ESTIMATES OF AADT: QUANTIFYING THE UNCERTAINTY

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ABSTRACT

Annual average daily traffic (AADT) values are a key variable in many models and policy decisions; however, these are simply rough estimates of traffic counts along the vast majority of roadway sections. This research quantifies the level of uncertainty in AADT estimates by quantifying different errors that emerge, from extrapolating short-term local counts over time and space. Factoring errors (from use of day of week and month of year factors, based on permanent detector station count patterns) are investigated across roadway and area types, for both Minnesota and Florida automatic traffic recorder (ATR) sites. Errors resulting from spatial extrapolation (due to reliance on a nearby count site's AADT as a proxy) also are studied, as a function of distance to the nearest sampling site, using predictions of network travel patterns in Austin, Texas and freeway traffic counts from California's Performance Measurement System (PeMS). Temporal errors, from extrapolation of counts forward in time, are quantified using 21 years of AADT values from Minnesota's permanent ATR sites. A table summarizing the nature and magnitude of these various errors serves as a reference for designers, planners and researchers, who rely on count data.

The analytical results of this investigation suggest a variety of recommendations for agencies seeking to reduce and appreciate errors in their AADT estimates. These include sampling in spring and summer months (on weekdays), pursuing appropriate site assignment to ATR groups, and recognizing the effects of distance to the sampling site – over time and space.

With adequate attention, (average) errors in AADT estimates can probably be reduced to the level of user-required accuracy. Nevertheless, these still will have an impact on investment decisions, crash rate calculations, travel demand model validation, and other analyses.

Keywords: Annual average daily traffic (AADT), traffic counts, VMT estimation, automatic traffic recorders

INTRODUCTION

AADT is a key variable in many models and policy decisions, producing vehicle miles traveled (VMT) estimates for analyses of crash rates, evaluation of infrastructure management needs, air quality compliance and validation of travel demand model predictions. Despite their importance, AADT values are simply rough estimates of traffic counts along the vast majority of roadway sections. In the U.S. these emerge from short-period traffic counts (SPTCs) in which one- to three-day samples are taken every few years at select points across large-scale networks. These counts are factored up to a yearly estimate based on year-to-year trends, sampling season and day-of-week factors developed using data obtained from permanent automatic traffic recorder (ATR) stations.

The number and spatial frequency of ATR sites and the durations and timing of the remaining network's SPTC vary by state and by region, as well as by functional class of roadway. For example, there are 240 ATR sites in Texas, 293 in Florida and 78 in Minnesota. In Texas sampling is done for 24 hours once every five years at roughly 90,000 sites, except in non-attainment regions, where the frequency is every three years and on-system highways, where counts are done annually. In Minnesota, the sampling is done annually, for 24 hours at roughly 78 sites. Differences in protocol, from state to state and site to site, shape the uncertainty or error in the resulting AADT estimates. It is very important that analysts, including designers, planners and policymakers, have a sense of the magnitude of these errors, in order to appreciate the reliability of their results, their designs and their policies. By attaching uncertainty information to AADT estimates (e.g., via the use of confidence intervals), more accurate results can be communicated and more robust decisions made. For example, in designing a road for the next 20 to 40 years, designers should recognize that even current AADT estimates based on short-period counts involve non-trivial error. More cost-effective and reliable designs to combat congestion may require substantial added capacity and/or road pricing policies, in order to incorporate 85% or more of future-demand scenarios. This paper seeks to quantify the uncertainty in AADT estimates to provide designers and policy makers with baseline values for these errors based on empirical analysis.

AADT can be determined precisely only at sites having permanent automatic traffic recorders (ATRs) that are accurately recording traffic flows throughout the year. In most states AADT is estimated by multiplying the short-period traffic counts (SPTCs) by day of week (DOW) and month of year (MOY) factors, from the ATR group to which the site is assigned. This assignment of an SPTC to ATR groups can be rather imprecise, and different states use different methods of assignment (FHWA 2001). The error resulting from applying the factors from ATR groups to SPTC to estimate AADT is called the factoring error. In this study, this error is considered by assigning sites using simpler but intuitive classification schemes, such as the location of the site (urban versus rural), functional class of the roadway (arterial, collector and freeway) and number of lanes (4 or fewer, 5 or more) on which the site is located. The ATR count data used in the analyses come from Department of Transportation staff in Florida (293 ATR sites) and Minnesota (58 ATR sites).

It is expensive to have short term counts on all roadway segments (e.g., every mile in a network) and/or every year; thus, the spatial and temporal frequency of SPTCs varies from state to state. For this reason, many segments are assigned an AADT estimate from the nearest SPTC location and rely on counts that are one to four years old. The errors involved in such estimates are referred to here as spatial and temporal errors, respectively. Since we do not have access to closely spaced traffic counts, spatial error is studied here using travel demand modeling results for network travel patterns in the Austin, Texas region and freeway traffic counts from PeMS data. The temporal errors are studied using 21 years of AADT values from Minnesota's permanent ATR sites (63 of which are in rural locations and 81 of which are classified as urban locations), between 1984 and 2004.

In this research, the relative magnitudes of errors in AADT estimates due to short-term sampling (i.e., day-to-day random variations in traffic counts), reliance on other sites' factors, misclassification, and spatial and temporal approximation were studied using Minnesota, Florida, Austin, and Southern California data sets. The following sections describe findings from related literature, the data and methodology used here, analytical results, and recommendations for sampling.

LITERATURE REVIEW

Despite the central nature of AADT estimates in a variety of transportation planning and policy practice, relatively little work exists in this topic area. Sharma et al. (1996) studied the precision of AADT estimates using traffic data from 63 ATR sites in Minnesota. The ATR sites were grouped into five clusters based on their characteristics. Two of the five groups represented regional routes with low seasonal traffic, one represented average rural routes, and two represented routes serving recreational areas. The results of the study show estimated AADT values to be off by at least 11% in 95% of the cases with "regional routes serving commuters and business trips" enjoying the smallest AADT estimation errors and heavy-traffic rural routes serving recreational areas suffering the highest errors. Sharma et al. concluded that it is most important to assign a site to its correct group; incorrect assignment carries the greatest potential for significant estimation error. They also found that estimation error falls only moderately with count duration, from 16.5% at 24 hours to 13.13% at 72 hours. Granato (1998) used a single ATR's data in Iowa to demonstrate how use of day-of-week (DOW) and month-of-year (MOY) factors reduces AADT error by roughly 25%, as compared to using one-day counts directly. He also found that longer counts (48 and 72 hours) contribute only minimally (error falls from 11.3% to 10.9%) in improving AADT accuracy. This research builds on such earlier work by investigating variability of AADT estimates across roadway locations and functional classes, using both Florida and Minnesota ATR data sets. It examines error for different classification schemes (including misclassification) and count durations (24, 48 and 72 hours), quantifying the relative contribution of different factors. Several more recent studies have looked at improving AADT forecasts. Most involve finding the most efficient (least-error) methods to predict AADT from SPTCs. In terms of AADT forecasts, Lam and Xu (2000) analyzed data at 13 locations and found that neural networks consistently performed better than regression analysis, and 8-hour counts (if AADT is estimated from something less than a 24-hour interval) are most appropriate. Tang et al. (2003) used historical and current-year partial daily flow data from a Hong Kong ATR to compare four different forecasting models (including neural nets, nonparametric regression, and autoregressive integrated moving average models), and they concluded that Gaussian maximum likelihood methods performed best. Jiang et al. (2006) used a weighted combination of past and present counts along 122 highway segments over a 10-year period to estimate AADT. They concluded that accuracy improved when the averaging was applied on a large scale, and that the number of SPTCs could be reduced on many segments.

None of the above mentioned studies has analyzed all the error types, especially those arising from spatial and temporal extrapolation of SPTC data. However, Eom et al. (2006) recently used spatial statistics to improve AADT prediction along non-freeway facilities in Wake County, North Carolina. They found that a model which takes both spatial trend and spatial correlation into account provides better predictions for locations where no observed count data exist. Similarly, Goel et al. (2005) used simple correlations between SPTCs and ARTS sites to improve AADT estimates. Error reductions were practically significant in cases where correlation was high, as expected. Nevertheless, the magnitude of spatial and temporal errors emerging from simple extrapolation is yet to be quantified. To address these gaps in existing literature, this study uses travel demand model estimates of network flows on an average weekday in Austin, Texas and ATR count data from Minnesota, between 1984 and 2004. In this way, it is able to quantify AADT estimation error, as a function of distance to sampling site and over one to four years of extrapolation. Moreover, none of the literature quantifies or summarizes all the errors associated with AADT estimation, making it difficult for designers, planners and policymakers to incorporate such errors in their decision making. By using the Minnesota and Florida ATR data to quantify the factoring error associated with site classification, (day of week and month of year (for different site types) and by recognizing the effects of count duration as well as spatial and temporal extrapolation, this paper seeks to quantify the magnitude and nature of all major sources of error in AADT estimation.

DATA COLLECTION AND DESCRIPTION

In this section, data sources are described and summary statistics examined. Generally, traffic data are collected at permanent (ATR) and temporary (SPTC) sites. At permanent sites, loop detectors, weigh-in-motion sensors, and/or other equipment is installed for year-round, long-term vehicle detection. Temporary sites use portable sensors, for 72 hours or less once every one to five years. The basic traffic count data used for analysis here were obtained from the Florida and Minnesota Departments of Transportation (FDOT and MNDOT). Network-level estimates of flow used for spatial error analysis come from the Austin travel model that was calibrated and applied by the consulting firm Smart Mobility (Marshall 2005). In addition, loop detector counts along sections of several Southern California freeways were obtained via PeMS, and used for spatial error analysis.

FDOT provided a CD-ROM containing traffic data of 293 ATR sites for the year 2004. Data were available on an hourly basis, and a functional class and area type were associated with each site. Since ATRs sometimes switch off, get moved, and/or lose their data-stream connection, 64 sites of these 293 permanent sites had incomplete traffic counts (i.e., fewer than 365 days worth of data). Table 1 provides additional details (on functional class and urban/rural location) of these ATR sites. GIS-encoded maps of all ATR and short-term count locations also were provided, along with AADT estimates at all 8,004 SPTC sites.

MnDOT staff emailed 2002 traffic data for 78 ATR sites, along with short-term counts at their 4,400 SPTC locations. Only 57 of the 78 ATR sites provided functional class, area type and number of lanes information, so this study relies only on those 57 sites for analysis. As shown in Table 1, 19 of these are coded as urban sites, and the other 38 are rural. Unlike Florida, most of Minnesota's ATR sites are labeled rural (38 vs. 19 urban sites in Minnesota), and lane-number information is given (as described in Table 1). In both cases, the majority of sites are labeled as arterials (rather than freeways or collectors).

Smart Mobility's 2005 predicted counts for Austin's over-10,000 coded links also include information on functional class, area type, and number of lanes (as shown in Table 1). While the Austin data cover all coded links in Austin's network, they are only predictions. Actual day-to-day counts may vary substantially across links, over space. For this reason, one week's worth of actual count data from California's PeMS data base (PeMS 2006) also was acquired. These counts come from loop detector stations along three of Southern California's Interstate freeways (I 110 S, I 405 S, and I 5 N) at average spacings of 0.51, 0.58, and 0.68 miles, respectively. Together, the Austin and PeMS databases provide a sense of spatial variations in AADT prediction error, with the PeMS allowing a closer, more realistic look (though on freeways only). Table 1 describes the Florida, Minnesota and Austin data by area type (urban or rural), functional class (arterial, collector or freeway) and number of lanes. As noted earlier, states and regions use different protocols in collecting short-term and permanent counts. These protocols impact the uncertainty or error in their AADT estimates. In Florida SPTCs are taken annually at roughly 8,000 sites, at a spatial frequency of around 0.8 centerline-miles in urban areas and generally between 2 and 10 centerline-miles in rural areas. (Florida Traffic Information 2004). In Minnesota SPTCs are taken annually at around 4,400 sites, with a spatial frequency of roughly 1 mile in the urban areas and 1.5 miles in rural areas. (Mn/DOT 2006) In contrast, Texas' short term counts are taken at approximately 80,000 sites total, at 1-, 3- or 5-year cycles, depending on whether the site lies along a state-system roadway or in a non-attainment area. They occur at an average spatial frequency of roughly 1 count per centerline mile (generally less than a mile in urban areas and potentially more than 5 miles in rural areas). (Crum 2005) Since SPTC data are taken for such a limited duration, the errors in their AADT estimates cannot be quantified without acquiring additional data. Thus, they were not examined here. However, an understanding of their duration and frequency is paramount in anticipating errors that emerge from their factoring and extrapolation over space and time.

METHODOLOGY

In this section the methods used to estimate and compare different types of error are described.

DOW and MOY factors were created on the basis of individual-site as well as grouped-site data. A year's AADT was estimated from each day's short-term count using a variation of the *Traffic Monitoring Guide*'s (FHWA 2001) standard formula:

$$AADT_{est,i} = VOL_i * M_i * D_i * A_i * G_i \quad (1)$$

where $AADT_{est,i}$ is the estimate of annual average daily traffic count (vehicles per day) at location i, VOL_i is the actual 24-hour axle volume, M_i is the applicable "seasonal" (MOY) factor (which may come from a group assignment), D_i is the applicable DOW factor for factor group h, A_i is an axle-correction factor for location i, and G_i is a traffic growth factor for factor group h (for inter-sample years).

Eq. (1) can be modified as necessary, depending on the conditions used to take the short duration counts. In this study, vehicle counts (rather than axle counts) were given and analysis was done for the same year's count, so axle-correction and traffic growth factors were not required. Moreover, every ATR site had (virtually) a full-year's data, so month-of-year and day-of-week factors could be created expressly and precisely for each location. In this way, Eq. (1) becomes the following:

$$AADT_{est,i} = VOL_i * M_i * D_i \tag{2}$$

The two relevant factors for ATR site *i*, M_i and D_i, were calculated as follows:

$$M_i = AADT_i / MADT_i \tag{3}$$

$$D_i = AADT_i / DADT_i \tag{4}$$

where $AADT_i$ is the true AADT (an average of all 365 days' counts), $MADT_i$ is the average daily traffic for the applicable month in question, at location *i*, and *DADT* is the average daily traffic for the applicable day in question (e.g., all Mondays in the year, or all Fridays in the year), at that location. In this way, if a particular month of the year, or day of the week, has unusually low or high counts (e.g., January and Sunday exhibit less-than-AADT traffic levels, typically), it will have a monthly or daily factor that corrects for this bias, raising or lowering the day's count to better reflect an annual (AADT) estimate. Data from each site were used both collectively and individually in determining these factors.

Since both actual and estimated AADT values were available for all ATR sites, percentage errors in AADT estimation were calculated as follows:

$$\%Error_i = 100 \frac{\left| AADT_i - AADT_{est,i} \right|}{AADT_i} \tag{5}$$

These are computed as absolute errors, for purposes of averaging, and to achieve a sense of the overall magnitude of uncertainty inherent in relying on a single day's data and/or relying on other sites' factors.

As noted, factors were created in three distinct ways: (1) using a site's own data for a set of idealized factors (resulting in estimates of pure sampling error), (2) relying on other similar sites' data for these factors (resulting in estimates of factoring errors), and (3) using an incorrect ATR group's data for these factors (resulting in estimates of misclassification error). For the second approach, group membership was determined on the basis of area type (urban versus rural), functional class (freeway versus arterial, and, in the case of Florida, collector), and, in the case of Minnesota, number of lanes (2 to 4 lanes, versus 5 or more).

Misclassification error occurs when a site is assigned to an incorrect ATR group. This leads to application of the average factors of the (incorrect) ATR group to the site and may cause large errors in AADT estimation at that site. For example, if an urban site is misclassified as a rural site, the average factors of the rural ATR group are applied, in order to estimate the urban site's AADT. These errors were quantified for the sites in the Florida and Minnesota datasets (according to area type and functional class).

Spatial Error

Spatial error occurs when a roadway segment is assigned the AADT from its nearest sampling site, due to non-availability of more local counts. These errors were quantified as follows. The Smart Mobility-predicted flows on the Austin travel network were assumed to be the actual counts on each of the coded 10,594 links. Then, the midpoint of a particular link on a particular roadway was assumed to be the short term count location. The difference in flow from this location to (center points of) nearby links, along the same roadway, gave the spatial error involved in assigning the AADT at the short term count location to those links. The distance between mid-points of the links along the roadway was noted, in order to appreciate how such error varies with distance from the assumed short term count site. Errors were averaged for every 0.2 mile bin of values, in order to ascertain average error at a given distance. Seven distinct roadway sections were chosen from the Austin network, so that they included different area types, functional classes and numbers of lanes. And each provided the equivalent of three short-term count sites (using different links as starting points, or count sites). Thus, data for 21 hypothetical count sites was analyzed to estimate the extent of error likely caused by spatial extrapolation.

Of course, the Austin counts are simply model predictions, rather than actual counts. Actual counts may well vary greatly from day to day and link to link.
To address such potential variations in spatial error, a week's worth of PeMS data from 10 to 15 (consecutive) loop detector stations on each of three freeways (I 110 S, I 405 S, I 5 N) were used. Extrapolations were made to a distance of almost 3 miles, and a series of 5 to 6 consecutive stations were used as the "base" station (to predict downstream counts, up to 3 miles away).

Temporal Error
Of course, spatial extrapolation errors are compounded by temporal extrapolation (i.e., using 1 day's count rather than 365 days' count, and forecasting future year's counts). AADT values at Minnesota's 144 permanent ATR sites were used to analyze the inter-year variability in AADT. Error levels in AADT estimates resulting from 1 to 4 years of forward extrapolation were calculated based on 21 years worth of data (1984-2004).

Count Durations

The effects of longer short-period count durations also were studied, to appreciate how AADT prediction errors decline. To estimate AADT using 48- and 72-hour traffic counts, the DOW and MOY factors were modified. Daily counts on consecutive calendar days were combined, and 7 DOW and 12 MOY factors were created. In these cases, DOW really characterized two or three consecutive days of the week. MOY factors used either one-half, one-third or two-thirds of the multi-day counts that crossed their edges i.e., a sequence of 48 hours that overlapped with a different month was halved for the two months while a 72-hour count sequence that crossed months was divided either as one-third and two-thirds, or as two-thirds and one-third for the two months, depending on the overlap.

RESULTS AND DISCUSSION

The following describes error results, based on methodologies described above. Factoring errors are discussed first, followed by spatial and temporal errors, and finally, error variation by DOW, MOY, count duration and traffic flow levels.

Table 1 illustrates data used for quantifying factoring error across all sites and days of week for Minnesota and Florida ATR data, after clustering based on area type (urban versus rural), functional class, and number of lanes. These rely on factors from similar sites (as determined by area type and functional class), and thus present a common case. In Minnesota, roughly 40% of the sites exhibited average AADT estimation errors within 6% of the actual values, and very few exhibit more than 60% error. In comparison, 32% of Florida's errors fell below 6%, and quite a few lied above 60%, with several sites exhibiting average errors as high as 90%. In terms of overall errors, Florida ATR sites were found to have a higher overall average error in AADT prediction (14%) as compared to Minnesota sites (12%). Thus, the factoring error is on the order of 10-15%, based on both Minnesota and Florida data. Tables 2 and 3 present the prediction error results for Florida and Minnesota by area type, functional roadway class, and number of lanes. As can be seen, a short-period count's site classification can have significant effects. The average errors in estimation of AADT range from 11.5% to 20% and the maximum errors can be as high as 81%. Freeways exhibit slightly greater uncertainty in both cases, compared to arterials and collectors in both Florida and Minnesota. Roadways with a high number of lanes (more than 5) have much larger errors than those having less than 5 lanes.

Figure 1 compares the various error components (from sampling, factoring and misclassification). When factors from the site's own traffic counts are used for its AADT estimates, the case is ideal (and unrealistic, of course), and the absolute average error is 6.69%, as compared to 11.65% when factors from similar sites (properly classified) are used. When sites are misclassified, factor-related errors rise to 19.35% in Minnesota. In Florida, the comparable values are 8.28% (pure sampling error, ideal factors used), 13.62% (proper classification factors used) and 15.09% (misclassified factors used). Clearly, classification plays a significant role.

Figure 2 shows the results of spatial error variation in the Austin travel model predictions. The results indicate that the average error (for 23 calculations) increases with distance, as expected: from 6.33% at just 0.2 miles away to a shocking 79.5% at just 1.6 miles. The percentage error is much higher for urban areas as compared to rural areas, and is consistently higher for 4 lane roads (as compared to 2 lane roads). The error appears to be quite small in rural areas (e.g., 2.14% within 1 mile), supporting, to some extent, the lower sampling frequencies that states show in these areas. However, such errors increase beyond 1 mile. In urban sites an average error of 20% was computed at distances of 0.5 miles, and 60% at 1 mile from count sites. For this reason, DOTs will no doubt want to sample urban locations more frequently than every mile. Arterials and freeways experience higher error (20%) compared to collectors (4.82%) at short distances, but lower error levels at longer distances. This may be due to the limited number of entry and exit ramps on freeways, versus the high frequency of intersections and driveways that occur along collectors. Higher errors for four-lane roads (as compared to two-lane roads) are consistent with the ATR results.

Figure 3 shows the variations in spatial error using PeMS 24-hour counts over the course of 7 consecutive days along I-110 S, I-405 S, and I-5 N. The spatial extrapolation errors rise quickly, to roughly 10% for I-5 and I-405 and around 40% for I-110 within a mile from the assumed count site. The results found here are comparable to the error data from Austin's freeway sites which have a 30% error at 1 mile from the count site. The jumps in these counts at the lower intervals of distance is somewhat troubling, particularly for I-110. The same day's data applied just one-half mile away yields sizable misprediction. In the case of I-110, the jumps render such spatial extrapolations practically useless to analysts. Freeways are relatively well controlled roadway environments, with few points of entrance and exit (though these points certainly can represent major ramps and facility merges). If misprediction can be so severe in these cases (consistent with the Austin TDM evidence), analysts should be highly skeptical of counts one or more miles away when seeking to estimate VMT, crash rates, emissions and other variables. Perhaps a combination of upstream and downstream counts will assist the prediction, as well as evidence from cross-street counts, to obtain a sense of whether traffic is being added or removed from the facility of interest. Alternatively, far more frequent SPTC spacings may be necessary, to ensure extrapolation does not exceed 0.5 miles, except in locations where traffic loads are known to be highly stable over space.

Figure 4 illustrates the error levels in AADT estimates resulting from 1 to 4 years of forward extrapolation. In general, the errors at urban sites were found to be greater than those at rural sites, consistent with the higher coefficients of variation witnessed at these sites in any given year. The average year–to-year increase in forward-prediction errors is about 3%, per year, with the greatest jumps in these Minnesota ATR data evident in the first and third years. In order to avoid the jumps that are likely to widen as time passes, and more uncertain elements enter the prediction picture, state DOTs aim for greater frequency in count measurements. Nevertheless, these results do not suggest any highly convex shape for misprediction levels over time, so more spatially regular (more tightly spaced) AADT measurements may be more worthwhile than more frequent measurement at fewer sites.

Table 4 summarizes the factoring, spatial and temporal errors described above. The error variation with distance from site and time of extrapolation is shown with a base factoring error of 12% (error at a site from site classification for DOW and MOY factors, with counts from the same site in the same year). It is found that the results of the Minnesota ATR temporal error and Austin data analyses are combined in the table and these suggest that errors rise quicker with distance, than with time of extrapolation. For example, taking count samples every 1 mile, every other year will result in average misprediction levels of 70% at all count sites in the off year, while taking samples every 2 miles, every year is expected to result in average misprediction levels of 125%. Thus, spatial extrapolation is not recommended beyond 1 mile. The table could be used by designers and planners to determine what error to correct for, if they are extrapolating the site count spatially or temporally. This table reflects only the average; therefore the actual error could be lower or higher, based on day of week, month of year, functional class of the roadway, count duration and actual value of count itself. These variations by these factors have been analyzed and summarized in table 5 and figures 6 and 7.

Table 5 presents the results of regression analysis of percentage error on different variables, including the DOW, MOY, functional class, area type and number of lanes, for both Florida and Minnesota. Counts taken along rural, arterial roadways with more than 5 lanes on a Sunday in January are also used as the base case, for comparison. A higher negative coefficient on a particular variable means lower error levels for that day, month or roadway type. For example, Minnesota's AADT errors tend to be lower on Mondays as compared to Tuesdays (coefficient of -6.00% vs. -5.08%). In Minnesota it was found that there is no difference in error between February and January and that March, July, November and December exhibit the highest errors, among months of the year. In contrast to the Florida results, urban area freeways (and roadways with 4 or fewer lanes) exhibited less error than their counterparts. Florida's data exhibits rather dramatic misprediction tendencies when counts come from September and November (an issue that may be specific to the 2004 data year). And errors tend to be larger along freeways and in sites classified as rural (and along arterials, as compared to collectors). Average errors tend to be lowest in the months of March through June in Florida (averaging 10%), and August through October in Minnesota (averaging just 6%), suggesting that those periods are most suitable for short term counts.

Figure 6 indicates that multi-day sampling offers little in the way of error reduction, averaging roughly 0.7% error reduction for each extra day of sampling (11.0 %(24 hours), 11.7 (48 hours) , and 12.6 (72 hours)) . These findings are comparable with the Sharma et al.'s (1996) results (where error fell from 16.5% at 24 hours to 13.13% at 72 hours) and Granato's (1998) results (where error fell from 11.3% at 24 hours to 10.9% at 72 hours).

Figure 6 also illustrates variations in AADT prediction error versus actual AADT. The errors are found to be high in both Minnesota and Florida, at very low AADT values. Then a lowering trend occurs with an increase in AADT values. The lowering is more evident in Minnesota where errors decrease from roughly 20% at 2,000 vehicles per day (vpd) to just 6% at 120,000 vpd. Evidently, traffic loads are much more predictable on high-volume roads in Minnesota but it should be noted that the higher volume roads tend to be freeways in urban areas, which, in general, enjoy lower AADT estimation error. Thus, 5+-lane facilities were associated with higher error rates, *ceteris paribus* (i.e., after controlling for facility type and location), in Table 4's regression results. It is important to recall that factors such as total flow have global as well as marginal roles.

CONCLUSIONS AND RECOMMENDATIONS

AADT estimates are fundamental to the analysis of transportation data sets and the management of transportation systems. Using several distinctive data sets, this research illuminates the magnitude and sources of uncertainty in such estimates. Many of the results appeared consistent across states which supports the notion of their transferability to other contexts. Consistent with expectations and practice, the sample counts taken over the weekends result in greater estimation errors, along with rural sites and multi-lane facilities, due to greater variation. Nevertheless, those with higher counts in Florida tend to prove more predictable overall.

Proper site classification is key, and tendencies may vary by state. These analyses of ATR data can be performed by any agency, to assess whether certain roadway types or times of year require greater sampling caution. Fine clustering, on the basis of functional class, lane count, and multiple area types, may prove very useful.

Spatial errors can increase dramatically beyond 0.5 miles (from the count site) in urban areas and 1 mile in rural areas; thus, caution is needed when assigning the AADT estimate of the nearest SPTC site to a roadway segment, and additional SPTC locations may be most prudent, particularly in locations where counts average less than 1 per mile.

Appreciation of the uncertainties inherent in AADT and VMT estimates is paramount for robust evaluations of crash rates, pavement deterioration, and other transportation data. This research seeks to enlighten the use of such estimates, and thereby enhances transport decision making. The summary table resulting from this work offers base estimates of factoring, spatial and temporal errors and details on how these errors vary by day of week, month of year, area type, functional class, number of lanes duration and distance to nearest SPTC station. Given the magnitude of errors witnessed here, transportation agencies may wish to increase the spatial frequency of their SPTCs as well as increase the frequency of counts at along urban freeways and other facilities exhibiting the greatest predictive errors. Investment, planning and design decisions stand to benefit greatly from better estimates of roadway use.

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LIST OF TABLES AND FIGURES

Table 1. Data description (Number of sites)

Classification	Sub-division	MNDOT	FDOT	Austin
		Number of sites (n)		Number of links
Area type	Urban	19	139	5822
	Rural	38	154	4772
Functional Class	Arterial	37	130	4807
	Collector	–	17	681
	Freeway	20	73	796
Number of lanes	1	0	–	394
	2	22	–	7550
	3	0	–	636
	4	28	–	1748
	5 or more lanes	8	–	266

Note: Florida did not provide lane count information, and none of the Minnesota sites was labeled as a collector.

Table 2. Average errors in AADT estimation for different site classification schemes in MN

Classification	Sub-group	MNDOT (#)	Absolute Avg. Error (%)			
			Min	Max	Mean	Std. Dev
Area Type	Urban	19	4.89	81.14	11.47	17.08
	Rural	38	7.06	38.8	12.84	5.88
Functional Class	Arterial	37	7.33	40.81	13.25	6.23
	Freeway	20	5.99	83.22	14.60	16.93
Number of Lanes	4 or fewer lanes	49	6.87	41.82	13.06	6.24
	5 or more lanes	8	8.4	80.17	18.48	24.97

Table 3. Average errors in AADT estimation for different site classification schemes in FL

Classification	Sub-group	FDOT (#)	Absolute Avg. Error (%)			
			Min	Max	Mean	Std. Dev
Area Type	Urban	123	5.62	37.77	14.28	6.06
	Rural	153	5.27	34.71	13.26	4.86
Functional Class	Arterial	123	5.62	37.77	14.28	6.06
	Collector	17	8.06	21.99	13.96	3.68
	Freeway	73	6.66	40.14	15.24	6.24

Table 4. Variations in average AADT estimation error over time, by distance from site

	Time since Count					
	Time of Extrapolation	**Same year**	**1year**	**2years**	**3years**	**4years**
Distance from Site	No DOW and MOY Factors	0%	4%	7%	8%	13%
0 miles (same site)	0%	12%	16%	20%	21%	26%
0.2 miles	7%	20%	25%	29%	30%	35%
0.5 miles	19%	34%	39%	43%	44%	51%
1 mile	41%	58%	65%	70%	71%	78%
1.5 miles	66%	86%	93%	99%	100%	109%
2 miles	93%	116%	125%	132%	133%	144%

Table 5. Regression analysis of AADT estimation error

Variable	**MNDOT**		**FDOT**	
	Beta	t-statistic	Beta	t-statistic
(Constant)	24.738	45.9	19.284	84.1
Monday	-6.004	-14.7	-8.770	-44.4
Tuesday	-5.082	-12.5	-8.933	-45.2
Wednesday	-4.999	-12.2	-8.998	-45.5
Thursday	-6.079	-14.8	-9.643	-49.0
Friday	-6.890	-16.8	-9.853	-50.0
Saturday	-3.196	-7.8	-6.701	-34.0
February	0.000	N/A	-0.508	-2.0
March	2.575	5.6	-2.222	-8.7
April	-0.906	-1.9	-1.958	-7.6
May	-2.703	-5.8	-2.125	-8.4
June	-3.194	-6.8	-2.484	-9.6
July	0.825	1.8	-0.679	-2.7
August	-0.757	-1.6	-0.283	-1.1
September	-1.527	-3.3	11.747	45.5
October	-1.445	-3.1	-0.070	-0.3
November	1.364	2.9	9.788	37.7
December	1.807	3.9	1.359	5.3
Urban	-3.202	-10.9	0.929	8.7
Collector	N/A	N/A	-0.129	-0.6
Freeway	-0.976	-3.4	2.400	17.7
4 or fewer lanes	-6.994	-19.1	-	-
Adj. R Square	0.0476	y= Error %	0.1106	y= Error %
Std. Error of Y|X	15.766		15.826	
N_{obs}	57		293	

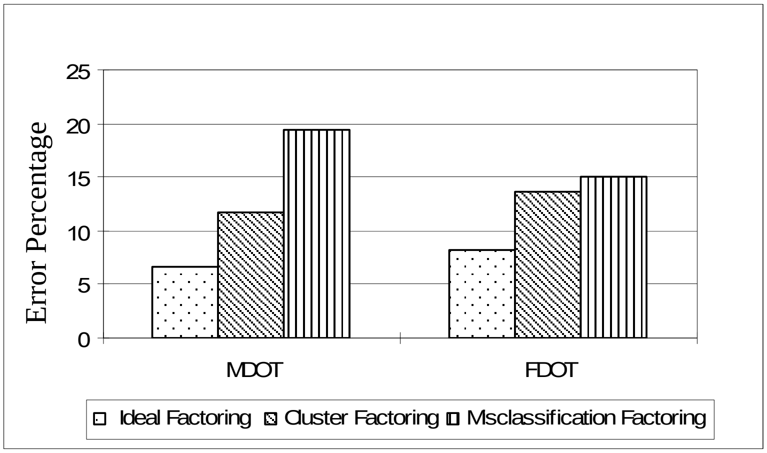

Figure 1. Variation in AADT estimate error by factoring method used (using Florida's and Minnesota's ATR data)

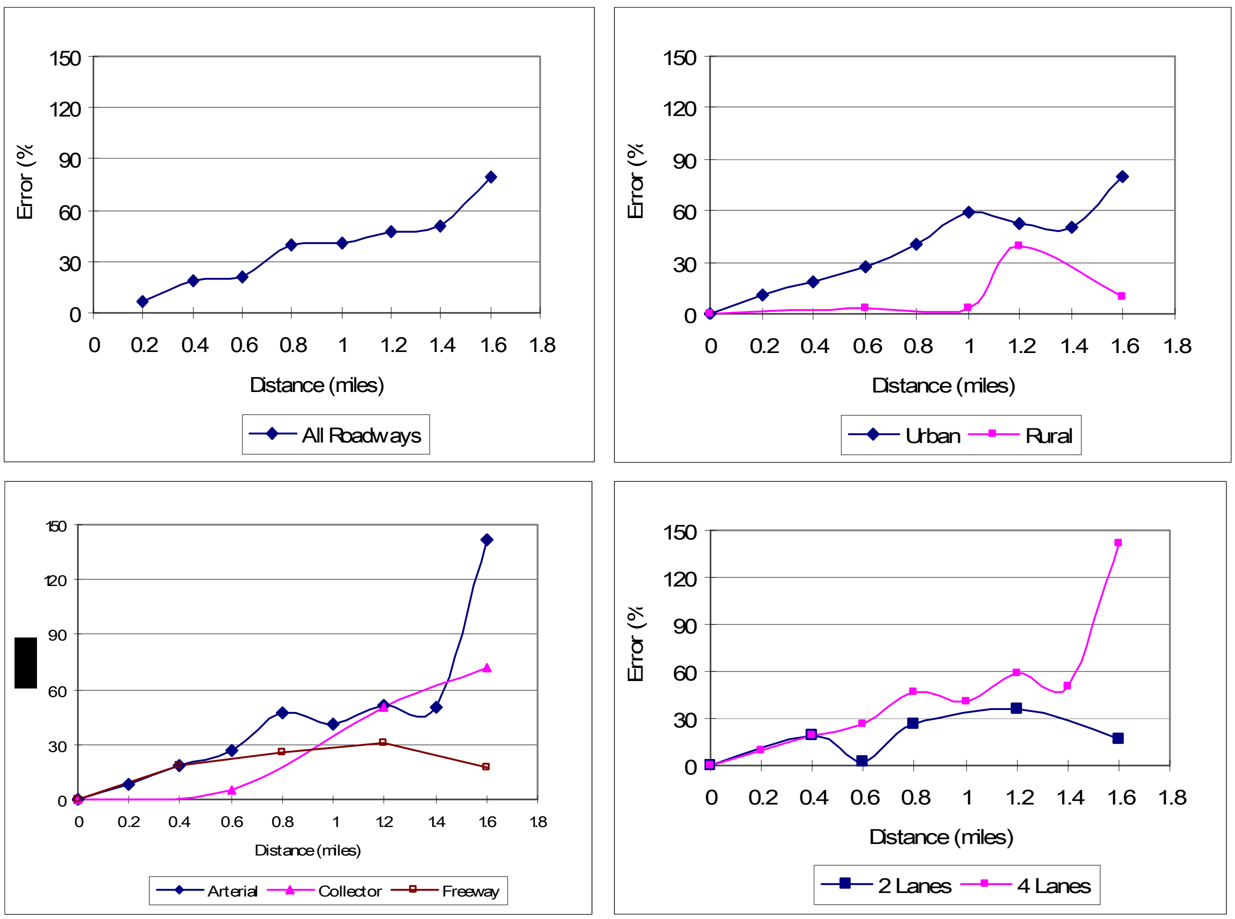

Figure 2. Spatial variation in AADT estimate error for different roadway and location types (using Austin TDM data)

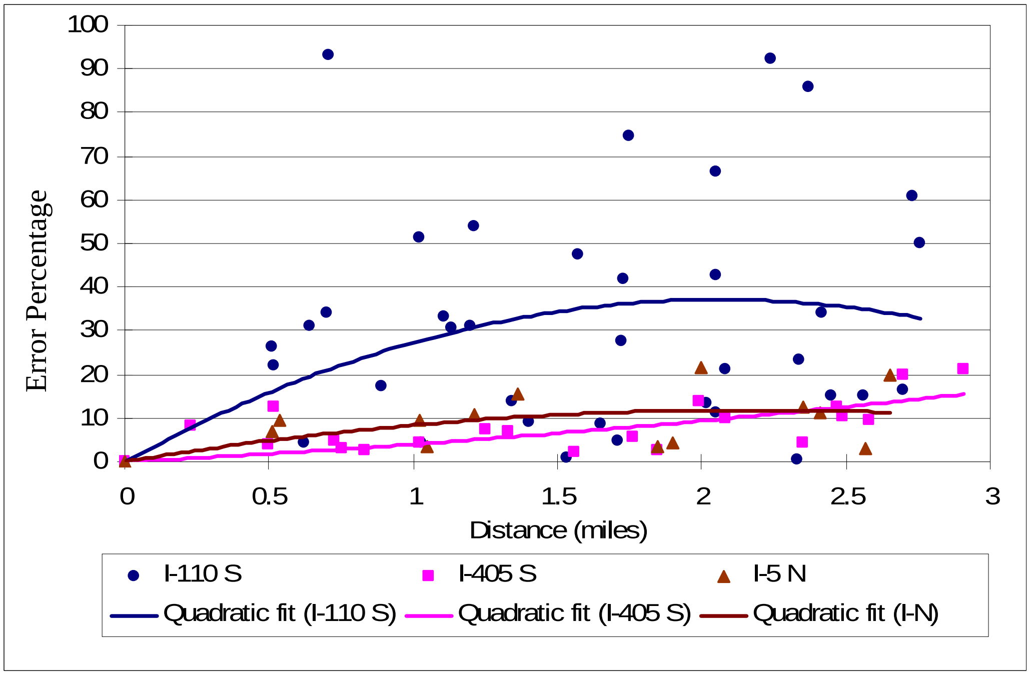

Figure 3. Spatial variation in AADT estimate error in AADT estimates for freeway sites using one week's worth of PeMS data at 3 Southern California sites

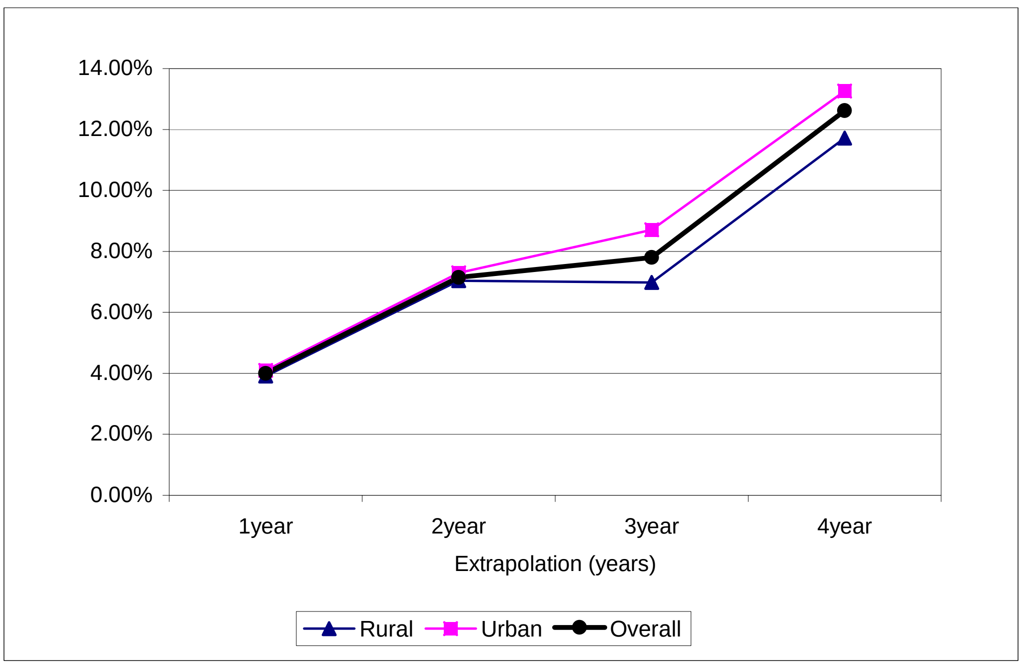

Figure 4. Temporal variation in AADT estimate error in AADT estimates from ATR sites in Minnesota

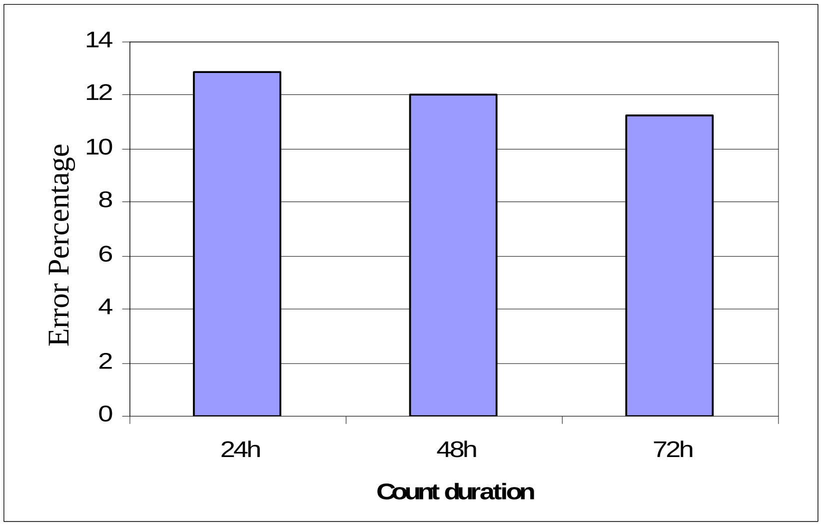

Figure 5. Effect of count duration on AADT estimate error (using Florida' ATR data)

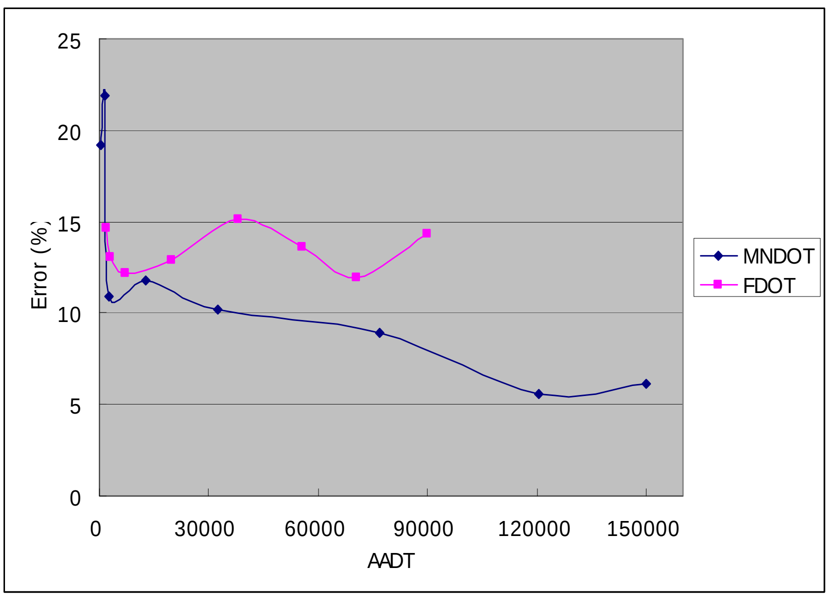

Figure 6. Variation in AADT estimate error, as a function of AADT (using Florida's and Minnesota's ATR data)