Calibration of Traffic Flow Models Under Adverse Weather and Application in Mesoscopic Network Simulation

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The weather-sensitive traffic estimation and prediction system (TrEPS) aims for accurate estimation and prediction of the traffic states under inclement weather conditions. Successful application of weather-sensitive TrEPS requires detailed calibration of weather effects on the traffic flow model. In this study, systematic procedures for the entire calibration process were developed, from data collection through model parameter estimation to model validation. After the development of the procedures, a dual-regime modified Greenshields model and weather adjustment factors were calibrated for four metropolitan areas across the United States (Irvine, California; Chicago, Illinois; Salt Lake City, Utah; and Baltimore, Maryland) by using freeway loop detector traffic data and weather data from automated surface-observing systems stations. Observations showed that visibility and precipitation (rain–snow) intensity have significant impacts on the value of some parameters of the traffic flow models, such as free-flow speed and maximum flow rate, while these impacts can be included in weather adjustment factors. The calibrated models were used as input in a weather-integrated simulation system for dynamic traffic assignment. The results show that the calibrated models are capable of capturing the weather effects on traffic flow more realistically than TrEPS without weather integration.

Driving behaviors and the resulting traffic flow characteristics during inclement weather are different from those observed during so-called normal conditions. On the basis of type (rain, snow, frog, wind, etc.), duration, and intensity of the weather, its impact on the performance of traffic networks may vary under different scenarios.

Maze et al. identified three predominant categories of variables that are affected by inclement weather: traffic safety, traffic flow relationships, and traffic demand (*1*). Andrey et al. found that, in Canadian cities, collision rates increase during precipitation by 50% to 100% relative to normal seasonal conditions (*2*). Similar findings are presented in the literature for cities in the United States (*3, 4*) and indicate that the duration and intensity of rainfall and snowfall have a positive and statistically significant relationship on the number of crashes. Maze et al. studied the freeway system in the Minneapolis–Saint Paul, Minnesota, metropolitan area and showed that adverse weather causes clear reductions in traffic speed: up to 6% for rain, 13% for snow, and 12% for reduced visibility (*1*). Ibrahim and Hall (*5*) analyzed the effects of adverse weather on the speed–flow and flow–occupancy relationships for Canadian travelers and found the effects of snow to be much larger than those of rain and to cause a reduction in free-flow speed of 38 to 50 km/h. The effects of weather on traffic volume are also evident from empirical data. The research conducted by Datla and Sharma indicates that the impact of cold and snow on traffic volume varies with the type of trip and hour of the day (*6*). From traffic data collected in Canada, they observed that commute trips experience the lowest reductions in volume because of snowy weather, of up to 14%, while recreational trips experience the highest reductions, of up to 31%. They also found that reductions in commute trips during off-peak hours (–10% to –15%) were generally greater than those during peak hours (–6% to –10%); however, an opposite pattern was observed for recreational trips. All these studies show that inclement weather may have a significant and comprehensive impact on the transportation system that cannot be ignored by planners and decision makers.

To mitigate the impacts of adverse weather on highway travel, the FHWA Road Weather Management Program has been involved in research, development, and deployment of strategies and tools for weather-responsive traffic management. In a project completed in 2006, the Road Weather Management Program used data from Seattle, Washington; Minneapolis, Minnesota; and Baltimore, Maryland; to develop statistical models and adjustment factors to quantify the impacts of weather on traffic flow (*7*). One of the challenges remaining is to integrate those models into decision support systems to help improve the performance of the transportation system during inclement weather conditions. The traffic estimation and prediction system (TrEPS) is a tool currently available for traffic planners and operators to assist with evaluating and implementing weather-responsive traffic management strategies. Weather-sensitive TrEPS capabilities aim for accurate estimation and prediction of the traffic states under inclement weather conditions.

Mahmassani et al. identified several key components within the TrEPS framework for which the impact of weather must be incorporated on both the supply and demand sides (*8*). One such element on the supply side consists of well-calibrated weather-integrated traffic flow models. Successful application of weather-sensitive TrEPS requires detailed calibration of weather effects on the underlying traffic flow models.

The main objectives of this paper are (*a*) to develop systematic procedures for calibrating traffic flow models under inclement

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weather by using commonly available freeway loop detector data and weather data collected from automated surface observing system (ASOS) stations and (*b*) to apply the calibrated models into a mesoscopic dynamic traffic assignment (DTA) framework. According to the developed procedure, traffic flow models in four U.S. cities (Irvine, California; Chicago, Illinois; Salt Lake City, Utah; and Baltimore) are calibrated, as are the quantitative weather impact on those models. The calibrated models are provided as input into an existing weather-integrated dynamic traffic simulation-assignment system, DYNASMART-P. The simulation results show that the calibrated models are capable of capturing the weather effects on traffic flow more realistically than TrEPS without weather integration.

The extensive set of parameter estimates compiled here, and the range of geographic and network situations considered, forms a rich library that could support future applications of simulation-based dynamic network models to address weather-related scenarios in locations where local data may not be available or where the time and resources available for a study may not allow full-blown local calibration.

Accordingly, the main contribution of the present work consists of (*a*) a systematic calibration process for capturing the weather impact on traffic flow relations, (*b*) an extensive calibration base confirming that an approach previously presented for one location is applicable in various locations in different regions of the United States, (*c*) a database that serves as a valuable library for application to locations where no local data may be available, (*d*) full integration of the weather-sensitive traffic flow models into mesoscopic DTA simulation framework, and (*e*) validation and application of the entire simulation-based DTA model under weather conditions.

MODELING WEATHER IMPACT ON TRAFFIC

Although the effect of adverse weather on traffic flow may appear evident and easy to perceive, for modeling purposes, development of an accurate quantitative description of the effect is still important. Hall and Barrow studied the effect of adverse weather conditions on the flow–occupancy relationship by using freeway traffic data for Ontario, Canada (*9*). They found that adverse weather affects the flow–occupancy function by reducing the slope of the curve that corresponds to the uncongested traffic state. Similar findings by Ibrahim and Hall indicated that the maximum flow rates of highways are reduced by inclement weather (*5*). They also observed that adverse weather causes a downward shift in the speed–flow function. These weather effects are modeled statistically by using regression analysis, and the results are quantitatively documented for both rainy and snowy conditions. Rakha et al. studied the impacts of inclement weather on some key traffic stream parameters for several different metropolitan areas in the United States (*10*). They calibrated a Van Aerde traffic flow model by using loop detector data and concluded that the impacts of weather on traffic increase as rain and snow intensities increase. In their study, they also proposed and developed so-called weather adjustment factors (WAFs), which are to be multiplied by base clear-condition variables to compute parameters under the impact of weather. Parallel efforts have been ongoing in Europe to incorporate the effect of adverse weather in traffic models to support system management actions (*11*). In addition, some researchers have proposed and developed methods to incorporate weather effects into the DTA framework. Antoniou identified characteristics of a traffic flow model under different weather conditions (dry and wet), and proposed online calibration procedures for DTA models (*12*). Dong et al. recognized the application of DTA simulation tools to support transportation network planning under adverse weather conditions and developed a methodology to incorporate weather impacts into the DTA framework (*13*). Recently, Mahmassani et al. followed the methodology and demonstrated the use of weather-sensitive DTA models for different road networks (*14*).

Modified Greenshields Traffic Flow Model

The dynamic traffic assignment system used in this study, DYNASMART-P, has two types of modified Greenshields models for simulating traffic propagation (*15*). The first type is a dual-regime model in which constant free-flow speed is specified for the free-flow conditions (first regime) and a modified Greenshields model is specified for congested-flow conditions (second regime) as shown in Figure 1. Dual-regime models are generally used for freeways because freeways typically have more capacity than arterials and can accommodate dense traffic (up to 2,300 passenger cars per hour per lane) at near free-flow speeds (*16*). In contrast, arterials have signalized intersections, and therefore a slight increase in traffic would elicit more deterioration in their prevailing speeds than for those of freeways. Therefore, arterial traffic relations are better explained by using the other type of modified Greenshields model, the single-regime model. All the traffic data used in this study come from loop detectors installed on highways. Therefore, the dual-regime model is chosen to fit the collected historical data.

The mathematical expression of the dual-regime modified Greenshields is shown in Equation 1. Six parameters affect the shape of the model: breakpoint density (k_{bp}), free-flow speed on link *i* (u_f), speed intercept (v_f), minimum speed on link *i* (v_0), jam density on link *i* (k_{jam}), and shape parameter (power term, α):

$$v_i = \begin{cases} u_f & 0 < k_i < k_{bp} \\ v_0 + (v_f - v_0)\left(1 - \dfrac{k_i}{k_{jam}}\right)^{\alpha} & k_{bp} < k_i < k_{jam} \end{cases} \quad (1)$$

where v_i is the speed on link *i*, and k_i is density on link *i*.

Description of WAF

WAF, proposed by Rakha et al. to quantify the effect of inclement weather on traffic flow model parameters, is computed as the ratio of the parameter under inclement weather conditions relative to the parameter obtained during normal weather (*10*):

$$\mathrm{WAF}_i = \frac{f_i^{\text{weather event}}}{f_i^{\text{normal}}} \quad (2)$$

where

WAF_i = WAF for parameter *i*,
$f_i^{\text{weather event}}$ = value of parameter *i* under certain weather event, and
f_i^{normal} = value of parameter *i* under normal condition.

As many researches have found that the variation in the weather effects on traffic flow is associated with the type of weather condition (*5, 7*), the current authors assume that WAF is closely related to three variables that are representative of severity of the weather

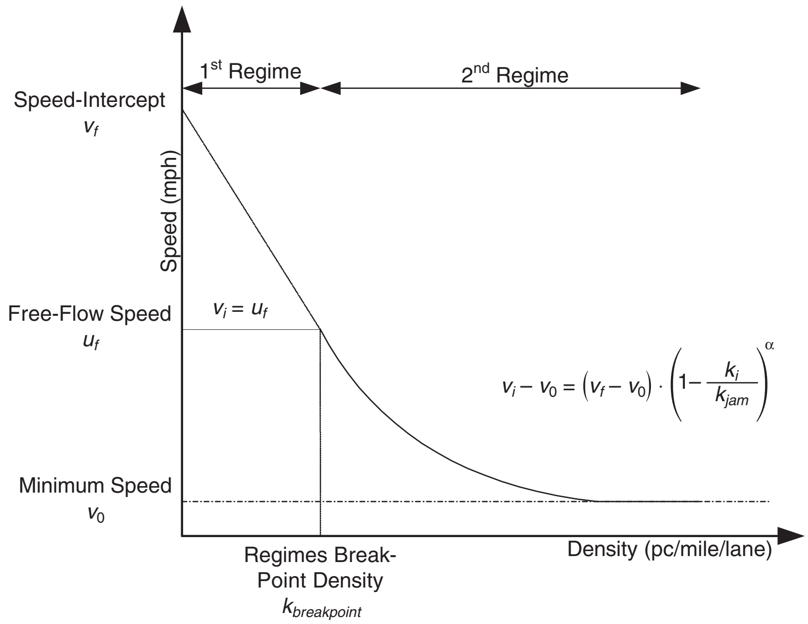


FIGURE 1 Modified Greenshields model [dual-regime model (k_i = density on link i; v_i = speed on link i; pc = passenger cars)].

condition: visibility, rain intensity, and snow intensity. Specifically, a linear functional form is used to model WAF as follows:

$$\mathrm{WAF}_i = \beta_{i0} + \beta_{i1} \cdot v + \beta_{i2} \cdot r + \beta_{i3} \cdot s + \beta_{i4} \cdot v \cdot r + \beta_{i5} \cdot v \cdot s \qquad (3)$$

where

v = visibility (mi),
r = precipitation intensity of rain (in./h),
s = precipitation intensity of snow (in./h), and
$\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}$ = weather adjustment coefficients to be estimated.

STUDY AREAS AND DATA DESCRIPTION

The data used in this study were obtained from the four metropolitan areas of Irvine, Chicago, Salt Lake City, and Baltimore. These four areas were chosen because their locations are distributed across the continental United States, from the West Coast to the East Coast, and each can represent the weather and traffic conditions in its own geographical territory. Calibration of weather-sensitive TrEPS models requires availability of both weather data and traffic data.

Two major public sources archive weather data in the United States: ASOS stations located at airports and roadside environmental sensor stations (ESSs) available from the Clarus initiative. As the historical weather data from ESSs have a time resolution of 20 min and have been available only since 2009, ASOS data with 5-min resolution were used in conjunction with traffic detector data collected and aggregated over 5-min intervals. ASOS 5-min weather data are available on the National Oceanic and Atmospheric Administration's National Climatic Data Center (NOAA NCDC) site (ftp://ftp.ncdc.noaa.gov/pub/data/asos-fivemin). The weather data recorded by ASOS stations are reported in METAR (meteorological terminal aviation routine weather report) format, a prevailing format used by aviation organizations, which includes various weather information such as visibility, precipitation type and intensity, temperature, dew point, wind direction and speed, and the like. Table 1 summarizes the airports at which ASOS stations are located for the four study sites and the periods for which 5-min ASOS data are available from the NOAA NCDC website.

The primary source of traffic data used in this study for calibration of traffic flow models is loop detectors installed in freeway lanes. They are available from several web-based data archive systems (like PeMS, GCM, CATT Lab, etc.). Historical traffic data with 5-min aggregation interval from 2005 through 2009 are used. The distribution of selected loop detector locations in the four study areas are presented in Figure 2. In the selection of detector locations and the collection of data, the following criteria were mainly considered:

- Choose detectors as close as possible to ASOS stations, ideally, no farther than 10 mi from ASOS.
- Remove the influence of other external events such as incidents–accidents, work zones, and special planned events.

TABLE 1 Airports with ASOS Stations and Available Periods for Data

Airport	Location	Available ASOS Data
John Wayne	Irvine, Calif.	2005–present
Midway International	Chicago, Ill.	2005–present
O'Hare International	Chicago, Ill.	2000–present
Salt Lake City International	Salt Lake City, Utah	2000–present
Baltimore–Washington International	Baltimore, Md.	2000–present

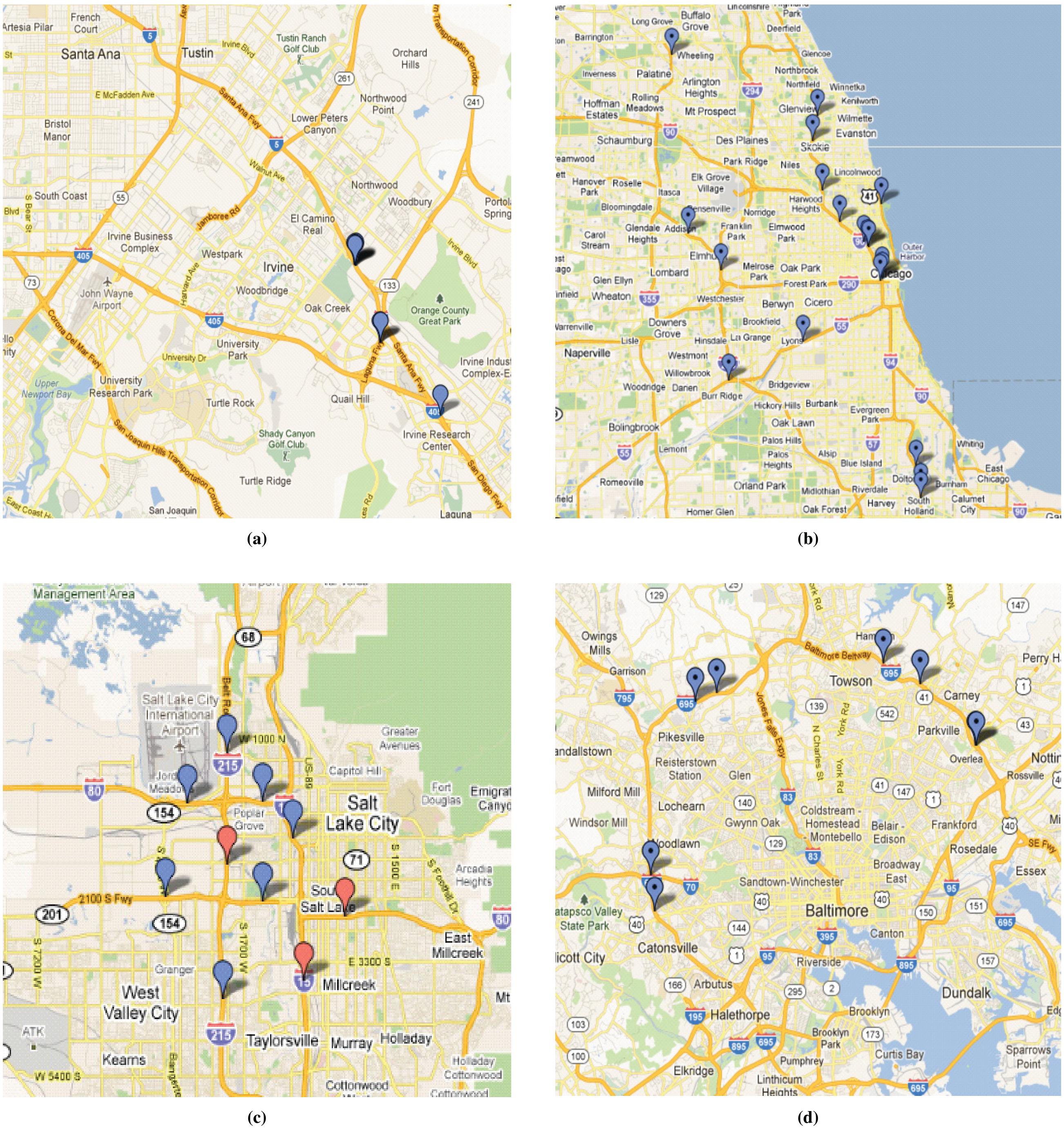


FIGURE 2 Maps of selected detector locations in four study areas: (*a*) Irvine, (*b*) Chicago, (*c*) Salt Lake City, and (*d*) Baltimore.

• Include various facility–lane types and calibrate them separately for each type. For instance, types can be classified as main lines, on-ramps, off-ramps, and high-occupancy vehicle; the number of lanes could be further distinguished.

• Find segments that experience a wide range of traffic regimes (i.e., free-flow, stop-and-go, and congested states).

CALIBRATION PROCEDURE

Data Preparation

Three major variables of traffic states used for TrEPS calibration are link volume (or flow rates), occupancy, and speed. To calibrate the modified Greenshields traffic flow model, occupancy data need to be further converted into density. Cassidy and Coifman have shown that occupancy is linearly related to density by the effective average vehicle length (*17*). The exact relationship between these two variables can be expressed as follows:

$$k = \frac{52.8}{L_v + L_s} \cdot o \tag{4}$$

where

k = density [vehicles per mile per lane (vpmpl)],
L_v = average vehicle length (ft),
L_s = average sensor length (ft), and
o = occupancy (%).

In this study, L_v is assumed to be 5 m (approximately 16.4 ft) and L_s is set to 2 m (approximately 6.5 ft).

The traffic and weather data at 5-min intervals are then matched together in relation to the time stamps to classify each traffic observation into different weather categories. Weather categories are defined on the basis of precipitation type and the intensity. With normal weather (in which no precipitation is observed) as the base case, three levels of precipitation intensities (light, moderate, and heavy) are used for both rain and snow. Table 2 shows the seven weather categories and the corresponding precipitation intensity ranges: normal (no precipitation), light rain (intensity less than 0.1 in./h), moderate rain (0.1 to 0.3 in./h), heavy rain (greater than 0.3 in./h), light snow (less than 0.05 in./h), moderate snow (0.05 to 0.1 in./h), and heavy snow (greater than 0.1 in./h). The values for the intensity range are based on the literature (*1, 7, 18*). For the Irvine network, no snow precipitation was observed for the years 2005 through 2009. For the Salt Lake City and Chicago networks, the moderate and heavy categories were merged for both rain and snow because traffic data for heavy rain–snow did not sufficiently cover the whole density range to enable calibration. A complete description of weather categorization for different networks is given in Table 2, where a check mark indicates that the collected data were sufficient to calibrate the traffic flow model for that corresponding weather category.

Procedure for Calibrating Traffic Flow Model

After traffic data are categorized, parameters in the modified Greenshields model are estimated for each weather condition by using a nonlinear regression approach. The following steps describe the procedures for calibrating the dual-regime model, which is used in most cases when traffic data are collected from freeways:

1. Plot the graph of speed versus density, and set initial values for all the parameters (k_{bp}, v_f, v_0, k_{jam}, and α) on the basis of observations.
2. Calculate the predicted speed value ($\hat{v}_i$) for each observed density (k_i) by using Equation 1 and the parameters initialized in Step 1.
3. Compute the squared difference between observed speed value (v_i) and predicted speed value ($\hat{v}_i$), for each data point, and sum the squared error over the entire data set.
4. Minimize the sum of squared error obtained in Step 3 by changing the values of the model parameters.

Research by Mahmassani et al. uses an approach that divides the data into two parts (free-flow and congested parts) and estimates the two regimes separately (*8*). The main advantage of the nonlinear regression method used in this paper is that it estimates the model as a whole, which gives a smooth joint point at the breakpoint density. Step 4 is implemented by Microsoft Excel Solver, which uses the generalized reduced-gradient algorithm to find the optimal solution. After examination of the observed traffic data, the minimum speed (v_0) and jam density (k_{jam}) appear to be insensitive to weather conditions. For the Irvine and Baltimore networks, the minimum speed is assumed to be 10 mph, while for Chicago and Salt Lake City, a minimum speed of 2 mph is used. The selection of a minimum speed value is based on long-term observations obtained from loop detector data at selected locations. The jam density is assumed to be 225 vehicles per mile per lane (vpmpl) for all four networks.

Procedure for Calibrating WAF

Once speed–density functions for the seven weather conditions are obtained for each location, linear regression is conducted to estimate

TABLE 2 Weather Categorization for Four Studied Networks

	Weather Condition (precipitation intensity)						
Network	Normal (no precipitation)	Light Rain (<0.1 in./h)	Moderate Rain (0.1–0.3 in./h)	Heavy Rain (>0.3 in./h)	Light Snow[a] (<0.05 in./h)	Moderate Snow[a] (0.05–0.1 in./h)	Heavy Snow[a] (>0.1 in./h)
Irvine	✓	✓	✓	✓			
Salt Lake City	✓	✓	✓		✓	✓	
Chicago	✓	✓	✓		✓	✓	
Baltimore	✓	✓	✓	✓	✓	✓	✓

NOTE: ✓ = data sufficient for calibration; blank cells = data not sufficient for calibration.
[a]Liquid equivalent snowfall intensity.

the weather adjustment coefficients in Equation 3. The detailed steps in the calibration procedure are as follows:

1. For each weather condition *c,* calculate WAF for each parameter *i* such that $\text{WAF}_i = f_i^c / f_i^{\text{normal}}\ \forall c$, where f_i^c denotes the value of *i* under condition *c,* f_i^{normal} denotes the value of *i* under the normal (no-precipitation) condition.
2. Assign WAF_i to corresponding traffic–weather data such that each observation has a structure similar to the following: [time, traffic data (volume, speed, density), weather data (v, r, s), WAF_i].
3. For each parameter *i,* estimate coefficients β_{i0}, β_{i1}, β_{i2}, β_{i3}, β_{i4}, and β_{i5} by using Equation 3 to conduct the regression analysis given WAF_i as a dependent variable and weather data (v, r, s) for all observations as independent variables.

CALIBRATION RESULTS

The procedures developed in the previous section are applied to calibrate the traffic flow model and WAFs in the four selected study areas. Mahmassani et al. have followed similar steps to calibrate weather-sensitive traffic flow models by using data collected from the Hampton Road network in Virginia (*8*). Their research showed that different weather conditions do not have significant impact on the magnitude of the shape parameter (α). As a result, in this study, the shape parameter was considered a decision variable only under clear weather conditions in the optimization process, as described in Step 4 of the calibration process for the traffic flow model, while under other weather conditions (i.e., rainy and snowy), it is set as a constant that is equal to the value obtained under clear weather.

The goodness of fit of the nonlinear regression model, used for evaluating the estimation results, can be measured by the root mean square error (RMSE). The smaller the RMSE is, the better the model represents the data:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(v_i - \hat{v}_i\right)^2} \tag{5}$$

where

v_i = observed speed value,
$\hat{v}_i$ = predicted speed value, and
N = number of observations.

Another measurement is the R^2 value, which is computed in the same way as in linear regression models. The R^2 value is the ratio of the regression sum of squared errors (SSE) to the total sum of squares [SST (Equation 5)], which explains the proportion of variance taken into account in the dependent variable by the model. The closer R^2 is to 1, the better the model fits the data.

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST}} = 1 - \frac{\sum\left(v_i - \hat{v}_i\right)^2}{\sum\left(v_i - \bar{v}_i\right)^2} \tag{6}$$

Examples of calibrated speed–density curves for each network are presented in Figure 3. Observations have shown that the overall speed for both uncongested and congested regimes decreases as weather conditions become severe. A snow event, especially moderate or heavy snow, causes significant reductions in speed, as shown in the Chicago, Salt Lake City, and Baltimore networks. The quantitative values of the calibrated model parameters are tabulated in Table 3 for some selected highway segments.

On the basis of the calibrated traffic model of the four networks, the WAFs for several key parameters [maximum flow rate ($q_{\max}$), speed intercept (v_f), breakpoint density (k_{bp}), and free-flow speed (u_f)] are computed by using Equation 2. The maximum service flow rate ($q_{\max}$), and free-flow speed (u_f), were found to be sensitive to the intensity of both rain and snow. As the rain or snow intensity increases, maximum flow rate, speed intercept, and free-flow speed are reduced. The literature shows similar findings (*5, 10*). Increasing snow intensity has also been found to reduce breakpoint density; however, the effect of rain on breakpoint intensity is not as clear as that for snow, as in some networks it decreases with rain intensity (e.g., Irvine), while in other cases it increases (e.g., Baltimore). In summary, the effects of rain intensity and snow intensity, respectively, on different traffic flow model parameters are presented in Figures 4 and 5. The calibration results of WAF for the four networks are provided in Table 4. The significance of model parameters (*p*-values) is presented in parentheses under each point estimator in the table. The low R^2 values of breakpoint density (k_{bp}) suggest that this parameter is insensitive to visibility and precipitation intensity levels.

VALIDATION

Besides the supply side traffic flow model and WAF calibration, some other components of weather-sensitive TrEPS must be tuned before DTA simulation can be conducted, including estimation of the demand side parameters, driver behavior modeling, and the like. Detailed implementation of those tasks are beyond the scope of this paper; however, some relevant studies can be found in the literature (*19–21*). In this study, the origin–destination matrix is calibrated by using a bilevel optimization method (*22, 23*) that is based on the historical static origin–destination matrix and time-dependent count data on selected links.

After the supply side and demand side parameters are obtained, the capability of capturing weather effects on the traffic flows is tested by performing simulations with specific weather scenarios. Given the time required for full calibration of the network model, the weather-related validation is conducted on one of the networks. The Chicago network is selected for this purpose. First, days with rain or snow events between 5 and 10 a.m. are identified, and the traffic observations are collected for each identified day. Each weather scenario is simulated with the calibrated origin–destination matrix with and without WAFs in DYNASMART-P. Then the simulated results are compared with the actual observations under the specified weather condition.

Performance measure of simulation is considered at two levels: aggregated network level and individual link level. At the network level, two measures of error are used: $\text{RMSE}_{\text{flows}}$ and $\text{RMSE}_{\text{speeds}}$. $\text{RMSE}_{\text{flows}}$ represents the discrepancy between the observed and the simulated link counts for all periods for all links. Similarly, $\text{RMSE}_{\text{speeds}}$ represents the discrepancy between the observed and the simulated link speed for all periods for all links. These two quantities are calculated by means of the following equations:

$$\text{RMSE}_{\text{flows}} = \sqrt{\frac{\sum_{l=1}^{L}\sum_{t=1}^{T}\left(M_{l,t} - O_{l,t}\right)^2}{LT - 1}} \tag{7}$$

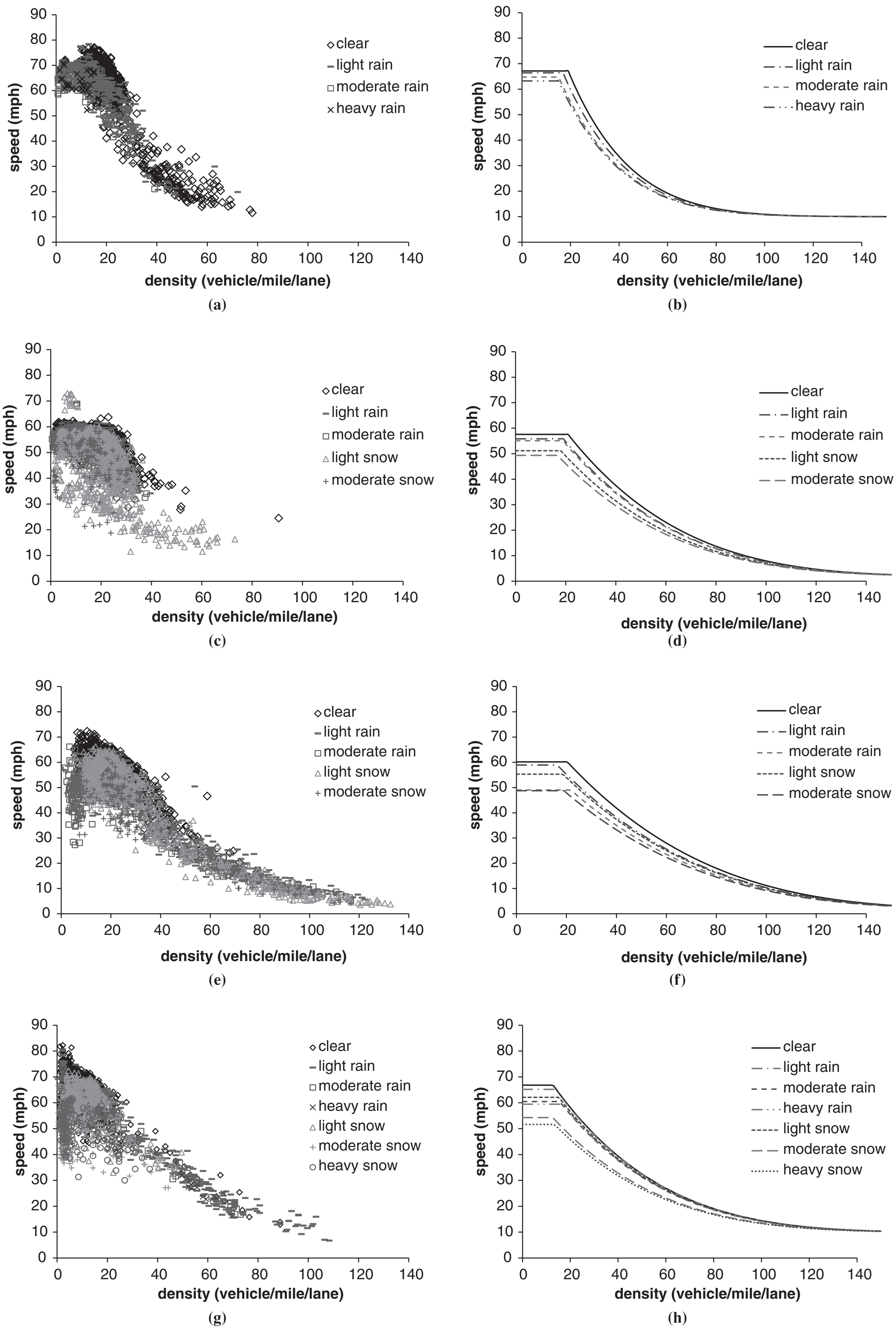


FIGURE 3 Examples of raw traffic data (left column) and calibrated speed–density curves (right column) under different weather conditions for (*a*, *b*) Irvine, (*c*, *d*) Salt Lake City, (*e*, *f*) Chicago, and (*g*, *h*) Baltimore networks.

TABLE 3 Traffic Flow Model Calibration Results of Selected Highway Segments in Each Network

Network	Highway	Weather Condition	q_{max} (vehicles/5 min)	v_f (mph)	Alpha	k_{bp} (vpmpl)	u_f (mph)	v_0 (mph)	k_j (vpmpl)	No. of Observations by Regime		RMSE	R^2
										1	2		
Irvine	I-405	Normal	835	110.75	7.13	16.03	69.45	10	225	513	1,775	4.81	.90
		Light rain	735	103.96	7.13	15.59	66.30	10	225	163	298	4.67	.92
		Moderate rain	647	98.15	7.13	14.89	64.07	10	225	75	46	5.68	.84
		Heavy rain	605	90.15	7.13	10.90	66.24	10	225	13	19	5.13	.78
Chicago	I-94	Normal	591	89.15	3.92	20.88	61.48	2	225	654	1,074	6.37	.78
		Light rain	579	90.10	3.92	23.51	57.11	2	225	727	1,002	5.79	.86
		Moderate rain	486	78.46	3.92	21.43	52.90	2	225	78	166	4.42	.80
		Light snow	576	99.10	3.92	20.65	60.27	2	225	306	418	9.09	.79
		Moderate snow	399	78.96	3.92	23.00	52.41	2	225	5	86	13.30	.68
Salt Lake City	I-15	Normal	735	87.24	4.38	19.66	59.14	2	225	2,041	381	1.86	.88
		Light rain	675	82.11	4.38	17.53	58.18	2	225	622	182	2.91	.78
		Moderate rain	690	82.84	4.38	19.04	56.90	2	225	368	20	3.09	.37
		Light snow	565	69.51	4.38	11.92	55.20	2	225	417	721	9.16	.53
		Moderate snow	514	68.08	4.38	13.37	52.54	2	225	96	62	7.41	.49
Baltimore	I-695	Normal	676	85.34	4.81	12.84	66.80	10	225	743	265	5.52	.58
		Light rain	653	85.60	4.92	13.94	65.19	10	225	178	440	4.05	.94
		Moderate rain	559	80.21	4.72	14.91	60.79	10	225	17	52	3.36	.93
		Heavy rain	589	97.48	5.66	21.63	59.39	10	225	80	20	3.91	.90
		Light snow	608	85.39	5.18	15.45	62.14	10	225	209	65	5.53	.57
		Moderate snow	489	73.70	6.03	13.14	54.33	10	225	389	62	7.42	.16
		Heavy snow	425	79.41	6.90	16.14	51.53	10	225	133	31	6.18	.28

NOTE: No. = number.

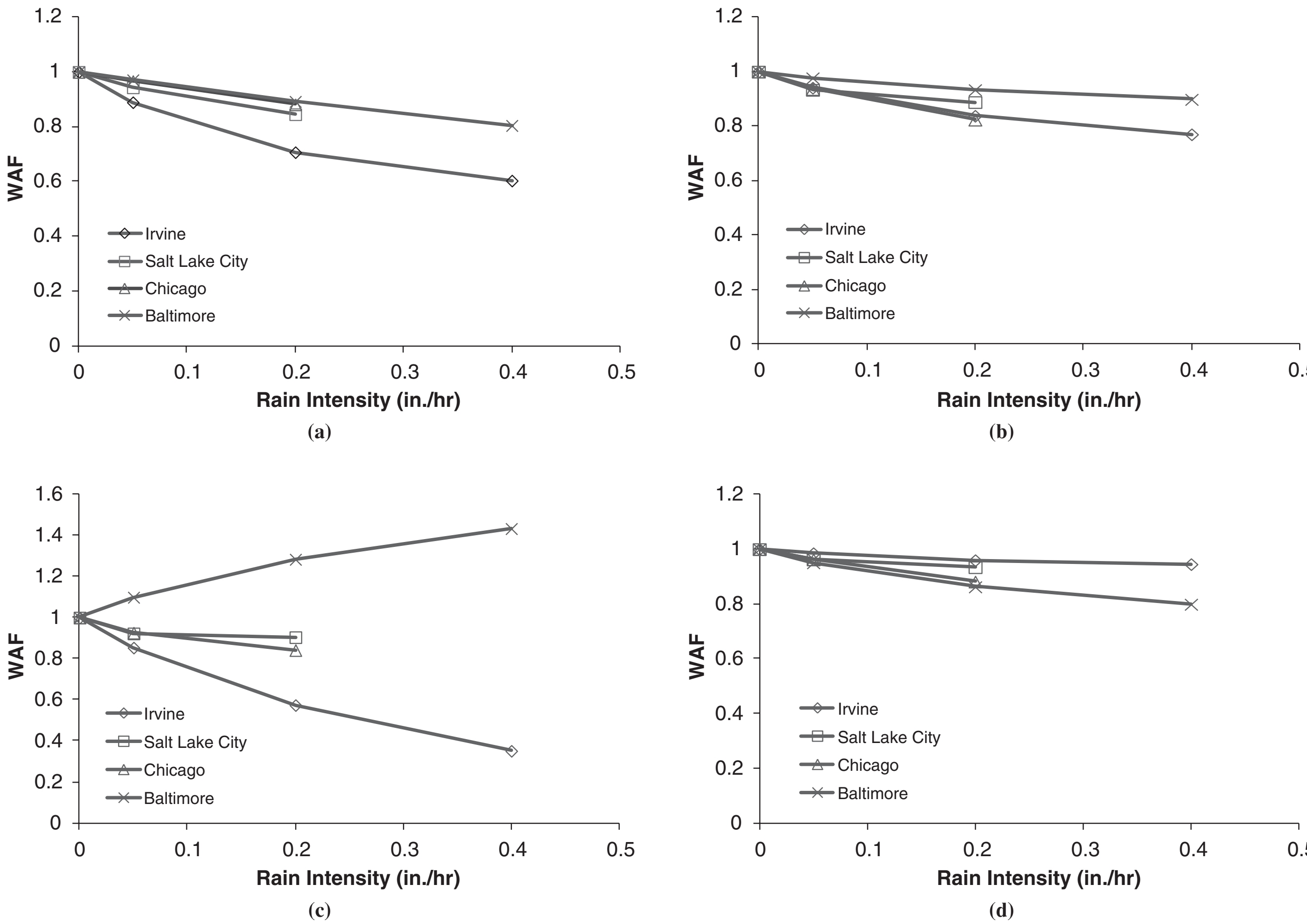


FIGURE 4 Effect of rain intensity on WAFs for (*a*) maximum flow rate (q_{max}), (*b*) speed intercept (v_f), (*c*) breakpoint density (k_{bp}), and (*d*) free-flow speed (u_f).

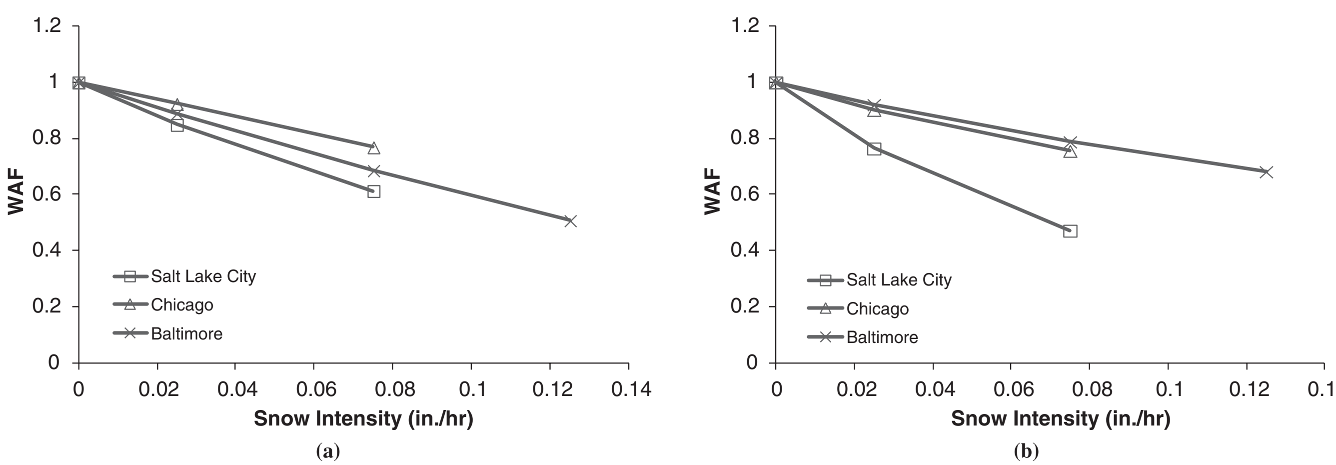
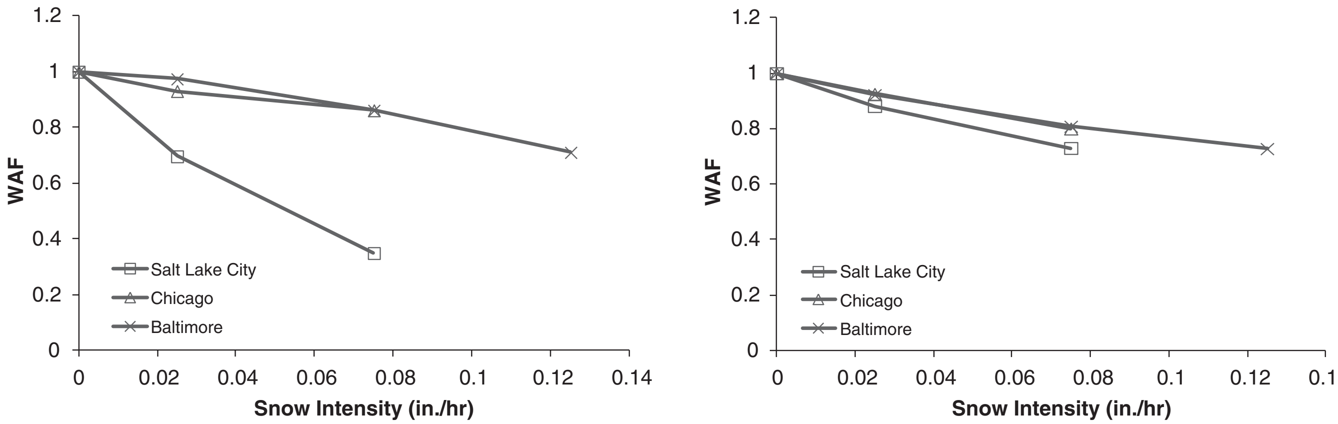


FIGURE 5 Effect of snow intensity on WAFs for (*a*) maximum flow rate (q_{max}) and (*b*) speed intercept (v_f).

(continued)



(c) (d)

FIGURE 5 *(continued)* **Effect of snow intensity on WAFs for (*c*) breakpoint density (k_{bp}) and (*d*) free-flow speed (u_f).**

TABLE 4 Calibration Results of WAF

Network	Parameter	β_0	β_1	β_2	β_3	β_4	β_5	R^2
Irvine	q_{max}	0.8424	0.0154	0.0244	0	–0.1942	0	.7251
		(<.001)	(<.001)	(.159)		(<.001)		
	v_f	0.9188	0.008	–0.0665	0	–0.0965	0	.7227
		(<.001)	(<.001)	(<.001)		(<.001)		
	k_{bp}	0.8203	0.0178	–0.5202	0	–0.2078	0	.4305
		(<.001)	(<.001)	(<.001)		(<.001)		
	u_f	0.9778	0.0022	0.0033	0	–0.0268	0	.3704
		(<.001)	(<.001)	(.069)		(<.001)		
Salt Lake City	q_{max}	0.9202	0.0077	–0.1242	–2.8739	–0.0801	–0.3076	.6361
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
	v_f	0.7887	0.0209	0.8547	–0.6376	–0.1641	–0.8786	.8187
		(<.001)	(<.001)	(.041)	(<.001)	(<.001)	(<.001)	
	k_{bp}	0.6933	0.0305	1.4373	0.8021	–0.2161	–1.3046	.4389
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
	u_f	0.8993	0.0098	0.411	–0.6111	–0.0887	–0.4044	.8748
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
Chicago	q_{max}	0.9979	0.0003	–0.3312	–3.0583	–0.0436	–0.0046	.6919
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
	v_f	0.9254	0.0071	–0.1071	–1.6901	–0.1026	–0.1902	.9061
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
	k_{bp}	0.8713	0.0122	0.5052	0.1758	–0.17	–0.2138	.2413
		(<.001)	(<.001)	(<.001)	(<.001)	(.071)	(<.001)	
	u_f	0.9702	0.0029	–0.2695	–1.8068	–0.0437	–0.115	.7569
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
Baltimore	q_{max}	0.9874	0.0015	–0.3753	–3.3884	–0.0243	–0.1267	.6397
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	
	v_f	0.957	0.0044	–0.0738	–1.8262	–0.0294	–0.1302	.6987
		(<.001)	(<.001)	(<.001)	(<.001)	(.012)	(<.001)	
	k_{bp}	1.0894	–0.0081	0.3924	–3.5266	0.1371	0.1888	.2572
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(.188)	
	u_f	0.9303	0.0068	–0.1044	–1.1713	–0.0733	–0.1662	.8466
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	

NOTE: *p*-values are in parentheses.

TABLE 5 RMSE Values for Selected Snow Scenario, Chicago, January 7, 2010

Weather Features Presence	Value
$RMSE_{speeds}$	
With	22.69
Without	35.56
$RMSE_{flows}$	
With	53.24
Without	67.35

$$\mathrm{RMSE}_{\mathrm{speeds}} = \sqrt{\frac{\sum_{l=1}^{L}\sum_{t=1}^{T}\left(MS_{l,t} - OS_{l,t}\right)^2}{LT - 1}} \tag{8}$$

where

$M_{l,t}$ = simulated link flow on link l at time t,
$O_{l,t}$ = observed link flow on link l at time t,
$MS_{l,t}$ = simulated link speed on link l at time t, and
$OS_{l,t}$ = observed link speed on link l at time t.

Table 5 shows the results based on the test from using a snow scenario observed on January 7, 2010, in Chicago. The lower $RMSE_{speeds}$ value with weather features indicates that the discrepancy between the overall simulated and the observed link speeds is much smaller when weather specific parameters are used. In other words, the use of the WAFs captures the weather effect on the road traffic and therefore produces more realistic simulation results. Similarly, for the link counts, an equivalent pattern is observed; that is, the counts are matched better in the simulation by using weather features. The overall experiment results reveal that the weather-sensitive TrEPS indeed has the ability to model the effect of weather conditions.

Graphical comparison is made at the individual link level. Figure 6 presents observed and simulated speeds with and without weather-specific parameters on a selected link. Figure 7 presents observed counts versus simulated counts with and without weather-specific parameters on a selected link. The link level comparisons show that the simulation results that consider the snow effects are closer to actual traffic conditions than those that ignore the weather effects.

CONCLUSION

Systematic procedures for calibrating weather-sensitive traffic flow models for application in a TrEPS mesoscopic network simulation model were developed in this paper, from data collection through model parameter estimation to model validation. The methods are demonstrated and applied in four networks in the United States by using publicly available traffic and weather data. The results show that inclement weather can affect traffic flow by changing the values of some model parameters (e.g., heavy snow could reduce free-flow speed and the maximum service flow rate on highways by 30% to 40%). Observations have shown that impact increases with the severity of weather condition (visibility, rain–snow intensity), results that are consistent with findings in the literature. The results of the DTA simulation-based model validation show that, when a well-calibrated traffic flow model is integrated in TrEPS, it can produce more realistic traffic conditions under weather conditions than without considering any weather effect. The methodology developed in this paper could be incorporated with weather-responsive traffic management systems and therefore provide a tool for better modeling of the effect of adverse weather on traffic system properties and performance and for supporting the analysis and design of traffic management strategies targeted at such conditions. Given the diverse range of geographic regions of the site locations considered in this study, the extensive set of parameter estimates compiled here provides a rich library that could support future applications of simulation-based dynamic network models to address weather-related scenarios in locations where local data may not be available or where the time and cost available for the study may not allow full-blown local calibration. Additional validation and consideration of more sites would contribute to expanding the database and advancing the state of the art and practice in modeling of weather-response network traffic.

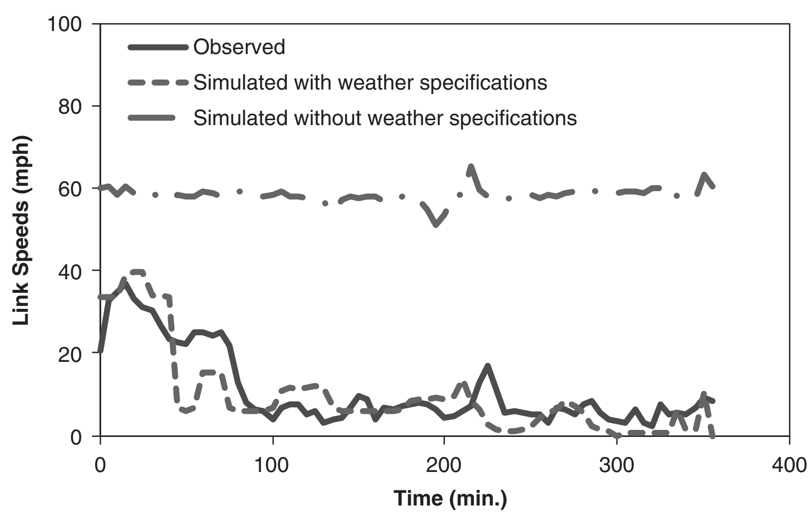
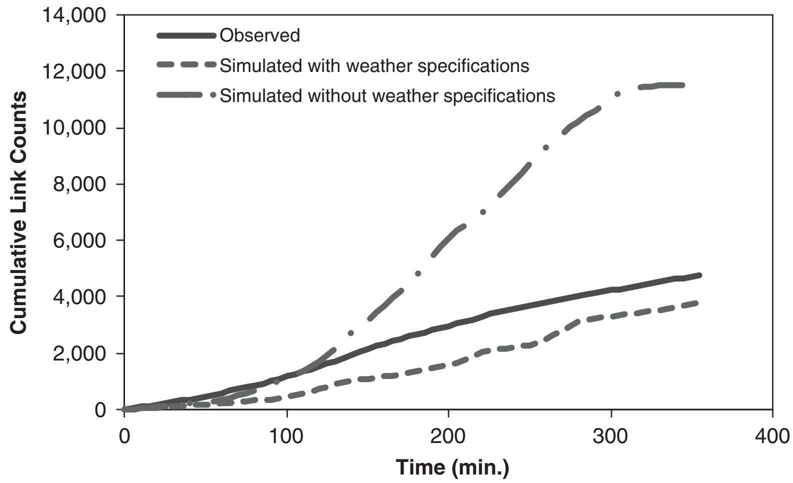
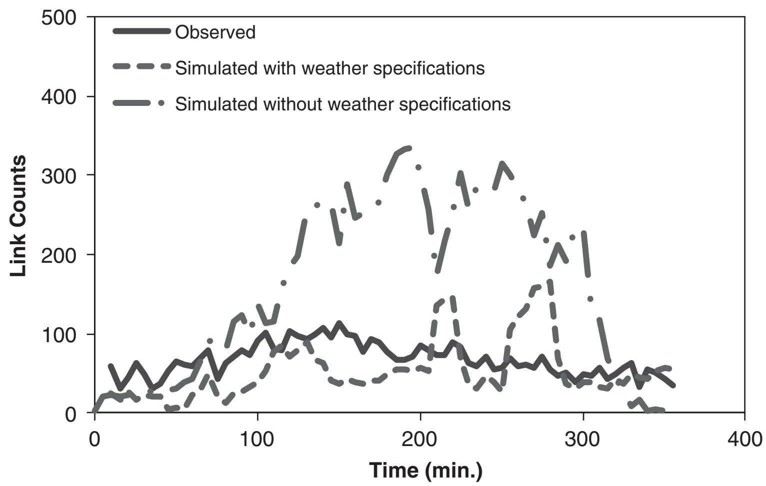


FIGURE 6 Observed and simulated speeds on selected link in Chicago network.



(a)



(b)

FIGURE 7 Observed and simulated counts on selected link in Chicago network.

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