Title

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Author

Ritchie, Stephen G.

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Stephen G. Ritchie

Department of Civil Engineering and
Institute of Transportation Studies
University of California, Irvine

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Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

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ABSTRACT

This paper describes a statistical framework that can be used for analysis of statewide traffic count data. It also provides a basis for designing a streamlined and cost-effective statewide traffic data collection program. The procedures described were developed as part of an in-depth evaluation study for the Washington State Department of Transportation. They were used to develop recommendations for an improved, statistically-based, statewide highway data collection program. The program is intended to be implemented readily, and is consistent with the FHWA Highway Performance Monitoring System and the recent FHWA draft Traffic Monitoring Guide. In the latter case, several modifications (improvements) to the statistical framework for volume counting and vehicle classification were investigated, particularly for deriving estimates of annual average daily traffic (AADT) from short duration axle counts at any location on the state highway system. AADT estimates can be derived for each vehicle type, if desired. The estimation of associated seasonal, axle correction and growth factors is also described. The methodology enables the statistical precision of all estimates to be determined. The results obtained from applying these procedures to Washington State traffic data are presented.

1. INTRODUCTION

For many years, State Departments of Transportation (DOTs) have had responsibility for collecting a large amount of highway data. This has been undertaken to assist planning, design and operations functions, as well as to comply with requirements and needs of other agencies; for example, at the federal level. However, collection of large amounts of data is very costly. In a climate of increasing fiscal austerity at all levels of government and in all program areas, it is therefore important not only that the right type of data are collected, but that they are collected most efficiently. Moreover, the data should meet the needs of its users with respect to type, amount, form, accuracy and availability. A statewide highway data collection program should satisfy these criteria in an up-to-date and cost-effective manner.

This paper describes a statistical framework that can be used for analysis of statewide traffic count data, and provides a basis for designing a streamlined and cost-effective statewide traffic data collection program. The procedures described were developed as part of an in-depth evaluation study for the Washington State Department of Transportation (WSDOT), and were used to develop recommendations for an improved, statistically-based, statewide highway data collection program (1).

Several studies have been reported in recent years that relate to general efforts to develop more cost-effective approaches to statewide highway data collection. These include the work of Hellenbeck and Bowman (2), which proposed a general statewide traffic counting program based on the Highway Performance Monitoring System (HPMS) (3); the study by Wright Forssen Associates (4) which evaluated, and developed improvement recommendations for, the highway data program of the Alaska Department of Transportation and Public

Facilities; and work by the New York State Department of Transportation to streamline and reduce the cost of its traffic counting program (5). While each of these studies provides useful background and guidance, the conceptual basis of Hallenbeck and Bowman (3) in utilizing the HPMS framework for purposes of statewide highway data collection was explored in this study. Other relevant and useful works in the general area include (6), (7), (8a,b), (9), (10), (11), (12) and (13). Also, a comprehensive account of sampling theory as it has been developed for use in sample surveys is given by Cochran (14).

In this paper, a statistical framework is presented for volume counting and vehicle classification, and particularly for deriving estimates of annual average daily traffic (AADT) from short duration axle counts at any location on a state highway system, using Washington State and WSDOT as a case study.

2. ANNUAL AVERAGE DAILY TRAFFIC (AADT)

2.1 Basic Model

A basic model for estimating AADT for a particular highway segment based on a single, short-duration count is as follows:

$$AADT = VOL\ (F_S)\ (F_A)\ (F_G) \qquad (1)$$

where:

- VOL = average 24-hour volume from a standard WSDOT 72-hour Tuesday-Thursday short count
- F_S = seasonal factor for the count month
- F_A = weekday axle correction factor if VOL is in axles; equal to 1 if VOL is in vehicles.

F_G = growth factor, if VOL is not a current year count; equal to 1, otherwise.

In order to determine the relative precision of an estimated AADT from equation (1), the coefficient of variation (ratio of standard deviation to mean) must be found. This can be obtained from the following approximate expression:

$$cv^2(AADT) = cv^2(F_S) + cv^2(F_A) + cv^2(F_G) \tag{2}$$

where each cv^2 is the squared coefficient of variation of each variable. Thus, the coefficient of variaton of the AADT estimate is:

$$cv(AADT) = [cv^2(F_S) + cv^2(F_A) + cv^2(F_G)]^{0.5} \tag{3}$$

The relative precision (%) at a 100 (1 - α)% confidence level is then given approximately by :

$$\text{precision }(AADT) = \pm\, 100 Z_{\alpha/2}\ cv\ (AADT)\ \% \tag{4}$$

where $Z_{\alpha/2}$ is a standard normal statistic corresponding to the 100 (1 - α)% confidence level (found in tables of any statistics book).

Also, a 100 (1 - α)% confidence interval is defined approximately as:

$$AADT \pm Z_{\alpha/2}\ AADT\ cv(AADT) \tag{5}$$

The Z statistics corresponding to 95%, 90% and 80% confidence levels are 1.96, 1.645 and 1.282, respectively.

2.2 Seasonal Factor Analysis

2.2.1 Factor grouping

The data for analyzing seasonal factors were basically obtained from WSDOT Annual Traffic Reports [15 a, b, c, d, e], which list the monthly permanent traffic recorder (PTR) traffic volumes throughout each year.

Several alternative methods for performing seasonal factoring were evaluated. The primary ones considered were:

- continued use of existing WSDOT Data Office procedures (1)
- cluster analysis of PTRs
- procedures suggested in the FHWA draft counting guide (13)
- a revised FHWA procedure using linear regression.

The chosen strategy was the fourth of these options. The approach uses the basic method recommended by FHWA. The state highway system is stratified by geographic region and functional classification. The strata are then examined to determine which have similar seasonal patterns and which, therefore, might be combined. PTR data from 1980 through 1984 were used to calculate the appropriate factor groups. The chosen groups were:

- rural interstates
- urban roads
- other rural roads in the Northeast part of the State
- other rural roads in the Southeast part of the State
- other rural roads in the Northwest part of the State
- other rural roads in the Southwest part of the State

- central mountain passes.

With the exception of the central mountain group, each factor group is defined by functional class of road and county boundaries. (Note that the urban group contains all urban classified state highways regardless of county locations.)

The advantages of the adopted approach are as follows:

- the seasonal factors are statistically valid, meaning that the precision associated with any AADT estimate based on these factors can be calculated.
- the overall errors associated with this approach are equal to or smaller than the errors associated with any other seasonal factoring approach considered.
- the factoring procedure is transparent to any user of volume information, thus allowing the recalculation of the raw traffic count at some later point in time if it is desired.

Each of the other seasonal factor procedures had drawbacks that were judged unacceptable. For example, in the case of cluster analysis:

- the clusters computed were not consistent across years, i.e., PTRs changed groups from year to year, meaning that roads should change groups as well, but no method was available to make that adjustment each year (1).
- individual road sections are not easily or accurately assigned to cluster groups, irrespective of the difficulties mentioned above.
- the total error in the AADT estimate (including seasonal variation, daily variation, and variation in the axle correction factor) was only marginally better than by the recommended

approach, prior to including the indeterminate error that is present as a result of the first two points.

2.2.2 Regression models

Seasonal factors for each month of the year were therefore derived for each of the seven factor groups described earlier. The modified FHWA approach adopted basically involved a regression analysis for each factor group for each month, of AADT versus the average 24-hour short count volumes that could be formed for each PTR from 72-hour Tuesday-Thursday counts in that month. The resulting regression coefficient of the short count volume is then the derived seasonal factor for that factor group and month. This approach corresponds to the manner in which short counts are actually taken and converted to AADT estimates by WSDOT.

The first seasonal factor regression model estimated was as follows (note that the constant term is suppressed):

$$AADT = \beta \, VOL + u \qquad (6)$$

where AADT and VOL as defined previously, β is the regression coefficient (seasonal factor) to be estimated and u is the error term. Such an equation would typically be estimated by ordinary least squares (16). However, one of the required assumptions of that method is homoscedasticity, which means that the variance of the error term, u, is constant regardless of the magnitude of VOL. It often happens that this assumption is not valid (the case of heteroscedasticity) and the model must be reduced (by a transformation) to a form where the error term does have a constant variance.

Estimation of equation (6) revealed the presence of heteroscedasticity for some factor group and monthly traffic count datasets. Further, a consequence of this problem was that estimated variances would be biased and would underestimate the true variance. To address this issue, a commonly used transformation was employed to to reduce equation (6) to a homoscedatic form. It was assumed that the variance of the error term was known up to a multiplicative constant:

$$\text{var}(u) = \sigma^2 \, VOL^2 \tag{7}$$

Dividing through equation (6) by VOL, we have

$$\frac{AADT}{VOL} = \beta + \frac{u}{VOL} \tag{8}$$

Substituting $e = \frac{u}{VOL}$, we have:

$$\frac{AADT}{VOL} = \beta + e \tag{9}$$

where $\text{var}(e) = (1/VOL^2)\ \text{var}(u)$

$$= (1/VOL^2)\ \sigma^2\ VOL^2$$

$$= \sigma^2$$

Thus, the variance of the error term, e, in equation (9) is constant, σ^2, and ordinary least squares estimation methods can be applied. The form of equation (9) is now so simple that computerized regression packages are not really required. The estimation results can be obtained as follows:

$$\hat{\beta} = \sum_{i=1}^{n} \frac{AADT}{VOL_i} / n \tag{10}$$

$$\hat{\sigma}^2 = [\sum_{i=1}^{n} (\frac{AADT}{VOL_i} i) - \hat{\beta})^2] / (n-1) \tag{11}$$

$$var \quad (\hat{\beta}) = \hat{\sigma}^2 / n \tag{12}$$

and the t-statistic on $\hat{\beta}$ is:

$$t_{\hat{\beta}} = \hat{\beta} \sqrt{n} / \hat{\sigma} \tag{13}$$

In equations (10) and (11), the subscript i refers to each short count in the month for the factor group, and n represents the number of counts.

Finally, we must derive the relative precision of our AADT estimates. In applying the seasonal factors from equation (9) to counts in the following year, we are actually forecasting the value of ratio $\frac{AADT}{VOL}$ in the equation. Therefore, the appropriate variance measure is the variance of the prediction error for the forecast ratio of $\frac{AADT}{VOL}$. It can be shown that this variance is given by:

$$\sigma^2 (1 + 1/n) \tag{14}$$

for each factor group and month. The required coefficient of variation for equation (3) is then:

$$cv(F_S) = \hat{\sigma}\ (1 + 1/n)^{0.5}\ /\ \hat{\beta} \qquad (15)$$

It is interesting to note that this theoretically derived result is equivalent to that obtained by more qualitative reasoning in (2) and (13).

2.2.3 Results

The seasonal factors for 1984, derived using the procedures above, are presented in Table 1 for April through September (the period when WSDOT performs the vast majority of its traffic counting), and Table 2 for October through March. Because of the high variability of factors for the central mountain group, this group was treated separately.

The coefficients of variation, based on equation (15) are presented in Table 3. These have been used to calculate relative precision levels of April - September AADT estimates, as shown in Table 4, without incorporating axle correction or growth factors.

It is also interesting to note how the AADT precision levels vary as a function of the number of PTRs in each factor group. Little improvement in relative precision was obtained beyond about 6-8 PTRs per group. Thus, in terms of statistical precision of AADT estimates only, little is gained by having additional PTRs. However, as discussed in (1), there may be other reasons for maintaining larger numbers of PTRs in any group, such as the automatic collection of vehicle classification data.

2.3 Axle Correction Factor Analysis

Axle correction factors are required to convert short count volumes into AADT estimates when those short counts are obtained using equipment that records axles rather than vehicles. Calculation of the factors requires vehicle classification information (percent vehicles in each class, as well as knowledge of the number of axles per vehicle in each vehicle class, as discussed in section 3.

The average number of axles per vehicle, A_V, in a given factor group (typically highway functional class) is given by:

$$A_V = \sum_C (\text{Axles}_C)(P_C) \tag{16}$$

where Axles_C = number of axles per vehicle in class C

P_C = proportion of vehicles in class C (system-level estimate).

The variance of A_V is then given by

$$\text{var}(A_V) = \sum_C (\text{Axles}_C)^2 \ \text{var}(P_C) \tag{17}$$

where var (P_C) is the variance of vehicle class C proportion, from a vehicle classification study.

Thus, the coefficient of variation of A_V is:

$$\text{cv}(A_V) = \left[\sum_C (\text{Axles}_C)^2 \ \text{var}(P_C)\right]^{0.5} / \left[\sum_C (\text{Axles}_C)(P_C)\right] \tag{18}$$

However, the desired axle correction factor, F_A, is actually the inverse of A_V:

$$F_A = A_V^{-1} \tag{19}$$

It can be shown by a first-order Taylor series approximation that:

$$cv(F_A) = cv(A_V) \tag{20}$$

This result permits the coefficient of variation of the axle correction factor to be derived readily from equation (18), for insertion into equation (3).

Table 5 presents the estimated axle correction factors for eight functional classes of highway, together with relative precisions and coefficients of variation.

2.4 Growth Factors

Growth factors often represent a relatively minor part of the factoring process to obtain AADT estimates from short counts. However, at times an old count must be converted to a more recent AADT by means of a growth factor. Several methods exist for estimating growth factors. In general, the approaches are fairly crude ways of attempting to account for traffic growth or decline over time. The analysis discussed in this section was exploratory only, although the results appear reasonable.

Simple growth factors were estimated for each of the previously identified seasonal factor groups, for the periods 1982-83 and 1983-84. The factors were obtained by forming the ratio of AADT in the more recent year to that in the earlier year for each PTR in a group, and applying the same regression analysis procedure as discussed in section 2.2.2. In one group, there was one PTR, and in a seocnd group, no PTR, for both years, so that coefficients of variation of the factors, F_G, could not be formed. Table 6 presents the estimated growth factors for each period, together with their coefficients of variation.

3. VEHICLE CLASSIFICATION

3.1 Data Analysis

Because of the limited nature of vehicle classification counts taken by WSDOT in recent years, the best available dataset for statistical analysis was from a 1980-81 study for FHWA in the State. Unlike volume counting, which has a system of PTR stations for continuous monitoring, it is not presently possible to derive vehicle classification seasonal factors for conversion of a single (say 24-hour) classification count to an annual average estimate for a given highway segment. Rather, the data available only permit an approximate systemwide plan to be developed for an annual counting program on different functional classes, in order to derive annual average vehicle classification results. Improvements to the Department's current vehicle classification activities are discussed further in (1).

The 1980-81 data consist of 248 manual 24-hour vehicle classification counts. The data were collected at 31 locations across the State, with 4 weekday counts (one per season) and 4 weekend counts (one per season) at each location. For analysis purposes, the data were reduced to six vehicle types:

1. cars
2. 2-axle trucks
3. 3-axle trucks
4. 4-axle trucks

5. 5-axle trucks

6. 6+ - axle trucks

In addition, a slightly more detailed set of functional classifications was retained for initial analysis than was used in the seasonal factor development. These functional classes consisted of eight groups: interstates, principal arterials, minor arterials and collectors, for both rural and urban locations.

The principal analysis method used was a 2-stage cluster sampling approach with multiple strata. The first set of strata corresponded to functional classes. Within strata, the primary sampling units or clusters were possible count locations, and the secondary or elementary sampling units were days at each location (required to be the same at each location in a stratum). The second stratification was introduced with respect to weekdays and weekend days because vehicle classifications were noticeably different across these strata, with truck percentages often being considerably lower on weekend count days. The population sizes for each stage were taken to be the number of HPMS population sections in each functional class in the case of locations, and at the second stage simply the number of weekdays and/or weekend days in a year. Allowance was also made in the analysis for the fact that the second stage units were not of equal size (as is often assumed in cluster analysis) due to the daily variations in traffic volume throughout the year.

Within each functional class, and for each vehicle class C, the average (weighted) vehicle proportion, P_C, was estimated as follows:

$$P_c = \left(\sum_{i=1}^{n} p_i \right) / n \qquad (21)$$

where

$p_i = w_1 p_{i1} + w_2 p_{i2}$

p_i = proportion at location i

p_{i1} = weekend proportion at location i

$$= \left(\sum_{k=1}^{m_1} C_{ik1} \right) \Big/ \left(\sum_{k=1}^{m_1} X_{ik1} \right)$$

p_{i2} = weekday proportion at location i

$$= \left(\sum_{j=1}^{m_2} C_{ij2} \right) \Big/ \left(\sum_{j=1}^{m_2} X_{ij2} \right)$$

C_{ik1} = total number of vehicles of type C at station i on weekend day k

C_{ij2} = total number of vehicles of type C at station i on weekday j

X_{ik1} = total number of vehicles at station i on weekend day k

X_{ij2} = total number of vehicles at station i on weekday j

p_{i1k} = proportion observed on weekend day k

p_{i2j} = proportion observed on weekday j

m_1 = number of weekend days at each location

m_2 = number of weekdays at each location

w_1 = 2/7, w_2 = 5/7

n = number of count locations.

The variance was obtained from:

$$\text{var}(P_C) = (1-f_1)(s_1^2/n) + [w_1^2(1-f_{21})s_{21}^2/(nm_1) + w_2^2(1-f_{22})s_{22}^2/(nm_2)] \quad (22)$$

where $f_1 = n/N$

N = population size of HPMS segments for functional class

$$f_{21} = m_1/104$$

$$f_{22} = m_2/261$$

$$s_{21}^2 = \left(\sum_{i=1}^{n} s_{21i}^2\right)/n$$

$$s_{21i}^2 = \sum_{k=1}^{m_1} (p_{i1k} - p_{i1})^2 / (m_1 - 1)$$

$$s_{22}^2 = \left(\sum_{i=1}^{n} s_{22i}^2\right)/n$$

$$s_{22i}^2 = \sum_{j=1}^{m_2} (p_{i2j} - p_{i2})^2/(m_2 - 1)$$

$$s_1^2 = \sum_{i=1}^{n} (p_i - P_c)^2 / (n-1)$$

Thus, the coefficient of variation of the estimate is:

$$cv(P_C) = [\text{var}(P_C)]^{0.5}/P_C \quad (23)$$

The relative precision (%) at a 100 (1 - α) % confidence level is then given approximately by:

$$\text{precision } (P_C) = \pm\ 100\ Z_{\alpha/2}\ cv(P_C) \tag{24}$$

In addition to the analysis approach above, which distinguishes between counts on weekdays and weekends by introducing sample stratification, estimates for P_C were also calculated without this stratification by pooling weekday and weekend counts at each location. For this simpler formulation, P_C is calculated from:

$$P_C = \left(\sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij}\right) \Bigg/ \left(\sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij}\right) \tag{25}$$

where C_{ij} = total number of vehicles of type C at station i on day j

X_{ij} = total number of vehicles at station i on day j

f_1 = as before

f_2 = m/365

m = number of days sampled at each station

n = number of count locations

The variance of P_c is then calculated from:

$$\text{var}(P_C) = (1 - f_1)(S_1^2/n) + f_1(1-f_2)(s_2^2/mn) \tag{26}$$

where s_1^2 = as before

$$s_2^2 = \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{ij} - \bar{p}_i)^2 / [n(m-1)]$$

$$\bar{p}_i = \sum_{j=1}^{m} C_{ij} / \sum_{i=1}^{m} X_{ij}$$

$$p_{ij} = C_{ij} / X_{ij}$$

The coefficient of variation and precision of P_C are then calculated as before by equations (23) and (24) respectively.

3.2 Results

Table 7 presents the classification count results for each functional class. These averages are based on the weighted weekday and weekend counts. Table 8 shows the relative precision of these results at a 90% confidence level. Clearly, the precision of the estimates for large trucks (5 or more axles) is relatively poor, although this was not unexpected given the limited nature of the counts and the inherent variability of truck travel as a percentage of total daily volume. Table 9 gives the coefficients of variation for each vehicle class proportion.

The estimation of annual average daily truck traffic volume, AADTT, can be accomplished readily by applying the analysis results above and extending the AADT estimation equations in section 2.1:

$$AADTT = VOL\ (F_S)(F_A)(F_G)(P_C) \quad (27)$$

where P_C = the appropriate vehicle proportion estimate from Table 7 and all other notation is as defined previously. It must be remembered that this

AADTT estimate is based on system-level vehicle classification data, and not a specific truck count for the section where the volume count, VOL, was taken.

The coefficient of variation can be obtained from:

$$cv(AADTT) = [cv^2(F_S)+cv^2(F_A)+cv^2(F_G)+cv^2(P_C)]^{0.5} \qquad (28)$$

where $cv(P_C)$ is given by Table 9. The relative precision at a 100 $(1 - \alpha)\%$ confidence level is then given approximately by:

$$\text{precision } (AADTT) = \pm 100\ Z_{\alpha/2}\ cv(AADTT)\% \qquad (29)$$

As an example, consider the calculation of an annual average daily 5-axle truck volume on a rural interstate segment, based on a short duration axle count in June.

Average 24 hour volume VOL = 50,000 axles.

F_S	=	0.960	(Table 1)
F_A	=	0.423	(Table 5)
F_G	=	1.0	(since this is a current year count)
P_C	=	0.083	(Table 7)
$cv(F_S)$	=	0.064	(Table 3)
$cv(F_A)$	=	0.062	(Table 5)
$cv(F_G)$	=	0.0	(since we do not use an estimated factor)
$cv(P_C)$	=	0.215	(Table 9)

Thus, from equation (21), the estimate of daily 5-axle trucks is:

AADTT = 50,000 (0.960)(0.423)(1.0)(0.083)

= 1,685 5-axle trucks.

From equation (22), the coefficient of variation of this estimate is:

$$CV(AADTT) = [(0.064)^2 + (0.062)^2 + (0.0)^2 + (0.215)^2]^{0.5}$$

$$= 0.233$$

Finally, from equation (23), the relative precision of this estimate at a 90% confidence level is:

$$\text{precision (AADTT)} = \pm 100 \quad (1.645)(0.233)\%$$

$$= \pm 38.3\%$$

which means that we can be 90% confident the true value of AADTT is within about 40% of the estimate of 1,685 5-axle trucks per day.

3.3 Sample Design

The results obtained from these analyses of vehicle classification data provided some basis for developing the study recommendations for this data item (1). This section presents some of the findings related to design of a sample for collecting vehicle classification data.

Of interest is how the statistical precision of classification estimates is affected by sample size and choice of confidence level. To gain further insight into these relationships, a number of tabular and graphic reports were generated.

For example, Table 10 shows the variation in precision achieved with a number of different sample designs, in the case of rural interstates. These results are based on a cluster-analysis, as before, but with pooled weekend and weekday counts, without stratification. It can be seen that the precision levels are more sensitive to the number of locations chosen than the number of days surveyed per location. For a given number of classification counts, the results indicate that it is better to take all of those counts at different locations, with only one count per location, on randomly chosen days during the year.

To avoid the added complexity, and cost, to the Department of having to take at least two counts per location (one weekday, one weekend) at every sampled location, as required by the stratified cluster analysis procedure, it was decided that for purposes of sample design and implementation, a pooled cluster analysis approach should be used without stratification by day of week. All this would mean in practice is that the count day(s) at a location would be chosen randomly from all days in the year. Given the nature of the data on which the analyses were based and the interim nature of any recommended manual count program (due to introduction of automatic vehicle classifiers by the Department, see (1)), this approach was judged appropriate.

Also investigated was the effect of both confidence level and number of counts (or locations counted) on the precision of vehicle proportions. To achieve both smaller precision levels and higher confidence levels requires that more counts be taken. In the case of 5-axle trucks on rural interstates it was noted for example that the major improvement in precision came form taking around 20 counts, and that the improvement in precision for successive counts was relatively small. However, the magnitude of the precision was still undesirably high. The implication is that to achieve precise results, a much larger number of vehicle classification counts is required (than the Department currently collects). The detailed recommendations that were developed on the basis of these results are reported in (1).

4. CONCLUSIONS

A rigorous statistical approach to statewide data collection and program design permits the estimation of data precision, and can provide a rational basis to assist in allocating limited resources among the various possible data collection activities. A statistical approach is also important because the desired precision and confidence level have a major impact on sample design and cost. There is little point collecting more precise sample data at a higher level of confidence than is required by the data users, particularly when very considerable cost savings can be realized from smaller sample sizes. Conversely, when resources are limited, and insufficient for the desired sample size, trade-offs between precision and level of confidence can be made explicit. Further discussion of this issue is presented in a companion paper (1).

This paper has presented a statistical framework for volume counting and vehicle classification, and particularly for deriving estimates of AADT from short duration axle counts at any location on a state highway system. AADT estimates can be derived for each vehicle type, if desired. The estimation of associated seasonal, axle correction and growth factors was also described. The methodology enables the statistical precision of all of these estimates to be determined.

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LIST OF TABLES

Group	Month					
	April	May	June	July	Aug.	Sept.
Rural Int.	1.132	1.126	0.960	0.907	0.849	0.990
Urban	0.966	0.952	0.903	0.894	0.878	0.907
NW	1.023	0.995	0.921	0.848	0.812	0.957
SW	1.087	1.055	0.935	0.823	0.769	0.925
SE	1.137	1.077	0.956	0.896	0.855	0.979
NE	1.025	0.927	0.895	0.754	0.779	0.882

Table 1. 1984 Seasonal Factors for April - September

Group	Month					
	Oct.	Nov.	Dec.	Jan.	Feb.	March
Rural Int.	1.274	1.220	1.116	1.554	1.425	1.238
Urban	1.045	1.006	0.935	1.088	1.033	0.988
NW	1.236	1.124	1.067	1.296	1.558	1.075
SW	1.467	1.283	1.067	1.408	1.259	1.145
SE	1.500	1.318	1.043	1.595	1.472	1.259
NE	1.339	1.176	0.981	1.200	1.184	1.163

Table 2. 1984 Seasonal Factors for October - March

Month	Factor Group					
	Rural Int.	Urban	NW	SW	SE	NE
Jan.	0.172	0.090	0.149	0.216	0.196	0.074
Feb.	0.150	0.073	0.105	0.154	0.190	0.100
March	0.113	0.057	0.102	0.147	0.180	0.146
April	0.109	0.062	0.095	0.132	0.144	0.123
May	0.089	0.070	0.078	0.108	0.138	0.080
June	0.064	0.057	0.095	0.082	0.118	0.077
July	0.057	0.063	0.092	0.077	0.115	0.104
Aug.	0.064	0.042	0.090	0.143	0.090	0.097
Sept.	0.090	0.059	0.069	0.129	0.112	0.086
Oct.	0.167	0.112	0.150	0.217	0.239	0.176
Nov.	0.255	0.090	0.130	0.186	0.250	0.115
Dec.	0.078	0.073	0.084	0.114	0.088	0.083

Table 3. Coefficients of Variation of 1984 Seasonal Factors, $cv(F_S)$

Month	Factor Group					
	Rural Int.	Urban	NW	SW	SE	NE
April	18	10	16	22	24	20
May	15	12	13	18	23	13
June	11	9	16	13	19	13
July	9	10	15	13	19	17
August	11	7	15	24	15	16
September	15	10	11	21	18	14

Note: 90% Confidence Level

Table 4. Relative Precision (%) of Seasonally Adjusted AADT Estimates From Short Counts in Each Month (Without Incorporating Axle Correction or Growth Factors)

Functional Class	F_A*	% Precision**	$cv(F_A)$
Rural Interstate	0.423	10.2	0.062
Rural Principal Arterial	0.461	8.8	0.053
Rural Minor Arterial	0.471	4.8	0.029
Rural Collector	0.459	10.7	0.066
Urban Interstate	0.454	3.9	0.023
Urban Principal Arterial	0.463	6.8	0.041
Urban Minor Arterial	0.482	2.1	0.013
Urban Collector	0.495	1.6	0.010

* weekday factors

** 90% confidence level

Table 5. Axle Correction Factors

Group	Period			
	1982 - 83		1983 - 84	
	F_G	$cv(F_G)$	F_G	$cv(F_g)$
Rural Int.	1.065	0.020	1.024	0.037
Urban	1.175	0.306	1.046	0.066
NW	1.052	0.110	1.016	0.055
SW	1.059	---	1.094	---
SE	1.041	0.060	1.041	0.042
NE	---	---	---	---

Table 6. Growth Factors

Functional Class	Vehicle Class 1	2	3	4	5	6
Rural Int.	87.0	3.1	0.6	0.3	8.3	0.8
Rural P.A.	90.3	3.2	1.0	0.1	5.0	0.3
Rural M.A.	92.2	2.9	0.9	0.1	3.5	0.5
Rural Col.	89.3	3.5	3.0	0.3	3.6	0.3
Urban Int.	91.1	2.8	0.7	0.4	4.5	0.4
Urban P.A.	90.8	3.1	0.6	0.2	4.9	0.4
Urban M.A.	94.4	2.8	0.8	0.2	1.7	0.2
Urban Col.	95.1	3.4	0.4	0.1	0.9	0.1

Table 7. % Vehicles by Type in Each Functional Class

Functional Class	Vehicle Class					
	1	2	3	4	5	6
Rural Interstates	4	11	13	35	35	33
Rural Principal Arterials	3	7	50	43	43	48
Rural Minor Arterials	2	9	22	45	33	68
Rural Collectors	7	29	82	62	91	69
Urban Interstates	1	8	13	22	20	14
Urban Principal Arterials	3	17	22	39	41	40
Urban Minor Arterials	1	26	31	67	19	44
Urban Collectors	1	25	35	43	34	86

Note: 90% Confidence Level

Table 8. Relative Precision (%) of Vehicle Classification Results

Functional Class	Vehicle Class					
	1	2	3	4	5	6
Rural Interstates	0.024	0.068	0.079	0.213	0.215	0.201
Rural Principal Arterials	0.018	0.044	0.303	0.263	0.259	0.294
Rural Minor Arterials	0.010	0.057	0.134	0.271	0.201	0.416
Urban Interstates	0.007	0.050	0.077	0.131	0.119	0.088
Urban Principal Arterials	0.018	0.103	0.134	0.237	0.247	0.241
Urban Minor Arterials	0.008	0.157	0.187	0.405	0.114	0.266
Urban Collectors	0.007	0.150	0.216	0.260	0.207	0.522

Table 9. Coefficients of Variation for Vehicle Proportions in Table 7

			Vehicle Class					
No. Locations	No. Days	No. Counts	1	2	3	4	5	6
2	1	2	9	37	81	95	105	105
2	5	10	6	23	39	68	71	69
4	1	4	7	26	57	67	74	74
4	5	20	4	16	27	48	50	49
8	1	8	5	18	40	47	52	52
8	5	40	3	11	19	34	35	34
20	1	20	3	12	25	29	33	33
20	5	100	2	7	12	20	21	21
40	1	40	2	9	18	20	23	23
40	5	200	1	5	8	13	14	14

Note: 90% Confidence Level

Table 10. Relative Precision (%) of Rural Interstate Vehicle Classifications for Different Sample Designs