the overall AF mean varies with functional class. This partially accounts for the entry of 1.7 percent in Table 6.5 for the overall functional class effect. The log transformation is one way to reduce the effect of skewness, but, for simplicity, logs were not used here.

appreciable in the context of AFs. Thus some of the AFs differ with functional class in ways that are of practical importance. This can also be inferred from tables of AFs . For example, for vehicle Class 9, the January Sunday factors for functional Classes 2 and 11 are 2.91 and 5.23. In many cases (e.g., January Mondays, February Sundays) even functional Classes 1 and 2 (both rural; all sites are from Vermont) differ appreciably.

6.4. SCHEME 3 (SHORT-TERM AXLE TO AADL)

In Scheme 3, short-term axle (tube) counts (no vehicle classification) are used to estimate loads. (This scheme would most likely be used with a site where short-term class or volume counts are unavailable.) Assume here that these counts are annualized using axle correction factors from permanent axle counters. The rationale for this, as opposed to using WIM data to both annualize the short-term axle counts and to compute AADL estimates from them, is that permanent axle counters are less expensive and more common than permanent WIM sites. The AADA values are then converted to AADL estimates using conversion factors computed from the permanent WIM data.

For this report at least, Scheme 3 is simpler than Schemes 1 or 2. Mean standard ESALs per axle are computed for each site, direction, and year, and analyzed just as standard ESALs per vehicle were analyzed under Scheme 1—except overall, not separately for each vehicle class. The R^2 statistic for this ANOVA is .52 and the significance level for functional class is .0012. The functional class means, standard errors of the mean, and prediction standard errors are in Table 6.6. Functional Class 12 clearly seems to carry the heaviest load per axle. Classes 1 and 2 are very similar, and differ from Class 11 by about 15 percent. The higher variability of the ESALs is a reflection of the general behavior of ESALs, not a few outliers.

6.5. CONCLUSIONS ABOUT FUNCTIONAL CLASS COMBINATIONS

Functional class differences in Region 1 traffic are statistically significant and big enough to be of practical importance. Functional Class 12 bears heavier traffic than the other classes. Functional Classes 1, 2, and 11 seemed similar under the Scheme 1 analysis, but Class 11 differed from 1 and 2 under Schemes 2 and 3. Functional Classes 1 and 2 are quite similar, especially under Schemes 1 and 3. However, functional Classes 1 and 2 do exhibit some differences under Scheme 2. Further, all of the functional Class 1 and 2 data analyzed here is from Vermont. Although it might be appropriate in certain contexts for Vermont to combine Classes 1 and 2, there is not a sufficient basis here for concluding that Classes 1 and 2 should be combined in general. The only Class 7 data considered here is from site CT974, which in many ways seems anomalous. Nevertheless, there is no basis for combining Class 7 with other classes.

In general, there does not appear to be sufficient support in this data for combining functional classes. Furthermore, the one-way ANOVA approaches taken here seem to provide a workable

Table 6.6. Means, Standard Errors, and Prediction Standard Errors for Weights and Standard ESALs per Axle (Scheme 3)

Functional Class	Mean Weight (kips) per Axle	Std. Err. Weight Mean	Std. Err. New Predicted Weight	Mean ESALS per Axle	Std. Err. Mean	Std. Err. New Predicted
1	10.0969	0.3408	1.1305	0.1271	0.0206	0.0683
2	10.2117	0.5389	1.2051	0.1222	0.0326	0.0728
7	4.6824	1.0779	1.5243	0.2078	0.0651	0.0921
11	9.2917	0.3811	1.1432	0.1454	0.0230	0.0691
12	10.9529	0.4820	1.1807	0.2900	0.0291	0.0714

method for data sharing, that is, for cross-site extrapolation without combining functional classes. The ANOVA approach also and accounts, via prediction standard errors, for within-class site-to-site variability. The Scheme 2 analysis suggests that if anything, functional classes might in fact be defined even more specifically. This idea is also supported by differences in regulations. For example, the vehicle Class 9 weight limit in Rhode Island is 120,000 pounds. These differences between sites should not automatically preclude cross-site (or cross-state) extrapolations, however, but they do point out the necessity for a proper accounting for site-to-site variability.

7. ERROR PROPAGATION AND THE QUESTION OF COMBINING VEHICLE CLASSES

This section is about the process of combining conversion factor estimates, which were discussed in Sections 4 and 6, with short-term traffic counts or WIM data, to produce AADL estimates. Three examples are given, one for each of Schemes 1, 2, and 3, which illustrate the computation of AADL estimates and standard errors for each vehicle class and over all classes. The examples demonstrate, in a way from which a general principle can be inferred, that there is not much to be gained by combining vehicle classes. The examples also illustrate the reduction in the relative variation in overall estimates as opposed to class-specific estimates, because of statistical cancellation of errors.

Like the intermediate statistics, the basic formulas for load estimation under Schemes 1, 2, and 3 also differ:

$$\text{Scheme 1:}\quad \text{AADL estimate} = \sum_{\text{vehicle classes}} (\text{short class count})\times(\text{class AF})\times(\text{load per vehicle})$$

$$\text{Scheme 2:}\quad \text{AADL estimate} = \sum_{\text{vehicle classes}} (\text{short-term WIM})\times(\text{WIM AF})$$

$$\text{Scheme 3:}\quad \text{AADL estimate} = (\text{short axle count})\times(\text{axle AF})\times(\text{load per axle})$$

Each of the components in each of these formulas is subject to error because of statistical sampling. A proper assessment of the statistical error is needed to put the estimates in proper perspective: How accurate are they? Are they even worth computing? Which terms in the estimates cause the most impact on the overall error? Where might resources best be spent reducing the overall error? Answering any of these questions is good reason for computing approximate standard errors for load estimates.

Although the above formulas are straightforward, error propagation under them is considerably more difficult. The terms for the different vehicle classes may be correlated. Therefore, to estimate the overall standard error, the correlations should, strictly speaking, be propagated through the formulas. Doing that first requires estimating the correlations, which is a problem in multivariate analysis (here, multivariate ANOVA). Then, the correlation estimates must be incorporated into overall variances. That is **not** straightforward, because of the sum-of-products forms of the AADL estimates. Furthermore, data from the same sites might be used to compute different factors. For example, data from the same continuous monitoring sites might be used to adjust single-day vehicle counts to AADT estimates and to convert AADT estimates to AADL estimates. Modeling the correlation between the different adjustment and conversion factors would be difficult.

Therefore, two further simplifying assumptions will be made here—that estimates for different vehicle classes are statistically independent and that the different adjustment or conversion factors are also independent.[19] The assumptions allows us at least a first approximation of the variance of the overall AADL estimates, without a whole lot of technical development.

Under independence, the variances of sums of products can be derived from the following two basic statistical formulas for random variables (X's and Y's)

$$\text{Variance}\left(\sum_i X_i\right) = \sum_i \text{Variance}(X_i), \tag{7.1}$$

and

$$\begin{aligned}\text{Variance}(X \times Y) = \;& \text{Variance}(X) \times \text{Variance}(Y) \\ &+ (\text{Mean}(X))^2 \times \text{Variance}(Y) \\ &+ \text{Variance}(X) \times (\text{Mean}(Y))^2 .\end{aligned} \tag{7.2}$$

The last equation may be rewritten as

$$\text{Std.Err.}(X \times Y) = \text{Mean}(X) \times \text{Mean}(Y) \times \left[\text{CV}(X)^2 \times \text{CV}(Y)^2 + \text{CV}(X)^2 + \text{CV}(Y)^2\right]^{1/2} \tag{7.3}$$

Because a standard error is the square root of a variance or variance estimate, the standard error of a sum of independent random variables is the root sum of squares of their standard errors. In the above AADL estimates, each term in the summation for Schemes 1 or 2, or the entire expression under Scheme 3, is a product to which (5.3) can be applied.

To illustrate, consider again the count AFs and the single-day, August Wednesday classification count of 285, discussed in Section 4 and Section 6.1. Recall that the AF for Vehicle Class 5 and Functional Class 12 was .882, and the Class 5 AADT estimate for the new site was AF × Count = 227.5. Good scientific procedure dictates that we should assess how accurate the AADT estimate actually is. From the above propagation of error theory (variance of products), the standard error of the AADT (AF × Count) is

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[19]How good these assumptions are depends on the particular scheme formula and terms. Long-term sites, which are assumed to be selected randomly, are likely to have correlations in the estimation errors for the various vehicle classes. However those estimates are not load totals, but are loads per vehicle or axle, or year-to-day adjustment factors, and are therefore certain to be less correlated than load estimates themselves. The random errors for each short-term site on the other hand are mainly due to counting and are therefore likely to be approximately independent across vehicle classes. In practice, **different** data might be used for different adjustment or conversion factors or the factors may be sufficiently different in nature, in which case the factors might satisfy the statistical independence assumption.

$$\text{Mean(AF)}\times\text{Mean(Count)}\left[[\text{CV(AF)}\times\text{CV(Count)}]^2 + [\text{CV(AF)}]^2 + [\text{CV(Count)}]^2\right]^{1/2}.$$

From an approximation based on the Poisson statistical distribution for counts [11], an approximate CV for the count 285 is $1/285^{1/2}$=.059. From Table 6.1, the CV for the AF (prediction context) is .201/.882=.228. Entering these into the above equation, and the AF and Count for their means, gives 59.2, the standard error of the AADT estimate for the new site. It is interesting to note that because the AF CV (.228) is much bigger than the Count CV (.059), most of the variability in the Class 5 AADT is coming from the AF, not the single-day count.

Example 7.1 (Scheme 1). Consider the following single-day classification counts from a "hypothetical" short-term site of functional Class 11. The counts are actually from MA001 South, Tuesday, 4/2/96, but assume here, as an example for Scheme 1, that they are from a new site.

Vehicle Class	Single-day Count
4	198
5	2404
6	536
7	32
8	509

Vehicle Class	Single-day Count
9	1995
10	33
11	29
12	7
13	0

Under Scheme 1, adjustment factors are used to compute class-specific AADT estimates from the single-day counts. Vehicle-class-specific count AFs and AF standard errors were computed from a one-way ANOVA in raw AFs for April Tuesday vehicle counts as they were in Section 6.1 for August Wednesdays. This gives the following table of count AFs and standard errors.

Vehicle Class	Count AF	Std. Err.
4	0.98	0.50
5	1.10	0.38
6	0.96	0.19
7	1.40	0.82
8	0.94	0.20
9	0.94	0.17
10	0.87	0.29
11	0.95	0.42
12	1.75	0.89
13	1.18	0.28

A single AF does not adjust the single-day count to the AADT, exactly, for every day in a day-of-week and month combination. Only the **average** for the month and day-of-week is adjusted exactly.

Thus, in a proper statistical accounting for error, the departures of single-day counts from the means for their corresponding day-of-week and month must also be accounted for. For this, the following approximation can be used.[20]

$$\text{Variance of Single-day count} \approx \text{Mean of Single-day count} \tag{7.4}$$

Formula (7.4) can be used with approximation (7.2) to compute an approximate standard error for the AADT estimate, that is, for the product of a single-day count and an AF. From the magnitudes of the single-day counts, AFs, and AF standard errors, it can be shown that the AADT standard error is not sensitive to this approximation.[21]

Load conversion factors (kips per vehicle) from Table 6.4, for functional Class 11, were multiplied by the class AADT estimates to get class-specific load estimates, as well as a total AADL, as in Table 7.1. Table 7.1 also contains prediction standard errors from Table 6.4, AADL standard errors, and coefficients of variation[22] (CVs) for the AADLs. The class-specific AADL standard errors are computed by substituting the AADT and conversion factor estimates and standard errors, computed using (7.4), into formula (7.2). Then, by formula (7.1), the standard error of the overall AADL estimate is the root sum of squares of the class-specific standard errors.

From Table 7.1, the overall AADL is 180 thousand kips per day. The overall prediction standard error is 27 thousand kips per day. The "exact" value, computed directly from the MA001 South data, is 167 thousand kips per day, about one-half standard error below the estimate.

Table 7.1 illustrates an important point:

> The contributions of the low-frequency truck classes, such as 7 and 10-13, to overall load estimates are minor (here about 4 percent). Whether or not these vehicle classes are combined with others is not important from the standpoint of overall load estimation, because those classes do not contribute much to the overall load.

The same applies to the individual and overall standard errors. Note that this applies to any such combination of low and high frequency totals and is not unique to site MA001.

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[20]This approximation follows from the Poisson statistical distribution for counts. See [11].

[21]This follows because formula (7.2) reduces to

$$\text{Variance(Single-day count} \times \text{AF)} \approx (\text{Mean(Single-day count)})^2 \times \text{Variance(AF)},$$

which does not depend on the variance of the single-day count.

[22]The coefficient of variation (CV) is the ratio of the standard error to the mean.

Table 7.1. Scheme 1 Computation of AADL Estimates and Standard Errors

Vehicle class	4/2/96 Count	AF	AF std. err.	Class AADT	AADT std. err.	Factor (kips/ vehicle)	Factor std. err.	AADL (kips)	AADL std. err. (kips)	CV
4	198	0.97	.50	193	100	29.6	2.1	5,712	2981	.52
5	2404	1.10	.38	2655	904	13.4	1.4	35,662	12731	.36
6	536	0.96	.19	517	102	34.2	3.0	17,690	3818	.22
7	32	1.40	.82	45	28	72.3	8.3	3,236	2052	.63
8	509	0.94	.20	477	104	32.2	2.9	15,340	3628	.24
9	1995	0.94	.17	1874	348	52.5	6.9	98,311	22497	.23
10	33	0.87	.29	29	11	70.6	13	2,016	868	.43
11	29	0.95	.42	27	13	54.7	6.9	1,502	766	.51
12	7	1.75	.89	12	8	65.2	9.9	797	546	.69
13	0	1.18	.28	0	0	93.6	11	0	0	.
All								180,266	26659	.15

The CVs in Table 7.1 illustrate the reduction of the overall CV relative to the class-specific CVs. What an acceptable CV is depends on the application. In many applications CVs of .5 or so are considered high, but CVs of around .15—the overall CV here—are acceptable.

Example 7.2 (Scheme 2). The AADL computation for Scheme 2 analysis starts with short-term loads, which are converted directly to AADLs in a manner analogous to the adjustment of short-term counts. The AFs are computed from the April Tuesday ANOVA discussed in Section 6.3 (tables not included here). Table 7.2 is thus computed, again using formulas (7.1) and (7.2).

The "exact" AADLs, computed directly from the MA001 data series, are 167 thousand kips and 4,560 ESALs. From Table 7.2, the exact AADLs are 1.6 and 1.4 standard errors below their respective estimates. Observe the reduction in the relative variation, expressed as CV, for the overall-vs-class-specific estimates. The overall CVs are better. This is due to statistical cancellation of errors and the intermixing of high and low-frequency totals and is not unique to site MA001.

Example 7.3 (Scheme 3). On 4/2/96, 19,331 axles were counted at MA001 South. To put these on an annual basis, an AF was computed from a one-way ANOVA in the average-annual-to-average-daily axle ratios. The AF estimate for MA001 South is .953 ± .193 (prediction standard error). From Table 6.6, the factor for converting AADA to AADL for weight in kips is 9.29 ± 1.14 (prediction standard error) and .145 ± .069 for ESALs. Table 7.3 is obtained by the same approach as for Scheme 1, but without vehicle classes and with axle counts rather than vehicle counts.

Table 7.2. Scheme 2 AADL Estimates by Vehicle Class for Weight (kips) and "Standard" ESALs

CLASS	Analysis for Weight (kips)						Analysis for "Standard" ESALs					
	4/2/96 Weight	**AF**	**Std. Err. AF**	**AADL**	**Std. Err. AADL**	**CV**	**4/2/96 ESALs**	**AF**	**Std. Err. AF**	**AADL**	**Std. Err. AADL**	**CV**
4	6,646	1.02	0.68	6,748	4,514	.67	148.4	1.09	1.35	161.5	202.3	1.25
5	39,426	1.06	0.34	41,780	13,312	.32	1005.0	1.20	0.67	1205.0	669.6	0.56
6	21,941	1.03	0.28	22,661	6,189	.27	837.2	1.50	0.88	1254.4	733.9	0.59
7	2,606	1.79	1.17	4,676	3,058	.65	152.0	2.82	2.71	428.8	414.2	0.97
8	18,504	0.99	0.28	18,391	5,141	.28	362.3	1.19	0.66	431.4	239.1	0.55
9	123,726	1.01	0.26	124,388	32,536	.26	3675.2	1.29	0.66	4729.8	2413	0.51
10	2,566	0.93	0.39	2,376	1,008	.42	69.8	1.22	0.89	85.3	62.7	0.73
11	1,775	0.99	0.44	1,766	782	.44	55.2	1.25	0.79	68.7	44.1	0.64
12	546	1.84	0.96	1,003	522	.52	13.2	1.94	1.77	25.6	25.0	0.98
13	0	1.11	0.56	0	0	.	0.0	1.29	3.46	0.0	0.0	.
Ω				223,788	36,499	.16				8390.5	2662	0.32

Table 7.3. Scheme 3 AADL Estimates for Weight (kips) and "Standard" ESALs

Axles	Axle AF	AF SE	AADA	**AADA SE**	Units	Conv. Factor	**Conv. Factor SE**	AADL	AADL SE	CV
19331	.953	.193	18427	3730	kips	9.29	1.14	171,216	40780	.24
					ESALs	0.15	0.07	2,679	1408	.53

The weight AADL estimate is pretty good: 171 thousand kips as opposed to the true value of 167 thousand. That may be involve some luck, however, as the ESAL AADL is not nearly so good: 2,679 as opposed to a true value of 4,560. The ESAL estimate is 1.3 standard error below the true value, not unusual in the context of its standard error. The ESAL CV of .53 indicates that the axle-count-based ESAL load estimates are quite noisy. Perhaps that is to be expected when ESAL AADLs are estimated from single-day axle counts.

8. CONCLUSION

The finding of this report is that from the standpoint of load estimation, (1) there is little to be gained by combining vehicle classes, and (2) there is not sufficient evidence to support combining functional classes. Combining vehicle classes would not improve load estimates because of the way the individual-class data enters into the expressions for total load. The low-frequency classes do not contribute much to the total, so there is little to be gained by combining them with other classes. Regarding functional classes, the Region 1 data exhibits substantial differences among some of the classes. Functional Classes 7, 11, and 12 each exhibit unique behavior under one or more of the data analysis schemes considered here. Although functional Classes 1 and 2 are appear similar in most cases, the only Class 1 and 2 data considered here is from Vermont, which is insufficient for supporting a general recommendation about combining functional Classes 1 and 2.

In addition to their roles in estimating loads, vehicle classification percentages for each functional class are required to be reported by each state, each year, as part of the state's HPMS submittal. This data is used in the Highway Statistics publication and in the needs model run by FHWA Headquarters.

This report demonstrates that the same approach to seasonal and day-of-week adjustment of overall traffic volumes can be applied to class-specific volumes and ESALs and loads. The report also demonstrates that ANOVA is a reasonable method for combining continuous traffic monitoring data across states, for computing combined-data estimates of various adjustment and conversion factors, and for accounting for statistical error in subsequent extrapolations of the combined-data estimates to new (short-term) sites. A proper accounting for statistical error is imperative for proper understanding and control of any statistical process, and especially so in a shared-data environment. The one-way ANOVAs done here are simple enough to do with an ordinary spreadsheet program.

The WIM data collection and analysis system in Region 1 could be improved in several ways. WIM data, especially when converted to ESALs is inherently noisy. Data adjustments such as the truncation procedures considered in Section 2, data transformations such as logs, and nonparametric statistical procedures all might improve the ultimate signal-to-noise ratio of the WIM data. The plots in Appendix C show that application of a data quality control procedure such as cusum charting would likely lead to improved data quality.

To the extent feasible, the choices of continuous monitoring sites should be made so that the sample of continuous sites reflects the WIM data from short-term sites, to which adjustments and conversions, computed from the long-term data, are applied. In short, the site selection should either be or emulate random sampling. (For more on the importance of random sampling, see [12].)

In addition to random sampling, several other assumptions about statistical independence were made to facilitate a workable analytical approach. Directions within sites and years were both regarded as random. In a more detailed analysis, their correlations could be modeled. The computations in Section 5, based on formulas (5.1) and (5.2), assume statistical independence between various factors and between terms for different vehicle classes. These correlations could also be modeled, for example, using a one-way **multivariate** ANOVA.

Adjustment factors are inherently biased high, because their short-term (e.g., average for particular day-of-week and month) components enter as denominators. The bias follows from a statistical property of reciprocals (that the expectation of a reciprocal equals or exceeds the reciprocal of the expectation). This bias, which was also observed empirically in a study of traffic monitoring data from Florida and Washington [13], should be explored.

Other schemes, in addition to Schemes 1, 2, and 3, could be explored, for example, a scheme in which short-term WIM data is combined with long-term classification counts to yield AADLs. The procedures implemented here for a "standard" ESAL could be packaged for easy recomputation for an ESAL defined for any particular roadway characteristics of interest. The ANOVA methods used here could be extended and refined. The log transformation should be more carefully investigated as a means of making the data more normal-like. Residual plots should be considered more carefully in this context and for identifying outliers. For the sake of simplicity, differences due to both year and direction have been ignored in the methods considered here; those differences should also be considered.

9. REFERENCES

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APPENDIX A. COMPUTATION OF ADJUSTMENT FACTORS

In this appendix we consider the computation of adjustment factors (AFs) for converting single-day traffic volume counts to estimates of overall annual average daily travel (AADT). Three types of factors are considered: monthly (seasonal), day-of-week, and axle correction. This discussion is based on the 1995 *Traffic Monitoring Guide* (TMG).

Monthly adjustments are made to account for seasonal differences in traffic volumes. We compute monthly (seasonal) AFs as follows (TMG, pp 3-2-6 and 3-2-9): For a site *j* in a functional class *i*, consider the vector of 13 values:

$$< AADT_{ij} , M_1 ADT_{ij} , M_2 ADT_{ij} , . . . , M_{12} ADT_{ij} >,$$

where $AADT_{ij}$ denotes annual average daily traffic (total for year divided by number of count vdays in year) and, similarly, $M_l ADT$ is the average daily traffic for month *l*. For each site *j*, compute the site-specific monthly AFs:

$$< FM_{1ij},\ FM_{2ij},\ .\ .\ .\ ,\ FM_{12ij} > \ = \ < \frac{AADT_{ij}}{M_1 ADT_{ij}},\ \frac{AADT_{ij}}{M_2\ ADT_{ij}},\ .\ .\ .\ ,\ \frac{AADT_{ij}}{M_{12}\ ADT_{ij}} > .$$

Day-of-the week adjustments are made to account for daily differences in traffic volumes, particularly differences between weekdays and weekends. The calculation of day-of-week factors is similar to the monthly factor calculation (TMG, p 3-3-16): For the l^{th} month and the j^{th} site in functional class *i*, consider the vector of monthly and daily average daily travel:

$$< M_l ADT_{ij} , D_1 T_{ijl} , D_2 T_{ijl} , . . . ,D_7 T_{ijl} >,$$

where $D_k T_{ijl}$ is the average of the daily traffic (total count for the days divided by number of count days) for the k^{th} day of the week of the month *l* for site *j* in functional class *i*. For example, $D_2 T_{ij6}$ is the average of daily travel on Mondays in June for site *j* in functional class *i*. For each site *j*, compute the site-specific day-of-week factors.

$$< FD_{1ijl} ,\ FD_{2ijl} ,\ \dots ,\ FD_{7ijl} > \ = \ < \frac{M_l\ ADT_{ij}}{D_1 T_{ijl}},\ \frac{M_l\ ADT_{ij}}{D_2 T_{ijl}},\ \dots ,\ \frac{M_l\ ADT_{ij}}{D_7 T_{ijl}} > .$$

For each site *j*, overall AFs for both day-of-week and month are then simply the product of the daily and monthly factors:

$$AF_{ijkl} = \frac{AADT_{ij}}{M_l\ ADT_{ij}} \times \frac{M_l\ ADT_{ij}}{D_k T_{ijl}}.$$

For a single site, the procedure could thus be simplified by computing the month-day-of-week adjustment factors as the ratios of the AADT to the average count for each month-day-of-week. (The monthly averages cancel).

AFs for different sites within the same functional class are averaged to produce AFs representative of the functional class. For functional classes with more than one long-term site, however, there are variations possible in the averaging process: Monthly and day-of-week AFs can either be multiplied first and then averaged (variation 1) or averaged first and then multiplied (variation 2). Further, in either approach "average" AFs can also be computed by averaging the numerator for all sites and the denominator for all sites and then taking the ratio of the averages (variations 3,4). In variations 3 and 4, however, this approach leads to only one AF average, and therefore does not provide a means for assessing site-to-site variability, which is necessary for deciding about combining sites into functional classes. Variations 1 and 2 provide site-specific AF estimates, which can be compared. Variation 1 is simpler than variation 2, because only the combined (i.e., month-times-day-of-week) AFs need be considered, rather than separate AFs for both month and day-of-week as well as their combination. For this reason, variation 1 is the approach used in this document.

Some traffic monitoring devices count pulses, that is axles, rather than vehicles. For these, axle correction factors can be computed as in the TMG (p 3-3-17**)**: For the j^{th} site in functional class i, compute the site-specific axle correction factor:

$$CF_{ij} = \frac{\text{total vehicle count for year}}{\text{total axle count for year}}.$$

APPENDIX B. FHWA VEHICLE CLASSES

FHWA Class	Definition
1	Motorcycles
2	Passenger cars
3	Other two-axle, four-tire single unit vehicles
4	Buses
5	Two-axle, six-tire, single-unit trucks
6	Three-axle single-unit trucks
7	Four-or-more-axle single-unit trucks
8	Four-or-fewer-axle single-trailer trucks
9	Five-axle single-trailer trucks
10	Six-or-more-axle single-trailer trucks
11	Five-axle multi-trailer trucks
12	Six-axle multi-trailer trucks
13	Sever-or-more-axle multi-trailer trucks

APPENDIX C. CUSUM QUALITY CONTROL PLOTS

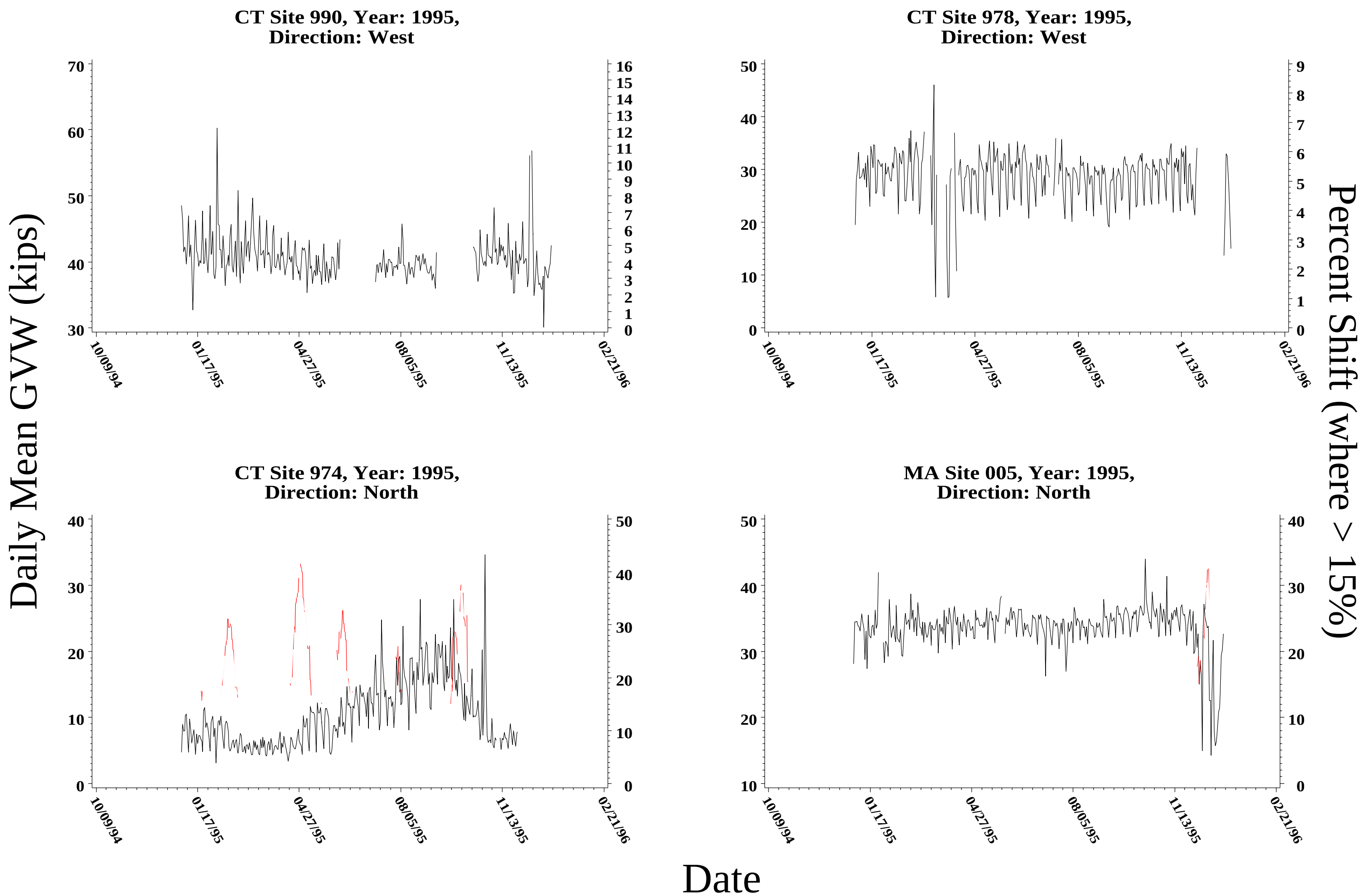

Figure C. Cusum quality control plots. Red indicates a possibly important change.

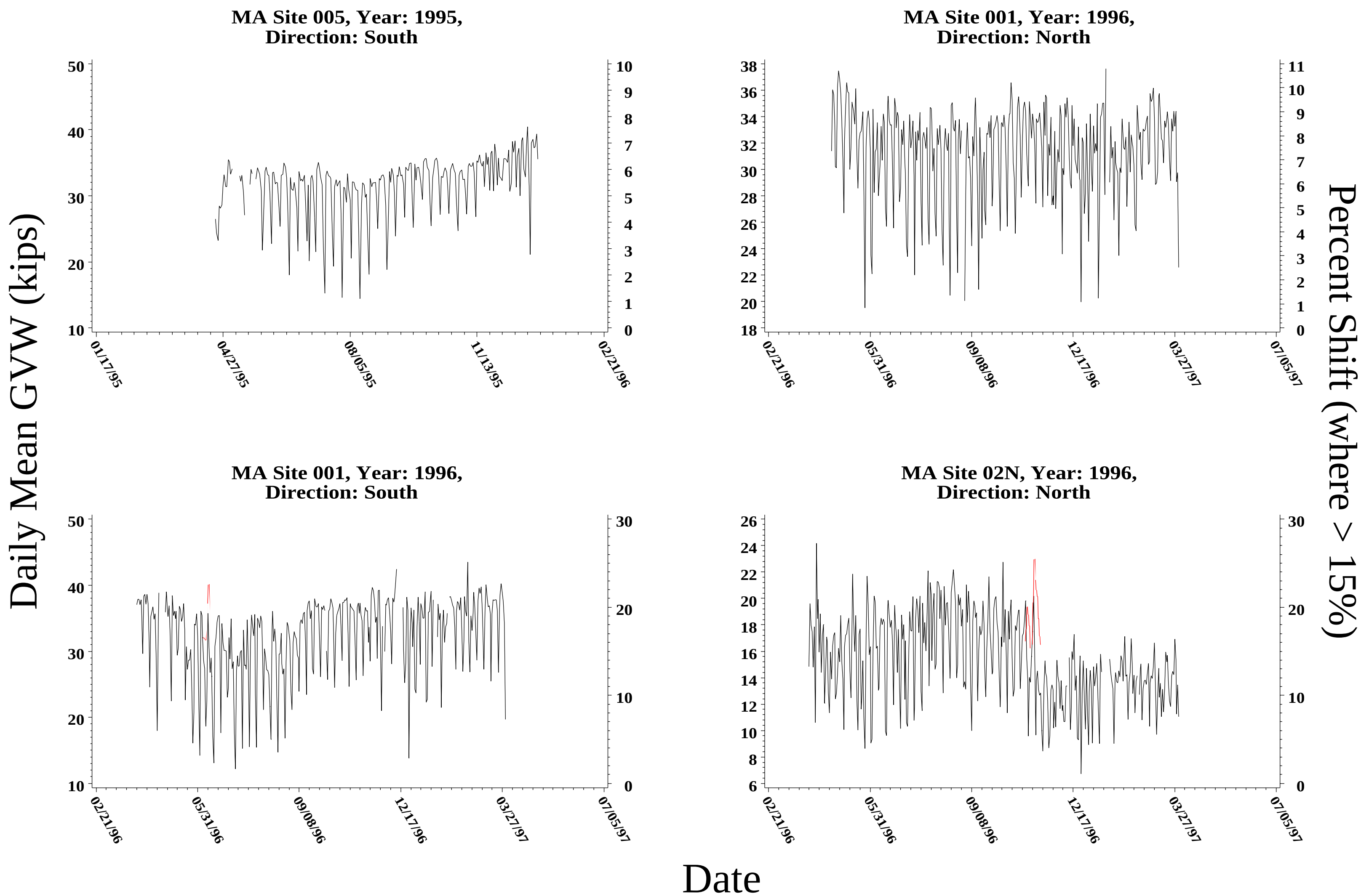

Figure C (cont’d). Cusum quality control plots. Red indicates a possibly important change.

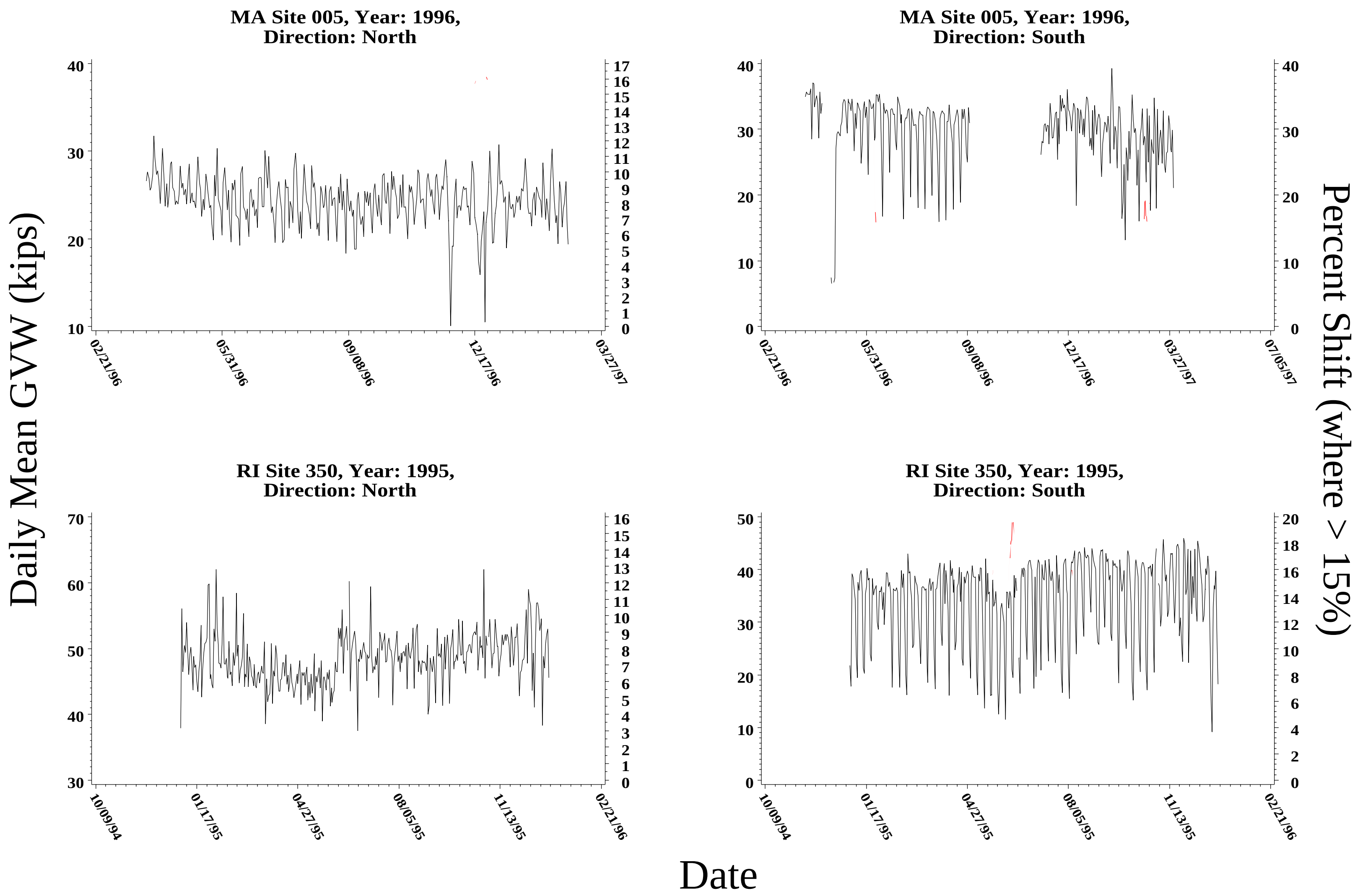

Figure C (cont'd). Cusum quality control plots. Red indicates a possibly important change.

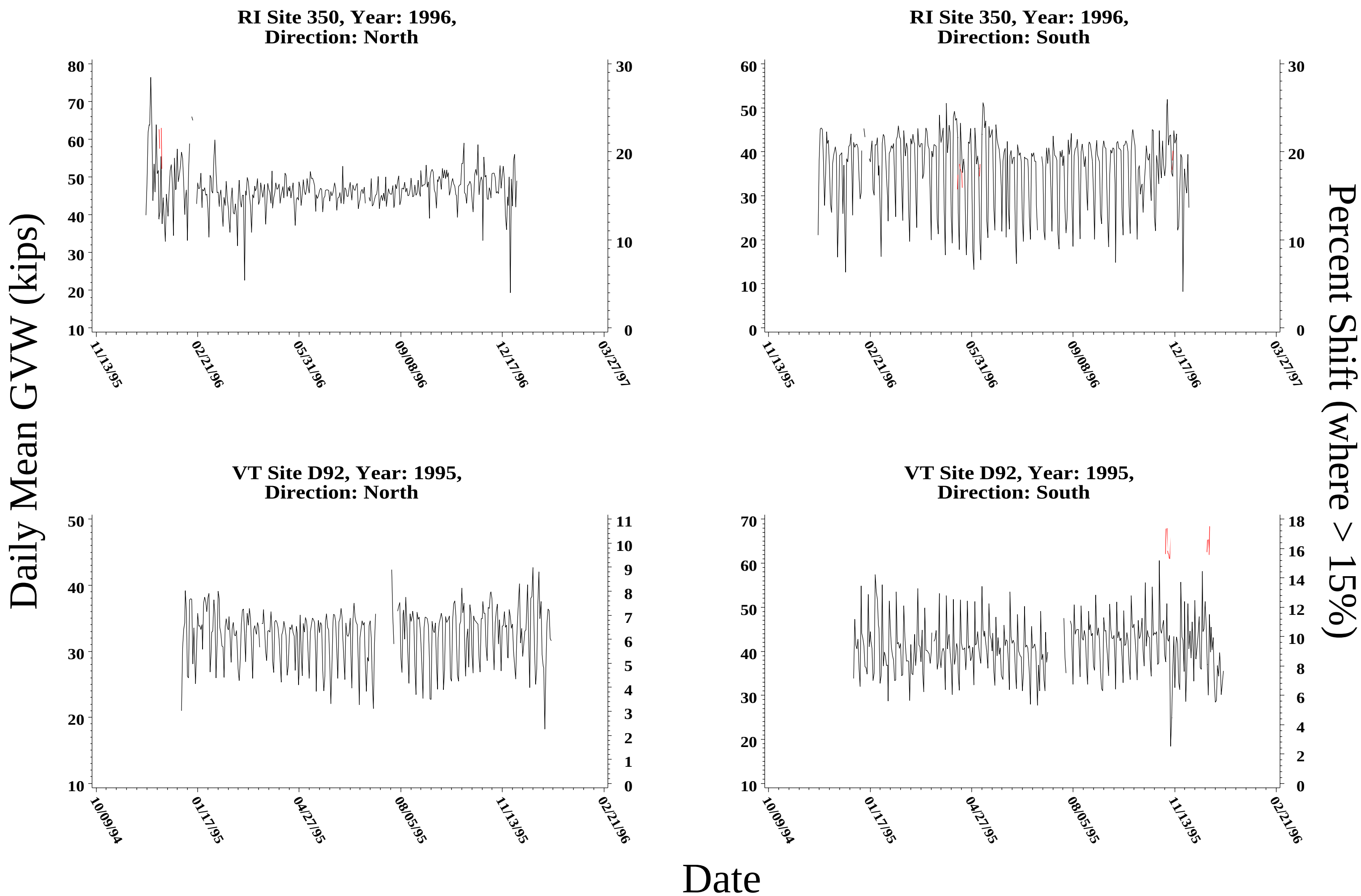

Figure C (cont'd). Cusum quality control plots. Red indicates a possibly important change.

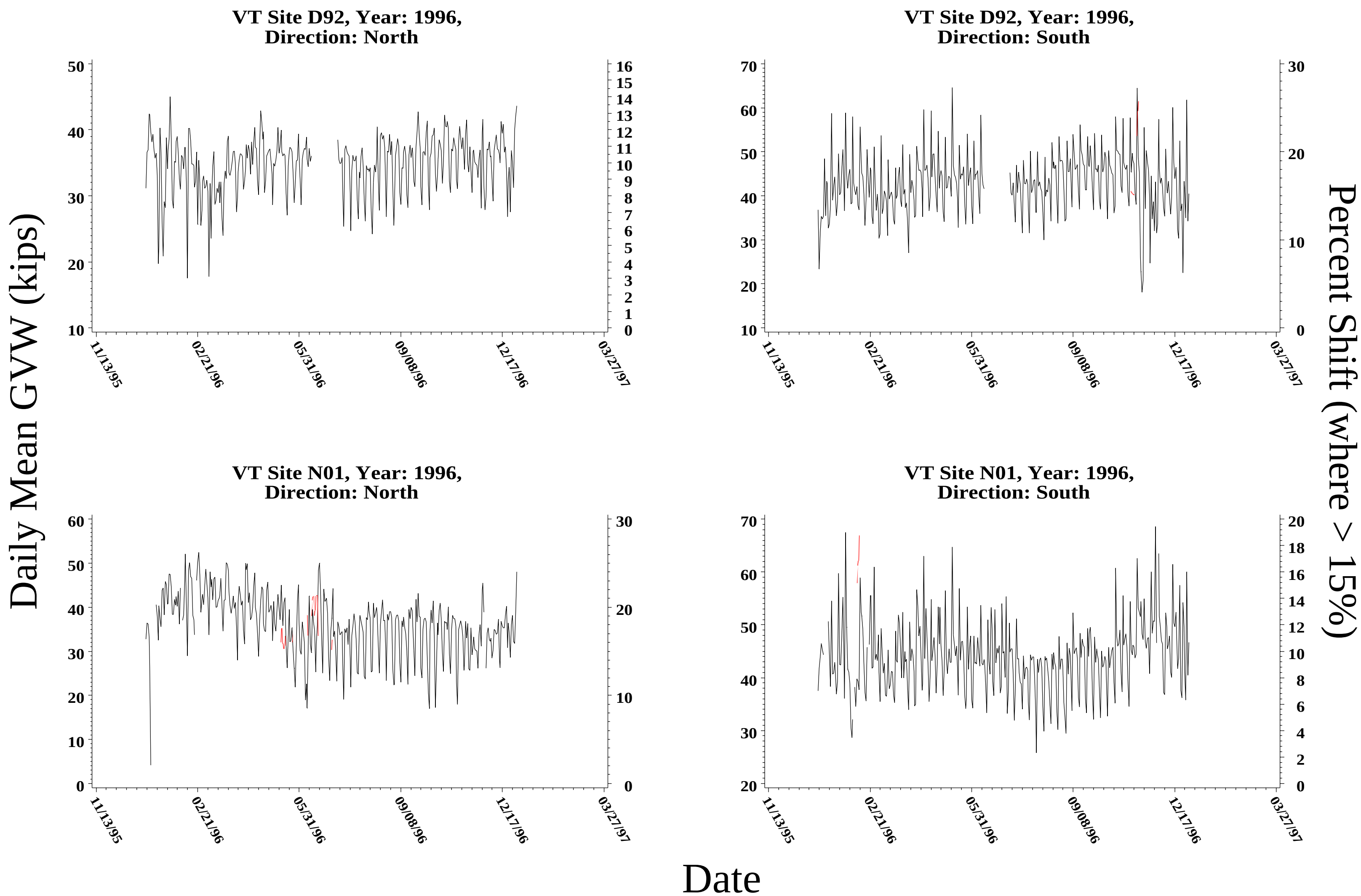

Figure C (cont'd). Cusum quality control plots. Red indicates a possibly important change.

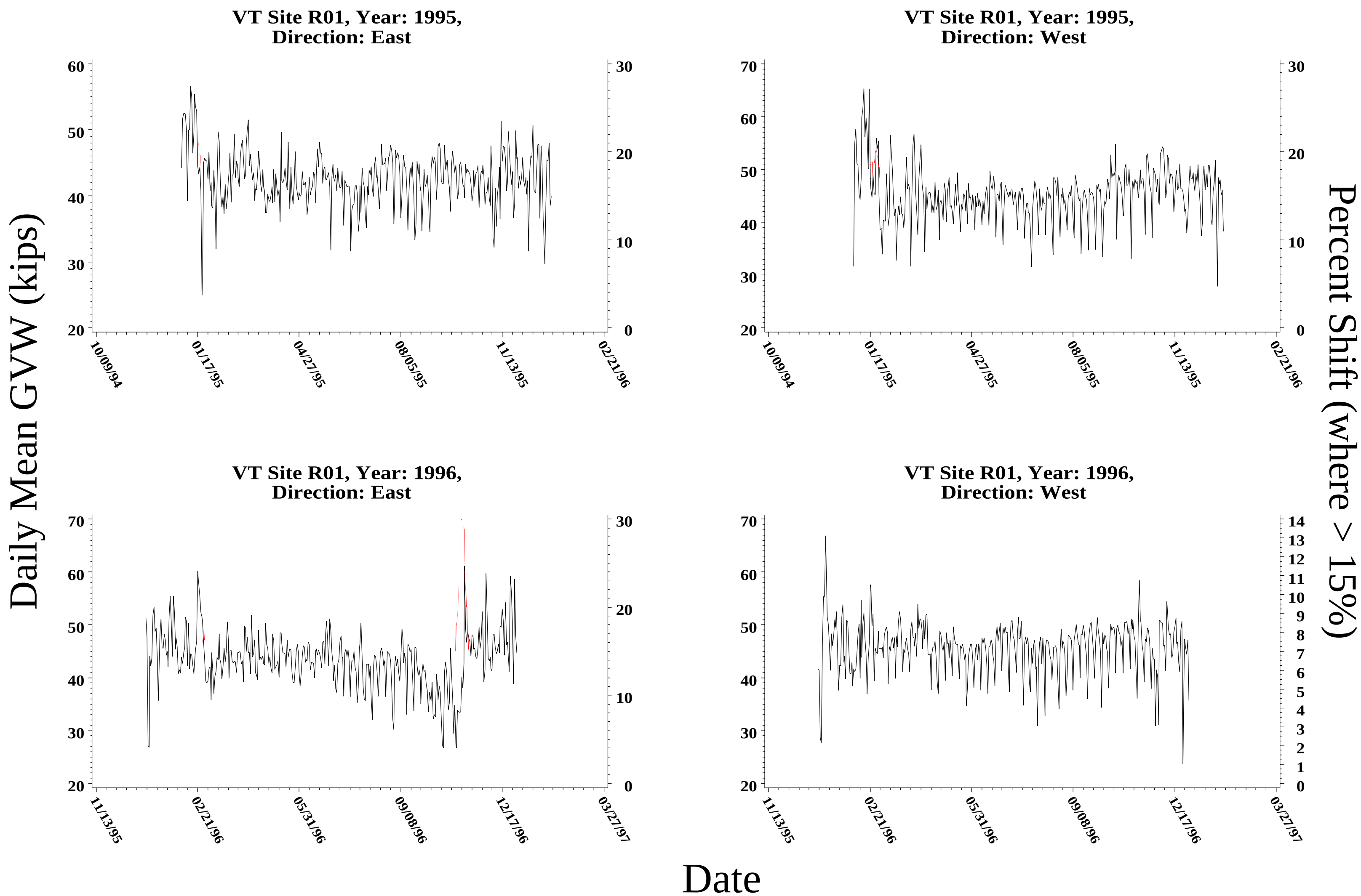

Figure C (cont'd). Cusum quality control plots. Red indicates a possibly important change.

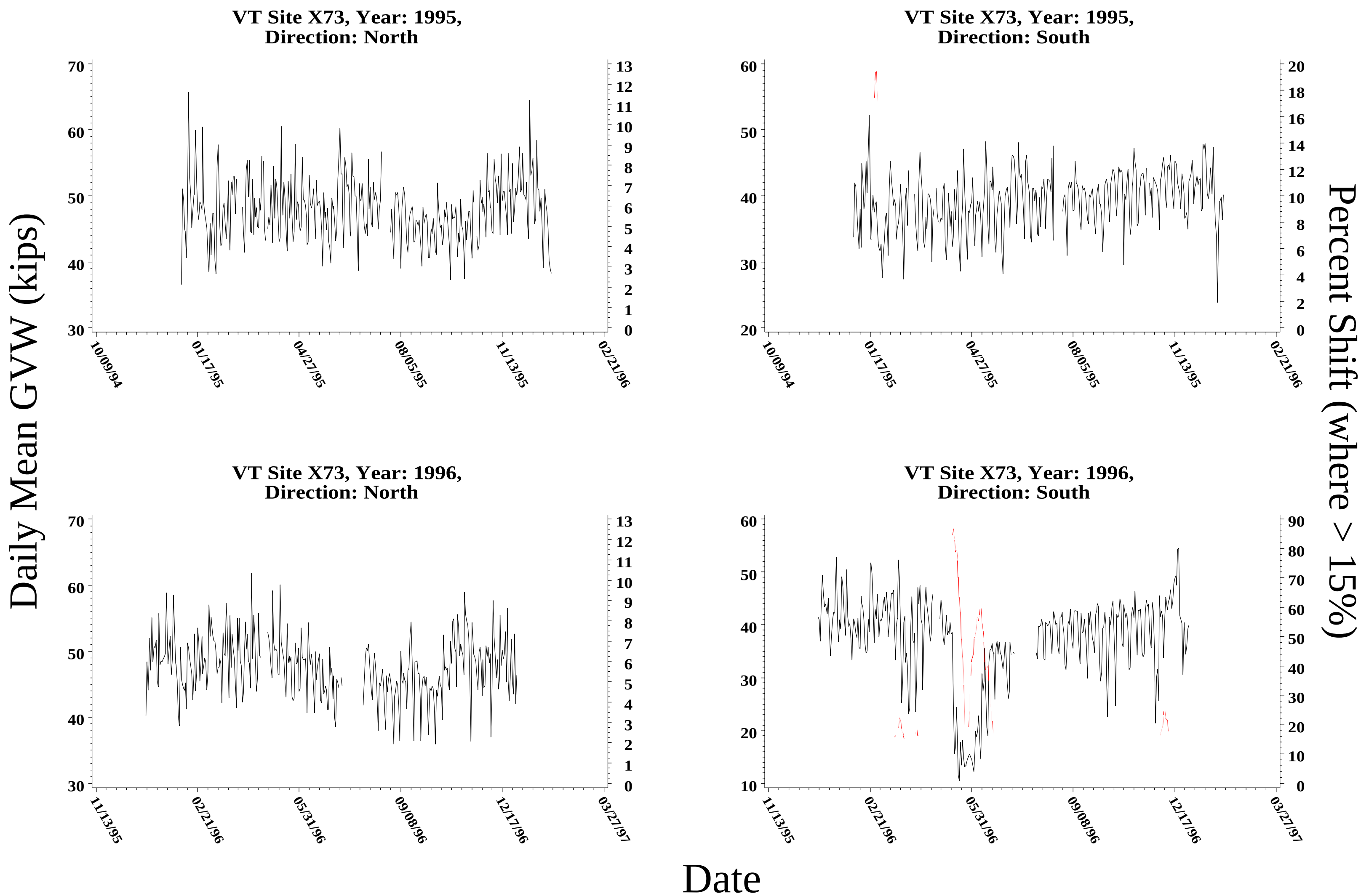

Figure C (cont'd). Cusum quality control plots. Red indicates a possibly important change.

APPENDIX D. DAY AND MONTH WEIGHT AND STANDARD ESAL SUMMARY STATISTICS FOR REGION 1

Table D.1. Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
CT974	Su	N	22	5523	16	15	14	17	1	.	.	.
		kips	38	767	39	361	53	63	27	.	.	.
		CVk	60.5	75.3	96	91.8	62.6	53.5	.	.	.	.
		ESAL	1	38.2	2.2	18.7	0.5	0.9	0	.	.	.
		CVE	143.1	230.1	272.3	108.4	135	105.1	.	.	.	.
	M	N	36	9690	310	82	37	129	13	1	.	.
		kips	81	1619	265	270	47	186	49	10	.	.
		CVk	116.4	80.4	85	174.1	72.2	90.3	57.3	.	.	.
		ESAL	15	71.7	8.2	8.7	0.6	3.5	0.4	0	.	.
		CVE	200.8	159.2	137	206.7	121.2	163.5	159.6	.	.	.
	Tu	N	33	9907	350	108	48	113	9	1	.	.
		kips	68	1729	261	212	47	149	66	39	.	.
		CVk	87.9	70	108.7	120.4	95.6	67.7	45.8	.	.	.
		ESAL	9.5	81.1	5.3	6.9	0.6	2.1	0.8	0.2	.	.
		CVE	192	175	120.4	143.7	221	117.3	102.4	.	.	.
	W	N	19	8983	349	84	70	105	14	.	.	.
		kips	38	1584	267	191	58	156	52	.	.	.
		CVk	41	65.5	81.4	107.9	57.7	67.4	37.2	.	.	.
		ESAL	1.6	63.1	6.9	5.1	0.6	2.8	0.2	.	.	.
		CVE	164.5	176.3	133.5	131	115.2	130.9	80.2	.	.	.
	Th	N	21	8756	270	106	62	107	10	1	1	.
		kips	49	1557	211	203	70	137	75	31	104	.
		CVk	99.4	57.7	68.9	191.7	68.1	58.6	43.2	.	.	.
		ESAL	2.7	75.7	4.3	7.6	1.4	2	2.4	0.1	1.4	.
		CVE	139.8	254	110.6	264	96.1	116.3	125.6	.	.	.
	F	N	24	9216	343	59	70	115	17	1	.	.
		kips	52	1743	249	202	67	163	56	48	.	.
		CVk	119.9	64.8	86.6	97.2	80.8	80	35.1	.	.	.
		ESAL	9.6	120.7	5	6.8	1.6	2.9	0.4	0.5	.	.
		CVE	219.2	269.5	115.7	149.1	187	136.9	120.7	.	.	.
	Sa	N	20	6928	113	50	24	36	5	.	.	.
		kips	31	1109	97	130	45	82	55	.	.	.
		CVk	57.9	76.3	96	193.4	93.9	59.6	51.1	.	.	.
		ESAL	1.5	69.5	2.7	4.2	0.8	1.4	0.3	.	.	.
		CVE	283.3	219.7	166.1	244.3	216.6	102.7	124.6	.	.	.

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
CT978	Su	**N**	437	5186	407	155	432	1739	18	68	5	.
		kips	341	1045	249	331	383	1921	61	98	55	.
		CVk	57	39.2	49.1	32.8	42.8	36.5	44.4	72.6	34.8	.
		ESAL	4.3	6.4	3.2	7.8	6.7	28.6	0.5	2.2	0.6	.
		CVE	71.1	103	110.1	47.5	59	52.3	97.7	130	120.2	.
	M	**N**	1028	12606	2643	870	2729	9773	280	320	14	9
		kips	757	3540	1899	1373	2182	10940	492	421	94	146
		CVk	38.4	34	41.4	53.1	33.8	38.7	58.2	60.4	58	66.5
		ESAL	28.8	39.5	32.4	41.9	33.2	154.5	10.1	8.8	2.1	3.8
		CVE	46.8	46.2	52.6	55.3	40.3	44.9	77.6	84.7	150.2	82.3
	Tu	**N**	1096	14881	3219	999	3400	11510	350	438	23	14
		kips	761	3997	2154	1402	2484	12177	543	510	97	152
		CVk	32.3	23.8	30.8	41	29.3	24.9	52.2	51.3	47.4	38.6
		ESAL	29.2	42.2	35.8	43.4	37.6	165.2	10.5	10.7	2.2	3.9
		CVE	39.6	42.4	38.5	55.1	32.2	28.8	75.8	60.3	100.8	61.1
	W	**N**	1162	14682	2869	877	3373	11084	312	496	21	13
		kips	834	4105	1993	1286	2517	12233	535	599	82	169
		CVk	19.5	22.9	27	56.9	23.8	24.9	50.9	45.7	56.7	63.9
		ESAL	30.9	46.2	34.2	39.1	36.9	176.6	13.8	12.5	1.3	5.7
		CVE	30.9	31.2	36.9	68.2	37.3	37.2	69.2	64.9	111.7	95.4
	Th	**N**	1002	14300	2717	819	3279	10529	308	432	24	13
		kips	707	3889	1836	1202	2458	11223	511	524	69	154
		CVk	38.2	35	35.9	66.8	36.1	34.8	48.7	50.5	55.3	36.5
		ESAL	27.3	44.2	29.2	37.7	38.4	161.1	9.7	12.1	0.7	4.2
		CVE	42.3	45	40.5	87	46.5	42.8	66.6	63.6	107.9	82.2
	F	**N**	1006	14870	3082	856	3354	10904	284	385	33	10
		kips	725	3989	2146	1235	2487	11655	501	454	103	162
		CVk	29.5	33.1	35.3	57.6	33.4	33.4	49.4	58.9	52.2	124.8
		ESAL	29.5	41.3	38.6	39.8	38.4	171.5	10.8	10.8	1.1	4.6
		CVE	43.4	48.8	43.1	76	43.2	49.5	75.5	75.4	87.1	189.4
	Sa	**N**	582	7351	1015	425	602	3357	33	136	14	.
		kips	457	1691	676	633	487	3596	101	188	80	.
		CVk	43.7	31.6	32.8	46.7	33.2	28.7	56	55.7	42.4	.
		ESAL	5.5	12.4	9.9	16.2	7.8	47.2	1.6	4.7	1	.
		CVE	58.1	42.3	40.4	56	78.5	35.7	104.4	76.3	90.4	.

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
CT990	Su	**N**	2111	11198	1230	27	1588	31439	279	3089	116	2
		kips	1655	2636	569	69	1325	42151	351	4019	212	54
		CVk	24.8	27.7	37.4	128.1	37.5	23.2	71.7	66.4	59.2	34
		ESAL	21.2	27.5	4.5	1.3	29.6	761.4	4.1	105.7	1.9	0.4
		CVE	44.2	56.4	59	185.6	67.1	44.8	94.6	95.5	114.9	93.3
	M	**N**	1619	31887	5469	2334	10933	93897	1069	8398	250	22
		kips	1267	10107	3594	4268	8976	113634	1463	10338	451	215
		CVk	33.1	27.2	34.9	61.6	30.9	24.8	31.4	56.1	47.7	57.7
		ESAL	14.8	161.5	61.5	175.1	167	1586.3	18.8	207.6	4.1	5.4
		CVE	41	35.7	48.1	68.1	39.2	29.7	54.4	62	56.1	73.3
	Tu	**N**	1489	35503	6274	2249	15099	109737	1450	13385	588	35
		kips	1058	10702	4030	3588	12085	124110	1795	16251	1098	168
		CVk	34.4	21.6	25.7	55.5	22.4	20.6	36.2	39.2	38.5	80.3
		ESAL	11.2	166.1	62.2	136.6	247.2	1615.2	20.8	333.7	10.9	4.6
		CVE	44.1	25.9	32.5	59.8	29.6	26.3	42.8	42.1	44	128.2
	W	**N**	1545	36177	6301	2269	15816	112223	1413	13599	706	26
		kips	1131	11213	4120	3705	12978	129611	1744	16895	1272	168
		CVk	24.5	11.8	15.9	49.5	11.3	10.4	32.5	31.9	44.7	63.8
		ESAL	13	169.4	66.6	141.5	259.1	1688.4	19.5	346.9	13.3	4.2
		CVE	39.9	17.5	32.2	54.3	19.7	23.4	38.1	33.8	51.3	102.2
	Th	**N**	1674	37274	6225	2378	15989	103608	1483	12893	690	23
		kips	1246	11522	4083	3823	13085	118516	1848	16030	1139	161
		CVk	31.4	16.9	27.5	52.2	14.2	15.2	39.2	30.7	55.4	60
		ESAL	13.9	176.6	62.2	141.9	260.4	1553.7	22.4	334.1	11.9	4.5
		CVE	41.9	23.9	37.5	58.8	20.7	23.8	51.7	32.8	63.4	108.3
	F	**N**	2161	37189	5751	2308	14517	93063	1197	11714	621	25
		kips	1660	11362	3759	3812	11935	104303	1508	14365	1200	180
		CVk	27.8	17.3	22.7	53.3	17	15.5	40.7	27.9	34.5	56.7
		ESAL	19.8	177.5	61.3	142.5	243.8	1281.5	19.4	287.7	12.2	5.4
		CVE	36.1	22.5	37.6	57.3	22.1	22.3	50.1	28.1	45.3	121.9
	Sa	**N**	2420	17561	1895	426	5408	40893	481	7916	506	1
		kips	1873	4632	1084	674	4859	50171	610	10323	988	87
		CVk	28.1	18.6	21	115.1	17.7	14	76.5	23.9	36.6	.
		ESAL	22	56.5	14.5	25.4	119.6	696.2	7.1	239.3	10.5	3.2
		CVE	34.6	31.1	41.2	130.6	26.2	26.2	88.4	26.1	44.1	.

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
MA001	Su	**N**	8528	97425	6480	259	7618	27527	520	880	148	.
		kips	3138	10556	1832	370	2427	17112	458	583	118	.
		CVk	23.3	46.6	26	189.5	20.3	18.9	59.5	39.3	47	.
		ESAL	70.5	159.9	30.5	19	38.4	425.6	14.5	20	2	.
		CVE	25.9	59.7	43.8	183.1	36.4	22.3	77.3	53.1	106.8	.
	M	**N**	17688	256191	49840	2462	47584	181722	4316	2534	379	27
		kips	5983	36442	18848	1964	17380	107720	3308	1489	266	110
		CVk	21.7	22.8	27.6	61.6	22.7	22.3	38.6	28.6	51.6	43.9
		ESAL	146.3	704.2	604.1	91	342.1	2726.3	89.3	41.4	5.7	3.4
		CVE	29.5	24.8	33.8	60.9	29	32.9	48	37.3	89.9	85.1
	Tu	**N**	18895	273604	56185	2649	53303	189265	4692	4109	558	45
		kips	6313	39252	21562	2061	19696	111989	3660	2507	383	130
		CVk	20.6	19.1	15.9	65.6	16.4	14.8	31.2	24	40.3	56.8
		ESAL	154.1	755.3	722.3	98.5	392.9	2911.6	98	74.6	7.3	3.7
		CVE	28.9	19.4	25.2	57.7	24	29.7	43.3	34.6	66.5	103.3
	W	**N**	19489	274945	55368	2922	52596	186463	4423	4176	598	38
		kips	6503	39296	21039	2364	19320	109880	3494	2581	396	109
		CVk	25	25.3	26.6	61.6	23.8	24.2	32	23.2	41.2	47
		ESAL	160.5	767.5	705.6	111.1	386.6	2886.7	97.4	77.9	7.3	2.7
		CVE	31	27	32.6	63.2	33.4	35.3	42.3	39.5	71.6	79.4
	Th	**N**	20146	282205	56899	3122	53260	192897	4616	4239	667	56
		kips	6620	39779	21446	2420	19295	112474	3545	2553	444	128
		CVk	20.6	23.1	23	64.5	20.3	20.6	30.8	20.7	40.8	75.9
		ESAL	163.8	769.5	721	113.6	385.3	2940.1	97.8	75.4	8.4	3
		CVE	29.2	24.7	29.8	61.2	29.3	31.8	40.6	26.7	63.4	98.6
	F	**N**	19752	294803	56279	3134	53024	184958	4411	3700	601	43
		kips	6647	41331	21917	2459	19687	110726	3515	2307	405	113
		CVk	20	21.1	18.3	66.8	18.3	15.2	34.8	22.7	40.4	51.2
		ESAL	169.9	803.4	763.4	114.2	417.7	2986.2	100.9	73.1	8.2	3.3
		CVE	31.4	23.5	24.8	63.2	33.7	27.6	44.2	32.4	71.2	109.6
	Sa	**N**	10890	142590	18938	847	13637	61632	2026	2645	286	8
		kips	3881	17271	7059	685	4725	37356	1687	1691	206	111
		CVk	22.4	31.5	30.6	119	20.8	21.2	36.6	27.6	56.5	26.2
		ESAL	90.7	302.8	220.9	34.9	89.2	994.2	53.2	54.6	3.7	3.1
		CVE	31.1	36.1	48.7	111	36.6	44.3	54.5	36.5	79.9	79.6

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
MA02N	Su	N	87	3242	31	1	25	68	.	.	.	.
		kips	90	654	34	61	25	109	.	.	.	.
		CVk	76.5	105.3	69.8	.	37.9	50.7	.	.	.	.
		ESAL	1.7	24.4	0.2	1.3	0	2.2	.	.	.	.
		CVE	99.8	403.5	96.5	.	135.9	127.1	.	.	.	.
	M	N	379	11143	343	40	278	736	3	.	.	.
		kips	195	2961	233	128	190	670	48	.	.	.
		CVk	52.8	58	94.9	92.5	87.4	106.3	78.9	.	.	.
		ESAL	7	97.7	5.1	4.8	2.3	12.9	0.6	.	.	.
		CVE	114.7	207.4	130.6	113.4	102.8	120.4	168	.	.	.
	Tu	N	449	11211	389	60	281	835	5	.	.	.
		kips	230	3000	272	188	197	782	37	.	.	.
		CVk	50.6	38.1	78.6	101.8	73.1	99.2	29.3	.	.	.
		ESAL	9.5	88.3	6.5	7.3	2.4	16	0.1	.	.	.
		CVE	151.7	150.4	106.4	115	99.5	106.9	85.6	.	.	.
	W	N	387	10142	405	75	330	778	7	1	.	.
		kips	213	2764	280	189	219	745	38	37	.	.
		CVk	57.3	42.1	82.3	86.4	75.2	87	27.4	.	.	.
		ESAL	8	96.6	8.3	8.1	3.1	15	0.1	0.2	.	.
		CVE	139.8	177.5	141.9	113.6	99.5	104.5	140.8	.	.	.
	Th	N	382	11014	347	64	301	793	5	1	.	.
		kips	195	2960	216	188	192	762	98	85	.	.
		CVk	58.5	38.3	81	99.9	86.7	89	61.6	.	.	.
		ESAL	6.9	86.7	6.3	8.1	2.2	14.6	0.8	2.3	.	.
		CVE	105	126.1	206.9	159.9	101.1	93.8	39.2	.	.	.
	F	N	515	12485	414	57	326	824	7	1	.	.
		kips	264	3251	246	180	195	793	79	37	.	.
		CVk	60.7	39.9	83.3	72	88.3	92.9	57.2	.	.	.
		ESAL	10.9	92.5	5.2	5.7	2.4	17.4	3.4	0.3	.	.
		CVE	129.6	129.2	106.5	97.3	123.7	109.4	122	.	.	.
	Sa	N	152	5788	101	19	46	132	.	.	.	.
		kips	103	1302	80	148	45	172	.	.	.	.
		CVk	79	64.8	76.7	46.8	63.2	82.6	.	.	.	.
		ESAL	4.4	36.1	2	5.5	0.7	4.3	.	.	.	.
		CVE	250.6	167.7	143.9	63.3	290.5	158	.	.	.	.

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
MA005	Su	N	5015	106670	4764	371	7128	37547	2184	2858	325	2
		kips	928	7145	689	494	1114	12305	1035	907	173	84
		CVk	53.1	296.7	58.3	272.8	62.7	47	97.7	64.8	70.5	10.4
		ESAL	15.4	150.3	10.4	19.5	17.5	294.8	32.6	22.3	3	2
		CVE	63.1	917.7	79.4	286.4	71.9	81.1	121.9	101.2	95.6	23.2
	M	N	15088	281052	44797	2012	69038	204621	8707	5351	918	52
		kips	2446	21977	9307	892	12410	61777	4110	1721	391	110
		CVk	43.7	55.9	50.2	119.2	58.2	55.4	77.3	53.7	86	42.8
		ESAL	70.4	313.2	285.6	36.2	197.7	1240.2	123.3	42.6	7.9	3.2
		CVE	50.2	68.1	56.8	119.3	72.6	74.9	93.7	68.1	115.2	98.9
	Tu	N	16787	326593	47975	2295	81224	216259	9335	7786	1154	52
		kips	2639	25377	9882	1008	14844	64829	4381	2548	480	124
		CVk	38.8	69	45.2	117.4	52	53.4	77.2	53.5	76.1	48.1
		ESAL	77.8	373.8	299	43.4	241.3	1330	131.7	66.7	9.2	3.9
		CVE	46.2	106.3	49.5	120.8	64.4	72.6	93.1	66.2	104.1	122.8
	W	N	18853	320711	47544	2204	80951	219494	9445	7886	1328	34
		kips	2969	25301	9754	947	14682	65497	4374	2580	520	110
		CVk	39.8	71.5	44.7	116.3	50	51	77.4	50.1	74	45.6
		ESAL	83.6	372.3	289.2	39.1	237.1	1328.6	131.2	67.3	9.9	3.1
		CVE	50.3	93.6	50	114.2	61.4	71.2	92.8	66	105.6	104.4
	Th	N	17880	335011	48785	2395	79159	219342	9425	7851	1299	33
		kips	2805	26352	10092	1044	14480	65928	4386	2592	505	96
		CVk	39.9	72.7	44.4	108.7	51.5	51.5	73.5	53.3	87.9	54.2
		ESAL	78.4	388.9	299.9	43.2	235.7	1356.7	131.2	70.2	9.8	2.3
		CVE	43	134.4	52.5	109.3	65.6	71	89.6	68.3	121.1	126.2
	F	N	19413	360695	47603	2356	79595	213883	9194	7538	1017	49
		kips	3025	28434	9835	1027	14590	64813	4309	2517	415	105
		CVk	36.7	94.5	41.8	104.3	50.7	50.8	76.7	51.5	75	45.5
		ESAL	85.4	498.5	301.6	45.7	242.5	1372.4	131.6	69.7	8.4	2.9
		CVE	43.8	309	49	109.1	61.9	69.9	92.1	65.4	107	106.9
	Sa	N	7446	151533	17353	1037	16930	69862	4600	5614	558	14
		kips	1311	11209	3463	587	3030	21758	2175	1915	220	123
		CVk	44.4	215	46.7	147.5	45.6	52.2	91.9	51.6	72.6	56
		ESAL	22.6	212.1	110.3	24.7	50.7	518	68.7	54.2	3.7	4.6
		CVE	52.1	626	63.8	145.9	55.3	86.3	107.8	67.3	119.5	84.9

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
RI350	Su	**N**	1535	37264	2440	35	4606	17421	89	399	23	4
		kips	298	1562	345	65	788	5445	125	147	77	176
		CVk	64.8	75.5	46.1	84.5	40.5	30.1	53.7	61	73.3	67.4
		ESAL	7.9	19.7	8.8	3.1	28.6	282.5	5.4	7.4	4.4	11.9
		CVE	96	74.8	171.7	205.1	89.6	78.3	107.3	130.8	224.4	83.4
	M	**N**	2212	59444	12480	465	28204	95093	1285	1659	214	13
		kips	369	3953	2107	235	5687	28982	515	572	114	134
		CVk	68.7	28.2	35.2	80.5	31.4	30.1	88	40.1	53	36.7
		ESAL	14.6	107.9	97.4	16.4	234.7	1323	20.2	25.9	3.2	13.5
		CVE	126.7	43.2	79	115.1	62.4	50.7	120.4	61.8	167.1	89.4
	Tu	**N**	2402	66815	13806	664	33458	101239	1410	2674	391	23
		kips	383	4399	2440	325	6775	31019	575	891	162	174
		CVk	63.9	29.8	28.4	141.1	20	19.7	81.3	37.9	54.3	61
		ESAL	13.5	117.6	127.6	23.1	282.5	1521.9	23.6	43.7	4.7	13.7
		CVE	122.2	43.8	71.2	162.7	49.1	48.7	112.8	73	163.2	106.6
	W	**N**	2710	71561	13505	631	33032	99159	1358	2728	356	19
		kips	453	4862	2503	319	6964	31302	562	949	154	119
		CVk	60.1	39.7	28.9	120.3	19.3	19.4	86.4	35.3	57.5	44.5
		ESAL	18.8	138.3	133.2	23.2	298.5	1514.8	23.1	49.2	4.1	9.1
		CVE	100	40.4	81.1	172.6	46.4	45.6	128.6	65.8	151.6	125.2
	Th	**N**	2750	73544	13404	613	35137	99458	1426	2792	374	24
		kips	450	4877	2406	291	7259	30754	556	937	155	139
		CVk	60.5	32.3	32.2	119.8	22.2	24.2	76.5	34.4	64.6	57.9
		ESAL	16.8	140.3	128	20.5	319.4	1556.5	20.9	48.6	4.7	10.7
		CVE	103.2	41.1	73.2	126.6	48.5	56.4	115.5	63.6	165	134.7
	F	**N**	2968	77982	13346	603	33499	99957	1397	2617	352	21
		kips	483	5020	2407	302	6974	31129	565	896	152	106
		CVk	64.8	38.3	29.9	130	22.6	19.6	77.5	36.9	58.7	44.3
		ESAL	18.2	140.4	131.5	22.6	315.3	1550.6	23.1	47.1	4.6	6.7
		CVE	112.6	39.3	76.5	152	56.5	48	112.1	69	167.1	142.1
	Sa	**N**	1875	49903	4715	140	8625	33580	434	1779	157	7
		kips	351	2370	834	138	1723	10790	217	608	103	116
		CVk	55.5	56	40.4	95.1	26.8	28.3	81.4	41.2	57.9	54.2
		ESAL	10.2	44.4	45.1	12	78.2	622.7	9.5	35.8	2.7	7.2
		CVE	80.9	58	112.1	150.8	74.1	82	136.6	86.1	157	116.4

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
VTd92	Su	N	2696	14320	1656	86	2372	28493	532	83	116	3
		kips	466	694	223	58	398	9212	229	74	103	82
		CVk	57.6	51.5	44.9	98.7	39.3	77.4	85	73	78.3	28.1
		ESAL	6.9	8.6	3	1.2	8.4	232	3.9	1.3	2.1	1.6
		CVE	81.7	142.9	88.4	331	102.1	114.2	126.7	123.5	153.1	91.2
	M	N	3522	45288	9661	725	11611	87086	2263	354	467	71
		kips	519	2765	1416	185	1979	24200	749	117	168	91
		CVk	56.2	32	48.1	60.3	34.4	32	52.8	63.8	73.3	59.1
		ESAL	9.9	50.4	21	4.2	40.2	480.2	13.6	2.7	3	1.3
		CVE	130.2	102.6	66.8	109.8	84.8	58.1	85	136.9	192.9	131.5
	Tu	N	3842	49436	11442	772	12408	95428	2618	535	583	76
		kips	534	3144	1688	176	2049	26519	868	154	207	77
		CVk	40.8	19.7	40.8	59.8	26.6	25.8	44.2	59.6	67.9	47.7
		ESAL	10.8	63.1	25	3.9	38	533.9	15.9	3.5	3.6	1.3
		CVE	74.5	65.6	54.4	110.7	60.6	52.3	75.1	97.8	134.7	174.7
	W	N	3667	48954	10343	778	12560	95503	2609	568	557	72
		kips	517	3092	1512	186	2130	26771	879	159	197	93
		CVk	42.1	22.9	47.8	69.4	25.9	27	45.1	62	64.3	50.4
		ESAL	9.9	59.3	22	4.1	40.1	542.3	16.4	3.1	3.6	2
		CVE	60.9	82.9	53.2	114	63.5	52.5	75.6	105.7	112	122.1
	Th	N	4057	50728	10602	752	12821	94534	2648	537	567	83
		kips	569	3125	1565	184	2157	26775	897	153	205	97
		CVk	42.2	29.5	44.8	64.8	30.7	27.8	44.7	60.9	71.2	55
		ESAL	11.3	59.5	24	4.1	43.6	570.2	16.7	3.3	4.1	1.8
		CVE	78.2	79.4	62	105.6	67.6	56.9	73.4	115.2	173.8	150.6
	F	N	5129	53373	11498	904	13172	83439	2505	512	514	73
		kips	779	3276	1711	209	2220	22241	801	144	188	87
		CVk	37.2	26.1	36.3	61.5	26.9	22.9	40.9	59.4	66.6	40.6
		ESAL	15.4	60.1	26.6	4.5	45.4	419.6	13.8	3.1	3.4	2.2
		CVE	74.6	82.1	55.4	113.8	72.3	39.1	71.8	116.2	132.8	155.7
	Sa	N	3053	23649	4225	176	2284	27026	627	270	145	5
		kips	491	1181	596	85	354	7131	203	110	81	56
		CVk	50.5	36.1	47	63	71.5	21.2	64.1	71.5	55.2	21.4
		ESAL	8	14.2	9	1.8	8	141.4	3.8	2.7	1.4	0.6
		CVE	77.2	115.7	75.6	100.5	134.7	50.6	138.4	103.3	154	155

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
VTn01	Su	N	268	5242	619	20	842	16383	257	12	50	4
		kips	104	415	149	48	237	10045	183	42	90	97
		CVk	81.9	59.7	107	52.1	44.3	92	67.3	32.7	60.2	16.1
		ESAL	2.3	3.2	1.9	0.8	3.1	217.8	3.4	0.5	1.6	2.1
		CVE	191.1	134.2	171.5	135.1	103.8	112.2	143.7	105.8	109.2	45.5
	M	N	564	9980	2312	76	3329	33299	1534	261	176	8
		kips	162	1112	615	70	1037	17663	781	141	147	77
		CVk	73.5	36.6	57	57.6	28	35.3	38.5	39.9	53.8	30.9
		ESAL	3	22.1	10.3	2	15.8	309.2	8.5	3.2	3.8	1.4
		CVE	147	115.3	128.9	142.2	66.1	48.3	80.2	82	143.4	90.4
	Tu	N	596	10840	2429	96	3270	34933	1618	305	209	25
		kips	166	1186	614	72	968	17974	812	144	160	93
		CVk	70.1	40.2	54.4	65.6	29	35.4	40	49.4	64.3	46.4
		ESAL	3.9	20.9	8.4	2.1	13.1	325.2	10.6	2.8	3.8	3
		CVE	125.2	114.3	73	221.9	89.1	52.7	93.6	136.6	183	143.2
	W	N	508	10163	2234	90	3577	35253	1601	314	212	6
		kips	139	1145	588	66	1069	18683	817	155	151	72
		CVk	71	35.7	64.6	53.4	26.1	30.7	38.2	48.1	63.8	46.9
		ESAL	2.9	20.3	9.1	1.3	14.5	348.3	10.1	3.4	2.1	1.6
		CVE	139.7	89.3	160.2	108.8	76.5	46.6	74.9	109	99.8	171.4
	Th	N	616	11540	2236	90	4055	35311	1653	338	226	9
		kips	169	1247	572	76	1228	18412	819	174	172	87
		CVk	61.7	52.1	43.3	68.4	28.6	27.9	41.3	47.3	58.5	36.4
		ESAL	3.6	23.1	8.6	2.1	21.3	366	9.6	4.7	4.1	2.7
		CVE	133.5	100.5	82	166.8	133.8	53.9	77.3	170.4	182.7	144.8
	F	N	711	11712	2227	96	3384	29075	1360	344	184	14
		kips	197	1197	556	69	991	14101	654	167	146	84
		CVk	64.2	46.5	42.3	57.3	27.7	22.7	45.5	47.7	63.1	34.4
		ESAL	4.9	18.9	8.8	1	14.2	261.7	7.2	3.7	3.7	1.5
		CVE	132.1	88.1	86.1	132.5	83.9	48.1	78.6	113.3	190.2	135.6
	Sa	N	383	6633	937	54	1338	9391	386	114	49	1
		kips	122	572	232	92	389	4810	216	80	94	81
		CVk	67.6	70	61.1	190.4	48.4	28.4	59.2	57.5	47.6	.
		ESAL	2.1	6.8	3.7	2.8	6.3	87.5	3.6	1.7	2.4	1
		CVE	99.3	119.9	129.5	214.7	149.8	60	138.2	121.4	152.4	.

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
VTr01	Su	**N**	1313	8872	1602	38	2591	21147	381	101	14	3
		kips	232	400	205	56	393	5777	159	61	79	158
		CVk	92	42.2	119.2	54.5	38.5	34.2	81	47.7	33	22.5
		ESAL	4.4	5	2.8	1.5	8	109.6	3	1.5	1.8	5.4
		CVE	155.5	151.3	356.6	166.5	81.6	63	125.1	130.9	143.3	39.5
	M	**N**	1021	13855	2701	400	8221	73538	4701	379	480	49
		kips	158	821	351	153	1332	18481	1590	102	287	118
		CVk	79.2	31.7	49.2	82.4	27.5	22.9	53.7	56.1	77.4	42
		ESAL	3.9	14.7	7.2	5.1	25.2	337	48	2.1	10.5	3.1
		CVE	123.6	101.9	106.5	128.2	58.7	46.7	113.4	101.9	111.9	88.9
	Tu	**N**	957	15058	2909	397	9035	77437	4767	438	533	66
		kips	134	904	384	165	1473	19355	1581	115	280	134
		CVk	69.3	24.1	39.9	82.9	25.6	19.3	51.9	48.9	84.6	45.1
		ESAL	3.4	16.3	7.8	5	27.5	343.8	46.2	2.8	9	3.9
		CVE	133.1	89.5	100.4	117.8	62.3	48.5	105.7	126.8	117	82.6
	W	**N**	1032	14200	2636	392	9412	73959	5078	416	518	52
		kips	153	845	367	157	1548	18791	1701	107	289	117
		CVk	63	26.6	46.6	86.5	24.3	21	50.6	53.5	79	57.2
		ESAL	3.9	15	8.5	5.3	28.7	341.7	50.6	2.4	9.8	3.4
		CVE	121.5	80.8	108	134.3	52.5	45.7	113	120.9	107.8	109.8
	Th	**N**	1381	15366	2770	423	9205	73781	5097	421	587	50
		kips	204	912	372	161	1533	18529	1726	109	338	110
		CVk	70.8	26.2	41.1	96.8	26.5	22.5	50.4	49.2	79.5	35.6
		ESAL	5	17.6	8.1	6	30.5	334.5	51.2	2.6	12.4	3.1
		CVE	122.7	83.6	116.9	167.1	71.8	44.3	104.6	131.6	114.5	88.4
	F	**N**	1976	16847	3180	567	8990	70744	5248	476	632	57
		kips	327	955	434	196	1495	17746	1799	128	338	117
		CVk	114.6	24	37.7	90.7	25.1	22.8	52.4	47.5	90.9	37.5
		ESAL	7.7	15.2	9.4	6.5	29.3	321.6	54.2	3.1	11.6	3.2
		CVE	128.5	113.9	98.2	144.9	59.3	48.8	100.2	119.8	129.4	90.3
	Sa	**N**	899	9668	1595	163	4142	29414	1871	299	252	12
		kips	150	439	205	92	647	7538	639	98	218	112
		CVk	77.3	32	46.9	79.6	48.6	25	59.5	56	124.3	28.6
		ESAL	3.2	5.3	3.9	2.7	13.2	136.5	18.9	2.9	8.1	4.4
		CVE	167.8	129.4	137.6	174.6	73	52.4	124.3	129.8	148.3	71.5

Table D.1 (cont'd). Load Summary Statistics by Site, Day-of-Week, and Vehicle Class

Site	Da.	Stat.	4	5	6	7	8	9	10	11	12	13
VTx73	Su	**N**	2999	21249	1988	15	3820	42514	352	764	174	1
		kips	507	1061	258	56	544	13724	179	227	101	45
		CVk	56.4	201	52.4	78.4	51.1	66.2	73	55.2	63.2	.
		ESAL	7.1	6.5	2.7	1.3	8.7	312.6	3.6	5.6	1.7	0.1
		CVE	108.9	129.4	102.7	154.6	66.8	93.4	111.3	104.1	222.2	.
	M	**N**	2913	33009	6867	169	13378	111374	1292	2815	583	21
		kips	427	2147	925	83	2256	31292	431	809	199	83
		CVk	42.9	93.1	40.1	109.2	32.1	30.9	55.3	37.8	63.3	37.7
		ESAL	6.7	28	11.1	1.9	37.3	563	6.5	18.6	2.7	1.4
		CVE	83	61.8	71.5	159.5	52.5	50.4	78.1	61	93	95.4
	Tu	**N**	2788	35040	6499	219	14637	114911	1412	4438	759	15
		kips	388	2370	914	108	2539	32698	463	1230	235	94
		CVk	32.9	75.5	32.2	158.8	25.5	26.8	55.6	33.9	49.2	34.4
		ESAL	6	30.2	11.4	2.5	42.6	579.7	7.2	26.7	2.9	1.5
		CVE	59.9	60.5	54.7	133.7	43	48.8	80.3	54.7	77.7	69.7
	W	**N**	2891	34725	6186	185	14683	113789	1289	4308	792	22
		kips	434	2380	889	101	2598	33391	449	1245	268	89
		CVk	39.2	76.2	28.1	162.3	24.7	24.9	46.5	29.3	48	49.5
		ESAL	7	28.9	10.4	2	41	598.9	7.1	28.2	3.6	1.8
		CVE	100.9	67.4	79.5	137.2	56.2	46.1	75	101.9	80.1	123.9
	Th	**N**	3307	36607	6648	177	15420	115875	1490	4516	806	27
		kips	462	2430	920	89	2627	32656	488	1231	249	93
		CVk	37.5	82.3	34.4	97	26.1	24.5	49	32.9	54.8	38.2
		ESAL	7.2	31.2	11.4	2.1	44.4	588.7	7.6	26.9	3.1	2.1
		CVE	61.5	59.4	59.3	197.1	45.3	44	74.9	53.4	83	91.9
	F	**N**	4107	44437	6996	200	15071	105174	1240	4663	739	14
		kips	612	2652	949	95	2490	28404	402	1281	228	87
		CVk	38.6	116.1	28.6	82.4	22.7	19.8	48.5	31.2	51	41.2
		ESAL	9.7	29.6	11.9	2.6	42.8	492.6	6.2	29.5	2.8	1.4
		CVE	88.1	66.2	52.4	141.4	63.6	45.8	79.3	69.3	87.8	137.1
	Sa	**N**	2790	23960	3823	53	4366	36060	404	2723	311	1
		kips	452	1302	489	95	666	10031	178	782	118	89
		CVk	45	218.2	44.3	218.1	33.1	25.2	80.7	36.6	56.4	.
		ESAL	5.8	9.7	5.3	2	11.2	168.2	3.1	19	1.5	1.3
		CVE	65	95.9	88.8	155.4	86.6	53.7	109.7	70.2	94.7	.

Table D.2. Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
CT974	Jan	N	1	4906	131	26	28	46	9	.	.	.
		kips	26	1045	158	91	50	82	60	.	.	.
		CVk	.	47.3	75.8	59.3	87.7	53.7	56.5	.	.	.
		ESAL	1.1	11.1	3	2.1	0.8	0.7	0.6	.	.	.
		CVE	.	71.4	133.8	105.6	153.1	116.8	118.3	.	.	.
	Feb	N	3	4108	131	21	28	33	11	.	.	.
		kips	25	898	142	106	55	76	50	.	.	.
		CVk	5.3	43.7	66.7	130.6	103.5	57.4	35.9	.	.	.
		ESAL	0.4	6.5	1.7	2	0.9	0.4	0.2	.	.	.
		CVE	143.4	81.8	73.9	104.5	193.4	115.4	56.5	.	.	.
	Mar	N	5	4123	51	8	5	35	2	.	.	.
		kips	26	661	48	47	24	60	34	.	.	.
		CVk	6.3	24.1	57.4	29.4	18.4	59.3	55.1	.	.	.
		ESAL	0.2	2.2	0.5	0.4	0.1	0.3	0.1	.	.	.
		CVE	122	95.9	113.8	71.4	115.7	143.8	118.2	.	.	.
	Apr	N	11	4805	146	15	12	45	6	1	.	.
		kips	32	787	128	45	39	72	56	104	.	.
		CVk	47.8	38	74.8	46.1	72.8	62.7	36.6	.	.	.
		ESAL	0.7	4.2	0.8	0.3	0.1	0.5	0.2	1.4	.	.
		CVE	223.5	273.7	99.1	89.7	91.3	133	91.1	.	.	.
	May	N	9	4751	217	32	36	109	19	1	.	.
		kips	33	1090	230	87	57	222	62	48	.	.
		CVk	42.9	43.7	57.9	58.7	54.9	67	40.7	.	.	.
		ESAL	0.2	11.5	3.3	1.5	0.6	2.8	0.4	0.5	.	.
		CVE	151.5	87.1	73.1	71.6	96.7	87.8	108.3	.	.	.
	Jun	N	10	3691	229	40	33	98	12	1	.	.
		kips	26	1029	275	112	52	162	52	10	.	.
		CVk	21.8	34.6	50.3	91.5	65.4	53.4	51.5	.	.	.
		ESAL	0.6	10.1	5.6	2.2	0.6	2.1	0.7	0	.	.
		CVE	62.5	63.2	72.7	118.5	88.7	92.1	190.7	.	.	.
	Jul	N	19	3355	210	93	35	96	6	1	.	.
		kips	36	1015	274	339	57	180	54	31	.	.
		CVk	50.2	28.4	47.6	145.9	48	78.6	36.3	.	.	.
		ESAL	0.5	13.2	7.6	11.3	0.8	3.2	0.6	0.1	.	.
		CVE	91.3	76.1	58.3	168.8	97.9	149.7	136.2	.	.	.
	Aug	N	16	3515	367	168	68	81	4	1	.	.
		kips	33	1337	465	459	75	182	94	39	.	.
		CVk	43.5	29.9	87.7	102.8	69.9	59.3	26.1	.	.	.
		ESAL	1.1	28.1	14	18.3	1.9	4.8	4.1	0.2	.	.
		CVE	68.2	63.3	73.4	127.8	151.4	103.5	86.3	.	.	.
	Sep	N	17	4186	221	79	62	70	.	.	.	.
		kips	42	2016	304	280	67	202	.	.	.	.
		CVk	57.7	34.4	64.4	75.2	82.8	66.1	.	.	.	.
		ESAL	4.1	112.6	12.3	10.6	1.2	5.4	.	.	.	.
		CVE	157.8	106.2	103.3	94.6	156.8	85.6	.	.	.	.

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
CT974	Oct	N	24	7057	43	19	17	9	.	.	.	.
		kips	57	2479	84	135	39	123	.	.	.	.
		CVk	65.1	33.5	77.7	106	64.8	61.3	.	.	.	.
		ESAL	5.1	427.1	1.6	5	0.4	2	.	.	.	.
		CVE	121.4	85	148	136.6	138.5	114.9	.	.	.	.
	Nov	N	60	14506	5	3	1	.	.	.	.	.
		kips	110	3907	25	12	40	.	.	.	.	.
		CVk	86.8	38.9	44.1	101.4	.	.	.	.	.	.
		ESAL	22.5	203.7	0.3	0	0.7	.	.	.	.	.
		CVE	138	67.8	182.6	170.2	.	.	.	.	.	.
CT978	Jan	N	596	8176	1386	318	1577	5769	123	111	2	15
		kips	627	3141	1457	796	1856	9653	292	232	66	162
		CVk	39	45.8	52.1	43.8	57	52	61.4	52.8	28.2	58.7
		ESAL	27.4	32.7	24.2	23.8	33.8	164.8	5.5	6.8	0.8	4.6
		CVE	64.4	60.4	60.7	55.5	65	56.3	94.3	76	104.9	72.6
	Feb	N	639	7468	1233	501	1450	5140	101	133	1	12
		kips	750	3238	1389	1363	1832	9752	287	282	41	174
		CVk	30	44.4	50	46.4	57.1	51.4	61.7	59.6	.	87.9
		ESAL	30.6	36.6	22.9	48.9	33.2	173.4	5.4	7	1	5.8
		CVE	56.4	62.6	58.4	62.4	66.7	59.3	99.1	69.7	.	114
	Mar	N	121	1889	294	92	357	1283	44	33	7	.
		kips	356	1275	632	541	815	4067	455	204	252	.
		CVk	78	118.9	105.6	107.9	110.8	123.4	66.6	71.9	52.5	.
		ESAL	14.9	13.4	11.5	20.9	12.7	74.3	8.9	4.9	9.8	.
		CVE	95.7	144.1	123.7	115.3	115.5	131	93.1	100.1	67.9	.
	Apr	N	400	5525	992	303	1121	3903	68	62	1	17
		kips	514	2376	1226	792	1546	7434	270	149	55	132
		CVk	50.5	64.4	60.4	46.9	63	62.4	57.9	70.6	.	41.3
		ESAL	16	23	18.2	18.9	22.1	96.5	6.2	3.2	6.2	2.5
		CVE	74.9	84.6	72.9	55.1	75.9	64.7	107.4	98.6	.	65.5
	May	N	613	7962	1606	479	1780	5925	140	294	29	.
		kips	630	3288	1632	1055	1974	9491	418	579	72	.
		CVk	39.9	39.9	51.6	48.8	52.7	46.7	57.5	58.7	51.5	.
		ESAL	20.4	39.3	29	34.8	29.7	135.4	9.7	14.2	0.7	.
		CVE	56.9	58.9	66.3	69.3	57.7	50.5	84.7	67.1	108.1	.
	Jun	N	563	7782	1826	612	1709	5478	188	277	24	2
		kips	597	3278	1874	1362	1954	8734	540	527	79	72
		CVk	42.1	35.6	48.2	71.8	50.1	43.6	53	59.3	38.8	46.2
		ESAL	19.1	36.3	31.8	46.5	29	115.4	11.7	12.5	1.2	0.5
		CVE	64.9	50.3	57.9	83.9	53.5	51.3	74.8	82.3	138.8	65.7
	Jul	N	398	6211	1265	545	1264	4143	98	192	10	2
		kips	530	2931	1524	1420	1662	7298	375	375	79	137
		CVk	56.3	52.9	64.2	81.2	61	62.6	66.9	60.2	36.1	24.8
		ESAL	17.7	27.7	26.3	43.7	22.1	87.8	8.6	6.9	0.8	3.6
		CVE	83.8	71.3	76.1	89.3	60.2	66	93.2	67.3	62.1	69.1

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
CT978	Aug	N	684	9941	1909	611	2008	6881	192	262	23	.
		kips	696	3786	1884	1268	2155	10544	459	416	84	.
		CVk	28.5	33.3	46.6	63.5	47.2	42.1	62.7	54.1	68	.
		ESAL	20.6	34.7	31	35.3	30.4	129.4	9	7.4	1.1	.
		CVE	49.5	48.1	50.8	71.7	57	44.8	87.9	67.2	168.1	.
	Sep	N	729	9670	1886	466	1915	6430	198	268	9	1
		kips	764	3807	1877	947	2161	10035	592	473	117	125
		CVk	41.9	40.7	51.6	49.6	56.3	49.7	41.2	61.1	71.3	.
		ESAL	21	36.6	28.4	23.4	33.5	119.3	13	9.2	1.9	4.4
		CVE	63	60.7	61.4	63.4	57.9	56.3	74.7	78	72.7	.
	Oct	N	812	9652	2051	522	2155	7274	241	345	22	3
		kips	830	3768	2002	1036	2322	11437	637	556	107	140
		CVk	28.5	38.4	52.2	41.5	50.7	46.7	57.5	51.7	46.2	44.4
		ESAL	24.9	38.6	31.3	26.4	31.5	153.5	12.8	11.5	1.7	4.4
		CVE	49.1	55.6	58.3	45.9	49.6	49.5	63.2	58.8	95.8	122.4
	Nov	N	629	8172	1321	441	1633	5941	174	271	13	.
		kips	719	3514	1520	1121	2025	10568	601	502	98	.
		CVk	41.5	45.5	59.2	60.5	60.5	56.2	58.9	64.9	49.7	.
		ESAL	27.2	39.6	28.3	35	32.4	158.7	12.9	11.6	2.1	.
		CVE	71.9	67.3	74.2	66.1	62.8	64.8	81.7	80.7	120	.
	Dec	N	129	1428	183	111	200	729	18	27	.	.
		kips	494	1935	774	1551	1054	4669	320	371	.	.
		CVk	81	64.9	83.7	63.5	79.2	86.9	22.6	20.9	.	.
		ESAL	18.5	20.2	20.4	54.1	18	78.2	8.9	9.4	.	.
		CVE	101.5	90.7	90.7	75.1	86.7	88.3	50.7	11.7	.	.
CT990	Jan	N	991	18975	2900	1208	7840	61403	1011	4347	3	22
		kips	993	7729	2532	3105	8781	98413	1697	7457	91	130
		CVk	27.7	47	56.5	59.1	53.5	37.9	47.8	49.5	17.7	37.8
		ESAL	10.1	115.8	40.9	118.3	187.4	1402.6	20.2	158.4	2.4	2.8
		CVE	37	57.2	67.2	64.5	55.3	37.1	58.2	53.7	77	70.7
	Feb	N	1038	17916	2640	598	7336	55999	990	4118	2	32
		kips	1196	8254	2477	1499	9181	100505	1824	7877	76	217
		CVk	35.1	43.1	47.7	83.9	49.7	36.1	49.5	47.6	12.6	56.5
		ESAL	15.1	127.3	35.4	57.6	204.6	1504	20.7	171.2	1	5.5
		CVE	67.2	54.1	58.6	98.9	53.7	39.9	55.6	52.9	32.6	117.1
	Mar	N	1265	21042	3287	1153	8850	67600	1065	5273	5	36
		kips	1328	8830	2855	2887	10020	109757	1743	9257	53	238
		CVk	32.7	39.9	45.2	61.4	44.6	32.3	42.6	41.8	58.4	60.1
		ESAL	16.7	134.7	45.9	125.4	219.2	1614.6	20	208.3	1.3	6.9
		CVE	43.6	48	58.3	68.4	45.7	30.6	52.9	46.4	202.7	97.2
	Apr	N	1542	20785	3498	1242	7919	61649	1075	4649	7	24
		kips	1641	8751	3086	3374	9108	100516	1780	8291	111	183
		CVk	23.6	43.3	55.1	73.5	51.6	39	38.7	45.8	35.4	70.9
		ESAL	19.3	133	43.8	131	190.4	1357.9	19.4	179.8	2.6	5
		CVE	30.3	51.5	62.8	77	48.3	36.4	45.7	49	43.3	101

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
CT990	May	N	1620	23443	3921	816	8283	63541	580	9593	672	5
		kips	1657	9500	3351	1954	9176	98472	1014	15722	1079	98
		CVk	26.4	39.9	50.5	60.1	48.7	39.4	53	36.4	46.7	32.2
		ESAL	18.7	141.8	47.2	72.4	181.2	1232.7	11.7	316.5	11.6	2.5
		CVE	33.8	47.6	61.6	66.5	50.6	39.9	62.5	36.4	49.2	59.9
	Jun	N	298	3768	545	113	1373	10016	78	1589	95	.
		kips	1582	7909	2466	1194	7791	80372	730	13583	747	.
		CVk	49.6	60.1	66.6	98.2	61.6	53	75.9	42.7	45.8	.
		ESAL	18.8	122.4	38.2	39.6	127.5	961.5	7.5	264.9	6.9	.
		CVE	57.3	50.3	82.6	104.5	61.8	46.4	84.6	38.8	59.5	.
	Jul	N	1021	16295	2594	1205	5730	41703	410	6593	464	1
		kips	1525	9728	3389	4197	9284	96211	1092	16042	1106	66
		CVk	24.6	37.3	47.4	50.4	49.4	36.9	54.2	36.9	52.1	.
		ESAL	16.7	136.2	58.1	153.2	170.5	1160.1	14.8	309.5	11.4	0.8
		CVE	36.6	49.5	57.6	51	50.7	36.6	63.9	37.6	68.8	.
	Aug	N	1451	25406	4032	2000	9282	64811	676	10380	642	6
		kips	1527	10353	3583	5134	10182	101884	1240	17283	1045	106
		CVk	31	34.6	45.3	62.3	43.5	33.7	54.4	33.2	48.7	26.7
		ESAL	18.7	147.8	57.2	183.9	187.5	1270	17.1	346.6	10.7	2.9
		CVE	43.7	48	56.8	71.6	42.6	32.1	71.2	31.7	61.6	50.7
	Sep	N	399	6678	1074	204	2201	15903	142	2423	154	.
		kips	1453	8951	3093	1662	8325	83978	866	13803	863	.
		CVk	25.4	49.1	69.1	68.8	61	50.4	68	48.3	56	.
		ESAL	17.3	116.8	38.5	55.1	154	982.9	10.5	269	8.4	.
		CVE	39.7	61.2	77.6	71.2	57.5	42.1	78.4	44.4	65.8	.
	Oct	N	901	12989	2187	1034	5010	34823	339	5573	406	4
		kips	1738	9730	3519	4970	10196	101423	1108	17345	1227	119
		CVk	28.2	39.8	56.8	61	51.8	37.6	61.3	35.6	58.1	57.8
		ESAL	21.8	145.4	72.2	209.7	203	1355.1	15.1	378.1	12.5	5.9
		CVE	38.4	42.2	70.2	65.3	51.4	37.9	85.4	32.7	64.9	124.5
	Nov	N	1265	21239	3690	995	8313	58174	575	8987	561	3
		kips	1357	8989	3371	2494	9731	96657	1098	16056	940	111
		CVk	38.4	46.9	58	66.5	53.3	42.8	64.4	39.7	57.8	33.3
		ESAL	16	149.8	52.7	101.6	202.6	1337.9	14.3	362	9.2	2.4
		CVE	45.7	56.2	65.6	73.8	55.4	43.5	79.2	41.3	68.1	44.8
	Dec	N	1228	18253	2777	1423	7213	49238	431	7469	466	1
		kips	1286	7491	2479	3619	8318	78039	782	12849	809	89
		CVk	50.4	57.1	66.7	57.1	58.1	50.7	79.1	46.5	49.1	.
		ESAL	14	113.4	38.3	129.7	169.7	1011.4	9	274.3	7.7	1.4
		CVE	59.4	65.4	70.2	67	58.5	53.9	84.3	51.6	62.2	.
MA001	Jan	N	8289	120137	20987	634	20552	77310	1599	1799	202	20
		kips	4908	29464	13890	1033	13283	79875	2175	1957	269	138
		CVk	38.8	47.7	55.6	69.7	56.7	52.4	54	44.9	55.6	39.4
		ESAL	128.4	616	461.6	53.9	282.9	2135.9	62.8	66.3	6.1	3.9
		CVE	49.1	51.6	63	75	71.6	59.4	62.2	69.9	96.6	53.5

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
MA001	Feb	**N**	8636	103693	20964	720	20623	77558	1676	1834	248	10
		kips	5107	27552	13792	1042	13437	80669	2292	1956	293	85
		CVk	34.4	44.4	53.3	79.6	53.7	47.8	50.9	41	61.9	27.8
		ESAL	117.1	543.8	424.6	50.5	251.2	2012.7	63.8	53.5	5.2	1.7
		CVE	42.1	49.7	61.5	87.4	59.1	58	63.4	44.5	82.5	110.8
	Mar	**N**	9106	115695	23056	995	22370	90002	2061	2084	273	27
		kips	4822	27404	13952	1284	13251	86280	2570	2083	334	130
		CVk	36	45.4	56	76.7	56	50.8	51.6	41.2	55.3	57.4
		ESAL	110.8	529.6	447.3	63.7	257.9	2344.3	75	65.7	6.5	4.4
		CVE	39.2	49.7	62.2	82.1	61	60.4	59.5	43.9	82.5	103.3
	Apr	**N**	5529	66931	14671	711	13094	48710	1170	928	165	4
		kips	5677	30517	16986	1864	14354	90676	2832	1685	361	91
		CVk	29.2	41	50.1	57.1	50.6	46.9	54.1	44.5	48.4	17.5
		ESAL	136.2	664.9	592.8	94.9	282.7	2680.7	87.1	49.2	8.2	2.6
		CVE	39.5	47.5	57	56.7	60.4	49.1	60.4	51.3	75.7	60.9
	May	**N**	12342	153770	29288	1730	27350	97486	2718	1989	286	19
		kips	6661	34203	17891	2183	15742	92829	3435	1922	334	99
		CVk	31.1	42.2	50.4	69.3	49.5	46.2	43.1	39	60.3	43.7
		ESAL	172.9	660.5	604.8	100.1	322.2	2450	98.5	59.2	6.7	2.7
		CVE	38.3	45.5	57.4	62.8	57.1	51.4	48.8	43.3	79.2	97.1
	Jun	**N**	11537	179969	27845	1818	25641	92980	2344	1901	260	12
		kips	6421	36783	17273	2368	15130	91039	3089	1914	296	114
		CVk	28.2	41.1	53.1	78.3	52.6	49.1	48.5	39.6	51.6	38.5
		ESAL	154.8	585.7	543	104.9	289.4	2283.7	83	56.6	5.7	3.5
		CVE	36	45.9	58.2	75.8	56.9	54	53.4	43	69.4	88.1
	Jul	**N**	10323	178784	28675	1649	26471	94618	2374	1763	284	12
		kips	5578	36012	17024	2229	15142	88531	3029	1707	309	90
		CVk	26.6	40.7	51.4	63.1	50.4	48.3	63.5	46.1	61	33.2
		ESAL	124.9	567	515.5	97.9	281.8	2126.1	81.4	49	5.8	2.4
		CVE	32.8	45.2	58.1	57.9	54.9	56.2	74.9	50.1	79.6	83.1
	Aug	**N**	10057	175237	28425	1600	26568	93262	2307	1886	347	23
		kips	5671	36587	17366	2173	15675	89770	2973	1871	374	122
		CVk	26.9	38.2	48.7	77.7	49.4	46	51.6	38.5	49.2	69.3
		ESAL	131.1	572.3	537.4	94.8	287.5	2141.8	77.5	52.8	6.1	2.7
		CVE	33.2	42.7	54.1	74.8	54.3	49.9	54.7	40.2	65	92.3
	Sep	**N**	9862	140861	27544	1474	25409	88851	2179	2083	316	21
		kips	5485	32250	16984	2051	15159	85564	2731	2093	337	120
		CVk	32.6	42.9	53.3	86.9	55.5	50.8	54.9	47.5	48.1	35.4
		ESAL	128.3	600.4	551.4	92.9	299.3	2182.1	71.2	62.8	5.6	3.7
		CVE	37.3	47.4	59.8	84.8	59.4	57.4	59.1	50.3	87.3	76.4
	Oct	**N**	11187	133701	29501	1716	27704	95493	2511	2358	337	37
		kips	6066	32098	18259	2352	16418	91527	3211	2341	354	147
		CVk	27.9	38.9	47	75.9	47.9	44.3	50	41	51.4	89.9
		ESAL	153.8	672.6	638.4	114.9	346.6	2518.1	90.8	72.6	6.8	2
		CVE	33.3	42.3	53.4	73.9	53.3	49.9	55.4	43.1	82.9	105.2

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
MA001	Nov	N	9425	127940	26787	1405	23945	88866	2246	2001	292	20
		kips	5265	30558	17303	2037	14750	87795	2985	2057	338	145
		CVk	32.4	45.5	52.7	75.1	55.1	49.4	54.2	43.9	56.4	56
		ESAL	131.2	664.6	633.2	101.4	318.9	2410.5	86.3	65.2	6.6	4.8
		CVE	37.3	49.2	56.5	70.3	61.4	59.6	61.5	47.3	88.2	110.6
	Dec	N	9095	125045	22246	943	21295	79328	1819	1657	227	12
		kips	5416	30348	14935	1442	13808	81045	2475	1848	293	103
		CVk	34.1	47.9	57.5	90.6	57.3	52	57.5	43.8	71.6	33
		ESAL	150.8	682.7	550.7	76.2	305.5	2183.9	73.4	59	6.1	3.3
		CVE	45.5	50.6	62.9	91.5	68	59.9	63.6	46.8	103.2	106.4
MA02N	Jan	N	112	3548	53	27	89	2	.	.	.	.
		kips	153	1893	73	60	138	50	.	.	.	.
		CVk	76.2	49.6	55	86.5	96.6	32.4	.	.	.	.
		ESAL	16.2	49.3	0.6	1	0.9	0.4	.	.	.	.
		CVE	155.4	73.8	130.1	180.3	165.9	122	.	.	.	.
	Feb	N	150	3777	58	2	18	73	.	.	.	.
		kips	155	1859	68	15	52	93	.	.	.	.
		CVk	71	52.3	80.1	43.1	62	93	.	.	.	.
		ESAL	12.7	63.1	0.7	0	0.7	1.2	.	.	.	.
		CVE	162.7	83.7	138.2	104.3	150.8	244.6	.	.	.	.
	Mar	N	179	4280	58	3	32	122	.	.	.	.
		kips	162	1700	67	74	77	176	.	.	.	.
		CVk	77.3	65.2	78	34.8	53.1	124.8	.	.	.	.
		ESAL	5.9	34.1	0.7	6.9	0.8	1.8	.	.	.	.
		CVE	113.7	100.1	127.4	146.2	83.7	183.7	.	.	.	.
	Apr	N	157	8970	148	22	105	309	1	.	.	.
		kips	151	4628	154	96	117	438	34	.	.	.
		CVk	54.7	56.7	99.2	53.5	66.1	80.1	.	.	.	.
		ESAL	6.9	331.6	4.1	1.5	1.5	5.1	0.1	.	.	.
		CVE	96.5	107.2	164.8	55.5	89.7	96.7	.	.	.	.
	May	N	194	6130	266	67	257	537	4	1	.	.
		kips	178	2405	250	276	211	847	28	85	.	.
		CVk	55.1	41.2	75.8	72.4	88.2	78.2	29	.	.	.
		ESAL	5.3	47.3	3.8	9.4	2	14.9	0	2.3	.	.
		CVE	77.7	73.3	103.7	83.7	85.4	82.8	81.1	.	.	.
	Jun	N	228	6450	368	32	305	773	5	1	.	.
		kips	213	2466	382	124	256	1243	39	37	.	.
		CVk	58.4	42.6	62.3	78.8	75.6	72	40.1	.	.	.
		ESAL	5	38.4	7.7	3.9	2.5	23.1	0.2	0.3	.	.
		CVE	63.8	80.2	72.1	100.3	114.1	68.2	128.1	.	.	.
	Jul	N	146	5664	303	45	259	667	4	.	.	.
		kips	140	2200	349	166	224	1067	62	.	.	.
		CVk	52	40.9	53.1	61.7	77.8	66.3	82.6	.	.	.
		ESAL	3.7	28.5	7.6	6.4	2.7	24.5	2.9	.	.	.
		CVE	71.3	62.2	73.9	72.4	98.5	66	189.5	.	.	.

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
MA02N	Aug	N	258	5446	323	78	268	704	5	.	.	.
		kips	249	2306	367	222	290	1133	66	.	.	.
		CVk	56.9	46.2	55.3	76	60.9	60.6	41.6	.	.	.
		ESAL	5.7	40.4	10.3	8.6	4.1	24.3	1.4	.	.	.
		CVE	91.7	70.6	93.7	103	85.3	72.3	109.1	.	.	.
	Sep	N	324	5452	221	20	173	483	5	.	.	.
		kips	297	2484	256	115	163	827	98	.	.	.
		CVk	53.6	51.3	68.4	63.1	79.1	75.9	67.6	.	.	.
		ESAL	8.2	55.4	6.5	5.6	2.2	19.4	1	.	.	.
		CVE	78.1	65.9	96.6	75.7	121.5	87	87.6	.	.	.
	Oct	N	249	5467	166	45	119	292	1	1	.	.
		kips	205	2604	214	201	139	531	123	37	.	.
		CVk	48.9	45.6	95	107.1	68.7	81.5	.	.	.	.
		ESAL	5	79.4	11.5	10.4	2.4	14.9	6.1	0.2	.	.
		CVE	61.7	80.5	169	152.1	124.7	95.7	.	.	.	.
	Nov	N	178	5315	39	1	9	62	.	.	.	.
		kips	168	2388	64	40	22	106	.	.	.	.
		CVk	76.5	70	102.2	.	80	223	.	.	.	.
		ESAL	5.6	77.5	1.8	0.3	0.1	3.2	.	.	.	.
		CVE	91.7	133.1	156.2	.	163.9	352.7	.	.	.	.
	Dec	N	176	4526	27	1	15	55	.	.	.	.
		kips	189	1883	32	49	26	105	.	.	.	.
		CVk	84.1	61.7	104.9	.	61.9	155	.	.	.	.
		ESAL	10.5	48.6	0.5	0.9	0.1	1.8	.	.	.	.
		CVE	164.3	91	243	.	152.3	287.1	.	.	.	.
MA005	Jan	N	4335	93048	12654	387	18250	58095	2119	1634	228	13
		kips	1383	14120	5057	439	6275	32930	1819	1037	180	93
		CVk	51.2	55.6	70.2	99.4	68.3	64.5	96.6	56.8	67.6	42.2
		ESAL	45.8	193.5	161.3	21.6	94.1	679.4	54.9	27.1	3.3	2
		CVE	76.3	67.2	92.3	105.9	81.8	95.8	135.2	90.8	124.7	152.1
	Feb	N	4212	81812	11399	370	17261	53642	1747	1585	188	9
		kips	1386	13091	4675	361	6245	31169	1509	1043	166	115
		CVk	52.4	54.5	70.2	117.5	74.8	71.1	95.5	72.1	83.4	55.7
		ESAL	37.2	170	133.1	15.5	91	562.6	41.3	24.5	2.9	1.9
		CVE	76.8	70.7	82.9	142.2	83.8	98.1	126.3	84.8	147.1	95.3
	Mar	N	3776	63317	11040	268	14257	48677	1989	1334	170	9
		kips	1676	13333	6082	419	6818	37974	2406	1159	201	77
		CVk	43.9	54.2	64.2	102.3	66.8	56.8	66.3	67.8	55.2	35.2
		ESAL	47.6	193.7	185.2	20.5	102.1	749	72	29.3	3.3	1.3
		CVE	66.2	67.4	79.9	112.5	73.3	69.9	87.3	84.7	116.8	107.5
	Apr	N	6647	96743	16427	489	25490	73559	3565	2850	354	10
		kips	2105	15000	6413	481	8952	42716	3142	1808	271	93
		CVk	48.9	60.4	71.7	98.7	75.5	72.8	96.2	51.2	72.1	60.8
		ESAL	54.7	226.8	210.6	22.4	140.1	834.7	92.3	43.7	4.1	2
		CVE	68.3	81.4	77.6	122.1	87.5	98.6	123.7	69.1	119.3	125.5

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
MA005	May	N	10251	163090	26767	1046	41855	117486	6727	4447	664	18
		kips	2583	19751	8666	787	11748	55039	5053	2227	435	121
		CVk	49.3	51.5	62	106.5	70.7	65.8	83	51.9	72.9	53.1
		ESAL	65	277.4	272.1	33.1	181.7	1078	149.9	56	9.3	3.5
		CVE	61.3	62.8	73.6	123.3	79.4	77.3	94.8	65.4	103.4	104.3
	Jun	N	12383	211704	30405	1482	51626	140765	6745	5479	901	29
		kips	2882	23002	9207	1017	13863	63026	4746	2670	522	117
		CVk	47.6	47.8	60.3	92.1	68.2	62.2	80	48.5	72.2	40.9
		ESAL	73.2	320	274.2	42.2	230.8	1305.7	143.3	74.3	10.6	4.7
		CVE	58.2	61.4	63.1	95.4	77.6	72	92.9	60.9	98	107.9
	Jul	N	11290	220532	28403	1292	47530	131627	5637	5220	795	25
		kips	2569	22287	8249	867	12330	57638	3807	2484	476	112
		CVk	48.7	49.3	64.9	93.4	72.6	66.4	77.8	53.3	74.8	52.1
		ESAL	66.4	296.2	235.9	34.8	207.4	1219.5	115.7	69.6	9.6	2.7
		CVE	59.9	63.7	67.3	87.5	83.1	78.8	89.4	66	111	110.9
	Aug	N	12116	240333	30926	1466	52727	144222	6158	5896	865	33
		kips	2716	24154	8853	980	13709	62401	4069	2823	498	126
		CVk	44.2	45.4	59.8	82	65.9	61.1	72.7	47.6	86.9	45.4
		ESAL	68.4	309.5	238	37.2	226.1	1258.8	118.9	81.3	10	4.4
		CVE	57.1	57.3	61.5	83.8	74.5	73.3	83.8	59.9	121.9	102.7
	Sep	N	9249	157091	22632	976	38463	106277	4381	4313	638	20
		kips	2567	20918	8178	862	12158	56052	3475	2519	437	105
		CVk	46.6	52.5	67.6	96.8	75.4	70.5	78.9	55.5	88.3	45
		ESAL	65.8	275.1	240.7	35.5	190.7	1092.9	98.2	65.8	8	3
		CVE	61.3	62.8	70.8	96.8	86.4	84.1	92.9	65.4	117.4	80.1
	Oct	N	9704	137035	22253	2684	35485	98210	4034	4149	646	30
		kips	2942	20190	8739	2285	12115	55652	3377	2540	465	110
		CVk	42	48.6	63.3	97.9	72.4	67.3	77.9	47.5	87.3	49.6
		ESAL	70.5	280.5	277.1	91.8	194.1	1128.5	96	64.8	8.2	2.5
		CVE	54.8	62.4	65.3	103.2	82.4	80.2	89.8	59.7	115.6	103.2
	Nov	N	7967	144470	22798	1283	33891	99013	4619	3882	665	17
		kips	2216	19082	8340	1093	10769	52537	3822	2156	482	93
		CVk	53.3	56.8	65.9	104	80.8	70.6	86.2	57	81.8	48.3
		ESAL	66.3	293.5	276	48.1	183.4	1166.4	123.1	54	8.2	2.4
		CVE	79.5	74.9	74.5	99.7	92.7	89.1	100.9	75.3	105	118.2
	Dec	N	8552	273090	23117	927	37190	109435	5169	4095	485	23
		kips	1959	35255	6649	773	9799	48657	3685	1907	336	121
		CVk	60.2	166.4	72.5	115.4	83.8	75.9	91.5	60.4	83	43.2
		ESAL	66.1	907.1	192	37.6	175.2	1260.8	129	52.7	7.3	4.4
		CVE	77.7	326.9	76.5	119.9	93.5	95.6	102.8	82.9	110.8	86.9
RI350	Jan	N	1100	34220	5802	249	13683	44860	756	893	125	8
		kips	321	3490	1687	227	4718	22732	631	525	148	142
		CVk	61	59.2	60.5	125.1	59.1	53.8	130.6	61.1	67.3	70.2
		ESAL	13.4	93	87.2	13.4	219.4	1165.5	30	27.4	4.8	11.5
		CVE	139.2	81.4	107	134.7	85.1	99.9	155	86.5	209.4	147.4

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
RI350	Feb	N	853	26806	4648	107	12184	38826	373	911	116	6
		kips	288	3307	1474	137	4800	23012	347	601	114	118
		CVk	67.6	48.5	51.4	70.1	53.6	49.4	82.2	59.8	63	38.3
		ESAL	8.8	81.9	59.1	8.7	190.4	1104.6	12.8	29.1	2	9.6
		CVE	100.6	65.6	84.3	102.8	76	82.5	130.6	84.9	121.5	94.4
	Mar	N	1040	33626	5581	135	14814	45338	436	1152	154	7
		kips	292	3531	1504	158	4893	22482	310	643	142	132
		CVk	61.6	37.6	50.2	81.7	51.2	45.4	91.5	49.8	55.2	32.9
		ESAL	9.8	84.3	55.8	10.6	183.1	1012.6	10.2	30.4	3.9	7.8
		CVE	140.5	54.9	75.7	112.6	59.6	65.4	138.2	87.2	145.3	72.5
	Apr	N	1279	33426	6070	206	14711	44013	490	1189	140	1
		kips	375	3736	1808	239	5068	23128	338	706	137	46
		CVk	57.2	43.2	52.8	97.7	52.7	47.5	64.8	50.7	60.7	.
		ESAL	11.5	104.4	83.2	16.9	190.1	1050.4	10.9	33.9	4	0.1
		CVE	95.4	64.9	100.9	124.5	63.6	58.7	113.4	73.2	178.5	.
	May	N	1408	44263	6498	331	16431	49586	746	1398	168	5
		kips	376	4413	1918	305	5379	25614	572	797	145	118
		CVk	60.4	44.7	54.2	125.5	52	49.2	69.2	47.4	55.8	62.5
		ESAL	12.8	108.3	97.4	20.8	196.2	1260.9	20.9	37.2	3.1	12.1
		CVE	81.3	58.2	91.5	160.4	58.7	56	90.6	63.7	106.5	133.3
	Jun	N	1568	41180	6097	262	14914	42414	645	1275	142	11
		kips	461	4258	1989	281	5407	23681	516	801	137	155
		CVk	69.2	50.7	56.8	105.8	57.8	51	61.2	50.4	58.1	41.3
		ESAL	20.5	112.2	115.1	25.7	239.9	1236.4	21.7	48	5	12.4
		CVE	126.2	57.5	81.2	166.3	73.2	63.3	84.6	80.8	160.3	78.8
	Jul	N	1534	37468	6295	280	14759	43844	512	1281	130	12
		kips	418	3875	1897	274	4959	22657	414	738	129	144
		CVk	65.3	40.1	54.7	97.2	54	48.1	76.5	48.7	65.1	44.7
		ESAL	15.5	105.6	93.6	21.3	206.4	1084.2	18.2	39.4	4.9	12
		CVE	96.2	55.5	78	113.9	72.1	58.3	110.2	66.5	191.5	88.1
	Aug	N	1608	34152	6575	307	16042	44038	510	1444	155	12
		kips	463	3849	2121	304	5769	23707	414	902	138	173
		CVk	62.6	39.1	53.6	110	49.5	44.6	68.6	45.1	67.1	72.3
		ESAL	17.7	104.4	123.1	22.5	262.4	1128.9	18.3	49.5	3.8	17.5
		CVE	86.2	55.2	98.9	151.4	74.9	56.2	110.1	81.6	165.6	99.9
	Sep	N	1678	33421	6707	386	15471	44236	699	1360	164	12
		kips	499	3736	2033	410	5499	23431	518	821	136	144
		CVk	60.1	43	56.8	136.8	55.8	51.4	84.5	49.6	54.1	46.3
		ESAL	18.3	102	112.6	31.5	258.2	1142.7	19.5	42.5	2.9	11
		CVE	110	60.4	105.1	147.6	83.3	61.3	101.1	74.9	135.8	103.4
	Oct	N	1778	39985	7239	403	16905	51566	903	1433	200	14
		kips	506	4139	2160	383	5824	27229	657	799	151	102
		CVk	54.4	37.8	50.4	145.3	49.7	44.6	79.2	51.3	56.5	41.2
		ESAL	16	108	118	26.3	262.7	1461.2	25.9	36.8	4.9	5.3
		CVE	87.5	55.2	77.1	165.5	66.4	60.1	106.2	65.6	157	152.3

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
RI350	Nov	N	1247	39900	6357	274	13870	48959	782	1213	192	14
		kips	375	4186	2019	275	5174	27392	640	754	172	144
		CVk	59.5	68.6	52.8	121.3	60.3	49.9	77.9	52.8	63.2	70.2
		ESAL	12.4	112.2	112.4	19	252.2	1464.5	26.9	43.9	5.1	11.8
		CVE	104.5	73.6	98.4	138.8	77.1	65.5	120.3	88.7	130	143.5
	Dec	N	1359	38066	5827	211	12777	48227	547	1099	181	9
		kips	388	3742	1694	239	4444	24925	449	643	148	96
		CVk	65.8	74.9	58.7	100.5	64.8	52.6	76.5	57.2	62	30.9
		ESAL	14.1	95.2	90	16.1	204.9	1218.1	19	32.3	4.7	2.4
		CVE	142.1	80	113	112	100.2	76.8	121.3	108.5	166.9	94.9
VTd92	Jan	N	1817	22603	4038	285	5262	41603	1021	308	230	29
		kips	408	2265	925	142	1394	18099	521	170	155	83
		CVk	60.2	48	57.7	64.1	61.7	51.6	58.8	59.5	75.7	52.2
		ESAL	6.8	43.6	14.3	3.4	26.1	373.7	8.4	4	2.8	1.4
		CVE	72.9	89	87.6	138.2	104.7	88.7	100.7	131.8	168.9	138.5
	Feb	N	1765	21019	3052	320	4527	36384	878	192	209	9
		kips	418	2178	725	156	1224	16981	475	118	143	83
		CVk	40.2	45.6	48.5	61.3	57.6	47.1	61.1	57.7	61.3	32.9
		ESAL	6.5	34.3	10.2	2.6	17.1	304.8	6.8	2.3	2.2	2.2
		CVE	82.8	72.5	78.5	94.2	68.4	58.7	94.1	94.5	159.3	109.1
	Mar	N	1752	22470	3906	364	5393	40662	1075	218	230	32
		kips	412	2115	877	144	1361	17303	549	121	149	83
		CVk	57.7	48.9	56.7	74.9	59.3	47.2	65.7	60.9	69.1	40.5
		ESAL	6.1	30.4	12.8	2.3	20.1	296.6	7.8	1.8	2.1	1.6
		CVE	88.1	72.5	90	109.4	73.1	58	87.6	86.8	113.8	153.5
	Apr	N	2213	22413	5252	435	5616	44660	1354	207	212	34
		kips	545	2186	1216	178	1484	20089	734	116	145	90
		CVk	47.3	49.8	59.3	73	57.5	48.6	65.4	66.2	63.6	39.1
		ESAL	8.6	34.4	16.9	4.1	25.1	390.7	12.2	2.2	2.4	2.1
		CVE	60.6	78.3	71.2	121.9	74.4	62.2	90.2	124.8	114.6	151.3
	May	N	3004	25989	6832	420	6751	49985	1650	249	334	31
		kips	695	2454	1548	181	1753	21984	902	124	225	86
		CVk	42.9	44.5	55.2	65.1	53.6	46.9	58.2	59.3	76.9	50.2
		ESAL	12	39.1	22.4	3.8	33.8	455.1	16.1	2.9	4.2	2.3
		CVE	65.2	69.2	69.1	105.1	62.4	60.1	80.1	106	117.6	172.2
	Jun	N	1916	19199	5164	260	5087	34783	891	231	172	25
		kips	650	2695	1691	167	1900	22426	681	171	149	100
		CVk	35.3	41.9	59.2	61.7	48.3	44.4	61.7	61.8	59.4	59.1
		ESAL	12.7	43.4	22.5	3.9	35.2	441	10.6	4.2	2.3	2
		CVE	69.1	72.7	59.7	112.9	69.5	58.8	78.6	87.1	93.9	109.3
	Jul	N	1547	16398	4124	217	3634	28972	759	129	151	34
		kips	591	2469	1513	161	1520	20497	674	104	153	96
		CVk	31.6	42.7	62.2	71.1	56.8	49.7	65.1	55.1	69.5	69.8
		ESAL	8.7	33.9	18.7	3.6	24.7	374.3	11.7	1.9	2.3	1.8
		CVE	45	72.5	71.6	112.5	62.2	62.9	86.3	105	114.3	144.8

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
VTd92	Aug	N	2575	29178	6637	366	7093	50365	1365	314	254	35
		kips	647	2827	1602	184	1950	23404	783	155	164	80
		CVk	36.4	37.5	59.8	59	50.9	45	57.8	59.8	60.1	46.4
		ESAL	11.7	40.7	22.2	4.9	41.1	498.7	15.3	3	3.2	1.4
		CVE	61.1	59.9	59.8	105.4	63.7	64.6	83.6	92	158.6	131.5
	Sep	N	2687	26091	6030	355	6511	48443	1270	313	321	31
		kips	673	2604	1508	182	1835	22736	767	162	215	78
		CVk	32.9	45.5	59.7	69.7	56.8	50.8	65.4	62.8	66.1	48.5
		ESAL	12.2	47.5	22.7	4	36.3	481	15.6	3.6	3.6	0.8
		CVE	54.9	116.3	62.2	106.7	62.6	70.2	87.6	88.7	101.3	138.1
	Oct	N	2898	27017	5651	399	6696	50962	1300	306	296	42
		kips	705	2749	1402	193	1887	23532	748	148	182	92
		CVk	40.6	45.6	51	69.5	54.6	46.8	54.2	60	67.4	54.8
		ESAL	14	73.7	24	4.3	41.8	531.6	16	3.4	3.5	2
		CVE	56.6	108.9	60	92.6	63.3	59.9	77.7	79.5	110	141.4
	Nov	N	1895	28983	4416	404	5303	41319	1043	204	297	33
		kips	481	2707	1113	185	1557	19375	607	129	244	81
		CVk	49.8	64.8	60.3	78.1	63.1	52.5	63.9	75.8	83.4	52.6
		ESAL	13	58.2	20	4.4	41.9	459.4	13.6	3.5	6.6	0.8
		CVE	99.9	110.7	91.8	149.7	108.9	82.8	101.4	149.1	176	118.7
	Dec	N	1897	24388	4325	368	5355	43371	1196	188	243	48
		kips	453	2433	1043	181	1509	18993	670	124	171	102
		CVk	65.8	56	61.1	73.1	63.5	54.1	64.1	71.8	67	48.3
		ESAL	11.4	55.6	18.3	4	37.5	383.9	12.4	2.9	3.1	2.2
		CVE	154.4	104.9	97.5	114.2	135.4	74.1	97.1	124.6	152.7	144.9
VTn01	Jan	N	146	3355	716	28	1400	13135	519	104	85	8
		kips	93	727	364	65	820	13066	490	119	138	70
		CVk	67.6	46.2	51.6	48.6	53.1	47.8	51.1	63	68.3	27.2
		ESAL	2.4	13.7	5.6	2.1	11.1	228.9	5.5	2.3	2.9	0.8
		CVE	188.9	94	108.6	124.1	85.5	80.3	83.1	119.8	144.7	87.4
	Feb	N	179	3493	737	55	1454	13515	719	110	93	9
		kips	103	800	395	66	862	13904	714	140	178	65
		CVk	61	48.5	46.6	54	51.9	53	50.5	54.2	67.3	16.9
		ESAL	3.3	15.4	6.8	0.8	12.3	281.5	8.9	3.6	6.6	0.7
		CVE	184	95.5	113.9	142.5	80.6	77	88.2	138.4	183.3	45.1
	Mar	N	206	4003	863	61	1578	17300	769	111	101	9
		kips	109	731	342	60	775	14606	614	113	176	85
		CVk	80.2	44.9	48.8	55.1	52.4	46.3	58.7	47.5	69	36
		ESAL	2.6	12.9	5	0.9	10.3	242.6	6.9	2.6	4.9	2.1
		CVE	157.8	85	115.7	152.9	92.7	62.2	97.1	86.9	136.2	124.3
	Apr	N	177	3855	987	45	1705	18231	646	115	66	4
		kips	87	776	411	58	861	16217	613	127	134	75
		CVk	70.5	44.3	50.5	62.9	46.8	46.9	42.7	45.1	57.7	25.6
		ESAL	1.9	14.4	5.6	1.2	11.4	290.8	10.5	3	3.5	1.5
		CVE	161.2	82.8	88.3	181.5	71.7	65	73.6	94.7	126.1	92.8

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
VTn01	May	**N**	270	4643	1256	58	1801	19410	836	120	95	4
		kips	136	852	476	70	857	16107	689	119	146	96
		CVk	72.7	40.2	49.5	57.7	51.7	50.9	60.8	40.5	61.5	23.4
		ESAL	1.9	14.8	6.2	1.8	10.9	284.9	9.2	2.7	3.9	1.9
		CVE	86	75.8	97.2	186.2	79.9	64.5	77.7	82	142.3	87.5
	Jun	**N**	273	4994	1230	56	1445	15192	742	123	72	3
		kips	149	842	524	80	712	13431	634	129	134	135
		CVk	69	48.4	74.5	60.1	62.3	58.8	65.9	63	55.4	11.3
		ESAL	3.5	14.1	8.9	3.4	11.9	287	8.8	3.2	1.7	7.6
		CVE	141.9	110.8	110.3	209.7	154.8	72.6	104.3	139.9	90.9	58.1
	Jul	**N**	333	8044	1541	55	1505	15004	760	142	68	2
		kips	155	1413	699	92	735	13515	657	131	110	78
		CVk	49.3	50.2	87.9	68.4	47.6	55.1	70.2	48.7	53.6	51.6
		ESAL	3.4	33.2	13.5	3	12	283.1	8	2.8	1.4	2.5
		CVE	107.1	137.9	169.6	118.8	84.4	61.3	96.4	71.6	123.2	132.7
	Aug	**N**	378	7474	1289	60	1885	16631	799	164	110	4
		kips	166	1129	520	116	883	14397	703	157	142	84
		CVk	53.3	32.8	61.2	160.4	44.5	49	57.6	42.6	57.5	32.3
		ESAL	3	13.4	5.6	2.7	9.8	230.9	7.4	2.7	1.5	1.4
		CVE	148	90.8	86.9	195.7	69.6	51.8	94.1	70.9	101.1	99.4
	Sep	**N**	545	6226	1072	32	1784	15917	629	160	112	5
		kips	259	1077	467	73	906	14314	601	154	164	77
		CVk	49.8	36.5	53.9	59.2	52.4	53.2	65.1	48.5	65.2	41
		ESAL	5.4	15.5	6.7	1.6	13	247	6.7	3.1	3.3	1.8
		CVE	117.2	76.6	88	98.2	104.1	56.4	99.6	111.9	132.9	166.3
	Oct	**N**	572	7985	1410	31	1900	16983	726	195	113	10
		kips	263	1349	626	59	956	15108	652	189	145	114
		CVk	55.3	53.4	65.2	44.1	44.8	48	57.3	41.6	58.2	54.2
		ESAL	5.4	20.7	9.2	1.3	14	283.1	7.4	4.4	3.5	4.1
		CVE	102.5	86	73.2	103.9	81.4	54.8	90.7	82.7	163.2	146.6
	Nov	**N**	271	6877	970	23	1709	16378	631	182	113	6
		kips	134	1181	459	51	978	15788	568	206	157	94
		CVk	66.6	81.9	47.4	55.8	50.8	53.1	70.2	54	55.4	28.3
		ESAL	3.8	17.3	8.5	0.8	23.5	367.8	5.9	6.6	3.4	3.6
		CVE	151.9	143.2	85.8	127.6	159.9	73.6	91.4	178.6	216.5	118.4
	Dec	**N**	296	5161	923	18	1629	15949	633	162	78	3
		kips	135	878	413	51	837	13950	548	151	117	88
		CVk	58.3	42.7	68.6	52	53.9	60.9	64.6	40.3	60.2	23.1
		ESAL	2.4	12.2	5.7	1.2	11.8	263.2	6.9	2.5	2.1	1.6
		CVE	110	96.5	98.9	139.1	88.3	81.1	148.1	117.8	130.2	78.8
VTr01	Jan	**N**	907	7636	1623	296	3840	34844	3101	183	429	50
		kips	274	752	409	222	1139	15469	1959	100	478	150
		CVk	111.7	41.6	63.7	77.2	50	46.4	63.5	53.6	91.8	49
		ESAL	9.5	20.7	10.9	9.7	30	383.8	78.6	2.6	20.5	5.4
		CVE	132.7	90.2	145.3	121.2	84.9	83.3	111.1	107	109.7	86.2

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
VTr01	Feb	N	974	6432	1575	240	3793	34586	3293	154	396	31
		kips	296	679	392	171	1135	15398	2049	87	414	120
		CVk	120.7	39.7	49.6	81.2	43.7	39.9	62.1	59.8	72.5	43.6
		ESAL	5.7	15.5	8.6	5.7	22.6	282.3	68.6	2	14.4	3.2
		CVE	135.1	105.6	127.7	148.9	79.4	69.7	129.4	117.6	103.4	85.3
	Mar	N	898	6854	1740	250	4035	37604	3157	180	292	11
		kips	254	638	394	167	1111	15340	1754	83	316	104
		CVk	127.3	41	51.3	90.6	45.1	39.2	57.6	53.5	77.4	46.7
		ESAL	5.4	9.7	8.6	4.9	23.1	264.9	49.3	1.7	9.7	2.7
		CVE	176.3	86.4	117.2	138.3	95	60	107.5	148.8	99.2	92
	Apr	N	399	6324	1373	226	3970	37308	2242	201	246	32
		kips	109	624	316	182	1065	15635	1310	93	274	105
		CVk	63.9	40.9	65.9	89.8	45.2	39.7	55.3	51.9	94	28.4
		ESAL	1.9	9.1	6.6	5.4	16.8	249.6	31	1.6	8.4	2.7
		CVE	84.9	89.4	134.2	115.9	54.7	50	74	99.1	99.4	80.3
	May	N	447	7332	1513	211	4635	41084	2609	208	269	23
		kips	114	707	324	168	1193	16709	1474	92	288	113
		CVk	76.3	38.6	48.7	82.4	42.4	39	58.4	50.6	81.8	38.8
		ESAL	2.3	10.4	5.9	5	18.1	271	42.1	1.9	10.1	3.2
		CVE	90.9	77.3	102.6	103.8	52.1	44	92.7	190.7	117.7	95
	Jun	N	642	8294	1593	269	4583	37875	2269	208	227	24
		kips	156	841	366	187	1223	16196	1309	102	266	107
		CVk	68.4	37.2	53.7	99.1	40	38.9	64	50	76.6	41.6
		ESAL	3.6	13.4	7.5	5.6	19.5	263.3	36.3	2.3	8.3	3
		CVE	100.5	103.3	105.7	135.3	55.3	45.2	99.9	160.5	109.8	63.3
	Jul	N	731	9707	1466	123	4861	33729	1873	284	199	12
		kips	179	903	322	100	1305	15009	1157	132	230	112
		CVk	49.1	30	54.9	87.6	40.9	41.5	66.6	49	59.6	35.6
		ESAL	3.7	11.7	6.1	2.8	23.2	269.4	30.9	3.3	7.2	3.4
		CVE	68.8	88.4	116.5	158.1	49.1	44.7	96.8	111.2	80	99.1
	Aug	N	705	10482	1349	135	5137	34573	1730	290	162	29
		kips	162	952	278	92	1387	15165	1008	131	186	115
		CVk	47	29	44	73.3	39.6	38.9	63.9	44	57.8	43.3
		ESAL	3.3	11.6	4.5	1.9	23.3	253.1	24.3	3.1	5.4	2.9
		CVE	68.6	80.2	119.2	101.4	44.6	39.4	90.1	104.1	77	85
	Sep	N	865	8773	1334	128	4747	33447	1630	234	220	19
		kips	232	850	300	121	1368	15285	1014	119	259	129
		CVk	55.8	32	53	75.1	46.1	41.8	72.3	58.7	70.8	36.7
		ESAL	4.8	10.7	5	3.5	27.5	285.1	28.4	3.9	8.2	4
		CVE	76.6	84.7	104.1	116.6	57	45.9	105.3	117.8	113.1	64.4
	Oct	N	957	7990	1320	82	4313	32079	1591	209	159	12
		kips	254	743	282	90	1174	13969	995	109	200	91
		CVk	63.3	39	60.4	59.3	52.9	47.8	69.4	47.6	73.1	26
		ESAL	5.1	11.1	5	3.2	21.1	244.2	24.5	2.7	5.4	1.8
		CVE	89.9	169.2	114.7	167	65	56.1	94.7	106.1	90.3	88.7

Table D.2 (cont'd). Load Summary Statistics by Site, Month, and Vehicle Class

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
VTr01	Nov	N	471	6830	1189	185	3779	30594	1608	158	173	17
		kips	124	653	281	144	1142	13859	986	101	239	113
		CVk	65	49	49	107.3	58	50.9	63.2	51.2	75.7	48.1
		ESAL	3.3	11.7	5.7	6.2	25.2	257.4	29	2.8	9.8	3.5
		CVE	115	126.2	99.4	200.6	84.4	62	105.6	94.7	108.5	101.2
	Dec	N	583	7212	1318	235	3903	32297	2040	221	244	29
		kips	157	694	316	164	1184	14052	1242	123	316	131
		CVk	99	45.8	57.2	86.8	49.9	48	71	50.2	85.6	38.9
		ESAL	5	17.2	7.7	5.6	28.1	274.1	38.8	2.9	12.8	3.4
		CVE	153.6	112.4	115.1	113.3	89.4	64.4	107.1	113.5	115.9	75
VTx73	Jan	N	2013	13772	3054	60	6537	53454	500	1953	377	8
		kips	511	1466	670	79	1781	23827	290	852	205	89
		CVk	55.3	40.4	44.5	58.2	52.1	43.4	55.1	51.4	62.8	29.3
		ESAL	9.3	23	9.3	2.5	33.5	462.8	4.9	20.4	3.1	1.6
		CVE	111	72	76.6	117.7	71.6	60.5	96.4	80.5	142.8	82.7
	Feb	N	1766	12074	2644	45	5547	46241	428	1780	318	5
		kips	493	1466	644	64	1738	23731	314	877	200	58
		CVk	60.6	42.4	40.2	65.9	50.3	42.9	66.6	44.8	57.7	24.8
		ESAL	7.5	22.1	8.1	1.4	31.2	424.5	4.8	20.8	2.6	0.6
		CVE	132.3	79.8	115.4	168.7	98.7	66.4	93.9	174.5	102.1	148.4
	Mar	N	1770	13278	2868	62	6045	50891	566	1778	339	8
		kips	447	1412	633	74	1684	24036	338	816	185	84
		CVk	55.5	44.1	48.5	65.5	54.8	46.7	69.7	49.8	60.9	30.7
		ESAL	6.4	20.8	9	1.4	30.3	465.5	6	17.8	2.4	1.4
		CVE	78.6	74.9	100.9	112	77	63.3	94.6	66.7	89.2	127.2
	Apr	N	1468	13024	2720	66	6190	49978	608	1692	346	6
		kips	396	1533	671	76	1868	25743	378	835	214	80
		CVk	32.8	42.4	47.9	58.2	51	46	61.3	45.4	62.1	24.8
		ESAL	5.6	21.3	8.9	2.3	30.8	491	6.2	17.8	3	1
		CVE	85.3	74.7	93.8	138.6	70.7	62.5	89	58	87.4	99.3
	May	N	1746	44455	3287	68	7418	57043	712	1906	372	15
		kips	416	4136	699	79	1891	25689	421	847	206	91
		CVk	39.8	160.4	49.6	71.1	52.6	53	63.7	54	58.9	50.9
		ESAL	5.9	24.9	8.2	2.1	27.1	473.8	6.9	17.2	2.4	1.4
		CVE	56.1	85.2	71.6	175.3	63.2	63	86.3	62.9	73.3	143.5
	Jun	N	1761	28774	3701	176	7570	58342	735	2188	355	10
		kips	416	2765	823	165	2060	27166	413	997	214	96
		CVk	32.3	94.3	46.1	162.9	48.6	45.5	56	46.3	64.3	28.6
		ESAL	6.6	29.9	9.7	3	32.7	500.7	6.6	21.5	3	2
		CVE	61.6	123.2	69.7	150.7	68.1	65.7	72.4	57.3	107.3	92.6
	Jul	N	883	9463	2045	120	3400	26869	385	971	127	3
		kips	378	1675	828	173	1562	21846	401	822	147	78
		CVk	45.1	49.1	63.6	148.8	62.3	56.3	73.6	58.3	62.6	44.8
		ESAL	5.7	19.2	9.2	2.6	22.5	370.6	5	17.9	2	1.6
		CVE	67.5	63.5	70.3	143.1	75.6	67.4	68.4	66.2	91.8	87.3

Site	Mo.	Stat.	4	5	6	7	8	9	10	11	12	13
VTx73	Aug	**N**	1975	19922	4228	115	8628	63107	811	2625	354	9
		kips	467	2086	924	99	2286	28446	441	1178	196	101
		CVk	30.3	31.6	41.2	152.7	42.8	39.1	61.3	41.4	52.7	32.3
		ESAL	7	23.7	9.7	1.8	32.9	443.8	5.9	24.4	2.3	2.6
		CVE	49.4	50.5	51.9	140.7	46.3	49	84.1	47.7	64.2	84.5
	Sep	**N**	2361	19520	4175	89	8486	59948	674	2499	418	14
		kips	588	2076	941	91	2283	27672	401	1156	233	90
		CVk	33.8	36	43	85.8	49.9	43.1	61.7	46.7	53.3	54.8
		ESAL	8.3	23.5	10.1	2.5	34.3	452.2	6.2	25.4	2.8	1.6
		CVE	48.3	56.3	54.1	135.3	62	53.1	91.6	57.9	76.4	118.2
	Oct	**N**	2492	19562	3662	60	7801	58787	678	2448	390	9
		kips	622	2004	837	71	2172	27336	383	1130	217	95
		CVk	36.8	42.1	38.8	58.6	51.9	41.4	55.8	48.2	60.1	49.9
		ESAL	8.7	21.6	9.6	1.9	35.1	461	6.2	25.1	2.6	1.7
		CVE	52.8	54.2	68.3	116.7	58.8	51.9	82.4	59.7	81.4	89.6
	Nov	**N**	1813	19624	3636	79	7145	60866	774	2299	467	9
		kips	439	2008	842	83	2094	29598	452	1098	259	85
		CVk	36.2	45	52.5	63	52.5	42.9	54.4	53.3	60.1	41.2
		ESAL	6.6	24.9	10	2.2	39.2	585.3	7.3	28	3.5	1.6
		CVE	57.6	63.4	83.2	128.8	65.8	64.4	84	76.1	85.1	110.9
	Dec	**N**	1747	15559	2987	78	6608	54171	608	2088	301	5
		kips	413	1642	660	77	1900	25088	353	1007	187	91
		CVk	39.5	50.4	48.6	63.1	58.6	50.4	65	52.1	63.8	34.5
		ESAL	6.7	24.3	8	2.5	36.8	483	6.1	26.8	2.4	2.4
		CVE	135.9	91.6	80.2	220.4	94.7	72.1	81.9	99.9	104.4	92.9

APPENDIX E. SAS MACRO FOR CONVERTING 6-DIGIT VEHICLE CODES TO THE 13-CLASS SYSTEM

```
**  MACRO TO CONVERT SIX-DIGIT CODES to 13-CLASS SYSTEM  **;

%MACRO CONVERT;
*6-digit-->13-class from Ralph Gillman (GM.PAS program).
Actually 15 class-system, 14=not used?  Vehicles that do not
conform to predetermined axle lengths and configurations are
placed in class 15.;

length vcode vc1 vc2 vc3 vc4 vc6 8;

vcode=substr(vehcode,1,4);

if vcode=0 then do;
  vclass=substr(vehcode,5,2);
  naxl_cd=.;
  cldirect+1;
  if vclass='15' then vcl15t+1;
end;

*NOTE: GM.PAS determines number of axles from six-digit
codes.  However the six-digit codes may be simply zeros
followed by the thirteen-class class.  In that case GM.PAS
computes the number of axles as from

    array axle_cnf{13} _TEMPORARY_ (2 2 2 2 2 3 4 4 5 6 5 6 7);

*THIS cannot be exact, however, because the axle
configuration and number of axles are not unique for each
class.  In this case I will simply use the number of axles
implied by the weights and spacings;

else do;
  vc1=substr(vehcode,1,1);
  vc2=substr(vehcode,2,1);
  vc3=substr(vehcode,3,1);
  vc4=substr(vehcode,4,1);
  vc6=substr(vehcode,6,1);
  select (vc1);
    when (0) do; vclass=2; naxl_cd=2; end;
    when (1) do;
      if vc4=1 then vclass=3;
      else vclass=4;
      nax_cd=vc4;
      if naxl_cd=1 then naxl_cd=2;
    end;
    when (2) do;
      if vc2 < 2 then vclass=3;
      else if vc2=2 then vclass=5;
      else if vc2=3 then vclass=6;
      else vclass=7;
```

```
      naxl_cd=max(2,vc2);
    end;
    when (3,4) do;
      if vc3 > 6 then vc3=vc3-5;
      naxl_cd=vc2+vc3;
      if naxl_cd < 5 then vclass=8;
      else if naxl_cd=5 then vclass=9;
      else vclass=10;
    end;
    when (5,6,7,8) do;
      if vc3 > 6 then vc3=vc3-5;
      if vc4 > 6 then vc4=vc4-5;
      if vc6 > 6 then vc6=vc6-5;
      naxl_cd=vc2+vc3+vc4+vc6;
      if naxl_cd < 6 then vclass=11;
      else if naxl_cd = 6 then vclass=12;
      else vclass=13;
    end;
    otherwise do;
      vclass=15;
      vcl15+1;
      put '0D0A'x 'ATTENTION:  UNCLASSIFIABLE VEHCODE --> vclass?????';
    end;
  end;
end;
%MEND CONVERT;
```