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ADVANCED ROAD SAFETY AND WEATHER WARNING SYSTEM (ARSAWWS)

Final Report

PennDOT/MAUTC Partnership, Work Order No. 3
Research Agreement No. 510401

October 9, 2006

By J. Aguero-Valverde, P. P. Jovanis and P. G. Knight

PENNSTATE

Pennsylvania Transportation Institute

The Pennsylvania State University
Transportation Research Building
University Park, PA 16802-4710
(814) 865-1891 www.pti.psu.edu

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Prepared for

Bureau of Planning and Research
Commonwealth of Pennsylvania
Department of Transportation

By

Jonathan Aguero-Valverde, Graduate Assistant
Paul P. Jovanis, Ph.D.

Pennsylvania Transportation Institute
The Pennsylvania State University
Transportation Research Building
University Park, PA 16802-4710

and

Paul G. Knight, Ph.D., State Climatologist
Department of Meteorology
The Pennsylvania State University

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16. Abstract

Roadway, traffic volume and crash data were analyzed to identify sites that are good candidates for improvement for weather-related crashes. These sites with promise were then shared with meteorology researchers on the team who used them to explore and identify significant weather-related signatures within meteorological data. These analyses were undertaken to determine the feasibility of an Advanced Road Safety and Weather Warning System, which would provide forecasts of significant weather events that could be broadcast to the public via communications outlets such as highway advisory radio, websites, changeable message signs and direct media broadcasts. The linked analysis of crash and meteorological data was a success.

While the specific findings of this particular study are applicable to PennDOT District 2-0, the methodology is applicable to any other PennDOT district with comparable data and extendable to any type of crash under investigation and even to other facility types. This approach can be particularly helpful when analyzing crash types that are relatively infrequent; the use of random effects might provide a means for accounting for random variability.

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INTRODUCTION

Weather-related crashes have been documented for some time and continue to occur on central Pennsylvania roads with horrendous loss of life, personal injury, extensive property damage, and delay and inconvenience to motorists. Between 1997 and 2004, approximately 40% of all reportable crashes in the region occurred under adverse weather conditions. Furthermore, those crashes accounted for more than 50% of all fatal and injury crashes.

There is a need to provide Pennsylvania Department of Transportation (PennDOT) managers with a list of road segments and travel corridors with high risk of weather-related crashes, which will need to be served by weather-based warnings as part of the traveler information system planned for District 2-0 ITS deployment. This task is known in highway safety as the ranking or identification of sites for engineering safety improvements or ranking of Sites With Promise (SWiPs) (Hauer, 1996). In the particular case of this study, the engineering safety improvement proposed is the installation of an Advance Weather Warning System; therefore, the crash type of interest was weather-related accidents and full Bayes hierarchical models were used to identify road segments for possible installation of the system.

The Federal Highway Administration (FHWA) has been seeking to better integrate the use of surface weather information into traffic operations (e.g., National Academy of Sciences, 2004). One area of particular interest has been the use of enhanced weather information and forecasting to improve response to winter road maintenance demands (e.g., Mahoney, 2003; Boon and Cluett, 2002). There has also been interest in user perception of web-based Road Weather Information System (RWIS) information for use by the general public for trip planning (e.g., Fayish and Jovanis, 2004; Fayish et al., 2005). Travelers in central Pennsylvania have expressed an interest in using RWIS information for trip planning if the relevant websites are readily accessible (Fayish and Jovanis, 2004; Fayish et al., 2005).

One of the most promising potential benefits of RWIS is the provision of information about adverse weather to travelers so that crashes may be reduced. Previous research has shown relationships between weather conditions and crash risk (Eisenberg and Warner, 2005; Marmor and Marmor, 2006; Zhang et al., 2005). This project seeks to identify sites with elevated weather-related crash risk, using historical crash and traffic information for Pennsylvania. PennDOT has expressed an interest in using the identified sites as part of a system of Highway Advisory Radio (HAR) websites and Changeable Message Signs (CMS) to warn travelers of potentially significant storms in their area (ARSAWWS, 2005).

Problem Statement

This project built a crash and weather system database for use in a prototype weather early warning system for roadway managers and motorists within PennDOT District 2-0. The system is based on analysis of past crashes in the region along with historical records of significant weather events. There are existing procedures that use data from crash, roadway inventory and traffic databases to develop safety estimates for road segments. This research enhances those studies by adding explicit consideration of weather conditions, as derived from regional road and weather information systems (e.g., RWIS), to the safety prediction. As part of this process, roadway volumes, matched in regional weather data, were analyzed and used to build the safety database. The research plan combined these four data streams (i.e., crash, roadway, traffic, and weather) to develop a system based on actual central Pennsylvania conditions.

Historical records of crashes in the region were searched from PennDOT files to systematically identify locations of high weather-related crash risk. The safety analysis was conducted using crash data from 1997 through 2004, excluding 2002. The final output of the project was the determination of areas and travel corridors that should be considered to be served by weather-based warnings as part of the traveler information system planned for District 2-0 ITS deployment. Once the crash locations were identified, meteorology staff at Penn State searched background weather data (using gridded data fields) for those dates and times to determine the predictability of the weather events in the District 2-0 region.

While the specific findings of this particular study are applicable to PennDOT District 2-0, the methodology is applicable to any other PennDOT district with comparable data.

Data Description

The area of study was PennDOT Engineering District 2-0, which includes the counties of Cameron, Centre, Clearfield, Clinton, Elk, Juniata, McKean, Mifflin, and Potter, covering the north-central part of the state. A total of 5,001 linear miles of state-maintained roads were reported in District 2-0 in 2004. Figure 1 presents the study region as well as the state-maintained roads included in the analysis.

A relational database was assembled with information from three different data sources: crash data, road inventory, and traffic data. All data were collected for calendar years 1997-2001 and 2003-2004. Crash data for year 2002 were missing due to changes in the Pennsylvania Crash Reporting System during that year; therefore, 2002 was omitted from the analysis. Once the database was assembled, road segments were divided into the four analysis groups:

1. Two-lane rural road segments,
2. Two-lane urban road segments,
3. Multi-lane rural road segments, and
4. Multi-lane urban road segments.

Crash Data

Crash data were obtained from the PennDOT Crash Reporting System. The data include reportable crashes for road segment and intersection locations (i.e., those that do not occur at a ramp junction). Road segments were given priority because of the ready availability of traffic and roadway information; data were not consistently available for ramps and intersections, particularly those intersecting non-state highways. Analyses of intersection crashes were completed for those intersections of state highways. The data include state roads only and do not include Pennsylvania Turnpike crashes.

For this research, weather-related crashes are defined as those crashes occurring under adverse weather conditions or when the road surface was wet or covered with snow, ice, or water. A special location code was created for each crash by concatenating the county, route and segment numbers in a single variable. This created unique location identification for each road segment. Then weather-related crashes were summarized by location code and year.

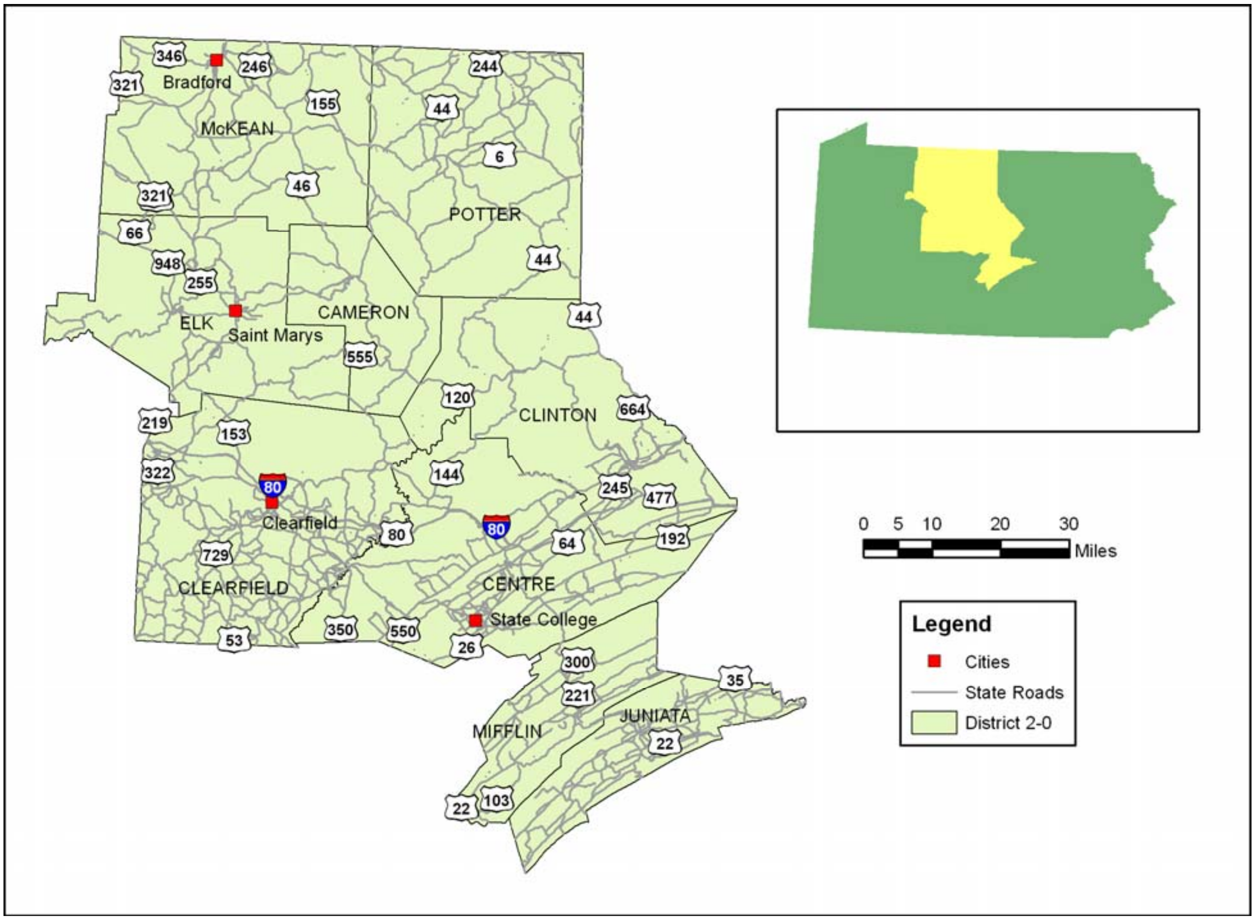

Figure 1. Area of Study.

Roadway Inventory Data

Roadway data were obtained from the Pennsylvania Road Management System (RMS). RMS includes data for each road segment such as County Number, State Route Number, Segment Number, Segment Length, Average Daily Traffic, Pavement Width, Travel Lane Count, Posted Speed Limit, Divisor Type, and Urban/Rural Code. These data were complemented with the State Roads Digital Map from Pennsylvania Spatial Data Access (PASDA) (Pennsylvania Spatial Data Access, 2005) to be able to "map" crash locations. In the case of divided highways, each direction of traffic was considered an individual segment in the road inventory and this convention was maintained in the analysis.

Traffic Data

Since the road inventory contains average annual daily traffic (AADT) data by segment from the latest year, it was necessary to obtain the historical AADT for each study segment from a different source. The historical AADT data came from the Pennsylvania State Highway Performance Monitoring System (HPMS) database. For divided highways, the AADT is reported for the two directions of traffic in HPMS. Since segments in each direction are being analyzed separately, an adjustment was made to assign the corresponding proportion of traffic to each direction based on the directional split in 2004 that was recorded in the road inventory database. Table 1 summarizes descriptive statistics of the variables included in the models.

Table 1. Summary Statistics of Variables Included in Road Segment Models.

Road Type	No. of Segments	Variable	Min.	Median	Mean	Max.	Stand. Dev.
Urban Two-Lane	560	Crashes	0	0	0.1949	5	0.50
		AADT	107	4676	5932	24083	4953.25
		Length (ft)	106	2301	2110	4370	869.68
Urban Multi-Lane	251	Crashes	0	0	0.2408	5	0.59
		AADT	1359	8119	8597	22675	3883.36
		Length (ft)	254	2393	2163	3914	852.32
Rural Two-Lane	6256	Crashes	0	0	0.1010	7	0.35
		AADT	39	786	1722	21059	2315.81
		Length (ft)	135	2509	2467	3992	616.31
Rural Multi-Lane	621	Crashes	0	0	0.3324	8	0.71
		AADT	661	9875	9329	29536	3471.37
		Length (ft)	234	2630	2503	3907	458.50

Extensive checks and verification were completed for the traffic data used in the analysis. Several telephone calls and communications were necessary before adequate data were available for the research. In all cases, PennDOT staff were attentive to project needs and worked diligently to provide the needed data. Care was taken to review road segments with short lengths and low AADT; discussions with PennDOT verified the accuracy of these values. The project would have benefited greatly from access to the new PennDOT data base C-DART, currently under development at PennDOT, which seamlessly relates crash, roadway and traffic data.

METHODOLOGY

Crash Analysis Background

The identification of high-risk sites is also known in the literature as the identification of Sites With Promise (Hauer, 1996). In the particular case of this study, the engineering safety improvement proposed is the installation of an Advance Weather Warning System; therefore, the crash type of interest was weather-related accidents and full Bayes hierarchical models were used to identify road segments for possible installation of the system.

In the Bayesian statistical framework, conclusions about parameters or unobserved data are made in terms of probability statements (Gelman et al., 2003). These probability statements are conditional in the observed quantities (the data, both dependent variables and covariates) and any prior knowledge on the model parameters. Therefore, Bayesian inference is based on the posterior distribution of the parameters of interest, given the data and the prior information on these parameters. In general, methods for summarizing posterior distributions are divided into two categories: empirical Bayes (EB) and full Bayes (FB) (Lawson et al., 2003). Within the FB category, posterior sampling has become very popular due to the advances in Markov Chain Monte Carlo methods.

Bayesian inference has a number of advantages over traditional statistical methods. Among them the Bayes method provides confidence (credible) intervals that are more in line with common-sense interpretations (Congdon, 2001). It also provides a way of including prior knowledge into the analysis in the form of prior distributions of parameters. Another advantage is the ease with which the true parameter density (possibly skew or even multi-modal) can be obtained (Congdon, 2003). In contrast, maximum likelihood estimates rely on asymptotic-normality assumptions that might produce imprecise estimates under small sample sizes. Bayesian methods also assist in the application of random effects models for pooling strength across sets of related units. This "borrowing strength" improves parameter estimation in spare data such as small area estimates (i.e., crash frequency models), especially when large variability between analysis units makes it difficult to distinguish chance variability from actual differences in the estimates. This is the main reason why several authors have been encouraging the use of FB models with random effects on traffic safety (Tunaru, 1999; Miaou and Lord, 2003; Lord et al., 2005; Miaou and Song, 2005; Aguero-Valverde and Jovanis, 2005). Full Bayes models take full account of the uncertainty associated with parameter estimates and provide exact measures of uncertainty on the posterior distributions of these parameters, hence presenting an advantage over maximum likelihood and EB methods that typically ignore this uncertainty (Rao, 2003). As a result, maximum likelihood and EB estimates tend to overestimate precision.

Empirical Bayes methods for estimation of unsafe sites were proposed as early as 1981 (Abbess et al., 1981). These methods are frequently used to correct for regression-to-the-mean bias (Hauer et al., 2002). EB methods for ranking of sites by expected accident frequency as well as expected excess accident frequency have been used in several studies (e.g., Persaud et al., 1999; Heydecker and Wu, 2001; Hauer et al., 2004; Miranda-Moreno et al., 2005). The expected excess accident frequency is commonly referred as Potential for Safety Improvement (Persaud et al., 1999) or Potential for Accident Reduction (Heydecker and Wu, 2001) and is defined as the difference between the expected crash frequency in the site and the expected crash frequency in a group of similar sites. When the expected excess accident frequency is used, sites with significantly more crashes than what is normal at similar sites are believed to have some site-specific attributes that contribute to that excess (Hauer et al., 2002).

Full Bayesian hierarchical models have being used for ranking of sites only recently in a paper that used two different ranking criteria: ranking by probability that the site is the worst and ranking by posterior distribution of ranks (Tunaru, 2002). Others have suggested the additional concept of the decision parameter, which is site-specific and can include traffic flow, covariates, space and time effects as well as random effects (Miaou and Song, 2005).

In this research, full Bayes hierarchical models with random effects were used to estimate the expected excess crash frequency as well as the relative risk (RR) of experiencing a weather-related crash within each road segment, compared with the risk on a group of similar segments. The expected value as well as the confidence interval for the excess crash frequency and RR were estimated; hence, the precision of the estimates was available. The expected excess crash frequency was then used to rank the segments.

Modeling Approach

Consider the number of weather-related crashes at the *i*th segment and *t*th time period, Y_{it}, to be a random variable, which is Poisson and independently distributed when conditional on its mean μ_{it}:

$$Y_{it} \mid \mu_{it} \overset{\text{ind}}{\sim} \text{Pois}(\mu_{it}) \quad (1)$$

The expected number of crashes in a site can be defined as the product of the exposure to the risk and the risk of a motor-vehicle crash as follows:

$$\mu_{it} = \eta_{it}\rho_i \quad (2)$$

where μ_{it} is the expected number of crashes at segment *i* and time period *t*, η_{it} is the exposure function at segment *i* and time period *t*, and ρ_i is the normalized crash rate or expected crash risk by unit of exposure at segment *i*.

The exposure or Safety Performance Function (*29*) is defined as:

$$\eta_{it} = V_{it}^{\beta_V} L_{it}^{\beta_L} \quad (3)$$

where V_{it} is the AADT of segment *i*, L_{it} is the length of segment *i*, and β_V, β_L are parameters of the model. The risk is defined as:

$$\rho_i = \exp(\alpha + v_i) \quad (4)$$

where α is a constant and v_i is an unstructured random effect for segment *i* with a normal prior distribution with mean = 0 and variance = σ_v^2.

Since FB models were used, v_i and therefore ρ_i were estimated for weather-related crashes for the four different types of segments under study. Unobserved effects can be captured by v_i; therefore reflecting individual differences between segments. The risk ρ_i can be expressed as the product of the exponents of α and v_i, where exp(α) can be thought as the mean risk for all the segments under analysis and exp(v_i) can be considered a measure of the relative risk for each segment compared with the expected risk for all the segments of this type:

$$RR_i = \exp(v_i) \quad (5)$$

The full posterior distribution of v_i is estimated in the FB analysis; consequently, the credible set (confidence interval) for the relative risk is estimated.

The excess crash frequency can also be estimated using random effects. The excess crash frequency, δ_{it}, is defined as the difference between the expected crash frequency on segment *i* at time *t* and the expected crash frequency of a group of similar sites:

$$\delta_{it} = \eta_{it}\exp(\alpha + v_i) - \eta_{it}\exp(\alpha) \tag{6}$$

This can be simplified to:

$$\delta_{it} = \eta_{it}\exp(\alpha)(RR_i - 1) \tag{7}$$

RESULTS

Model estimation was performed using WinBUGS software (Spiegelhalter et al., 2006). Each model was run using two chains with different starting points. Generally, between 3,000 and 5,000 MCMC iterations were discarded as burn-in. Then, 50,000 iterations for each chain were performed and final values sampled every 10th observation to avoid autocorrelation in the chains. This yielded a total sample of 10,000 observations of the posterior distribution for each parameter. Table 2 presents the full Bayesian hierarchical models of weather-related crashes for the four different road types.

The variables incorporated into the models were significantly different from zero; however, the coefficient for length (β_L) was not significantly different from one, which means that the expected number of crashes in the four models could be regarded as proportional to the length of the segments. The coefficient for traffic volume (β_V) was significantly smaller than one for all the models; therefore, the expected number of crashes increased at a decreasing rate with traffic volume. Figure 2 presents the SPFs for the models assuming proportionality between crash frequency and segment length. Interestingly, urban segments were at the extremes, presenting the highest and lowest expected number of crashes by mile of road for two-lane and multi-lane roads respectively. By contrast, rural multi-lane segments presented a smaller expected number of crashes than rural two-lane segments.

The mean risk for each road type (exp(α)) was the most important factor in the SPFs order. With a value of 7.02*E-3 the urban two-lane roads presented the highest mean risk corresponding to the top curve. On the other hand, urban multilane roads presented a mean risk of 0.9*E-3, while the lowest curve and the rural two-lane and multilane roads had mean risks of 1.1*E-3 and 4.0*E-3, respectively (middle curves). Although there is a multiplicative effect for the volume variable ($V_{it}^{\beta_V}$), its effect was not as marked as the mean risk effect in the order of the SPF curves.

Table 2 also presents the goodness-of-fit measures commonly used in full Bayesian statistics: the posterior mean of the deviance and the Deviance Information Criterion (DIC) (*32*). The deviance is estimated in the same way for frequentist and Bayesian statistics while the DIC is the Bayesian equivalent of the Akaike Information Criterion (AIC). As in the case of their

Table 2. Full Bayesian Hierarchical Models of Weather-Related Crashes.

Road Type	Variable	Mean	Std. Dev.	95% Credible Set	
				2.50%	97.50%
Urban Two-lane	α	-4.959	0.426	-5.805	-4.128
	β_V	0.470	0.048	0.376	0.564
	β_L	0.952	0.116	0.730	1.179
	σ_v^2	0.434	0.078	0.295	0.603
	$\overline{D}$	3614.0			
	DIC	3784.0			
Urban Multilane	α	-6.924	1.531	-9.870	-3.887
	β_V	0.653	0.166	0.322	0.973
	β_L	0.799	0.166	0.483	1.130
	σ_v^2	0.624	0.130	0.403	0.911
	$\overline{D}$	1871.0			
	DIC	1976.0			
Rural Two-lane	α	-6.823	0.141	-7.096	-6.549
	β_V	0.704	0.018	0.671	0.738
	β_L	1.042	0.073	0.903	1.186
	σ_v^2	0.455	0.0340	0.393	0.528
	$\overline{D}$	24990.0			
	DIC	26170.0			
Rural Multilane	α	-5.528	0.922	-7.350	-3.757
	β_V	0.542	0.095	0.357	0.728
	β_L	1.030	0.228	0.589	1.491
	σ_v^2	0.503	0.059	0.397	0.629
	$\overline{D}$	5891.0			
	DIC	6178.0			

frequentist counterparts, deviance and DIC quantify the relative goodness-of-fit of the models; therefore, they are useful for comparing models.

The variance of the random effects (σ_v^2) was significant for all of the models, which means that the models present overdispersion. Urban multilane shows the highest overdispersion with a variance of 0.624, while the lowest value is for urban two-lane roads with a variance of 0.434. Rural roads present a variance of the random effects of 0.455 and 0.503 for two-lane and multilane segments, respectively.

Table 3 presents the top 5% of urban two-lane roads rank ordered by descending order of expected excess frequency. The table also presents the expected crash frequency and the relative risk for each segment as well as the 90% credible set for the three values. Rank tables for the other three road types are estimated but not presented here for brevity. The top-ranked segment

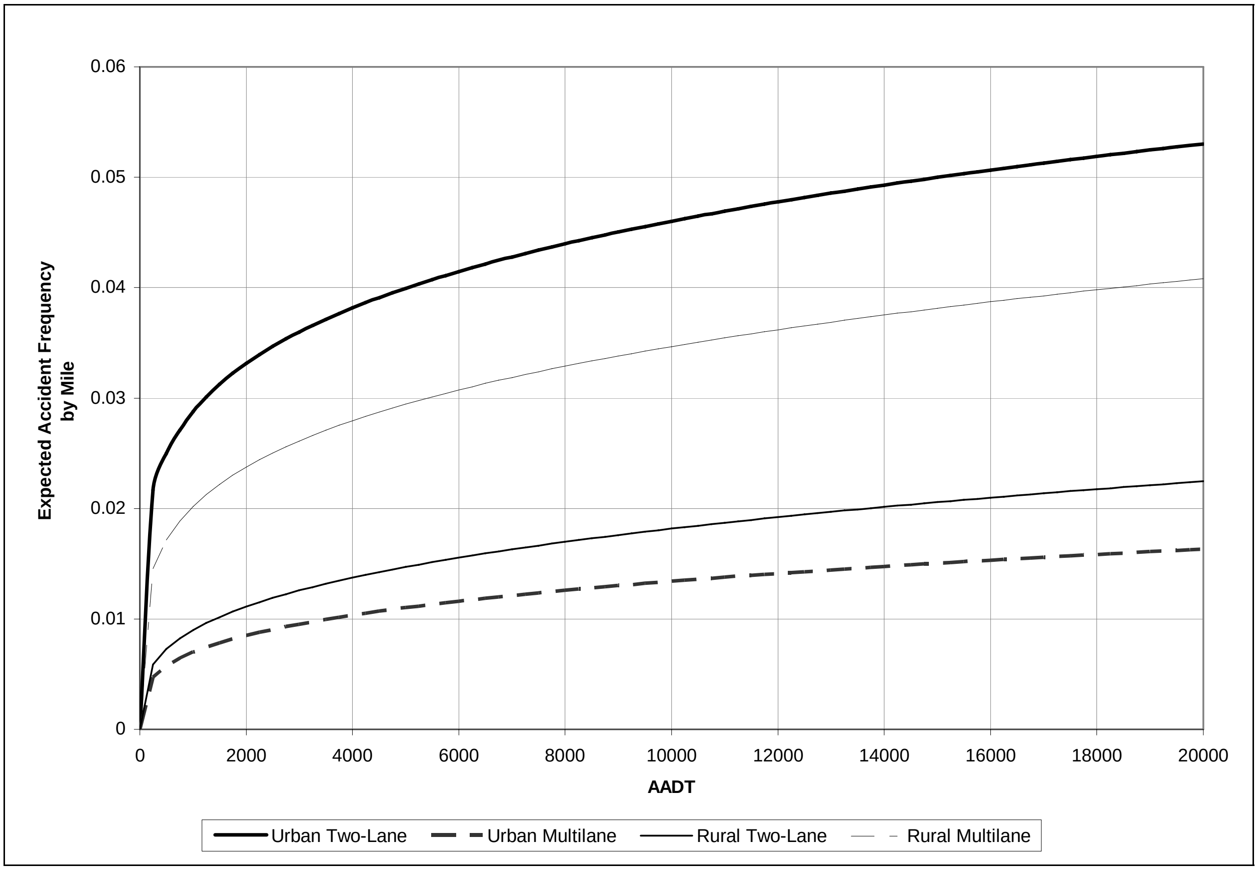

Figure 2. Safety Performance Functions by Road Type.

presents an expected excess of almost 1 crash per year or 350% more crashes than expected in similar sites as measured by the RR. In contrast, the third-ranked segment presents a smaller δ (approximately 0.8) but higher RR (6.6 or 660%). Since the RR measures a percentage while the excess measures an absolute number, the ranks for each of these two variables are expected to be different; however, in the case of urban two-lane roads in the study area the ranks are similar, at least in the top portion of the table. Twenty-three segments out of 560 (or 4.10%) have a 95% confidence or better of excess frequency being positive. Of those 23 segments, 20 are included in the top 5%. In fact, only segments ranked 13, 18, and 23 to 28 on the top 5% have lower than 95% confidence of excess frequency being positive. Similarly, 18 out of 251 (7.17%), 119 out of 6256 (1.9%), and 58 out of 621 (9.34%) segments have a 95% or better confidence of excess frequency being positive for urban multilane, rural two-lane and rural multilane roads, respectively.

Knowledge about the full posterior distribution of parameters is very important, as shown in Table 3 and Figure 3. For example, the ninth segment on the rank presents an excess crash frequency of 0.459 with a standard deviation of 0.282. Assuming this variable as normally distributed, the 90% confidence interval is (-0.003, 0.921); therefore, the value is not significantly different from zero at $\alpha = 0.05$. However, the 90% credible set (or confidence interval) from the full posterior distribution is (0.097, 0.860); hence, significantly different from zero. The full posterior probability density of the parameter shown in Figure 3.a sheds further light on the issue. The distributions of μ, δ, and RR present a heavy right side tail increasing the standard deviation, but the area under the curve to the left of zero is very small for δ. The probability of the excess crash frequency being smaller than zero is easier to observe by comparing the δ-plot in Figure 3.a with those in Figures 3.b and 3.c for segments ranked no. 1 and 23, respectively. The area under the curve to the left of zero for δ in segment 487 (Figure 3.b) is clearly small, while the area for segment 4 (Figure 3.c) is considerably larger. The same can be observed for the RR; the area to the left of one for the segment ranked no. 1 is small, while the area for segment ranked 23 is noticeably larger. The 90% credible sets for these variables are (2.012, 5.386) and (0.855, 3.331) for segments 487 and 4, respectively.

Finally, segments with significant excess crash frequency and RR were mapped to identify their locations as well as possible corridors or clusters of roads with higher risk of weather-related crashes; the map is not presented here for confidentiality reasons. Those segments are the candidates to be part of an information system to warn travelers of potentially significant weather events in their area.

METEOROLOGICAL ANALYSES

The premise of the meteorological component of this project is that atmospheric conditions which instigated weather-related crashes in District 2 had a repeatable signature. Simply put, the composite of snow, rain, wind, ice and fog accidents would reveal a similarity of atmospheric conditions with each different weather type. If this could be shown, based on existing data of crashes, then it was proposed that a scheme could be written that could uniquely and objectively identify those atmospheric conditions. This quantifiable measure of pressure, winds, temperature and moisture would essentially constitute a ‘fingerprint’ of those weather conditions associated with certain crashes. Provided there was a different signature for each, then it would be possible to compare that signature with numerical weather forecasts and ascertain how well the future (predicted) conditions might match past weather that was associated with some crashes.

Table 3. Top 5% Rank of Expected Excess Crash Frequency for Weather-Related Crashes in Urban Two-Lane Segments.

Segment	Rank	Expected No. of Crashes μ*				Excess Crash Frequency δ*				Relative Risk			
		Mean	Std Dev.	Credible set 5%	Credible set 95%	Mean	Std. Dev.	Credible set 5%	Credible set 95%	Mean	Std. Dev.	Credible Set 5%	Credible Set 95%
487	1	1.394	0.393	0.828	2.102	0.992	0.395	0.416	1.701	3.500	1.046	2.012	5.386
520	2	1.246	0.378	0.705	1.924	0.806	0.379	0.263	1.484	2.855	0.906	1.579	4.485
34	3	0.939	0.330	0.483	1.551	0.796	0.331	0.340	1.410	6.607	2.401	3.349	11.070
204	4	1.026	0.319	0.576	1.613	0.715	0.321	0.259	1.303	3.317	1.080	1.828	5.308
202	5	0.841	0.275	0.451	1.341	0.603	0.276	0.212	1.103	3.563	1.206	1.886	5.782
153	6	0.827	0.293	0.419	1.366	0.527	0.294	0.120	1.071	2.782	1.021	1.392	4.664
82	7	0.790	0.308	0.372	1.358	0.526	0.309	0.107	1.092	3.010	1.203	1.404	5.270
89	8	0.693	0.280	0.322	1.215	0.500	0.280	0.127	1.022	3.614	1.499	1.653	6.390
475	9	0.762	0.281	0.377	1.283	0.459	0.282	0.072	0.983	2.528	0.956	1.233	4.309
164	10	0.604	0.247	0.283	1.065	0.444	0.247	0.121	0.909	3.802	1.590	1.744	6.731
411	11	0.710	0.286	0.329	1.245	0.441	0.286	0.061	0.974	2.649	1.084	1.227	4.660
439	12	0.605	0.236	0.288	1.047	0.416	0.236	0.097	0.860	3.212	1.279	1.503	5.602
228	13	0.724	0.281	0.344	1.238	0.376	0.282	-0.004	0.894	2.096	0.834	0.990	3.655
474	14	0.629	0.248	0.298	1.091	0.353	0.248	0.022	0.814	2.292	0.921	1.081	3.989
483	15	0.635	0.248	0.300	1.102	0.353	0.249	0.019	0.820	2.265	0.907	1.067	3.981
87	16	0.526	0.216	0.238	0.925	0.350	0.216	0.061	0.749	2.999	1.250	1.341	5.315
440	17	0.538	0.221	0.248	0.950	0.342	0.222	0.050	0.753	2.749	1.148	1.248	4.890
71	18	0.660	0.256	0.313	1.128	0.337	0.257	-0.012	0.803	2.054	0.815	0.964	3.545
141	19	0.489	0.201	0.224	0.863	0.324	0.201	0.057	0.699	2.973	1.250	1.347	5.269
421	20	0.441	0.196	0.191	0.807	0.321	0.196	0.072	0.685	3.704	1.678	1.595	6.829
369	21	0.420	0.197	0.170	0.794	0.289	0.197	0.038	0.666	3.221	1.543	1.280	6.160
48	22	0.456	0.203	0.194	0.834	0.284	0.204	0.023	0.668	2.664	1.207	1.133	4.904
4	23	0.591	0.242	0.268	1.046	0.274	0.242	-0.047	0.730	1.876	0.781	0.855	3.331
72	24	0.557	0.231	0.251	0.986	0.264	0.231	-0.042	0.691	1.906	0.802	0.858	3.381
11	25	0.528	0.200	0.258	0.897	0.257	0.201	-0.016	0.628	1.957	0.758	0.941	3.356
154	26	0.512	0.212	0.226	0.909	0.255	0.213	-0.032	0.658	2.003	0.846	0.876	3.584
486	27	0.699	0.259	0.349	1.175	0.254	0.260	-0.103	0.734	1.583	0.601	0.774	2.710
517	28	0.474	0.200	0.208	0.840	0.250	0.200	-0.017	0.616	2.127	0.910	0.927	3.800

*These values are calculated for the latest year in the data (2004).

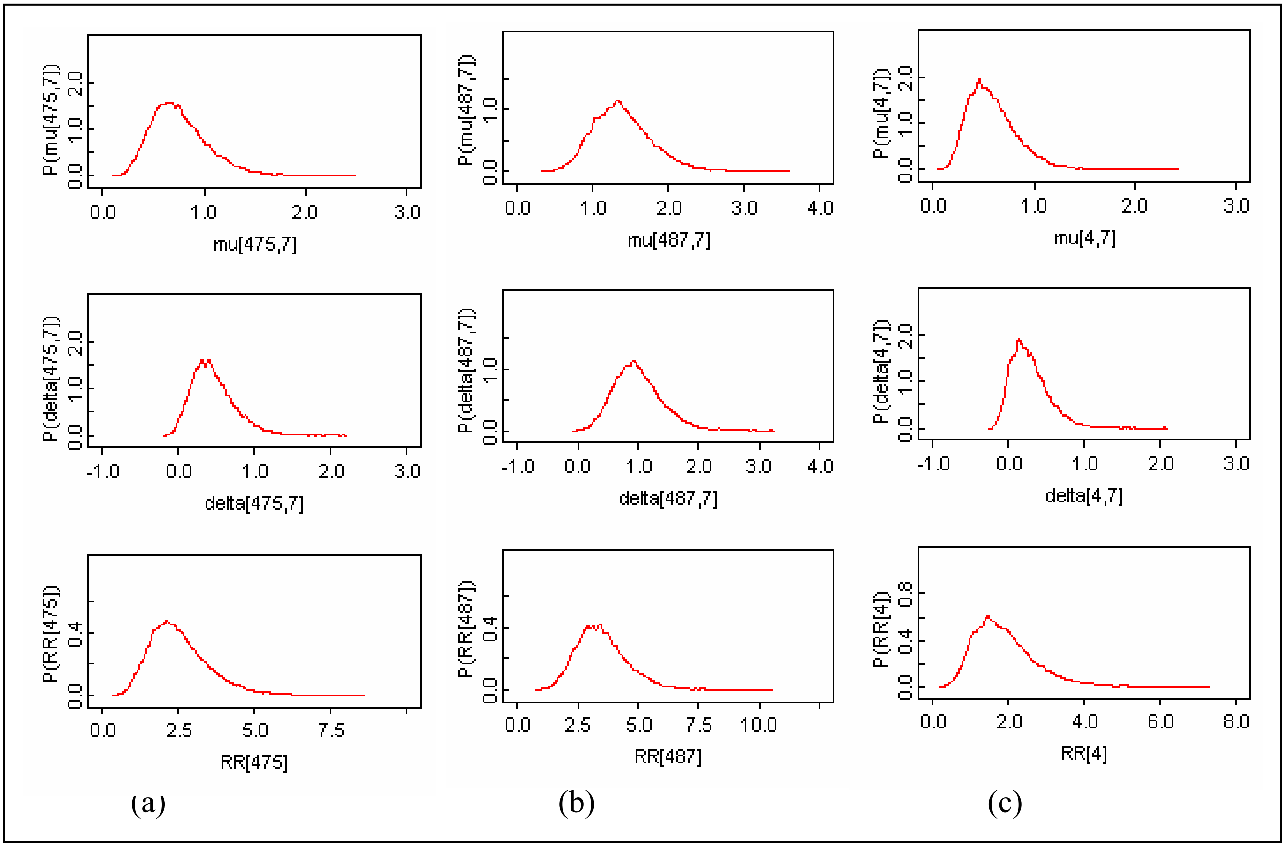

Figure 3. Posterior Probability Densities for several Parameters in the Urban Two-Lane Model.

The challenge of testing this premise had several components. First, a crash database where weather conditions played a role needed to be excerpted from the overall database (this is the information provided by the civil engineering research team). Road segments were converted into latitude and longitude values. The weather-related crashes then were sorted by their atmospheric components. Rain, fog and wind were relatively easy to sort. Snow and ice posed a more serious challenge. After reviewing the crash occurrences, these were divvyed into snow/ice storms and snow squall categories. The reason for this differentiation was due to the significant variation in atmospheric conditions associated with snowstorms compared with snow squalls. To accomplish the parsing of these events, all snow/ice related crash dates were reviewed using a daily weather map interface (http://docs.lib.noaa.gov/rescue/dwm/data_rescue_daily_weather_maps.html) to determine which type of event occurred. Having clarified these differences, the crash database could then be used to "train" the atmospheric measuring scheme.

The second challenge of testing the premise concerns the available meteorological data. Since an objective identification scheme was being developed, a suitable database was needed. The National Center for Environmental Prediction has compiled a "re-analysis" data set for the entire globe for every 6 hours from January 1948 to the present. Surface and upper air observations formed the basis of the global re-analysis (GR) (examples can be seen at:

http://hart.met.psu.edu/meteo497/mapper.html). A sophisticated program was employed to estimate values of temperature, pressure, wind and moisture at locations where few or no observations were available. The GR formed the foundation of the objective identification scheme. However, there were two issues. The data values are available at intervals (grid-points) that are spaced 190 kilometers apart, meaning that only a few grid values are located in Pennsylvania and only one in District 2. The other issue is related to interpreting the data. In the science of the atmosphere, it is not the absolute value of a quantity that is necessarily significant, but rather its departure from a longer-term normal or average value. Therefore, a daily mean and its associated standard deviation of each atmospheric field, for each time and all available vertical levels were computed (there are four daily time intervals, about a dozen layers, and at least five atmospheric values on each layer). This baseline was used to determine the variation from normal of key atmospheric fields for each weather-crash event. For example, low-level moisture is important for fog crashes, whereas the juxtaposition of surface low and high pressure is significant for snowstorms and their related crashes. Even further, there are two elements to each of these fields, the magnitude of the deviation from normal and its configuration (shape) in the atmosphere relative to where the accidents occurred.

From this, a new technique was developed that permits the objective identification of both the shape and magnitude of specific key atmospheric anomaly fields associated with each weather-related crash type. This technique has been peer-reviewed and a paper describing it is pending publication in the *Journal of Applied Meteorology and Climatology*. In most types, there are between 4 and 7 crucial atmospheric fields (such as wind direction at 5,000 ft for snow squalls). The weighting of each field's importance is included in this technique and a summary value called "event type score" is then produced. A series of statistical validations were performed to ensure the accuracy of this procedure. Figure 4 is an example of the outcome of this identification technique.

For the 107 snowstorm cases identified, the concentric circles show the frequency of (in this case) the lowest surface pressure when crashes occurred in District 2. This new technique takes into account the shape of the cluster of locations as well as the magnitude (strength) of the low-pressure system compared to long-term averages.

The research has yielded credible results, which are patterns that are unique to the weather hazard associated with crashes in District 2. (For a host of different events – see http://hart.met.psu.edu/bvroot/.) The graphs in Figure 5 show the difference between random events and those "trained" using the "fingerprinting" technique. This demonstrates a "proof of concept."

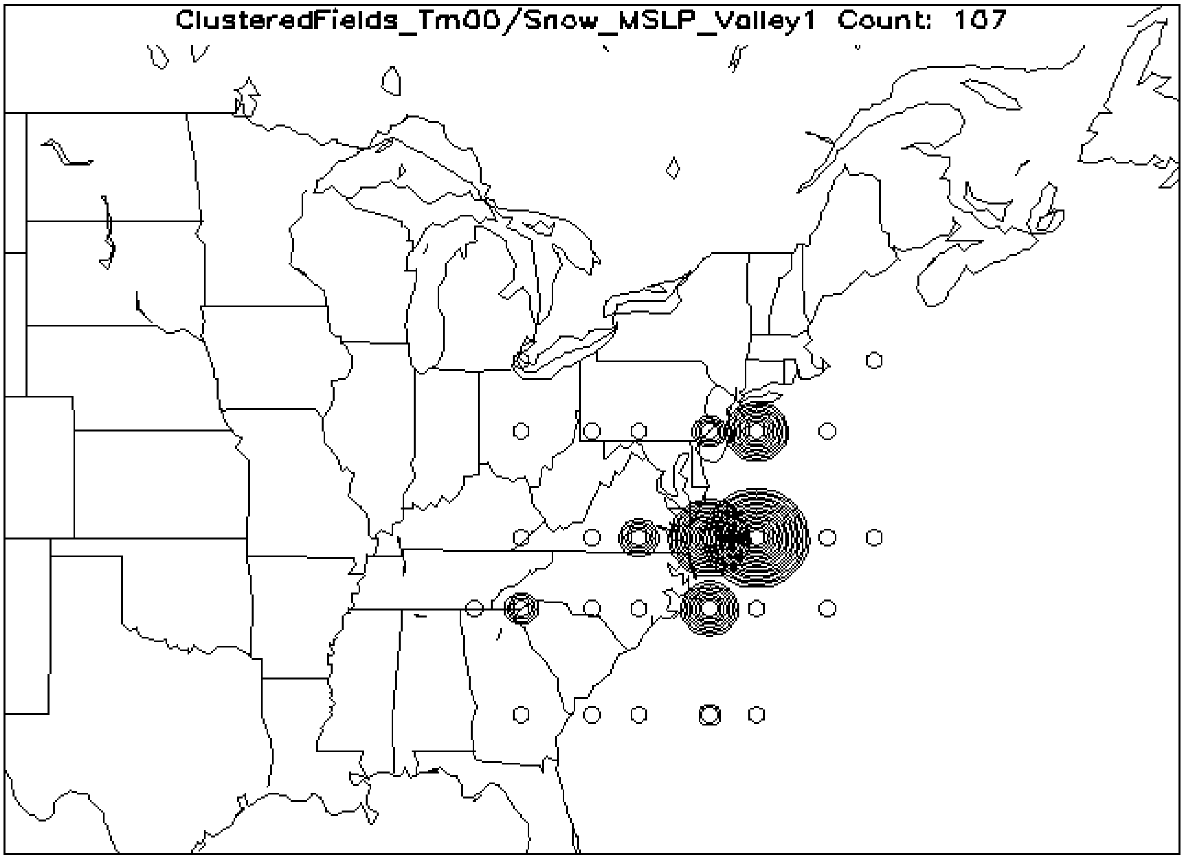

Figure 4. Example Identification of Shape and Magnitude of Key Atmospheric Anomaly Fields. The size and number of concentric circles are related to the frequency of (in this example) surface low pressure in that location when there was significant snowfall in District 2.

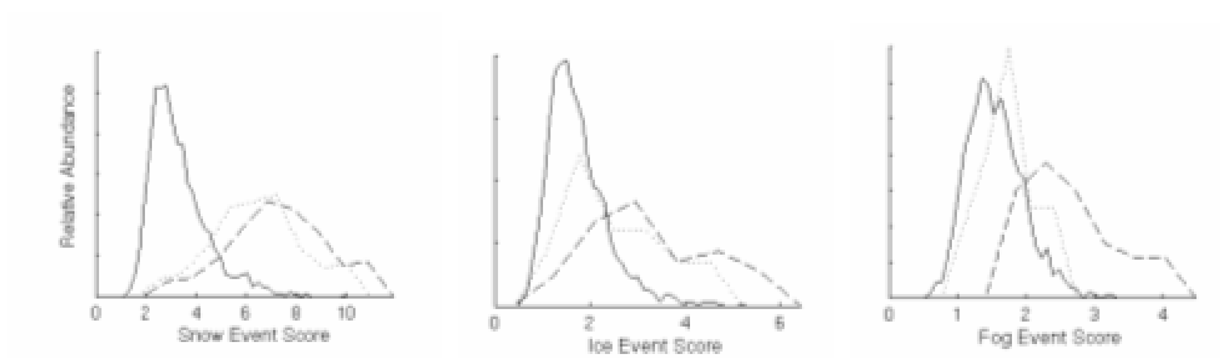

Figure 5. Distinction between Random and "Trained" Events. The dark solid line shows the "score" when random dates are selected to identify the fingerprints of a snow, ice of fog event. The dashed line shows the "score" in identifying the unique signature of these events selected from the crash dates. The higher scores indicate an identifiable signature has been found.

CONCLUSIONS

A full Bayes hierarchical model has been developed to identify sites with promise for weather-related crashes in Central Pennsylvania. The model is similar to others in the literature but allows the estimation of both the expected excess crash frequency and risk ratio. The full Bayes formulation also allows for the inclusion of a random effects term to help address individual site differences.

The number of segments found to have a significant excess crash frequency of weather-related accidents is different for each road type and varies from 2% to 9%. This percentage depends on the significance level selected and for this work, 95% confidence level was used. Since the excess crash frequency is a function of the relative risk, those segments with significant relative risk generally have a significant excess crash frequency as well.

The concept of relative risk may be a particularly useful tool for conveying the need for improvements to road users and decision makers. This concept expresses the increase in risk in terms of percentage with respect to a "normal population" and therefore may be more familiar to users from its use in epidemiology and health sciences.

Expected excess crash frequency, on the other hand, presents the advantage of being an absolute measure. This excess is more closely related with the crash reduction achievable with engineering improvements than the relative risk; therefore it is more useful for the selection of sites for further engineering analysis, including cost-benefit studies.

Knowledge of the precision of the estimates of excess crash frequency presents a clear advantage for decision making. Segments presenting high expected excess crash frequency with high statistical significance show potential for engineering improvements, while segments with high excess but lower statistical significance might be regarded as sites with less certainty in terms of their potential for safety improvement. Full posterior distribution sampling is also advantageous in this sense, since the precision is not established in terms of distributional assumptions, as in the case of normal distributed variables using the mean and the standard deviation, but drawn from the posterior distribution in the form of a credible set.

The use of random effects made possible the estimation of RR and excess crash frequency for each segment. Since random effects do not change over time they are likely to reflect site-specific differences, assuming that the segment characteristics remain relatively constant over time. Random effects also prevent regression to the mean bias by means of their prior distribution; while random effects capture unmeasured cofounders, they are part of a zero-mean normal distribution, which will pull the estimates to the mean.

The methodology presented here is extendable to any type of crash under investigation and even to other facility types. This approach can be particularly helpful when analyzing crash types that are relatively infrequent; the use of random effects might provide a means for accounting for random variability.

If this were a project seeking to identify sites for action, the natural step would be an investigation of crashes at actual sites. Perhaps crash reports would be reviewed to assess the particular details of the crashes. This detailed review would help ensure that the correct road sections were identified.

The inclusion of spatial correlation in addition to unstructured random effects is another interesting extension of the research. Spatial correlation will further improve site level estimation by pulling strength from adjacent sites. Because the proposed HAR and CMS are intended for transmission and use in an area, spatial correlation is worthy of additional exploration.

Other possible covariates can be included in the models as part of the risk estimation. In fact, when exploring particular engineering improvements, such as lane widening, the inclusion of covariates related to the improvements may be desirable, in this example lane width. Alternative prior distributions and the sensitivity of model results to these specifications can also be explored. Some other functional forms can be explored as well, using the flexibility provided by the FB approach.

It is important to recognize that there are additional ranking methods that can be used. Ranking by posterior mean of the decision parameter (excess crash frequency) was used in this study, but ranking by the probability that the site is the worst and ranking by posterior distribution of ranks have also been suggested by other researchers. A possible extension of this work is the comparison of different ranking methods.

There are several additional steps needed to make this useful to operations. First, during the past 6 months, the Pennsylvania climate office has acquired a more refined dataset for North America on which to base the training system. This new database is called the "North American Regional Reanalysis" (NARR), and its grid points are only 32 km (20 miles) apart or 6 times finer in resolution; its values are every 3 hours or twice the temporal resolution, and it contains 50 layers (four times the vertical resolution). In collaboration with the local National Weather Service Office (CTP), the climate staff has downloaded (6.3 terabytes), parsed, compressed and calculated the climatologic mean values of the NARR. The next step is to re-train the crash events using the NARR and recalibrate the event type scores for the higher-resolution data set. Once completed, the identification scheme would then be applied to the twice daily high-resolution computer forecasts for this region to objectively compare the forecast anomalies (compared with the NARR mean values) with the signature anomalies associated with past crashes. While this technique has been tested off-line, there is still some development required to link the real-time forecasts with the "fingerprints" of past crash weather occurrences. Threshold values will need to be established to reduce the false-positive alerts. Finally, the communication and interpretation of these alerts will need to be established with PennDOT.

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