10.3

ANALYSIS OF WEATHER IMPACTS ON TRAFFIC FLOW IN METROPOLITAN WASHINGTON DC

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1. INTRODUCTION

Anyone who uses surface transportation has been affected by delays caused by various forms of weather. Whether it is rain or snow, ice or fog, the result is usually the same. Travel delay rises as traffic flow decreases.

The Federal Highway Administration's (FHWA) Road Weather Management Program (RWMP) has been sponsoring research into the impacts of weather on surface transportation. One specific research task involved attempting to quantify the amount of travel delay imposed upon drivers due to the effects of inclement weather.

This paper will describe two different methods used to approximate travel delay impacts of weather along specific roadway segments around metropolitan Washington, D.C. Each method will use meteorological data sets of differing temporal and special resolutions in conjunction with travel time data.

The travel time data used in both models will first be described. Then, the two methods of analysis will be detailed along with their respective weather data. Results and conclusions from both analyses are then presented.

2. TRAVEL TIME DATA

Travel time data were obtained by accessing and archiving information from the SmarTraveler web site (www.SmarTraveler.com). The SmarTraveler Internet postings are publicly available, and list by roadway segment, travel time information as well as data on accidents, special programs, and road construction. Information is posted as early as 5:30 AM and extends to as late as 8:30 PM, excluding weekends and some holidays.

The travel time data were archived at approximately five-minute intervals for each of the 33 Washington, D.C. road segments for which SmarTraveler posts travel times. The travel time data that were used in this study ranged from 6:30 AM to 6:30 PM local time, Monday through Friday, between December 6, 1999 and May 31, 2001. Information on accidents, special programs and road construction were neither downloaded nor maintained as a part of this data archive and therefore were not used in this study.

The geographic coverage of the Washington, D.C. roadway network spans from the eastern suburbs in Maryland, across the District of Columbia to the western suburbs in northern Virginia. A graphical depiction of the road network can be seen in Figure 1.

The SmarTraveler network routinely reports travel time data for this region on 33 bidirectional roadway segments. These routes span a total of 711.8 miles. The average length of the segments is 10.8 miles with maximum and minimum lengths of 25.0 and 2.6 miles, respectively. Of the 33 segments, 18 are freeways and 15 are major arterials. The 18 freeway segments constitute 472.4 of the 711.8 miles. The 15 arterial routes constitute the remainder (239.4 miles). Appendix B, Table B1 provides a list and description of each road segment.

While data reported in the SmarTraveler network are not fully representative of road travel times, it is a credible estimation of real travel times. There are four factors that can impact the accuracy of the archived data. These are:

- The posted travel time information is a blend of various quantitative and qualitative data such as commuter call-ins using cell phones, incident reports, and vehicle (loop) detectors. Thus, although the data at an aggregate does represent the traffic characteristics of the road, it has inherent inaccuracies compared to actual roadway travel times.
- In the absence of incidents, weather, road maintenance activities, or other major events modifying traffic demand; SmarTraveler posts ***base travel times.*** Base travel times vary significantly by time of day but are repeated day after day in the absence of traffic events. Moreover, during extreme events, posted increases in travel times may be less accurate as compared to actual roadway conditions because roadway conditions change rapidly and are not easily captured through existing SmarTraveler data sources.

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- Examination of the data suggests that posted data during the peak traffic periods are modified much more frequently than during off-peak periods. For example, three to four distinct travel times may be posted during an hour of peak traffic while during off peak periods one travel time may be posted for three to four hours.

- SmarTraveler policy precludes posting of travel times that would indicate speeds greater than the speed limit. Thus, travel time posting when speeds are greater than the speed limit are increased from true travel time to speed limit travel time. This has substantive implications on the analysis of delay during congestion-free traffic periods.

- Although SmarTraveler updates travel times with regular frequency, time is required to process and post the data. This time produces a lag between actual and posted travel time.

These data limitations can significantly influence the analysis process and the resultant outcomes.

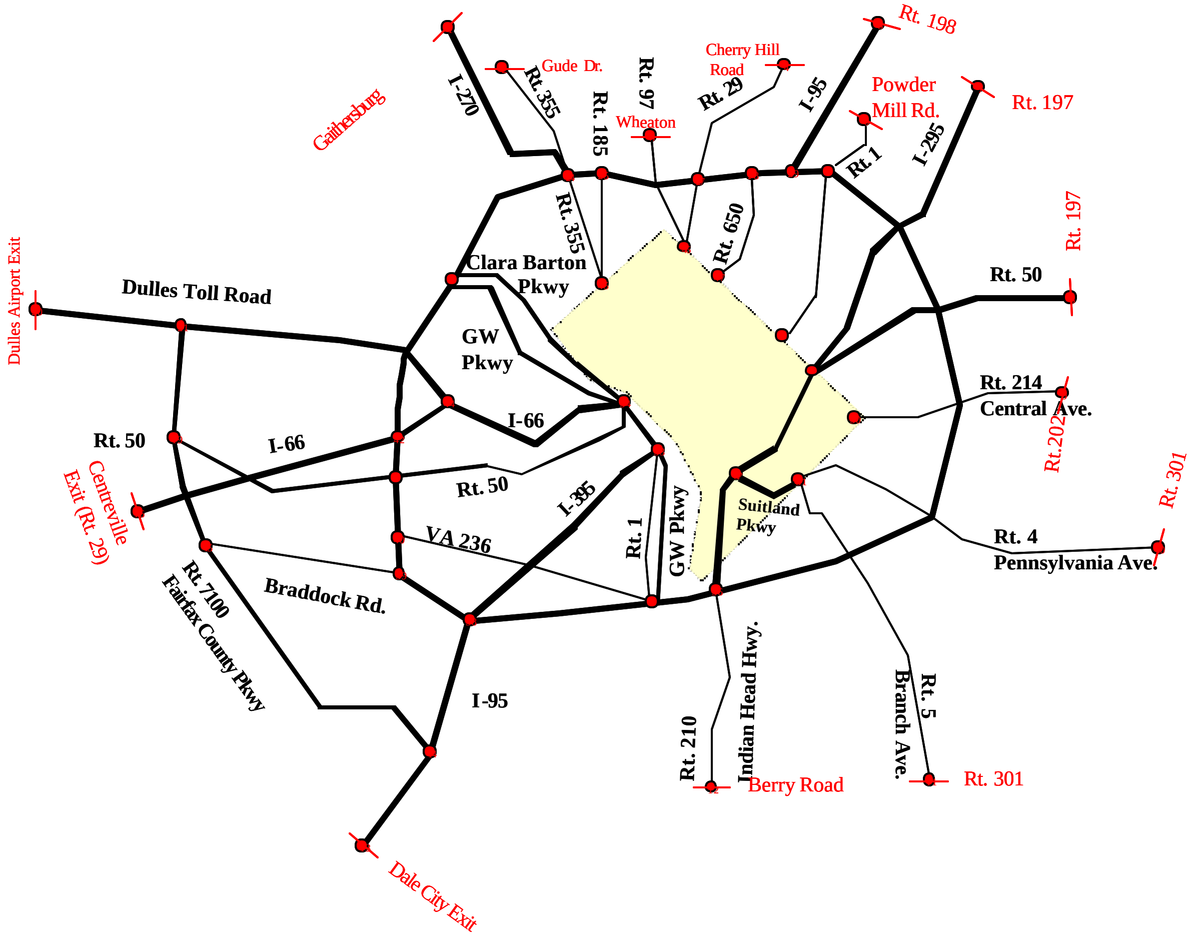


Figure 1 – Map of the Metropolitan Washington, D.C. Roadway Segments used in the Travel Time Analysis

3. METHOD 1: REGRESSION ANALYSIS USING SURFACE OBSERVATIONS

The first method that was used to analyze the effects of weather on the travel times included using data obtained from weather observations from three Washington area airports: Dulles International (IAD), Washington National (DCA) and Baltimore/Washington International (BWI). A map showing the locations of these airports can be seen in Appendix A, Figure A1.

An explanation of the data used, details of the analysis technique, and outcomes will be discussed in this section.

3.1 *Surface Data*

The National Weather Service (NWS) and Federal Aviation Administration (FAA) use a semi-automated system to observe key atmospheric elements at most major airports in the United States. The Automated Surface Observing System (ASOS), has sensors to take measurements of air temperature, dew point, wind speed and direction and rainfall accumulation. Complementary technologies, such as weather satellites, are used to provide estimates of total sky cover. However, human observers are maintained at many airports to augment ASOS for such phenomena as the occurrence of thunderstorms, hail, or snow accumulation or drifts.

3.1.1 *ASOS Data Set*

Archived hourly observations from ASOS were obtained for the test domain from the National Climatic Data Center (NCD), which is the repository of weather data from the National Oceanic and Atmospheric Administration (NOAA). A software program was developed to parse the 15,535 hourly observations into discrete elements. These elements included:

- Sky Cover
- Surface Visibility
- Observed Weather
- Precipitation Intensity
- Air Temperature
- Dew Point
- Wind Speed
- Hourly Rainfall Amount

A series of algorithms were created to convert the observational elements into categories that could be used for later processing. Table 1 shows the final list of elements that became variables in the regression analysis routines. It was hypothesized that each of the variables can have a direct impact travel speed and thus travel time on roadway segments.

The precipitation type and intensity parameter used a combination of observed weather, precipitation type and intensity information to create the four 'precip' categories.

The 'wind' parameter was selected because strong wind gusts can affect the handling and stability of vehicles, especially those with high profiles.

The 'vis' or visibility distance parameter was used to identify those times when surface visibilities had a significant impact on surface transportation.

The 'pcon' or pavement condition parameter was inferred from numerous inputs. Elements such as cloud cover, air temperature, humidity, precipitation intensity and wind speed were all used to estimate the condition of the pavement. Appendix B, Table B2 contains the decision scheme used to create these values.

Name	Description	Values	
precip	precipitation type and intensity	0 = None 1 = Light Rain/Snow	2 = Heavy rain 3 = Heavy Snow/Sleet
wind	sustained wind speed	0 = < 30 mph	1 = ≥ 30 mph
vis	visibility distance	0 = ≥ 0.25 miles	1 = < 0.25 miles
pcon	pavement condition (inferred)	0 = Dry 1 = Wet	2 = Snow/ice 3 = Black ice

Table 1 – Observational Elements Used in the Regression Analysis to Represent Surface Conditions

3.1.2 *ASOS Data Quality Issues*

Some data quality issues were associated with the use of ASOS. First, the NCDC archive was not complete for the analysis time period. At DCA, 20 hourly observations were not available. At IAD, eight observations were missing randomly through the data set. More importantly, all data were unavailable for an entire week during May of 2000. At BWI, 22 hourly observations were missing. In most cases, the weather was benign and the isolated missing observations could be filled in by interpolation. In the case of the missing data at IAD, data from DCA plus radar observations were used to fill and estimate the missing information.

A second data quality issue was associated with the way that ASOS reported hourly liquid equivalent values during snow events. In many cases, the hourly amounts were underreported from the system's tipping bucket rain gauge. For example, the total liquid equivalent reported from the DCA ASOS during the snowstorm of January 25, 2000 was 0.18 inches. The human augmented liquid equivalent was 0.85 inches. At a 10:1 ratio, that would mean that ASOS would underreport snow accumulations by 7 inches!

Finally, during mornings when there were heavy dew deposits, ASOS, on occasion, reported one or two hundredths of an inch of precipitation out of 'clear skies'.

These values had to be removed manually by inspection.

3.1.3 *Combining ASOS and Travel Time Data*

Travel time data were collected at a resolution of one observation per five minutes. The ASOS observational data were available at a frequency of once per hour. The method to combine these two data sets assigned all travel time observations 30 minutes before or after an ASOS observation to that weather observation. For example on any given day, a travel time observation at 7:30 AM would be assigned to the weather observation at 7:00 AM while a travel time observation at 7:35 AM would be assigned to the weather observation at 8:00 AM.

3.2 *Regression Analysis*

The technique used in this portion of the analysis was developed based on the strengths and shortcomings of the ASOS data. Since the weather data could not directly correlate with specific roadway segments (since the data were from airports), regression models were used to ***predict*** travel times on the roadway segments using the weather variables derived from the ASOS observations.

3.2.1 *Analysis Steps*

A two-step linear regression process was performed on each roadway segment by direction. First, the travel times were regressed against the weather variables of precipitation intensity and type, pavement condition, wind speed, and visibility for all ASOS sites. Thus, the regression models each consisted of 12 explanatory variables (3 ASOS sites x 4 variables). In this first step, both linear and quadratic forms of the precipitation and pavement weather variables were examined. Overwhelmingly, the quadratic form dominated in regression models and proved to be a better fit to the travel time data. The reduced linear regression models were selected based on the most effective weather variables (those with highest t-statistics and positive coefficients). The second step was to reduce linear regression models for each directed roadway segment to predict the base travel time and increases in travel time attributed to weather. The general form of the reduced regression model was:

$$\text{Travel Time} = \text{Base Travel Time} + B1*(\text{Pavement}_{\text{Airport}})^2 + B2*(\text{Wind}_{\text{Airport}}) + \ldots..$$

Average predicted delay by directed roadway segment was calculated as the sum of the values to the right of the “Base Travel Time” parameter divided by the number of observations. The average predicted delay by segment and direction were aggregated to derive a regional estimate of the impact of weather on delay. The amount of delay divided by the base travel time yields the percent increase in travel time attributable to weather.

This regression process was applied to two subsets of data: the historic peak 2-hour traffic period and the historic low (off-peak) 2-hour traffic period to assess the impacts of weather on increases in travel time (or delay). The off-peak period was defined for this study as the two-hour period with historically lowest travel times across the entire dataset. The peak period was defined for this study as the two-hour period with historically highest travel times across the entire dataset. Tables containing the average two-hour low and high traffic times of the day and travel times can be found in Appendix B, Tables B3 and B4, respectively.

The reduced regression models were then applied to a single day to illustrate the extent of weather delay predicted in the off-peak times during extreme weather. For example, the widespread snow event across the National Capital Area on January 25, 2000 was used. Regression models were fit to estimate the outcomes based on the most frequently occurring factors. That is, at extremes, model predictions may be significantly different than the observed variable. As such, the predicted outcomes were compared with SmarTraveler posted travel times.

3.2.2 *Implications of Data Quality on Analysis Outcomes*

The greatest shortcomings in this analysis were the absence of information on other variables affecting travel time beyond weather, the absence of roadway segment specific weather variables, and the qualitative nature of the travel time data. These shortcomings result in meaningless outcomes of regression analysis of weather impacts during the ***peak period*** as explained in Section 3.2.2.1. However, the data are better suited to conduct an off-peak analysis since congestion, incidents, and delay propagation effects are fewer. Yet, there are also other factors to consider in examining the quality of model outcomes during the off-peak regression analyses. These are explored in Section 3.2.2.2.

3.2.2.1 *Implication of Data Quality on Peak Traffic Regression Analysis*

By definition, peak period hours are those with the highest volume of trips. Accidents are much more frequent during the peak traffic periods as compared to off-peak periods and have greater impact in terms of increased delay during the peak traffic periods. Subsequently, increases in travel time (termed delay) for a given roadway are much more likely due to recurrent congestion, queue spillback, and incidents during the peak period as compared to off-peak periods.

Given the absence of information on congestion, queue spillback, and most importantly, incidents; models predicting delay during the peak period would be of very low explanatory power compared to similar models predicting delay during off-peak periods. In addition, given that (1) weather phenomena generally occur for multiple hours, (2) weather variables (in this domain) are constant across an hour, and (3) peak period travel times vary frequently within an hour; the existing weather variables prove incomplete in modeling or predicting peak-period delay.

For all of these reasons, it was found that these data were not well suited to conduct a peak-period analysis of the impact of weather on delay. Nonetheless, a preliminary regression analysis was conducted for the peak-period. Model R^2 values were in the range of 0.005 to 0.05, indicating that less than 5% of the variability in travel time data could be explained by the selected weather variables. This supports the hypothesis that existing weather variables cannot sufficiently explain variability in travel time data, and thus peak period analyses outcomes were meaningless.

3.2.2.2 *Implication of Data Quality on Off-Peak Period Regression Analysis*

The data were better suited to conduct an off-peak period analysis since congestion, incidents, and delay propagation effects are fewer. Moreover, travel time changes (variability) were minimal within any given hour. This was the case with hourly weather variables. The impact of weather on delay during the off-peak provides significant insight as a baseline for the impact of weather during the peak period. Therefore, for this study an analysis was conducted of the impact of weather during off-peak periods.

It should be noted that weather effects on any given roadway segment were inferred based on the weather at the three metropolitan Washington airport sites. Moreover, roadway segments were from a few to as many as 25 miles in length and weather could vary within the roadway segment. In addition, some error was introduced in the mapping of hourly ASOS data to five-minute travel time data. Hence, the physical state of the roadway could not be fully captured.

Regression models do not capture propagation of delay effects from roadway to roadway. These factors suggest that models of delay will vary by segment. Also equally important is that using the multiple and combinatorial ASOS weather sites in regression methods can lead to data fitting, thereby overestimating the impact of weather on delay.

3.2.3 *Analysis Outcomes*

Tables B5 and B6 in Appendix B present the reduced regression models, each model's R^2 value, and a measure of the goodness of fit of the regression model for each directional road segment. The higher the R^2 value, the more the weather variables explain the variation in travel times. On average, the R^2 value was 0.23 across the 66 regression models. Of the 66 models, most (41) consist of three variables while some (16) consisted of two variables and a few (nine) consisted of four variables. Pavement condition (pcon) was the most frequent explanatory variable, appearing in every model. Precipitation (precip) appeared in 11 of the 66 models while wind speed and surface visibility (vis) appeared in six and five of the models, respectively. All three-variable models, except one, are comprised of a variable from each of the three ASOS sites suggesting that conditions on the specific roadway are best described as a combination of conditions at the three ASOS sites.

Table 2 presents the outcomes of applying the regression models to calculate delay metrics attributable to weather. Across all roadways, the average roadway travel time was 17.0 minutes and the average percent of cases where weather factors cause delay is 13%. *When weather phenomena occur, the average regional increase in travel time is 14%*, translating to a 2.2-minute delay on a 17-minute trip.

For the January 25, 2000 snowstorm, the predicted increase in travel time was 53% which translated to an 8.3-minute delay for a 17-minute trip. The SmarTraveler site posted an increase in travel time for this example regionally as 155% or a 26-minute delay on a 17-minute trip for the two-hour period. The reality is likely to be somewhere between these two values.

4. METHOD 2: ANALYSIS OF MEANS BY PRECIPITATION CATEGORY

A second methodology was developed with the intent of trying to use higher resolution (both spatially and temporally) weather data to better approximate roadway conditions. For this portion of the project, radar data from an NWS Doppler radar were used. The radar was located just northwest of Dulles International Airport near Sterling, VA.

4.1 *Radar Data Set*

The 15,535 hours of ASOS observations were analyzed to determine the most likely times when precipitation could occur anywhere over the travel network. When complete, a total of 3,352 hours of archived radar data would be needed for the analysis. Archive level III, base reflectivity products (16-level/0.5 degree elevation) were ordered from the NCDC.

4.1.1 *Correlation of Radar Data to Road Segments*

Using a Geographic Information System (GIS), the azimuth and range reference frame of the radar were overlaid onto the roadway network (Figure 2). At this point, the task was to develop a translation of the GIS grid structure into computer code so that radar information could be directly associated with a specific segment. This was accomplished in two steps:

Step 1: With the road segments overlaid on the radar grid, every grid that fell on a road segment was designated as a primary grid. The azimuth and range of each primary grid was noted (Figure 3). A region, exactly one radar grid in depth around the primary grids, was recorded as secondary grids.

Step 2: The azimuth and range of each primary and secondary bin were translated into C programming code.

The designations of grids as primary or secondary were used in the processing algorithm for two reasons:

1. Using a combined primary and secondary region helped to better capture precipitation that was moving across a narrow road segment.

Table 2 - Off-Peak Predicted Impacts of Weather on Delay and Travel Time

ANALYSIS OUTCOMES FOR LOW 2-HOUR REGRESSION MODELS										
	NORTH/EAST DIRECTION					SOUTH/WEST DIRECTION				
Road No.	% Cases With Weather	Average Delay When Weather (minutes)	% Increase in Travel Time When Weather	Jan 25, 2000 Average Trip Delay	Jan 25, 2000 % Inc. Travel Time	% Cases With Weather	Average Delay When Weather (minutes)	% Increase in Travel Time When Weather	Jan 25, 2000 Average Trip Delay	Jan 25, 2000 % Inc. Travel Time
1	12%	3.4	12%	11.1	39%	10%	3.6	12%	12.3	41%
2	13%	2.3	11%	6.5	30%	10%	2.5	11%	8.5	39%
3	13%	2.3	26%	8.4	93%	14%	2.2	25%	8.9	98%
4	12%	2.8	16%	8.7	49%	10%	1.9	11%	6.1	35%
5	15%	0.8	5%	5.0	32%	12%	2.6	16%	10.2	64%
6	13%	1.2	8%	3.8	25%	12%	1.9	13%	6.7	44%
7	14%	3.1	11%	10.8	38%	13%	1.7	6%	7.4	25%
8	15%	0.8	6%	5.0	36%	11%	2.4	17%	8.5	60%
9	13%	1.9	10%	6.6	35%	9%	2.5	13%	8.2	43%
10	14%	1.9	9%	6.4	29%	11%	2.1	10%	8.1	37%
11	15%	1.2	9%	4.3	33%	11%	1.5	12%	5.5	42%
12	15%	1.3	5%	4.8	20%	12%	1.6	7%	5.6	23%
13	14%	1.5	25%	5.7	96%	12%	1.4	23%	5.5	92%
14	15%	2.1	15%	15.0	107%	11%	2.7	19%	9.6	69%
15	13%	1.2	9%	3.9	30%	12%	1.5	12%	5.4	41%
16	14%	3.2	9%	10.7	30%	12%	4.0	11%	19.8	57%
17	13%	1.8	14%	5.8	45%	11%	2.3	18%	8.2	64%
18	13%	1.5	15%	5.0	50%	12%	1.5	15%	5.2	52%
19	15%	1.6	20%	5.7	71%	12%	1.9	24%	6.7	83%
20	13%	0.8	8%	2.6	26%	11%	1.4	14%	5.0	50%
21	15%	2.6	18%	10.5	70%	12%	3.1	21%	12.2	82%
22	15%	3.0	17%	11.6	65%	12%	2.4	14%	8.6	48%
23	14%	1.9	10%	6.8	38%	12%	2.0	11%	7.8	43%
24	14%	2.4	17%	16.7	116%	11%	3.2	23%	11.1	79%
25	14%	2.9	24%	13.2	108%	12%	2.3	19%	8.1	67%
26	12%	4.2	25%	13.6	80%	9%	1.9	10%	1.4	7%
27	14%	1.8	17%	6.4	63%	11%	1.8	18%	6.8	67%
28	14%	3.3	22%	12.7	85%	11%	3.2	21%	11.4	77%
29	15%	1.4	7%	9.2	46%	13%	1.5	8%	7.9	40%
30	14%	2.3	11%	8.0	40%	12%	2.1	11%	7.5	38%
31	14%	2.3	15%	8.8	58%	12%	1.5	10%	5.3	35%
32	12%	2.4	13%	7.9	42%	11%	1.8	9%	6.2	33%
33	14%	3.3	11%	11.6	40%	11%	4.5	15%	16.7	58%

*delay and travel time values are those predicted by the regression models

Regional Average % Cases with Weather	13%
Regional Average Delay (minutes) when Weather	2.2
Regional Average % Increase in Travel Time when Weather	14%
Regional Average Delay Attributable to Delay Jan 25 2000	8.3
Regional Average % Increase in Travel Time when Weather Jan 25 2000	53%

Figure 2 – GIS representation of the NWS Sterling Doppler Radar domain overlaid on the metropolitan Washington Road Network. The radar is located at the far left. The blue lines are azimuth lines. The boxes represent radar grids used in the segment analysis.

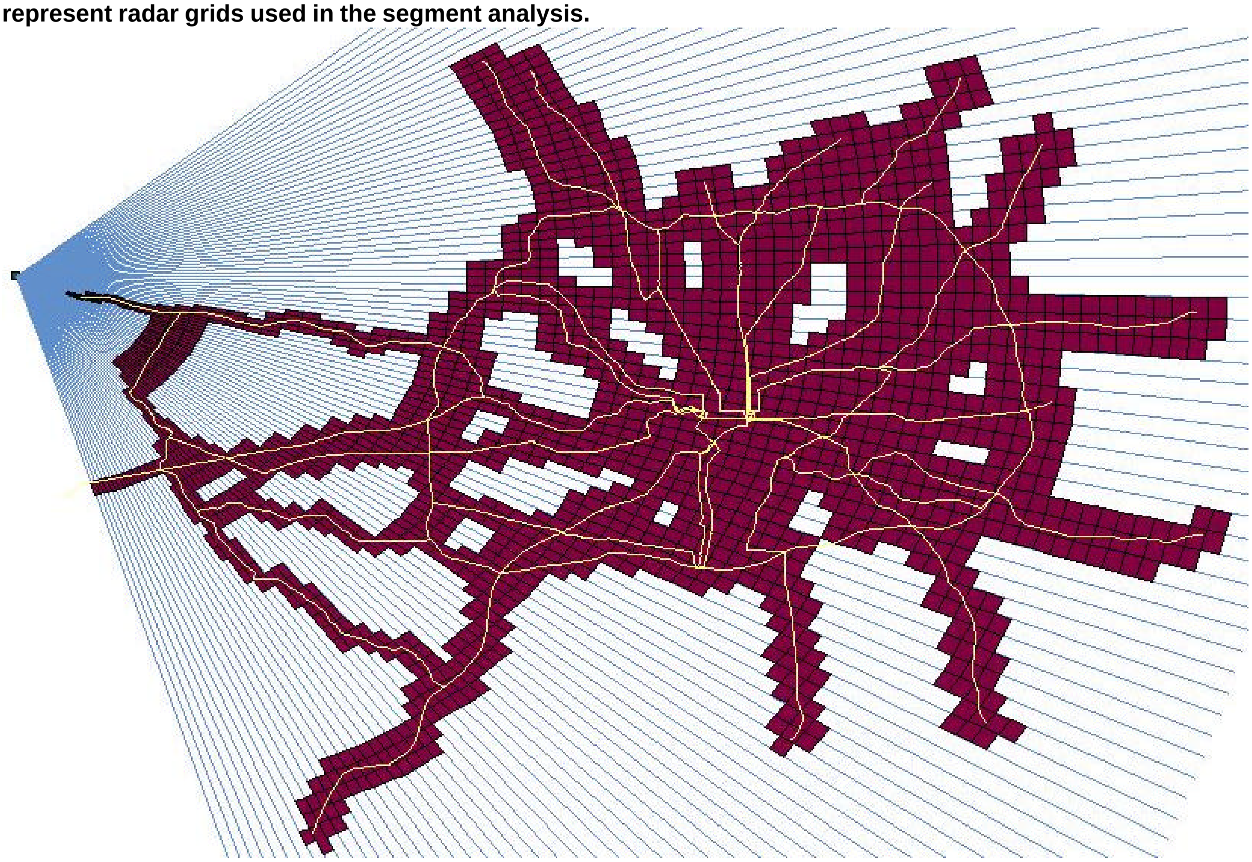
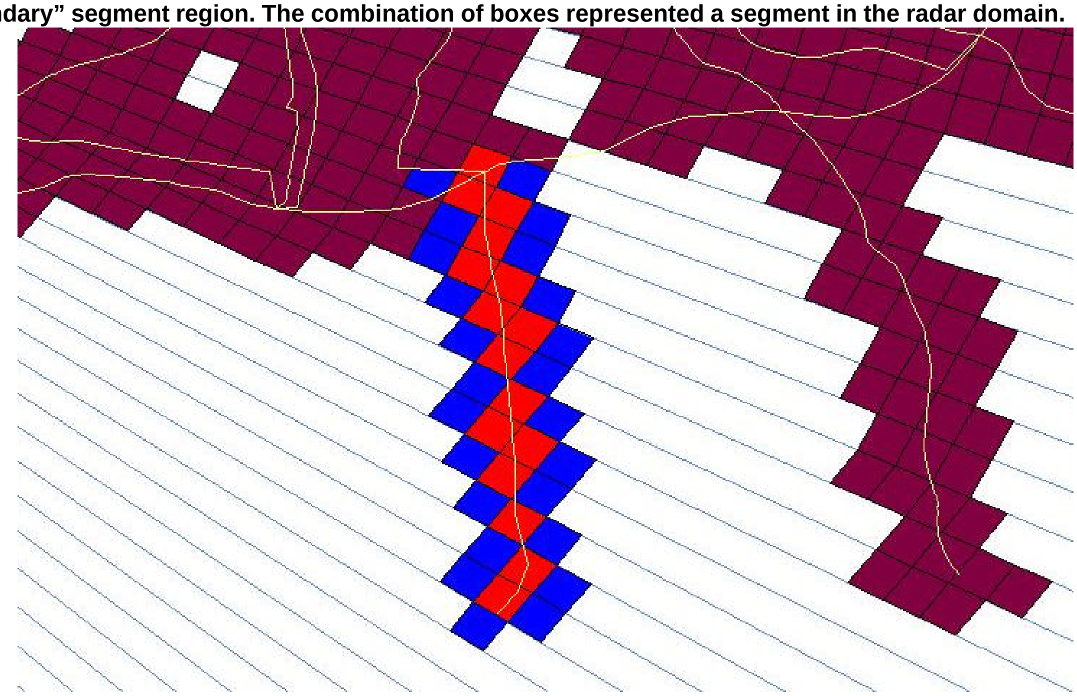


Figure 3 – The red boxes represent radar grids that lie on a road segment and are considered part of the "primary" segment region. The blue boxes surround the primary region and are considered part of the "secondary" segment region. The combination of boxes represented a segment in the radar domain.



2. The primary grids would be weighted more heavily than the secondary grids (e.g. 0.8 vs. 0.2) when developing an average reflectivity value for each roadway segment

4.1.2 *Z-R Processing*

Doppler radars estimate rainfall rates by sensing the reflectivity, or amount of reflected energy returned from a target. There is a relationship between reflectivity (Z) and rainfall rate (R) through the following relationship:

$$Z = aR^b$$

Where: Z = reflectivity factor ($mm^6 m^{-3}$)
R = rainfall rate ($mm\ h^{-1}$)
a,b = coefficient, exponent of R

For this task, reflectivity data were known for each radar bin. Once a weighted average reflectivity value for each segment was calculated, the Z-R equation was solved for R, rainfall rate. Coding within the radar product indicated whether the system was in precipitation mode (six minutes/volume) or clear air mode (10 minutes/volume). The result was an estimated rainfall total per volume in hundredths of an inch.

To accommodate for different seasons and drop size distributions, the formula coefficients were automatically modified. A cap of 0.50 inches per radar volume was also used to keep estimates within reason. Since radar data was processed during expected precipitation events, the chance of ground clutter contamination was held to a minimum and the accumulation cap was very rarely required. Table 3 shows the Z-R values and their estimated precipitation output.

Table 3 – Z-R relationships used for processing

Reflectivity, R (dBZ)	Standard Rate a=300, b=1.4 (inches/hour)	Tropical Rate a=250, b=1.2 (inches/hour)
15	<0.01	<0.01
20	0.02	0.02
25	0.04	0.05
30	0.09	0.12
35	0.21	0.33
40	0.48	0.85
45	1.10	2.22
50	2.50	5.80
55	5.68	15.14
60	12.93	39.53

To tune the algorithm, primary and secondary bin regions were placed over the three area airports. Hourly rainfall reports from the airports were used to compare with an hour's worth of radar estimated accumulations.

Appendix A, Figure A2 shows a comparison of the radar estimated precipitation (accumulated over an hour) and the ASOS rain gauge value at DCA. The radar estimation technique was able to capture the spikes and the trends in the gauge reading. While the radar estimates were generally lower than the ASOS observations, the onset time, ending time and magnitude of the event were captured for the travel time calculations.

Figure A3 compares radar estimated and ASOS liquid equivalents during a light snow event at DCA. Again, while the radar estimated totals were lower than actual measurements, the timing and fluctuation in the precipitation was properly captured.

4.1.3 *Radar Data Processing*

A program was written to read the radar files, parse their internal packets and unpack the run length encoded radial reflectivity data into arrays. Appendix A, Figure A4 shows the graphical user interface which contains a reflectivity scale, informational window and a display that overlays the airports (white circles) on the radar screen. The test domain lies within the area bounded by the two yellow radial lines.

Subroutines were written to represent each roadway segment. Once the volume-based rainfall estimate was generated for a segment, the data were written to one of 33 segment text files. Files for each of the area airports were also created for quality control (Appendix B, Table B7).

It was found that the radar data set was not complete. In order to salvage as many precipitation events as possible, a post-processing routine was written to fill in data gaps by interpolation. A maximum of two radar volumes (12 minutes) could be missed for the interpolation routine to fill in the holes. An example of a final output file can be seen in Appendix B, Table B8.

4.2 *Means Analysis*

Most of the processed radar data were available at six minute intervals. The travel time data were available at five minute intervals. The radar data were assigned to the closest travel time bin prior to analysis. This process is shown in Appendix A, Figure A5.

4.2.1 *Analysis*

Regression modeling predicted the increase in travel time based on linear relationships between weather variables and travel times. Radar data afforded the opportunity to go one step beyond because of the higher resolution data and simpler computations. The observed precipitation by roadway segment was used to evaluate the actual increase in travel time when precipitation occurred. This was done by first ordering the observed travel times during the peak or off-peak periods from lowest to greatest for each segment. Then, a percentile of the observations was used to establish a baseline travel time. These baselines included event-free travel time; a travel time representative of traffic without incidents or weather, but with recurrent congestion levels. For example, in a set of 200 observations, rank ordered from lowest to highest travel time, the 40^{th} in the order would constitute the 20^{th} percentile baseline travel time.

All of the travel time observations were then averaged where the precipitation observations were greater than a selected precipitation threshold (such as 0.01 inches per volume). This value corresponds to the average travel time with precipitation. Comparing the precipitation travel time against the baseline event-free travel time yields the impact of precipitation (or travel time increase) due to precipitation.

A sensitivity analyses based on varying the percentile used in the baseline travel time was conducted for two precipitation thresholds. The expectation was that as the precipitation threshold increased, the travel delay would increase. Conversely, as the percentile used in setting the baseline increased, the impact of weather would be lessened as more traffic events (low visibility, small incidents, etc) would creep into the baseline travel time.

4.2.2 *Implication of Data Quality on Means Analysis*

The means analysis of the impact of weather on travel time increases was relatively robust. However, the only weather element assessed was precipitation. That is, increases in travel time due to weather factors such as wind and low visibility were not assessed in this analysis. A lesser issue was SmarTraveler's policy of reporting speed limit travel times during off-peak periods. In such circumstances, the impact of precipitation producing delay may not always be captured. For example, the impact of precipitation causing driving speeds to be reduced from 75 mph to 65 mph (where speed limits are 65 mph) would not register in the travel time data. Thus, this analysis may underestimate the impact of precipitation on travel time increases during congestion-free traffic.

4.2.3 *Means Analysis Outcomes*

Appendix A, Figure A6 presents the travel time values associated with various percentiles for the peak and off-peak time periods. These values are based on the average travel times across the 33 roadway segments. As demonstrated in the figure, the baseline travel time in the off-peak is tremendously flat at 17 minutes while the baseline in the peak varies significantly corresponding to the percentile used. This means that the increase in travel time during the off-peak is not sensitive to the percentile used in baseline travel until extended beyond the 75^{th} percentile.

In conducting the means analysis, the 25^{th} percentile was used as the baseline travel time. The minimum precipitation value used to represent wet pavement was an estimate of 0.01 inches per radar volume. The 25^{th} percentile travel time during the peak period, averaged across the 33 roadway segments was 19.4 minutes whereas the average travel time across precipitation observations of 0.01 inches or greater was 23.4 minutes. This constitutes a four-minute delay, or *a 24% increase in travel time when precipitation was present*. The 25^{th} percentile travel time during the off-peak period was 16.8 minutes, whereas the average travel time across precipitation observations of 0.01 inches or greater was 17.4 minutes, or *a 3.5% increase in travel time when precipitation was present*. If this was applied to the 50^{th} percentile, then the travel time increases were 10.7% and 3.4% for the peak and off-peak, respectively. At the 50^{th} percentile, there would be a significant likelihood that some events such as small incidents or low visibility are incorporated into the baseline travel time.

When a higher cutoff for precipitation (0.03 inches per volume) was selected, the increase in travel time did not change substantially. During the peak, travel time increased to 25%, while the off-peak travel time increased by 3.7%.

5. CONCLUSIONS

5.1 *Implication of Analyses*

The average impact of precipitation on peak-period traffic is at least an 11% increase in travel time. It is very likely that the impact is much closer to 25% based on the means analysis. Regression analyses suggest that during the off-peak periods, travel time increases by approximately 13% due to an array of weather attributes including visibility, wind, and precipitation. The means analysis, measuring the impact of only precipitation, suggests that during the off-peak periods, precipitation causes a 3.5% increase in travel time. This estimate is likely to be lower than reality, however, due to data the limitations discussed previously.

5*.2 Next Steps*

A next step in utilizing these data sets is to generate regression models with binary variables (variables that contain only two values). Such models could be used to quantify the relative impact of specific weather phenomena on delay. These values can also be useful to the traffic management community in predicting increases in travel time when various weather phenomena are forecasted. However, before such analyses are approached, an accurate travel time data source is needed. Another avenue of study is to evaluate the relative impacts of weather and incident/congestion variables. For such analyses, however, one would require data sets on incidents and traffic demand that can be merged with the existing weather and travel time data sets.

Appendix A – Additional Figures

Figure A1 – Regional Map showing the three Airports used in the analysis and the Travel Network Domain (inside the red block)

Figure A2 – Comparison of Radar Estimated Rainfall to ASOS Hourly Accumulation at DCA

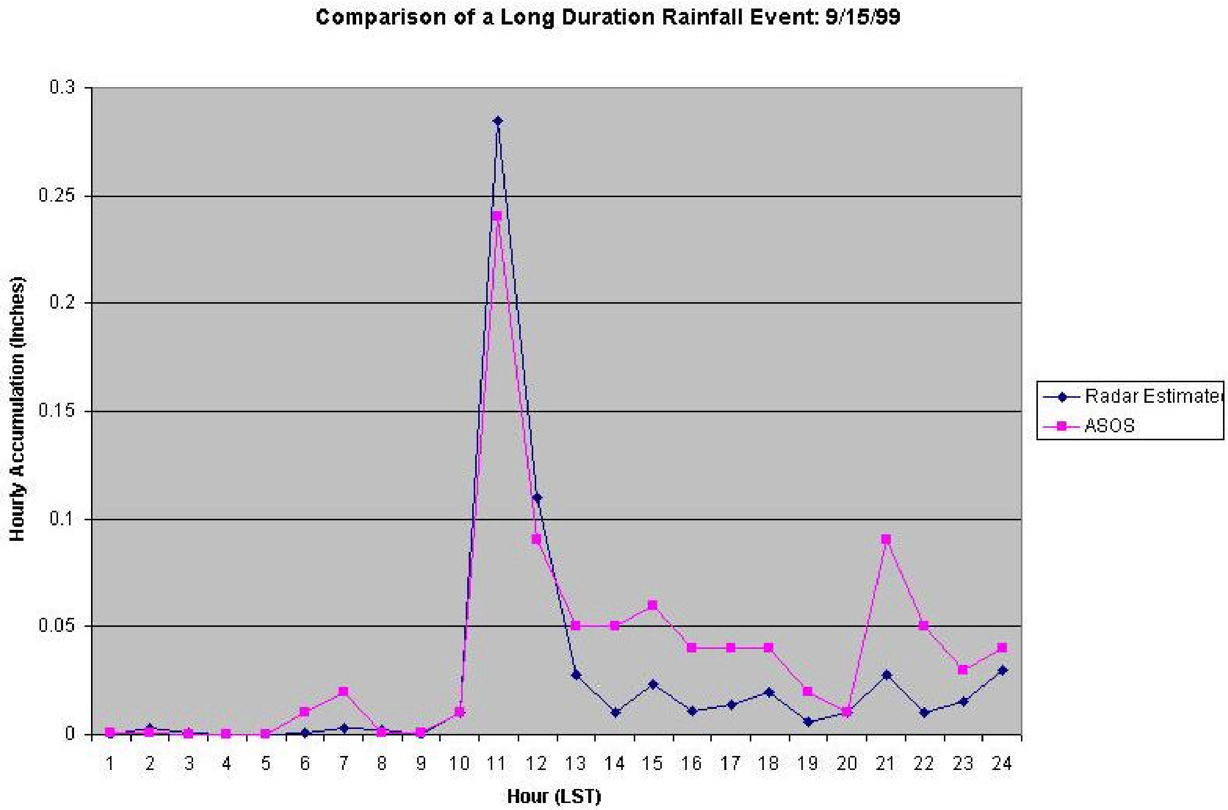


Figure A3 – Comparison of Radar Estimated Liquid Equivalent to ASOS Liquid Equivalent at DCA

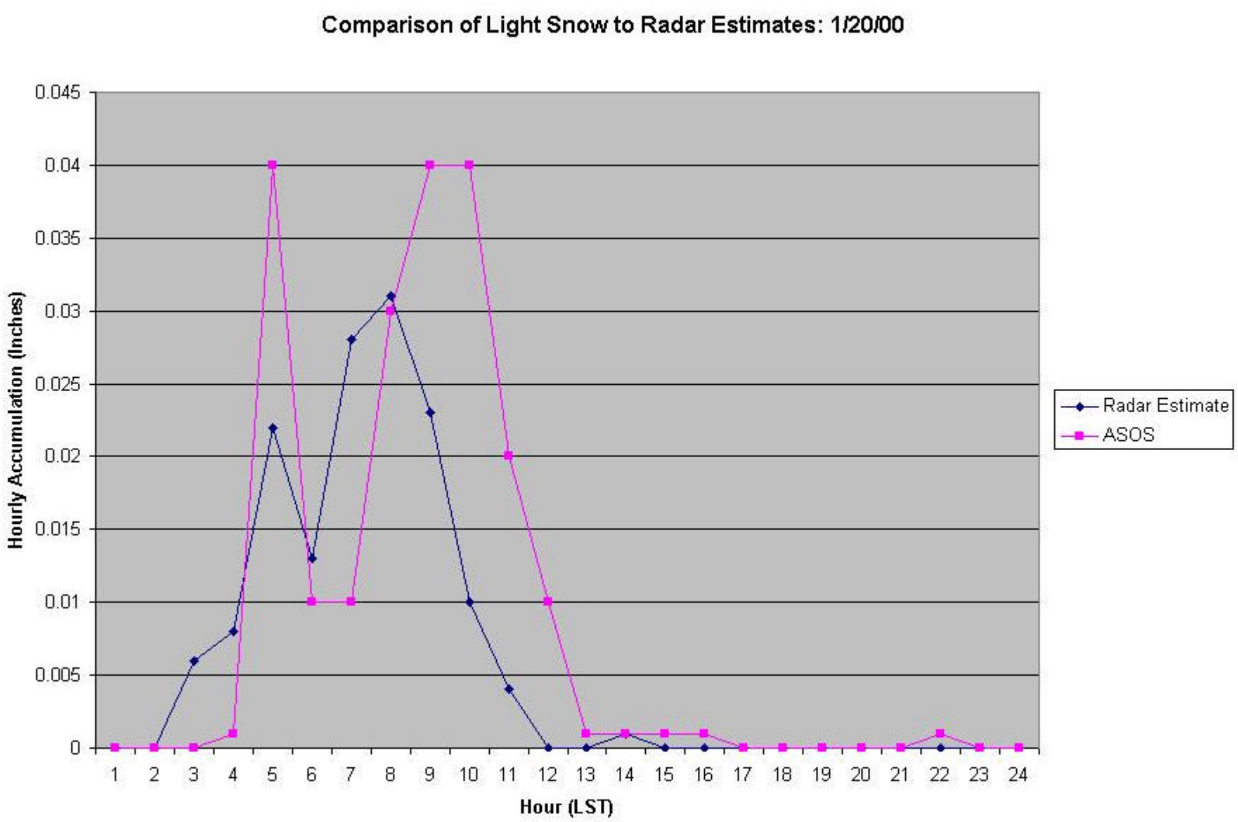


Figure A4 – Image of the Program Created to Process all of the Radar Data into Per Volume Rainfall Totals.

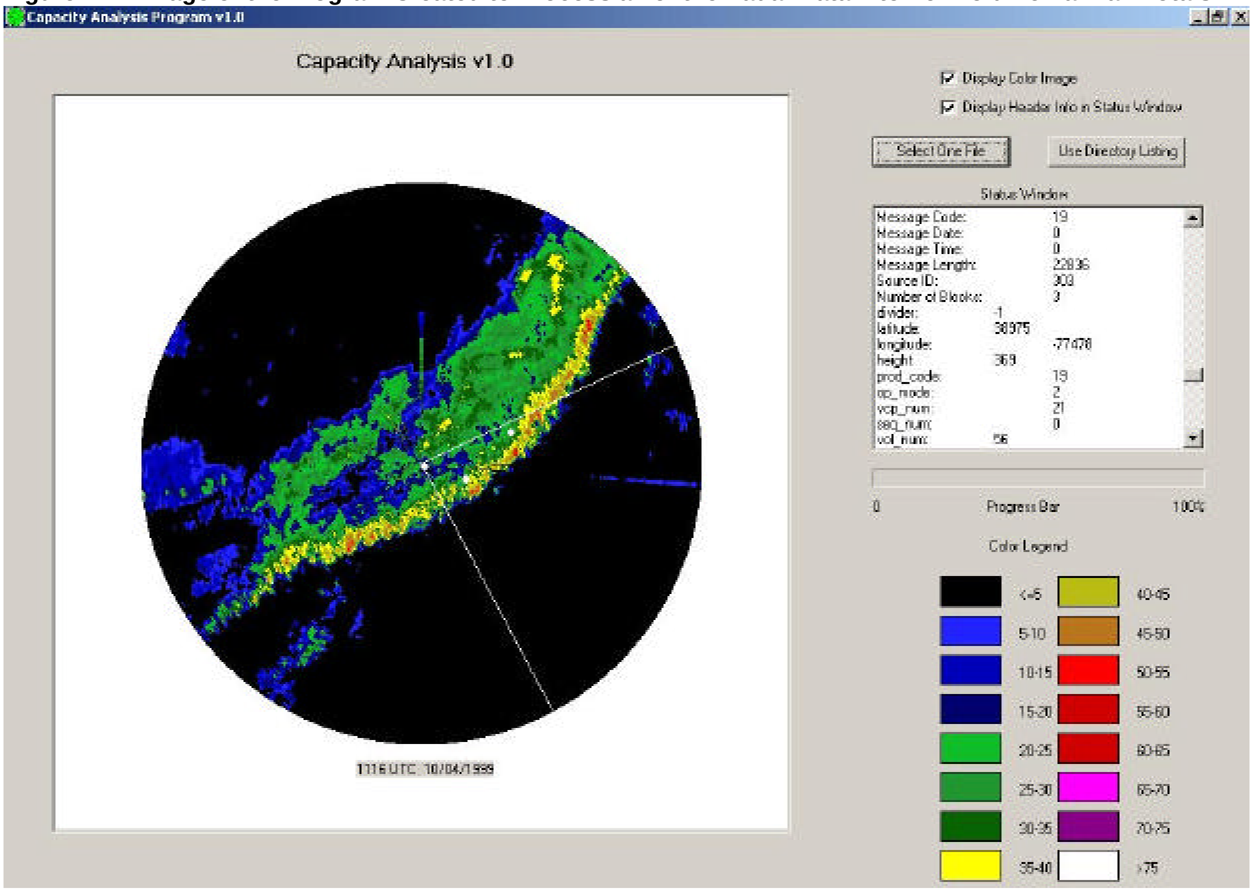


Figure A5 - Process for Combining Precipitation and Travel Time Data

PRECIPITATION DATA

Time	Precipitation
6:32 AM	0.0000
6:38 AM	0.0050
6:44 AM	0.0100

+

TRAVE TIME DATA

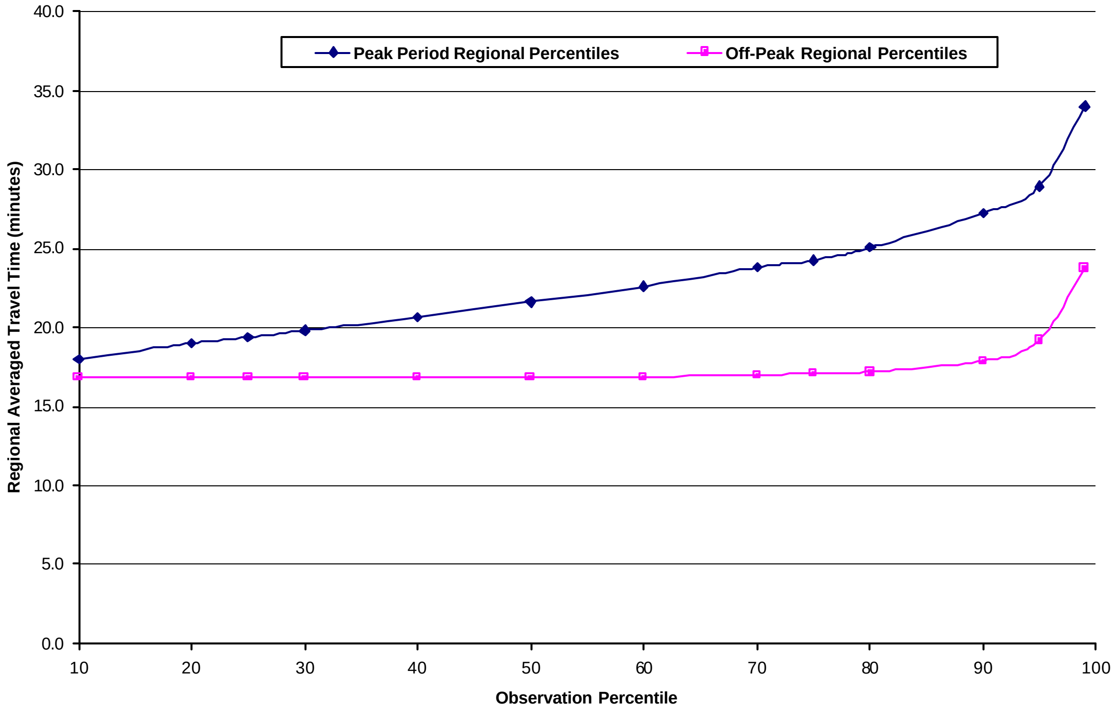
Time	Travel Time
6:30 AM	22 min.
6:35 AM	22 min.
6:40 AM	28 min.
6:45 AM	28 min.

=

COMBINED DATA WITH LINEAR INTERPOLATION

Time	Travel Time	Precipitation
6:30 AM	22 min.	0.0000
6:35 AM	22 min.	0.0025
6:40 AM	28 min.	0.0050
6:45 AM	28 min.	0.0100

Figure A6 - Travel Time by Percentile Observation



Appendix B – Additional Tables

Table B1 – Description of Roadway Segments in the Washington DC Metropolitan Area Network

Road Number	Road (SmarTraveler) Description	Length (miles)	Road Type
1	I-95/I-495 in MD btwn. Woodrow Wilson Bridge & College Park	25.0	Freeway
2	I-495 in MD between US 1 & the American Legion Bridge	17.4	Freeway
3	I-495 in VA between the American Legion Bridge & US 50	8.3	Freeway
4	I-95/I-495 in VA between US 50 & the Woodrow Wilson Bridge	13.2	Freeway
5	I-295 in MD between Laurel & East Capitol St. NE	10.9	Freeway
6	Suitland Pkwy. in MD between MD 4 & the Douglass Bridge	10.7	Freeway
7	G. W. Pkwy. in VA within I-495 (N. of DC and S. of DC)	16.5	Freeway
8	Clara Barton Pkwy. between I-495 & the Roosevelt Bridge	8.6	Freeway
9	MD 5/Branch Ave. in MD between US 301 & the DC Line	12.8	Arterial
10	MD 4 in MD between US 301 & the DC Line	12.6	Arterial
11	US 50 in MD between Bowie & Kenilworth Ave.	11.1	Freeway
12	US 1 in MD between MD 212 & the DC Line	8.0	Arterial
13	I-95 in MD between Laurel & I-495	6.1	Freeway
14	US 29 in MD between Cherry Hill Rd. & the DC Line	6.9	Arterial
15	MD 97 between Wheaton & the DC Line	4.8	Arterial
16	MD 355 between Gude Drive & the DC Line	12.0	Arterial
17	I-270 between Gaithersburg & I-495	9.1	Freeway
18	MD 214 between MD 202 & the DC Line	4.7	Arterial
19	MD 650 between I-495 & the DC Line	4.1	Arterial
20	MD 185 between I-495 & the DC Line	2.6	Arterial
21	VA 267 between Dulles Airport & I-66	14.4	Freeway
22	US 50 in VA between the VA 7100 & I-495	9.7	Arterial
23	US 50 in VA between I-495 & the Arlington Memorial Bridge	9.3	Arterial
24	I-66 between Centreville & I-495	12.5	Freeway
25	I-66 between I-495 & the Roosevelt Bridge	9.9	Freeway
26	I-95 between Dale City & I-495	14.0	Freeway
27	I-395 between I-495 & the Potomac River	9.5	Freeway
28	US 1 in VA between Kings Highway & the 14th St. Bridge	5.6	Arterial
29	VA 236 between I-495 & the King St. Metro	9.3	Arterial
30	VA 620 between the VA 7100 & I-495	8.9	Arterial
31	I-295 between I-495 & East Capitol St.	10.3	Freeway
32	MD 210 between Berry Road & the DC Line	8.4	Arterial
33	VA 7100 between Springfield Metro Station & VA 267	23.8	Freeway

Table B2 – Decision Scheme for the Determination of Pavement Condition Using Surface Observational Data
(In each case, road conditions were assumed to be **dry** (category 0) unless conditions met one of the algorithm requirements.)

<table>
<tr><td colspan="2">For a roadway to be classified as "wet" (category 1), a total of 16 different algorithms were used. The algorithms looked at different scenarios, such as:</td></tr>
<tr><td></td><td>1). If it is currently raining, then
- There must be either measurable rainfall in the gage or visibilities must be reduced enough to imply accumulating rain (this avoids indicating a wet roadway with isolated trace events).
- If the current rain only produced a trace accumulation, then we can look at the previous hour to see if measurable rain occurred. If it did and the temperature wasn't too hot (for evaporation) and clouds were thick enough then the roads were indicated to be wet.</td></tr>
<tr><td></td><td>2). If there has only been drizzle with trace amounts of precipitation, then depending on day or night conditions, the roads could be wet. Examples include:
- If it has been cloudy and drizzly, and it is night time, then look back 2 to 4 hours and determine if there has been measurable rainfall.
- If it is during the day, then the previous 2 to 4 hour rainfall must have accumulated enough to keep roads wet. In this case visibility and humidity come into play.</td></tr>
<tr><td></td><td>3). If moderate to heavy rain occurred within the last 4 hours (but not within 2 hours), then
- If it is at night, there must be light winds and high humidity for wet roads, or
- If it is during the day, it must be cloudy with high humidity and temperatures below 85 degrees.</td></tr>
<tr><td></td><td>4). If it rained in the last 3 to 6 hours (above a minimum threshold) and it is at night with high humidity and cool temperatures, then roads are wet.</td></tr>
<tr><td></td><td>5). To cover persistence situations, if there is a long duration period of cloudy and cool weather with high humidity and drizzle, then roads can be wet.</td></tr>
<tr><td></td><td>The bottom line with the wet roadway scenario is that any sun during the day with moderate humidity and winds can lead to high evaporation rates during warm weather. Minimum accumulation thresholds were lowered as the temperature lowered.</td></tr>
<tr><td></td><td>A wet roadway "lag" was built in to the algorithm to allow roads to be "wet" for a time after the end of rain events. The duration of the lag was determined by time of day and accumulated rainfall.</td></tr>
<tr><td colspan="2">For a roadway to be classified as "snowy" (category 2), 14 algorithms were used. Similar to the wet roadway category, time of day and surface temperature played a big part in the final determination. However, because ASOS has such a hard time quantifying hourly liquid equivalent precipitation, some algorithms used visibility as a predictor of accumulating snow. Some examples of the algorithm classes include:</td></tr>
<tr><td></td><td>1). The most straightforward situation occurs when the air temperature is below freezing and measurable snow has been reported during the hour (either by rain gage liquid equivalent or low visibility).</td></tr>
<tr><td></td><td>2). If it is night time and air temperatures fall between 32 and 36 degrees, then there must be a stronger correlation between hourly snow accumulation and lowered visibility.</td></tr>
<tr><td></td><td>3). If it is during the day, then if the air temperature is at or below freezing and it is cloudy and there is measurable snow, then the roads are snowy.</td></tr>
<tr><td></td><td>4). However, if it is during the day and air temperatures are between 32 and 36 degrees, then moderate or greater snow intensity must occur.</td></tr>
<tr><td></td><td>5). If it is not currently snowing, but it snowed within the last 2 hours, then different weights are placed on the time of day, amount of cloud cover, air temperature and hourly accumulated snowfall.</td></tr>
<tr><td></td><td>6). Persistence is built in to the algorithms so that multiple hours of very light snow could return a positive snow indication as long as cloud cover, temperature and time of day met specifications.</td></tr>
<tr><td></td><td>The snow "lag" time was longer for heavy events or nighttime snowfalls.</td></tr>
<tr><td colspan="2">For the roads to be classified as "icy" (also category 2), then a series of 10 algorithms was used. These algorithms were separated from the snow routines because ice has different properties than snow. For example, technically you can have snow with air temperatures above freezing. However, freezing rain is not supposed to happen with temperatures above freezing (however sleet can be). For this category, freezing rain and sleet were the main hydrometeors. Examples of the algorithms included:</td></tr>
<tr><td></td><td>1). If it is currently icing (freezing rain or sleet) and there has been a measurable accumulation and the temperature is at or below freezing, the roads are icy.</td></tr>
<tr><td></td><td>2). If it is nighttime and air temperatures are between 32 and 36 degrees, then if measurable sleet occurs, roads are icy.</td></tr>
<tr><td></td><td>3). However, if it is daytime with above freezing temperatures, then the sleet must be occurring with at least a moderate intensity.</td></tr>
<tr><td></td><td>4). If it is not currently icing, but it was during the last 2 hours, then if it is nighttime with freezing temperatures, then roads are still icy.</td></tr>
<tr><td></td><td>5). However, if it is during the day with temperatures above freezing, then clouds must remain cloudy with high humidity and liquid equivalent accumulations of sleet must meet minimum thresholds.</td></tr>
</table>

	6). Icing algorithms look back for 4 hours to determine if temperatures, cloud cover and accumulations warrant an ice lag.
For roads to be classified as "**black ice**" (category 3), then one algorithm was used based on the following premise:	
	- If it is nighttime or dawn and skies have cleared during the overnight (CLR or FEW) - Surface winds must be light (<5 mph) - Air temperatures must start out above freezing then fall to near freezing (<=35 by dawn). This temperature was used since the ASOS temperature instrument is in the air and there may be a significant lapse rate to the ground. - Dew points must rise to near freezing, or fog form These conditions would indicate the potential for black ice.

Table B3 - Average Two-Hour Low (Off-Peak) Time of Day and Travel Time

ROAD NO.	NORTH/EAST DIRECTION		SOUTH/WEST DIRECTION	
	2-Hour Off-Peak	Average Travel Time in minutes	2-Hour Off-Peak	Average Travel Time in minutes
1	12:15 PM - 2:10 PM	28.8	12:50 PM - 2:45 PM	30.4
2	9:30 AM - 11:25 AM	22.1	12:40 PM - 2:35 PM	22.4
3	11:25 AM - 1:20 PM	9.3	12:45 PM - 2:40 PM	9.3
4	11:15 AM - 1:10 PM	18.0	10:35 AM - 12:30 PM	17.8
5	7:50 AM - 9:45 AM	15.7	12:35 PM - 2:30 PM	16.3
6	10:00 AM - 11:55 AM	15.2	10:25 AM - 12:20 PM	15.5
7	11:15 AM - 1:10 PM	28.7	1:20 PM - 3:15 PM	29.3
8	7:55 AM - 9:50 AM	14.2	11:25 AM - 1:20 PM	14.6
9	10:05 AM - 12:00 PM	19.3	11:45 AM - 1:40 PM	19.2
10	10:05 AM - 12:00 PM	22.2	12:50 PM - 2:45 PM	22.2
11	9:20 AM - 11:15 AM	13.2	11:05 AM - 1:00 PM	13.2
12	9:40 AM - 11:35 AM	24.2	10:10 AM - 12:05 PM	24.2
13	12:00 PM - 1:55 PM	6.1	12:45 PM - 2:40 PM	6.2
14	1:45 PM - 3:40 PM	14.2	11:00 AM - 12:55 PM	14.3
15	10:05 AM - 12:00 PM	13.2	10:20 AM - 12:15 PM	13.3
16	9:40 AM - 11:35 AM	35.7	1:25 PM - 3:20 PM	35.6
17	9:50 AM - 11:45 AM	13.2	10:50 AM - 12:45 PM	13.3
18	10:00 AM - 11:55 AM	10.2	10:05 AM - 12:00 PM	10.2
19	10:05 AM - 12:00 PM	8.3	10:20 AM - 12:15 PM	8.3
20	9:45 AM - 11:40 AM	10.1	11:25 AM - 1:20 PM	10.1
21	1:00 PM - 2:55 PM	15.3	12:55 PM - 2:50 PM	15.3
22	12:50 PM - 2:45 PM	18.3	10:20 AM - 12:15 PM	18.2
23	11:25 AM - 1:20 PM	18.3	1:00 PM - 2:55 PM	18.2
24	1:45 PM - 3:40 PM	14.7	10:55 AM - 12:50 PM	14.5
25	1:20 PM - 3:15 PM	12.6	10:40 AM - 12:35 PM	12.4
26	12:05 PM - 2:00 PM	17.5	7:35 AM - 9:30 AM	20.0
27	11:35 AM - 1:30 PM	10.5	11:40 AM - 1:35 PM	10.4
28	12:05 PM - 2:00 PM	15.4	11:20 AM - 1:15 PM	15.3
29	1:40 PM - 3:35 PM	20.1	1:25 PM - 3:20 PM	20.1
30	10:40 AM - 12:35 PM	20.3	10:35 AM - 12:30 PM	20.2
31	12:00 PM - 1:55 PM	15.5	10:35 AM - 12:30 PM	15.4
32	10:35 AM - 12:30 PM	19.2	9:30 AM - 11:25 AM	19.1
33	10:25 AM - 12:20 PM	29.6	12:00 PM - 1:55 PM	29.5

Table B4 - Average Two-Hour High (Peak) Time of Day and Travel Time

ROAD NO.	NORTH/EAST DIRECTION		SOUTH/WEST DIRECTION	
	2-Hour Peak	Average Travel Time in minutes	2-Hour Peak	Average Travel Time in minutes
1	4:05 PM - 6:00 PM	35.9	7:15 AM - 9:10 AM	45.4
2	4:30 PM - 6:25 PM	35.7	7:25 AM - 9:20 AM	31.5
3	4:30 PM - 6:25 PM	12.8	4:30 PM - 6:25 PM	13.8
4	4:30 PM - 6:25 PM	25.6	7:50 AM - 9:45 AM	23.8
5	4:30 PM - 6:25 PM	23.5	7:15 AM - 9:10 AM	21.4
6	4:30 PM - 6:25 PM	20.8	7:15 AM - 9:10 AM	20.6
7	7:25 AM - 9:20 AM	40.4	7:15 AM - 9:10 AM	38.9
8	4:30 PM - 6:25 PM	17.4	7:20 AM - 9:15 AM	19.3
9	7:05 AM - 9:00 AM	25.3	4:05 PM - 6:00 PM	24.3
10	6:50 AM - 8:45 AM	27.8	4:30 PM - 6:25 PM	27.4
11	4:30 PM - 6:25 PM	18.1	7:10 AM - 9:05 AM	19.7
12	4:15 PM - 6:10 PM	29.8	7:35 AM - 9:30 AM	29.3
13	4:10 PM - 6:05 PM	8.7	7:20 AM - 9:15 AM	8.5
14	4:10 PM - 6:05 PM	18.1	7:20 AM - 9:15 AM	20.3
15	4:30 PM - 6:25 PM	15.9	7:30 AM - 9:25 AM	16.4
16	4:30 PM - 6:25 PM	42.3	7:25 AM - 9:20 AM	45.0
17	4:30 PM - 6:25 PM	18.9	7:05 AM - 9:00 AM	17.9
18	4:05 PM - 6:00 PM	12.8	7:05 AM - 9:00 AM	13.0
19	4:05 PM - 6:00 PM	12.2	7:10 AM - 9:05 AM	10.3
20	4:10 PM - 6:05 PM	13.3	7:25 AM - 9:20 AM	13.6
21	7:15 AM - 9:10 AM	21.3	4:05 PM - 6:00 PM	18.8
22	7:10 AM - 9:05 AM	24.7	4:30 PM - 6:25 PM	22.1
23	7:20 AM - 9:15 AM	24.6	4:30 PM - 6:25 PM	22.4
24	7:25 AM - 9:20 AM	24.2	4:30 PM - 6:25 PM	21.6
25	4:30 PM - 6:25 PM	18.2	3:25 PM - 5:20 PM	16.1
26	7:00 AM - 8:55 AM	25.4	4:30 PM - 6:25 PM	26.2
27	7:25 AM - 9:20 AM	19.0	4:30 PM - 6:25 PM	17.5
28	7:25 AM - 9:20 AM	21.6	4:25 PM - 6:20 PM	21.3
29	7:05 AM - 9:00 AM	23.6	4:30 PM - 6:25 PM	20.6
30	7:10 AM - 9:05 AM	27.6	4:30 PM - 6:25 PM	26.0
31	7:05 AM - 9:00 AM	20.8	7:10 AM - 9:05 AM	20.8
32	7:15 AM - 9:10 AM	24.7	4:30 PM - 6:25 PM	23.4
33	7:15 AM - 9:10 AM	39.0	7:10 AM - 9:05 AM	37.2

Table B5. Regression Model and R^2 Values for North/East Road Directions

Road	R^2-Value	Reduced Model Equation (TT = travel time in minutes) for North/East Direction
1	0.20	TT = 28.45 +1.61x IADpcon^2 +1.17x DCApcon^2
2	0.05	TT = 21.83 +1.41x DCApcon^2 +0.86 xIADprecip^2
3	0.34	TT = 8.98 +1.30x DCApcon^2 +0.51 xIADpcon^2 + 0.28x BWIpcon^2
4	0.14	TT = 17.7 +1.75x DCApcon^2 +0.43 xIADpcon^2 + 9.30x BWIvis
5	0.08	TT = 15.57 +0.36x IADprecip^2 +0.34 xBWIpcon^2 + 0.18x DCApcon^2
6	0.10	TT = 15.08 +0.70x DCApcon^2 +0.25 xIADpcon^2
7	0.27	TT = 28.3 +1.45x DCApcon^2 +0.70 xBWIpcon^2 + 0.56x IADpcon^2
8	0.23	TT = 14.04 +0.45x IADprecip^2 +0.31 xBWIpcon^2 + 0.12x DCApcon^2
9	0.22	TT = 19.03 +0.99x DCApcon^2 +0.66 xIADpcon^2 + 0.79x BWIvis
10	0.23	TT = 21.97 +0.82x DCApcon^2 +0.47 xIADpcon^2 + 0.32x BWIpcon^2
11	0.15	TT = 12.99 +0.82x DCApcon^2 +0.17 xIADpcon^2 + 0.10x BWIpcon^2
12	0.20	TT = 23.99 +0.85x DCApcon^2 +0.25 xIADpcon^2 + 0.09x BWIpcon^2
13	0.24	TT = 5.94 +0.82x DCApcon^2 +0.51 xIADpcon^2 + 0.10x BWIpcon^2
14	0.38	TT = 13.93 +1.84x BWIprecip^2 +0.42 xIADpcon^2 +12.11x BWIvis + 0.18 x DCApcon^2
15	0.15	TT = 13.02 +0.70x DCApcon^2 +0.27 xIADpcon^2
16	0.16	TT = 35.22 +1.99x DCApcon^2 +0.69 xIADpcon^2
17	0.18	TT = 12.92 +1.06x DCApcon^2 +0.40 xIADpcon^2
18	0.14	TT = 9.97 +0.91x DCApcon^2 +0.34 xIADpcon^2
19	0.19	TT = 8.06 +0.91x DCApcon^2 +0.40 xIADpcon^2 + 0.12x BWIpcon^2
20	0.11	TT = 10.01 +0.48x DCApcon^2 +0.17 xIADpcon^2
21	0.27	TT = 14.94 +0.96x DCApcon^2 +1.12 xIADpcon^2 + 0.54x BWIpcon^2
22	0.33	TT = 17.85 +1.07x DCApcon^2 +1.22 xIADpcon^2 + 0.61x BWIpcon^2
23	0.26	TT = 18.02 +1.11x DCApcon^2 +0.31 xIADpcon^2 + 0.28x BWIpcon^2
24	0.26	TT = 14.39 +2.30x BWIprecip^2 +12.64 xBWIvis + 0.32x DCApcon^2
25	0.28	TT = 12.16 +1.44x BWIprecip^2 +0.88 xIADpcon^2 + 0.86x DCApcon^2 + 2.69 x IADwind
26	0.13	TT = 17.01 +2.08x DCApcon^2 +1.32 xIADpcon^2
27	0.18	TT = 10.23 +1.01x DCApcon^2 +0.33 xIADpcon^2 + 0.26x BWIpcon^2
28	0.38	TT = 14.89 +1.84x DCApcon^2 +1.15 xIADpcon^2 + 0.18x BWIpcon^2
29	0.36	TT = 19.91 +1.16x BWIprecip^2 +0.34 xIADpcon^2 + 8.73x BWIvis + 0.15 x DCApcon^2
30	0.30	TT = 19.94 +0.98x DCApcon^2 +0.55 xIADpcon^2 + 0.48x BWIpcon^2
31	0.26	TT = 15.21 +1.31x DCApcon^2 +0.63 xIADpcon^2 + 0.26x BWIpcon^2
32	0.28	TT = 18.93 +1.18x DCApcon^2 +0.81 xIADpcon^2
33	0.22	TT = 29.17 +1.58x DCApcon^2 +0.80 xIADpcon^2 + 0.50x BWIpcon^2

Table B6. Regression Model and R^2 Values for South/West Road Directions

Road	R^2-Value	Reduced Model Equation (TT = travel time in minutes) for South/West Direction
1	0.06	$TT = 30.01 + 1.56 \times IADpcon^2 + 1.50 \times DCApcon^2$
2	0.05	$TT = 22.06 + 1.31 \times IADpcon^2 + 0.82 \times DCApcon^2$
3	0.30	$TT = 9.02 + 0.94 \times DCApcon^2 + 1.00 \times IADpcon^2 + 0.28 \times BWIpcon^2$
4	0.09	$TT = 17.52 + 1.10 \times DCApcon^2 + 0.43 \times IADpcon^2$
5	0.34	$TT = 15.91 + 1.23 \times DCApcon^2 + 1.05 \times IADpcon^2 + 3.43 \times DCAwind + 0.28 \times BWIpcon^2$
6	0.16	$TT = 15.24 + 0.93 \times DCApcon^2 + 0.40 \times IADpcon^2 + 0.35 \times BWIpcon^2$
7	0.20	$TT = 29.05 + 0.42 \times DCApcon^2 + 0.57 \times IADpcon^2 + 0.42 \times BWIpcon^2 + 0.39 \times BWIprecip^2$
8	0.23	$TT = 14.22 + 1.33 \times DCApcon^2 + 0.39 \times IADpcon^2 + 0.41 \times BWIpcon^2 + 3.49 \times BWIwind$
9	0.34	$TT = 18.92 + 1.33 \times DCApcon^2 + 0.71 \times IADpcon^2$
10	0.30	$TT = 21.91 + 0.64 \times DCApcon^2 + 0.99 \times IADpcon^2 + 0.40 \times BWIpcon^2$
11	0.19	$TT = 12.97 + 0.75 \times DCApcon^2 + 0.39 \times IADpcon^2 + 0.22 \times BWIpcon^2$
12	0.26	$TT = 23.94 + 0.65 \times DCApcon^2 + 0.43 \times IADpcon^2 + 0.31 \times BWIpcon^2$
13	0.24	$TT = 5.98 + 0.54 \times DCApcon^2 + 0.66 \times IADpcon^2 + 0.18 \times BWIpcon^2 + 1.02 \times BWIwind$
14	0.30	$TT = 13.88 + 1.39 \times DCApcon^2 + 0.64 \times IADpcon^2 + 0.37 \times BWIpcon^2$
15	0.17	$TT = 13.04 + 0.78 \times DCApcon^2 + 0.36 \times IADpcon^2 + 0.20 \times BWIpcon^2$
16	0.32	$TT = 34.99 + 2.70 \times BWIprecip^2 + 1.29 \times IADpcon^2 + 0.51 \times DCApcon^2$
17	0.24	$TT = 12.95 + 1.24 \times DCApcon^2 + 0.49 \times IADpcon^2 + 0.33 \times BWIpcon^2$
18	0.13	$TT = 10.02 + 0.76 \times DCApcon^2 + 0.36 \times IADpcon^2 + 0.18 \times BWIpcon^2$
19	0.23	$TT = 8.06 + 0.89 \times DCApcon^2 + 0.54 \times IADpcon^2 + 0.23 \times BWIpcon^2 + 0.95 \times BWIwind$
20	0.35	$TT = 9.95 + 0.69 \times DCApcon^2 + 0.33 \times IADpcon^2 + 0.22 \times BWIpcon^2$
21	0.37	$TT = 14.83 + 1.22 \times DCApcon^2 + 1.25 \times IADpcon^2 + 0.58 \times BWIpcon^2$
22	0.27	$TT = 17.90 + 1.15 \times DCApcon^2 + 0.68 \times IADpcon^2 + 0.31 \times BWIpcon^2$
23	0.31	$TT = 17.95 + 0.82 \times DCApcon^2 + 0.73 \times IADpcon^2 + 0.39 \times BWIpcon^2$
24	0.26	$TT = 14.06 + 0.98 \times IADpcon^2 + 1.06 \times DCApcon^2 + 0.74 \times BWIpcon^2$
25	0.21	$TT = 12.04 + 1.17 \times DCApcon^2 + 0.61 \times IADpcon^2 + 0.25 \times BWIpcon^2$
26	0.01	$TT = 19.74 + 1.43 \times BWIprecip^2 + 5.40 \times BWIvis$
27	0.24	$TT = 10.12 + 1.16 \times DCApcon^2 + 0.44 \times IADpcon^2 + 0.10 \times BWIpcon^2$
28	0.36	$TT = 14.87 + 1.87 \times DCApcon^2 + 0.70 \times IADpcon^2 + 0.28 \times BWIpcon^2$
29	0.31	$TT = 19.89 + 0.96 \times BWIprecip^2 + 0.57 \times IADpcon^2 + 0.18 \times BWIpcon^2 + 0.11 \times DCApcon^2$
30	0.30	$TT = 19.90 + 1.08 \times DCApcon^2 + 0.54 \times IADpcon^2 + 0.26 \times BWIpcon^2$
31	0.14	$TT = 15.18 + 0.84 \times DCApcon^2 + 0.34 \times IADpcon^2 + 0.13 \times BWIpcon^2$
32	0.23	$TT = 18.88 + 1.15 \times DCApcon^2 + 0.40 \times IADpcon^2$
33	0.37	$TT = 28.90 + 2.27 \times DCApcon^2 + 1.47 \times IADpcon^2 + 0.45 \times BWIpcon^2$

Table B7 – Example of an Intermediate Output File for Segment 1. The Average Reflectivity Values for the primary and secondary regions have DBZ units. Radar estimated precipitation values are located under "Main" and "2ndry" columns. Final reported liquid equivalent estimates are reported under the "final pcpn" column.

Segment 1

MO	DY	YEAR	Time UTC	Main DBZ	2nd DBZ	Main pcpn	2ndry pcpn	total pcpn	final pcpn
09	04	1999	1846	13.1	12.0	0.000	0.000	0.000	0.000
09	04	1999	1851	16.4	16.0	0.001	0.001	0.001	0.001
09	04	1999	1857	19.1	19.0	0.002	0.002	0.002	0.002
09	04	1999	1902	24.2	25.0	0.004	0.005	0.004	0.004
09	04	1999	1922	30.3	32.0	0.013	0.018	0.014	0.014
09	04	1999	1928	32.4	33.0	0.020	0.022	0.020	0.020
09	04	1999	1933	31.2	32.0	0.016	0.018	0.016	0.016
09	04	1999	2003	27.5	29.0	0.008	0.010	0.008	0.008
09	04	1999	2014	32.8	34.0	0.022	0.027	0.023	0.023
09	04	1999	2024	33.6	36.0	0.025	0.040	0.028	0.028
09	04	1999	2029	34.1	35.0	0.028	0.033	0.029	0.029
09	05	1999	0320	1.9	1.0	0.000	0.000	0.000	0.000
09	05	1999	0325	0.0	0.0	0.000	0.000	0.000	0.000

Table B8 – Example of a Final Output File for Segment 1. UTC times have been converted to Local Time. Actual values are tagged with "A", Interpolated values are tagged with "I".

Segment 1

MO	DY	YEAR	TIME	ZONE	PCPN	I
09	04	1999	1446	EDT	0.000	A
09	04	1999	1451	EDT	0.001	A
09	04	1999	1457	EDT	0.002	A
09	04	1999	1502	EDT	0.004	A
09	04	1999	1508	EDT	0.007	I
09	04	1999	1514	EDT	0.011	I
09	04	1999	1522	EDT	0.014	A
09	04	1999	1528	EDT	0.020	A
09	04	1999	1533	EDT	0.016	A
09	04	1999	1603	EDT	0.008	A
09	04	1999	1608	EDT	0.015	I
09	04	1999	1614	EDT	0.023	A
09	04	1999	1619	EDT	0.025	I
09	04	1999	1624	EDT	0.028	A
09	04	1999	1629	EDT	0.029	A
09	04	1999	2320	EDT	0.000	A