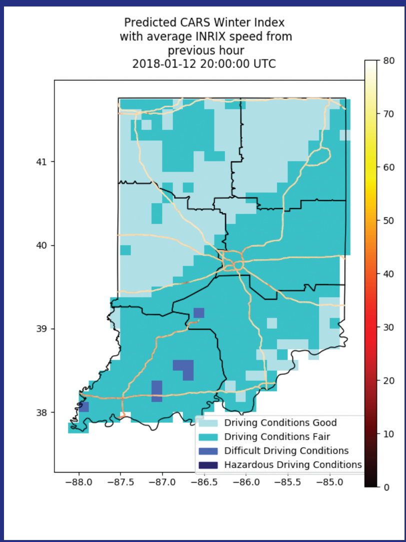
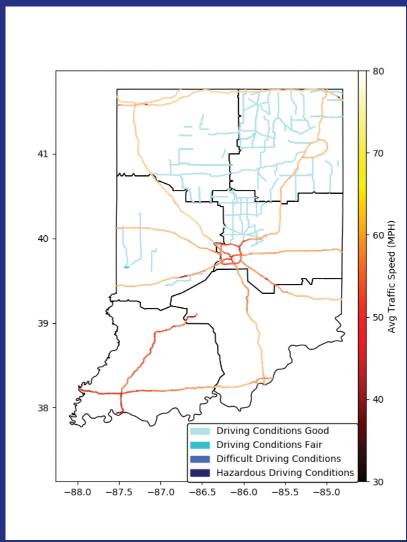
JOINT TRANSPORTATION RESEARCH PROGRAM

INDIANA DEPARTMENT OF TRANSPORTATION AND PURDUE UNIVERSITY

Automated Estimation of Winter Driving Conditions





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SPR-3821 • Report Number: FHWA/IN/JTRP-2018/22 • DOI: 10.5703/1288284316867

RECOMMENDED CITATION

Baldwin, M. E., Burris, K. D., & Elmore, K. L. (2018). *Automated estimation of winter driving conditions* (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2018/22). West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284316867

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JOINT TRANSPORTATION RESEARCH PROGRAM

The Joint Transportation Research Program serves as a vehicle for INDOT collaboration with higher education institutions and industry in Indiana to facilitate innovation that results in continuous improvement in the planning, design, construction, operation, management and economic efficiency of the Indiana transportation infrastructure. https://engineering.purdue.edu/JTRP/index_html

Published reports of the Joint Transportation Research Program are available at http://docs.lib.purdue.edu/jtrp/.

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Print ISBN: 978-1-62260-514-9

TECHNICAL REPORT DOCUMENTATION PAGE

<table>
<tr><td>1. Report No.
FHWA/IN/JTRP-2018/22</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient's Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Automated Estimation of Winter Driving Conditions</td><td colspan="2">5. Report Date
October 2018</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="2">7. Author(s)
Michael E. Baldwin, Kevin D. Burris, and Kimberly L. Elmore</td><td colspan="2">8. Performing Organization Report No.
FHWA/IN/JTRP-2018/22</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
Joint Transportation Research Program (SPR)
Hall for Discovery and Learning Research (DLR), Suite 204
207 S. Martin Jischke Drive
West Lafayette, IN 47907</td><td colspan="2">10. Work Unit No.</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
SPR-3821</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
Indiana Department of Transportation
State Office Building
100 North Senate Avenue
Indianapolis, IN 46204</td><td colspan="2">13. Type of Report and Period Covered
Final Report</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code</td></tr>
<tr><td colspan="4">15. Supplementary Notes
Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.</td></tr>
<tr><td colspan="4">16. Abstract
There is great potential for improvements in traveler safety and satisfaction as new sources of information are incorporated into advanced analytics and prediction systems. It is critical for transportation agencies to be able to monitor weather conditions in real-time as well as over the long-term for purposes of maintenance, planning, and performance evaluation. Travelers also use this information to plan their routes, make decisions on timing, and improve their awareness of potential hazards. A machine learning model was developed in this project to automatically estimate winter driving conditions in real-time using weather information as input. This system can provide rapid updates of changing conditions and help reduce the effort required to report driving conditions during intense winter storms. The system performed well in an experimental evaluation during the 2017-18 season. Seasonal analyses of winter precipitation that incorporated crowd-sourced observations were also generated and displayed significant differences from previous research.</td></tr>
<tr><td colspan="2">17. Key Words
road weather, machine learning, crowd-sourced observations</td><td colspan="2">18. Distribution Statement
No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.</td></tr>
<tr><td>19. Security Classif. (of this report)
Unclassified</td><td>20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages
21</td><td>22. Price</td></tr>
</table>

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EXECUTIVE SUMMARY

AUTOMATED ESTIMATION OF WINTER DRIVING CONDITIONS

Introduction

Real-time information regarding the status of the highway network has wide-ranging benefits. Knowledge of current traffic speeds, work zones, traffic cameras, and incident reports allows travelers to modify their routes and avoid potential hazards. In addition, operators of the transportation system rely heavily on such information to identify and verify incidents, manage winter maintenance resources, and issue advisories, resulting in improved safety and efficiency. INDOT uses numerous methods of communicating such information both internally and to the public, such as websites, "511" phone systems, and messaging signs. These systems have been evolving rapidly as new innovations are implemented, and customers have increasing expectations of continued advances.

It is critical for transportation agencies to be able to monitor conditions in real time as well as over the long term for purposes of maintenance, planning, and performance evaluation. INDOT uses the Condition Acquisition Reporting System (CARS) as a tool for communicating driving condition information along with weather-related impacts such as winter driving conditions, flooding, and weather warnings. During winter weather events, as staff observe conditions in real time, reports of winter driving conditions are submitted to CARS. There are practical limitations to this system since staff efforts during winter weather events are focused primarily on maintenance actions. During intense winter storms, it may be difficult for plow drivers and supervisors to report the driving condition. This provides motivation for this work in the development of automated tools that support the analysis and communication of information related to driving conditions.

There is great potential for improvements in traveler safety and satisfaction as new sources of information are incorporated into advanced analytics and prediction systems. In this project, we have developed innovative approaches to produce real-time estimates of winter driving conditions along with seasonal summaries of winter precipitation. High-fidelity weather information was integrated with CARS winter driving condition reports to develop a model that can accurately estimate driving conditions across the state based on weather variables. An experimental system was executed during the 2017–18 winter season to demonstrate the potential for automated estimates of driving conditions across Indiana. In addition, crowdsourced observations of winter precipitation were merged with standard observations at airports to generate high-quality seasonal analyses of winter precipitation frequency by type, such as snow and freezing rain.

Findings

- Several machine learning classification methods were tested and evaluated using a multi-year training data set. An experimental system was executed in real time during the 2017–18 winter season to demonstrate the potential for automated estimates of driving conditions across the state. A model based on the random forest approach was able to correctly classify examples from the test dataset at roughly 90% accuracy. The performance of this model fell to ~70% when applied to the 2017–18 season.
- Reduction in performance during the 2017–18 season was likely caused by "overfitting" to the 2014–16 data that was used to train the system, along with changes in the system used by the National Weather Service to provide short-term weather forecast information. Further research is needed to address these issues.
- In addition, crowdsourced observations of winter precipitation were merged with standard observations at airports to generate high-quality seasonal analyses of winter precipitation frequency by type, such as snow and freezing rain. These results provide a significant update to a recent Clear Roads study and contain a large number of observations that were unavailable in that previous study.

Implementation

The automated estimates for driving conditions will be refined as more information becomes available. A system for notifying INDOT staff of significant discrepancies between the current CARS reports and automated estimates will be implemented. This is a reasonable step between the current system and using the automated estimates as a "first guess" in the CARS reporting system. Monthly and seasonal analyses of winter precipitation types are available for planning and performance evaluation purposes via a web interface.

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1. INTRODUCTION

Traveler safety and customer satisfaction are critical components of INDOT's mission, goals, and values (Indiana Department of Transportation, 2018). Access to information regarding driving conditions is an important factor in improving both customer satisfaction and safety. Operators of the transportation system rely heavily on such information to identify and verify incidents, manage winter maintenance resources, and issue advisories; resulting in improved safety and efficiency. In addition, travelers benefit greatly from access to up-to-date information regarding the status of the road network (Toledo & Beinhaker, 2006). Customers also have increasing expectations of the system, including better access and improved quality of this information. To meet these needs, INDOT utilizes several methods for communication, such as websites, "511" phone systems, social media outlets, and messaging signs. In particular, INDOT uses the Condition Acquisition Reporting System (CARS) as a tool for communicating road condition information. During winter weather events, as plow drivers and supervisors observe driving conditions in real time, they submit reports of winter driving conditions to the CARS system. Travelers use this information to plan their routes, make decisions on timing, and improve their awareness of potential hazards.

Travelers have a very good understanding of how weather can impact driving conditions and there is considerable potential to improve traveler safety and satisfaction by incorporating weather information into transportation systems management and operations (Garrett et al., 2017). Since CARS reports are submitted manually, there are some practical limitations of this system. Staff effort during winter weather events is focused primarily on maintenance actions. During intense winter storms it may be difficult for plow drivers and supervisors to report the driving condition. This provides motivation for the development of automated tools to assist with the analysis and communication of driving condition information. By incorporating recent advances in environmental sensors, crowdsourced reported conditions, and prediction models improvements in estimation of the state of the road network can be realized. The value of such estimates could be boosted by expanding the information to include impacts on capacity, work zones, road maintenance strategy, snowplow routing, etc. Data availability and tools for analytics and prediction are developing rapidly, this is only expected to continue at an explosive pace as connected vehicles and other advances in technology are widely deployed.

Weather often plays a significant role in determining roadway mobility and safety, especially during the winter season (Juga, Nurmi, & Hippi, 2013; Kwon, Fu, & Jiang, 2013). Precipitation varies considerably over time and across locations during a storm, potentially causing large variations in driving conditions across the state. Rapidly changing weather conditions can also result in large variations in traffic speeds. The high degree of temporal and spatial variability in these important sources of information argues for the need to acquire, analyze, and communicate data rapidly and effectively. There are numerous sources of data related to weather and traffic; INDOT (and JTRP) have been leaders in the development and implementation of integrating, analyzing, and communicating this information via "tickers" and spatial maps (McNamara et al., 2016). Seasonal analyses of winter precipitation can also be useful for planning and performance evaluation purposes.

In this project, we have developed innovative approaches to produce real-time estimates of winter driving conditions along with seasonal summaries of winter precipitation. High-fidelity weather information was integrated with CARS winter driving condition reports to develop a model that can accurately estimate driving conditions across the state based on weather variables. Several methods were tested and evaluated using a multi-year training data set. An experimental system was executed in real time during the 2017–18 winter season to demonstrate the potential for automated estimates of driving conditions across the state. In addition, crowdsourced observations of winter precipitation were merged with standard observations at airports to generate high-quality seasonal analyses of winter precipitation frequency by type, such as snow and freezing rain.

The remaining sections of this report will provide information regarding the sources of weather information used, describe how the machine learning models were trained and evaluated, discuss an example case in detail, and provide seasonal summaries of winter precipitation types from standard and crowdsourced observations.

2. SOURCES OF INFORMATION

JTRP has maintained a database of weather and traffic information for several years. Numerous web-based mobility dashboards and tickers have been developed that utilize this database (Indiana Department of Transportation, 2018) including the weather ticker (McNamara et al., 2016). Purdue EAPS researchers continue to provide the weather data feed into this database (Baldwin, Snyder, Miller, & Hoogewind, 2015). For this project, weather-related variables were obtained from a variety of sources. These were all generated routinely by the National Weather Service, and are freely available in near real time for monitoring and predicting weather conditions. Variables were interpolated to a regular latitude/longitude grid across the lower 48 United States, using 1/8 degree grid spacing (approximately 12.5 km/8 miles). Weather variables represent spatial averages across an area represented by a grid box, at hourly temporal accumulation or average, ending at the valid time of the analysis. Traffic speed information and CARS winter driving index reports were also obtained from the JTRP database.

2.1 Traffic Speed Information

Crowdsourced probe vehicle data for traffic information were provided to JTRP by an independent contractor (INRIX). These reports were derived from cell phone data and fleet vehicles. Traffic speed information is displayed in several examples in upcoming sections of this report to provide evidence of winter driving conditions. To reduce computation time needed for data retrieval and processing, 15-minute median data was used for major roadways, and this was further averaged into hourly values to match the timing of the weather variables. Although traffic speed information was not used as a predictive variable in the machine learning system for this project, we plan to incorporate this information in future research.

2.2 INDOT Condition Acquisition Reporting System (CARS)

The INDOT CARS database includes categorical winter driving conditions along with other pertinent information. There are 709 unique road segments across that state that were available for CARS winter driving index reports, which were in categories of "good," "fair," "difficult," or "hazardous." One limitation of this dataset is that driving conditions are manually reported by INDOT staff; therefore the locations of these reports could be biased towards the location preferences of the reporters. In addition, winter maintenance efforts to improve the road condition may occur before the report is posted; therefore these reports could be skewed towards better conditions. Another factor which may decrease the frequency of "difficult" and "hazardous" conditions is that it may become increasingly difficult for the plow driver or supervisor to report the condition in those situations. CARS reports are available online at https://indot.carsprogram.org/.

2.3 North American Mesoscale (NAM) Model

The North American Mesoscale prediction system (NAM; Rogers et al., 2017) is a short-range weather prediction and data assimilation system that provides weather forecast information to the National Weather Service and other users. The NAM has horizontal grid spacing of 12 km with 60 vertical levels. Forecasts are updated every six hours and output is available out to 84 hours into the future. Hourly output covering the first six hours of the period were collected and used to estimate hourly weather conditions in real time. Besides precipitation amount, all weather variables for this project were obtained from the NAM and added to the JTRP database. Contained within the NAM dataset are categorical precipitation type variables (rain, snow, ice pellets, and freezing rain) that were used to estimate winter precipitation reaching the ground. These classifications are based on logic that involves vertical thermal and moisture profiles (Baldwin et al., 1994).

TABLE 2.1
Weather-related variables and units used in this project

Weather variable	Units
Specific humidity @ 2m	kg/kg
Air temperature @ 2m	K
Wind speed and gusts @ 10m	m/s
Surface temperature	K
Net surface solar and longwave radiation	W/m^2
Sensible, latent, and ground heat fluxes	W/m^2
Categorical precipitation types	binary (yes/no)
Visibility	m
Snow depth	m
Hourly precipitation	mm
Surface pressure	Pa
Energy required to melt new snow/ice in past hour (Qextra, Qtotmelt)	J

2.4 NCEP Stage IV Precipitation Analysis

The National Centers for Environmental Prediction (NCEP) Stage IV precipitation analysis (Baldwin & Mitchell, 1997) was used for information on precipitation in this project. Stage IV is an hourly mosaic of precipitation accumulation compiled using both rain gauge and radar data. These data are compiled by each of the 12 River Forecast Centers (part of the National Weather Service) located across the country. Stage IV precipitation analyses are represented on a grid with spatial resolution of 4 km and have available temporal aggregations of one hour, six hours, or 24 hours. More information about the NCEP Stage IV precipitation analysis can be found at http://www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/stage4/.

2.5 Summary of Weather-Related Variables and Data Sources

Table 2.1 lists the weather-related variables from NAM and Stage IV that were used in this project and their units.

3. MACHINE LEARNING

3.1 Overview

Machine learning and data science approaches have received a great deal of attention in recent weather and climate research due mainly to the rapid growth in data and the demand for improvements in forecasting and monitoring of weather events and their impacts on society. These techniques can recognize patterns and simplify complex information from wide-ranging sources and provide additional decision support for end-users. For example, McGovern et al. (2017) provide an overview of recent research in application of machine learning to a variety of weather prediction problems. Several of these are directly related to transportation, such as aviation turbulence (Williams, 2014), precipitation classification (Elmore et al., 2015), and severe hail (Gagne, 2016). Carmichael, Gallus, Temeyer, and

Bryden (2004) used an artificial neural network to develop a winter severity index for winter maintenance in Iowa. Machine learning and data science are also very active areas of research in transportation, such as hazardous condition warnings and traffic flow predictions (e.g., Cai et al., 2016; Lv, Duan, Kang, Li, & Wang, 2015; Oh, Oh, & Ritchie, 2005; Tang, Liu, Zou, Zhang, & Wang, 2017). In this project, we demonstrate the application of machine learning techniques with weather and road condition information with the goal of improving understanding and communication of the current state of the highway network.

For this project, we tested several different machine learning approaches in order to determine the best method for automatically estimating the CARS winter driving index based on weather variables. These approaches attempt to learn the relationship between some input (in this project: weather variables) and an output target, or label (CARS reports). When the output labels are distinct classes ("good," "fair," "difficult," "hazardous") this is known as a *classification* problem (Pedregosa et al., 2011). Machine learning models have the ability to adapt, or learn, from previously known examples of inputs and outputs, collectively called training data. Users of these models assume that they will be able to generalize to situations that are not included in the training data (Domingos, 2012) and will be useful for prediction and estimation purposes.

In this project, the machine learning methods that were found to be most successful in connecting input weather variables to output CARS winter driving condition reports were based on decision trees (Burris, 2018). Similar to other machine learning procedures, decision trees begin with input that consists of numerous attribute variables ("features"). These are used for the classification problem, so the output must be in the form of distinct classes or labels. Each input example (or object) starts at the root of the decision tree and passes through various branches, or nodes. Each node contains an attribute-based test which helps to discriminate different classes of objects. The final step of this process is the "leaf" which is the predicted class (label) that the model assigns to that set of input variables. Nodes are designed to maximize separation between input objects that are presented (Quinlan, 1986).

It is not unusual to find several machine learning approaches that can classify examples in the training data set with few mistakes. However, even if a decision tree is able to correctly classify every example in the training data, there is no guarantee that the tree will correctly classify examples from outside the training data. Since the training data probably does not contain every possible combination of input/output connections, it is very likely that this seemingly perfect tree found irrelevant and or noisy details within the training data. This is known as "overfitting," which is a widespread issue in machine learning and has aspects of both systematic error (repeatedly learning the wrong connection between input/output examples) and random error (learning random variations about input/output examples) (Domingos, 2012). Overfitting appears typically as overly complex decision trees with a huge number of nodes, branches and leaves. Overfitting can be reduced by requiring each leaf to represent a minimum number of examples, or by limiting the maximum "depth" of the tree (Pedregosa et al., 2011).

Random forests are collections of individual decision trees, where each tree casts a "vote" for the output label. By using a large number of randomized trees, the problem of overfitting can be diminished somewhat. Overfitting still occurs as an artifact of the individual trees, not the forest. Random forest models are relatively fast and easy to build since the individual trees are constructed from independent subsets of the training data, allowing for parallel processing (Breiman, 2001).

3.2 Model Development

3.2.1 CARS Report Preprocessing

Supervised machine learning models learn from previous examples, where the correct labels of all input features are known. These known examples are called the training data. For this project, the inputs were the weather variables organized on a regularly spaced grid (1/8 degree) at regular time intervals (hourly). However, the output labels are CARS reports, which do not correspond directly in either space or time to the gridded weather data. Therefore, before a training data set can be produced, the data must be transformed such that matched pairs of inputs and outputs can be obtained.

An archive of CARS reports was interrogated to assess this dataset. Burris (2018) found that it was often the case to find several road segments updated simultaneously with the same winter driving condition index. Reports were often provided a valid time that extended many hours, and sometimes days, into the future. Condition updates could also be issued for a segment before the original report expired. It seems reasonable to assume that the driving conditions would improve before an official CARS report was issued to represent that improved condition. For these reasons, the time of issuance for each CARS report was considered, rather than its timespan. We assume that the weather conditions occurring prior to the CARS report were the factors for determining the driving condition, so report times were rounded down to the hour in which they were issued.

Since CARS segments can span across several weather grids, the spatial extent of CARS reports were interpolated to the weather variable grid. Reports were obtained for the time period between November 2014 and December 2016. During this period, the CARS archive contained the locations of both the starting and ending points for every segment, and both of these were assigned the label of the CARS winter driving condition (converted to a numerical value, good = 1, fair = 2, difficult = 3, hazardous = 4). These values were linearly triangulated to the weather grid locations

(Barber, Dobkin, & Huhdanpaa, 1996). An example of this interpolation process is provided in Figure 3.1.

Interpolated values are rounded back to the ordinal numbers and converted to the categorical winter driving index labels. Weather variables at each grid location were paired with these interpolated CARS reports. This procedure was applied to every hour in the archive, resulting in 184,884 labelled examples that could be used for the training dataset. The distribution of these interpolated CARS winter driving index labels are shown in Table 3.1. The CARS reports were dominated by the "good" category (59% of the total), followed by "fair" (33%) and "difficult" (7%), while "hazardous" reports were extremely rare (less than 0.5% of the reports).

3.2.2 Evaluation of Model Training

The training data set was randomly split into two groups: 75% for training and 25% for testing/evaluation. Models were built and trained using the python programming package called Scikit-learn (Pedregosa et al., 2011), which is widely used for classification as well as other machine learning tasks. Since these different models all use the same input data format in Scikit-learn, it was relatively easy to test and compare the performance of several machine learning methods. The results of the machine learning model development and evaluation are briefly summarized in this report and are presented in more detail in Burris (2018).

A total of 16 different classification models were developed and evaluated to estimate the CARS winter driving index reports in the training data set (184,884 labeled examples). A sample of the output from these models is shown in Figure 3.2. After these models were developed using the random subset of the training data, they were tested using the remaining 25% and evaluated by comparing the predicted CARS conditions against the observed CARS winter driving index. Accuracy was summarized by simply dividing the number of correct classification predictions by the total number of examples (Table 3.2). Training accuracy is defined by the model fit to the examples used to train the model, testing accuracy shows how well that model is able to fit the examples that were not used to train the model. Model bias was defined for each CARS index category

TABLE 3.1
CARS winter driving index report distribution for the training data set (2014–2016)

CARS winter driving index	Good	Fair	Difficult	Hazardous
Number of occurrences	109210	61521	13564	589

Source: Burris (2018).

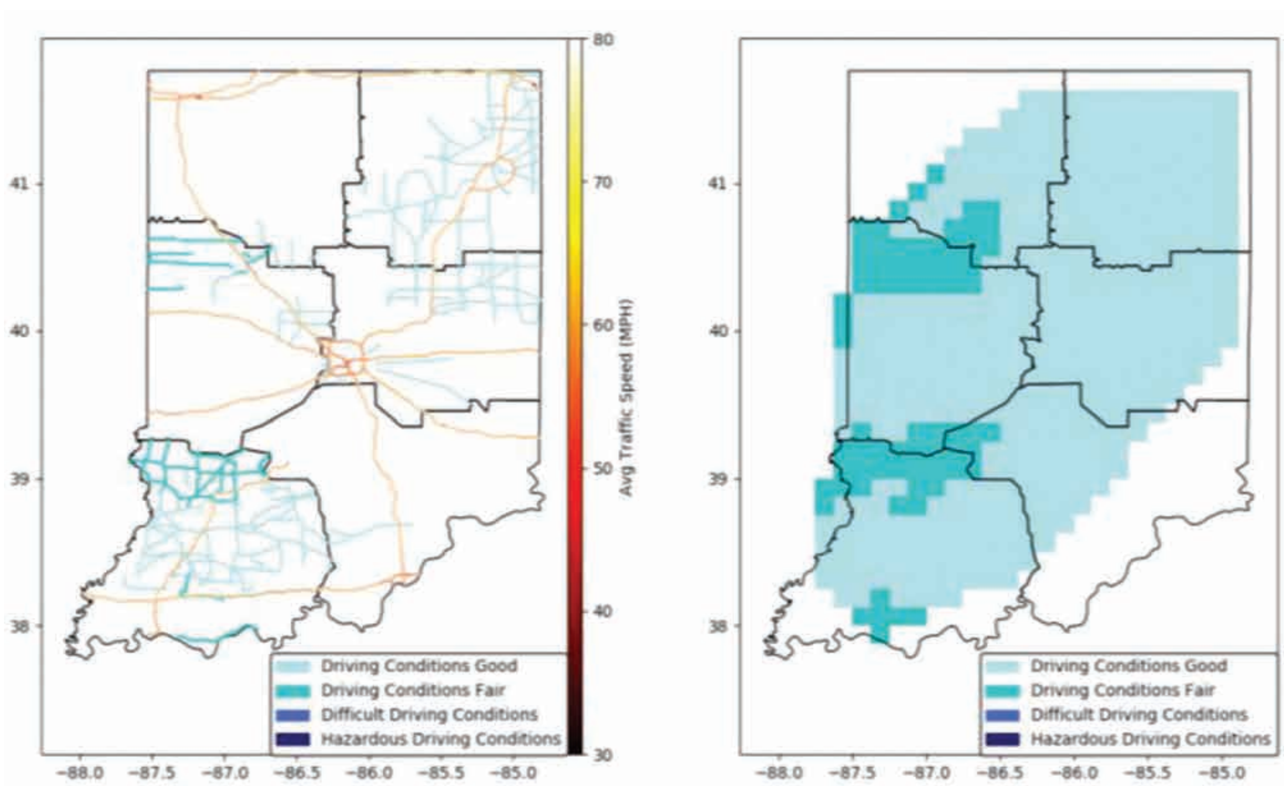

Figure 3.1 Example of interpolation process for CARS reports to the weather variable grid. Left panel displays CARS winter driving index reports and INRIX traffic speeds valid at midnight EST January 12, 2018. Right panel displays CARS reports interpolated to the 1/8 degree weather grid valid at the same time. (Source: Burris, 2018.)

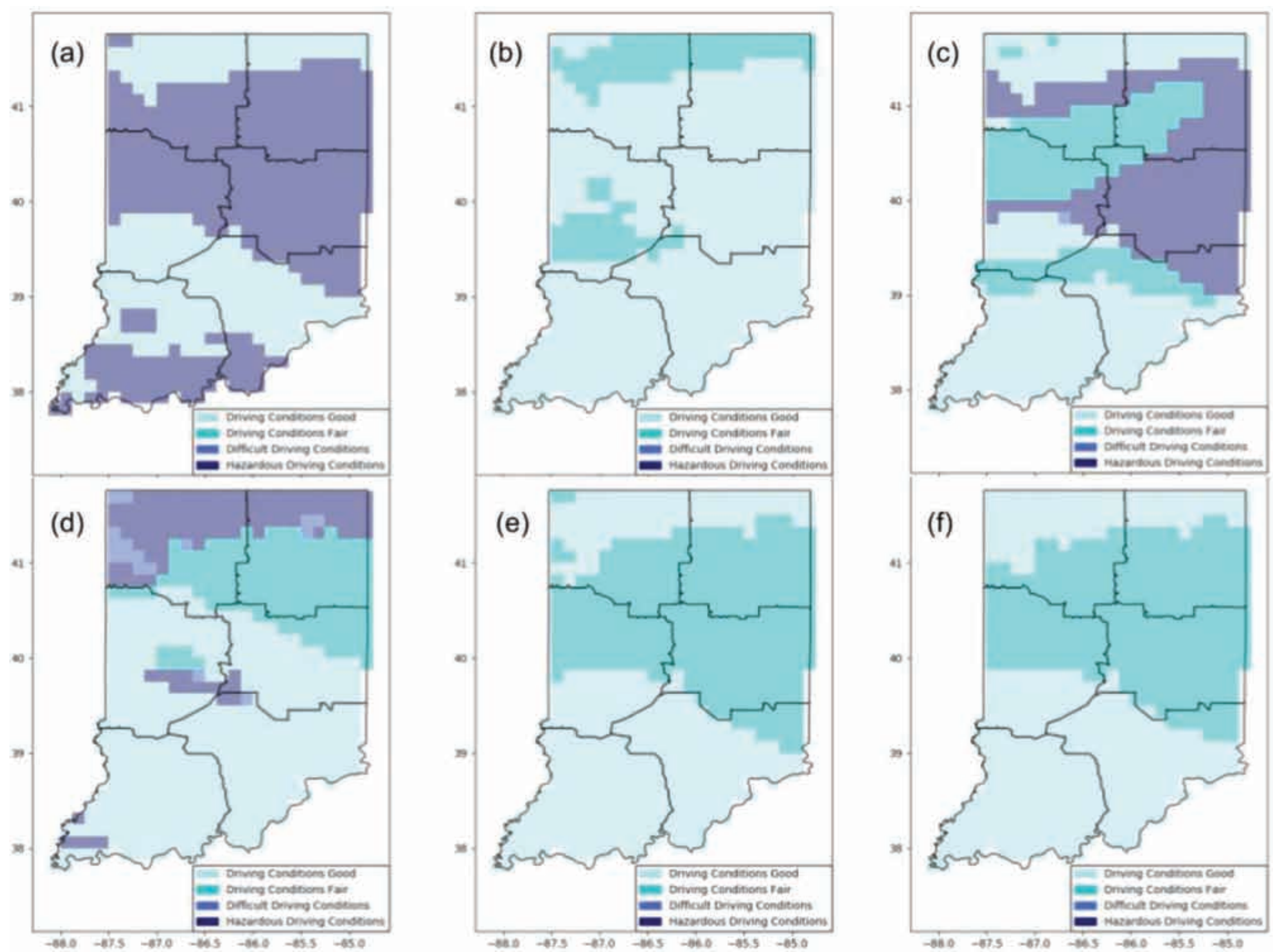

Figure 3.2 Examples of several machine learning models for input weather valid at 7:00pm EST December 30, 2017. Estimated CARS conditions are color coded from good to hazardous. Output from models are presented from: Bernoulli NB (a), random forest (b), decision tree (c), linear discriminant (d), k-nearest neighbor (e), and MLP classifier (f). (Source: Burris, 2018.)

TABLE 3.2
Performance of various machine learning classification models on 2014–16 training data set

	Accuracy		Bias				POD			
ML Model	**Training**	**Test**	**Good**	**Fair**	**Difficult**	**Hazard**	**Good**	**Fair**	**Difficult**	**Hazard**
BernoulliNB	0.57	0.57	1.26	0.11	2.99	0.00	0.87	0.05	0.59	0.00
Decision Tree	1.00	0.85	1.00	1.00	1.00	0.95	0.90	0.79	0.73	0.54
Extra Tree	1.00	0.83	0.99	1.01	1.01	0.90	0.88	0.76	0.67	0.47
Extra Trees	1.00	0.91	0.99	1.04	0.94	0.64	0.94	0.89	0.81	0.58
GaussianNB	0.32	0.32	0.66	0.02	0.00	188.13	0.53	0.01	0.00	0.96
k-NN	0.95	0.91	1.00	1.01	0.97	0.83	0.94	0.87	0.80	0.65
Linear Discrim.	0.67	0.67	1.18	0.78	0.61	0.89	0.86	0.44	0.25	0.06
Linear SVC	0.67	0.67	1.23	0.82	0.03	0.00	0.89	0.46	0.01	0.00
Log. Regr.	0.67	0.68	1.21	0.84	0.07	0.00	0.88	0.47	0.03	0.00
Log. Regr. CV	0.68	0.68	1.21	0.85	0.08	0.00	0.88	0.59	0.04	0.00
MLP	0.75	0.74	1.09	0.93	0.64	0.20	0.87	0.01	0.39	0.13
Near Centroid	0.57	0.56	1.32	0.02	2.30	14.19	0.89	0.02	0.44	0.22
Quadr. Discrim.	0.12	0.12	0.21	0.05	0.04	265.33	0.18	0.88	0.01	0.99
Rand Forest 10	1.00	0.90	0.99	1.03	0.93	0.68	0.93	0.88	0.79	0.54
Rand Forest 20	1.00	0.91	1.01	1.01	0.90	0.57	0.95	0.44	0.79	0.54
Ridge	0.67	0.67	1.25	0.79	0.03	0.00	0.89	0.44	0.01	0.00
Ridge CV	0.67	0.67	1.25	0.79	0.03	0.00	0.89	0.44	0.01	0.00

Source: Burris (2018).

as the ratio of the number of predicted conditions by the model to the number of observed CARS reports in that category only. Probability of detection (POD) was defined for each CARS category as the ratio of correct classification predictions in that category to the number of observed CARS reports in that category. Optimal values for accuracy, bias, and POD are equal to 1. These results show that the k-nearest neighbor, decision tree, and random forest methods were among the methods that showed the highest accuracy and good values for bias and POD for multiple CARS index categories in both subsets of the training data. Decision tree-based models can be developed quickly and can directly utilize input variables, factors that are advantageous for future model refinement. As a result, the random forest classifier was selected as the main method for further demonstration and experimental evaluation.

Another benefit of the decision tree-based models is they allow for analysis of the relative importance of each weather variable (feature) that is used as input to the system. The relative importance of weather variables for the decision tree approach is displayed in Figure 3.3. This shows that many of the weather variables displayed a relatively high degree of importance. The distributions of these weather variables can be analyzed by separating the values based on the actual CARS winter driving index value. Examples of these distributions for visibility and snow depth are shown in Figure 3.4 using box-and-whisker diagrams. The top and bottom of the "box" presents the 25th and 75th percentile values. The line in the middle of the box displays the median value, and the whiskers show the extent of the data (1st and 99th percentiles) and "outliers" are represented by dots beyond the whiskers. These plots are useful for briefly summarizing differences and similarities between variable distributions. If a variable shows separation between distributions for different label values, it can help to accurately discriminate between the different output labels. The visibility distributions show that higher visibility conditions are found more often in "good" CARS index (value = 1) situations and lower visibilities are found in "fair," "difficult," and "hazardous" reports (values = 2, 3, and 4). Snow depth is generally found to increase as the CARS driving index gets worse. These differences in weather variables are consistent with expectations: low visibility and increased snow depth tend to be associated with more difficult driving conditions.

3.2.3 Evaluation of Experimental System

The random forest model that was trained using the data from 2014 to 2016 was applied to real-time weather variables during the 2017–18 winter season. Graphical output from this system was posted to a webpage (Purdue Weather Earth Atmospheric Planetary Science, 2018) to allow for subjective evaluation of the estimated driving conditions. An example of this output is shown in Figure 3.5, the predicted CARS conditions were found on the left side and the official INDOT CARS program website was presented in the right side panel.

This experimental system was evaluated using a similar gridded approach to the evaluation of the training of the machine learning system (section 3.2.2). Between December 2017 and March 2018, 23,414 CARS winter driving index reports were issued that

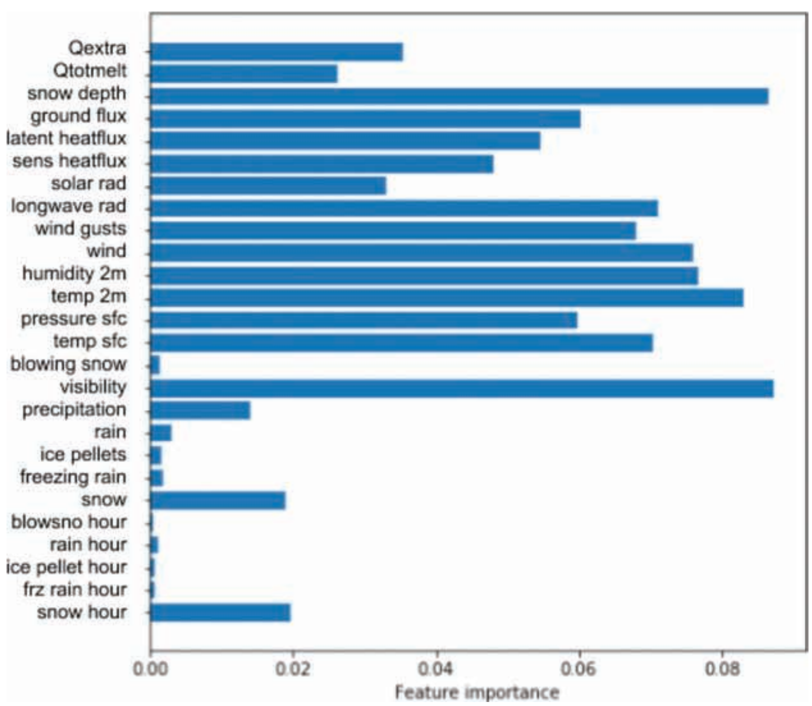

Figure 3.3 Feature importance from the decision tree machine learning model using the training data set. (Source: Burris, 2018.)

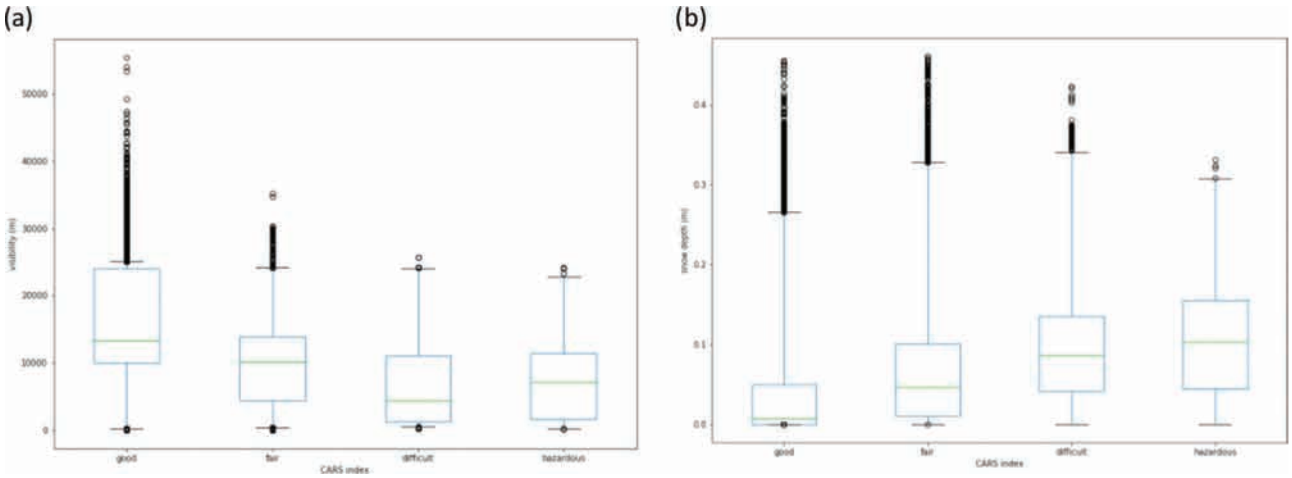

Figure 3.4 Box and whisker diagrams for weather variable distributions over specific CARS winter driving index categories. (a) Shows visibility in units of meters; (b) shows snow depth in units of meters.

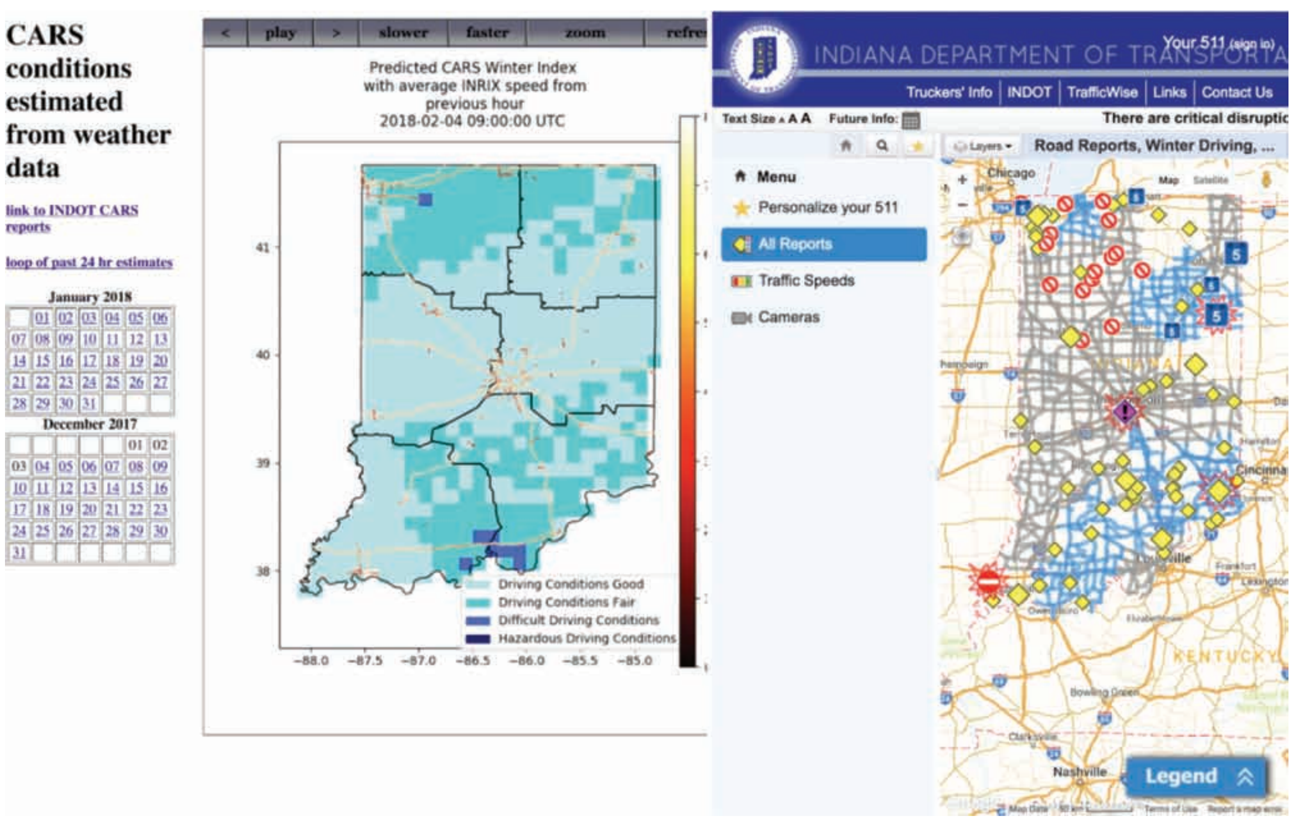

Figure 3.5 Example of experimental website for automatic CARS report estimates. (Source: Purdue Weather Earth Atmospheric Planetary Science, 2018.)

could be compared with the predictions from the random forest using real-time weather variables. The results of this evaluation are presented in Table 3.3. These results show a reduction in the performance during the 2017–18 winter season (overall accuracy around 70%) as compared to the test portion of the training data set (approximately 90% accuracy). The experimental system significantly underestimated the occurrence of degraded conditions, especially in the "difficult" and "hazardous" categories. Burris (2018) ran multiple experiments with under- and oversampling the training data set and was able to increase the frequency of estimates of "difficult" and "hazardous" conditions. However, the impact on the overall accuracy of these estimates was found to be minor.

TABLE 3.3
Performance of the experimental real-time machine learning classification with 2017–18 data

	Accuracy		Bias				POD			
	2014–16 Test	2017–18 Experiment	Good	Fair	Difficult	Hazard	Good	Fair	Difficult	Hazard
Random Forest	0.91	0.70	1.20	0.64	0.24	0.00	0.91	0.34	0.03	0.00

Source: Burris (2018).

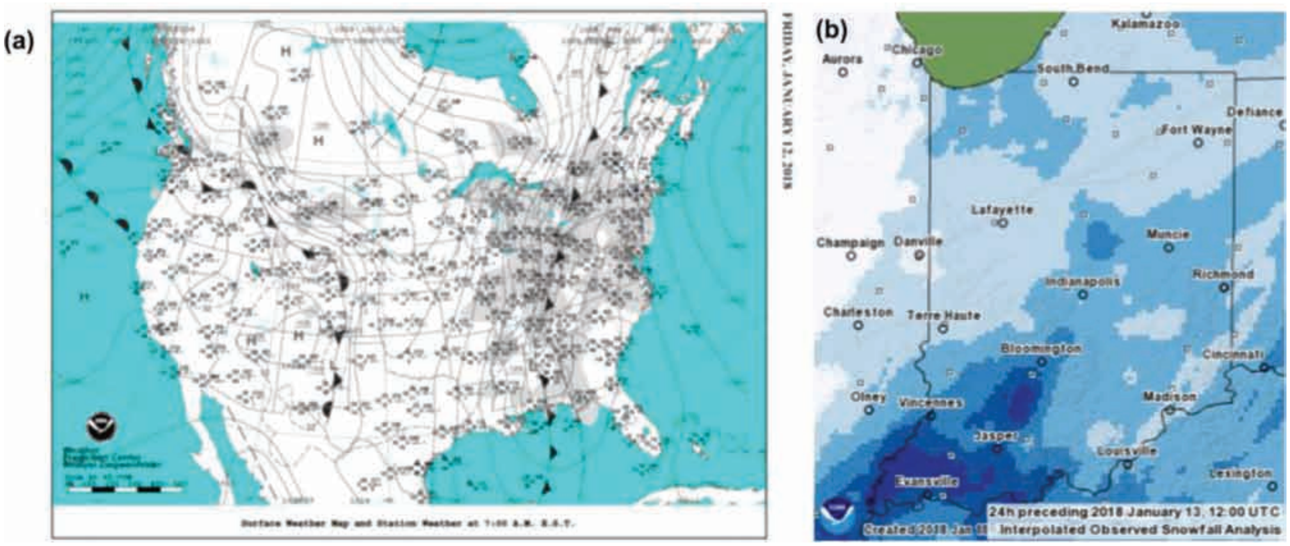

Figure 3.6 (a) Surface weather map valid 7:00am 12 January 2018 (National Centers for Environmental Prediction, Weather Prediction Center, 2018); (b) 24h snowfall accumulation preceding 7:00am EST 13 January 2018 (National Operational Hydrological Remote Sensing Center, 2018).

3.2.4 Case Study

In order to demonstrate the performance of this system, examples from a winter weather event are presented in this section. A case was selected where widespread winter precipitation was observed that showed an impact on the driving conditions across the state. On Friday January 12, 2018, a strong cold front moved across the state and produced a transition from rain to freezing rain, sleet, and snow (Figure 3.6). Temperatures quickly fell early Thursday night and early Friday morning, resulting in significant snow and ice accumulations mainly across the southern half of the state with numerous reports of 5 inches of snow and a report of 0.4 inches of ice near U.S. 52 between Indianapolis and Cincinnati (National Weather Service, 2018 a,b,c).

Examples for three different times during this winter precipitation event are presented in Figure 3.7. The top panels show the hourly precipitation color coded by NAM diagnosed winter precipitation type (snow in blue, freezing rain in pink, rain in green). CARS reports that were valid at the time are presented in the next row along with INRIX traffic speeds. The bottom row indicates estimated conditions from the real-time experimental random forest model. During the early part of this event, CARS winter driving index reports were “good” and the machine learning output is consistent with those reports (not shown). As the temperature drops, the western portion of the precipitation changes to freezing rain and sleet, updated CARS reports indicate “fair” conditions in the western portion of the state (Fig. 3.7d). The classifier depicts degraded conditions over a larger area than is shown by the precipitation, indicating that another weather variable (perhaps low visibility) has contributed to the classification (Fig. 3.7g). This pattern of estimated conditions is a good match to the actual CARS reports. Between 0300 and 0700 EST only a handful of CARS reports were issued and they all expired by 0700 EST. At the same time, freezing rain has moved into the eastern half of the state, and traffic speeds are noticeably slower on Interstates 65, 69, 70, 74, and 465 (Fig. 3.7e). While much of this traffic impact can be attributed to congestion from the morning commute, the previously observed weather strongly suggests that road conditions had been degraded by weather (Fig. 3.7b). The estimated CARS reports are in general agreement, with a large fraction of the state under “fair” conditions

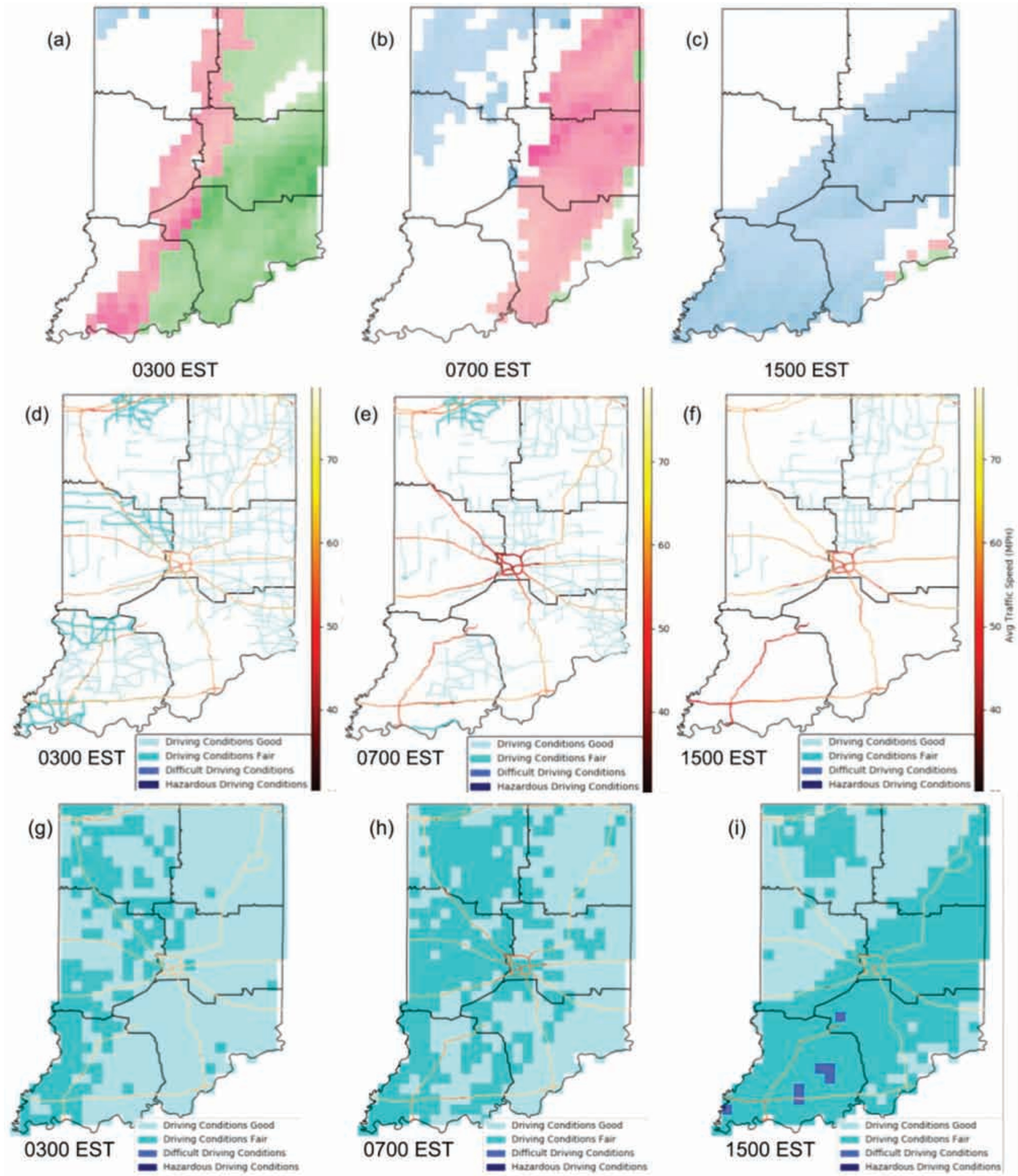

Figure 3.7 January 12, 2018 winter weather event. Top row displays observed precipitation color-coded by type (green=rain, blue=snow, red=freezing rain), middle row shows CARS winter driving index reports and traffic speed from INRIX, bottom row shows estimated CARS conditions from the random forest model. Left column is valid at 3:00am, middle column valid at 7:00am, and right column at 3:00pm EST on January 12, 2018. (Source: Burris, 2018.)

(Fig 3.7h). Throughout the rest of the day, the snowfall in northwest Indiana moves across the rest of the state (Fig. 3.7c), and slow traffic persists on the southern leg of I-69 (Fig. 3.7f). Despite the observed weather and traffic, no new CARS reports were issued for the southern half of Indiana after 0700 EST (Fig. 3.7c), and the "good" reports that were still valid expired within a few hours. Here the benefits of the automated system are highlighted as it continued to keep the majority of the state under "fair" conditions, with areas of "difficult" following the heavier snow in the southern portion of the state, especially in Vincennes district (Fig. 3.7i).

4. WINTER PRECIPITATION REPORTS

4.1 Overview

In this project, we were motivated by the availability of the multi-year database of weather information to provide INDOT with up-to-date analyses of the frequency of occurrence and timing of winter precipitation reports across the state. This information can be used to plan and prepare for winter maintenance actions for upcoming seasons and compare specific winter seasons to a multi-year average. These analyses incorporate standard meteorological observations at airport locations along with crowdsourced reports of precipitation.

The winter precipitation analyses were constructed by merging two different and independent data sources. The first source is the Automated Surface Observing System (ASOS; NOAA, 1998) operated by the National Oceanic and Atmospheric Administration (NOAA) and AWOS (Automated Weather Observing System, operated by the Federal Aviation Administration). These systems provide the standard, widely used observations of meteorological conditions located primarily at airports across the United States. For observation of winter precipitation, only the ASOS systems have a freezing rain detector; none of the AWOS systems in Indiana have one. Both ASOS and AWOS are reliable systems and both use the same optical sensor to detect precipitation. These precipitation sensors suffer from various limitations and not all ASOS stations are instrumented in an equivalent way. The primary limitation is that ASOS cannot correctly distinguish mixed precipitation type (rain and snow, or rain and ice pellets, or snow and ice pellets) if not augmented by a human observer (AWOS stations cannot be augmented). Nor can the sensor correctly diagnose the presence of sleet/ice pellets (NOAA, 1998). The only way ice pellets can be included in an ASOS report is if a human observer augments the report, and very few ASOS stations are manned 24 h a day. Thus, ASOS reports are a poor source of information about the frequency and extent of ice pellets. In addition, ASOS freezing rain sensors can commonly be in error (NOAA, 1998). While ASOS reports can contain freezing rain, freezing rain is missed under certain circumstances and freezing drizzle is likely misdiagnosed. None of the AWOS sites in Indiana are equipped with freezing rain sensors. Therefore only the ASOS stations can report freezing precipitation from the standard meteorological network. Finally these stations are far apart: there are only twelve ASOS and 41 AWOS across all of Indiana. Thus, many incidences of precipitation are missed because precipitation occurs between stations. This is even more pronounced for precipitation types that have high spatial variability, such as freezing rain.

The second data source is the Meteorological Phenomena Identification Near the Ground (mPING; Elmore et al., 2014) project. This project, launched 12 Dec 2012, allows participants to anonymously submit reports of precipitation types, including mixed precipitation types, using smart devices, such as smart phones and tablets. Location and time of report are derived from GPS, yielding unprecedented time and location accuracy. MPING reports are crowdsourced and tend to cluster around towns and cities, however mPING observations are significantly more widespread than the ASOS/AWOS locations. For similar reasons, mPING reports also display diurnal variability: people go to sleep at night and so the frequency of reports decreases, too.

All winter precipitation consists of four types; rain, snow, ice pellets, and freezing rain, along with mixtures of these four. In this project, each precipitation type is ranked based on impact severity on transportation and infrastructure systems. From lowest to highest impact, these are rain, snow, ice pellets, and freezing rain. When the precipitation type for mPING reports is a mixture, the reports are clustered based on the constituent with the highest impact. Thus, a mixture or rain and snow is clustered with snow, freezing rain mixed with ice pellets is clustered with freezing rain, etc., reducing the mPING precipitation types within each climatology to the four canonical types.

4.2 Analysis Procedure

All reports of winter precipitation were included in this analysis, regardless of precipitation rate or visibility reduction. The number of hours of each precipitation type was determined by counting reports over a hexagonal grid placed over the continental United States. Hexagons have the lowest perimeter to area ratio of any regular tessellation of the plane, which means that in practice the edge effects are minimized for hexagonal grids. In addition, for hexagonal grids, the distance between centroids is the same for all neighbors. The hexagonal cells were sized in such a way to avoid accentuating major population centers. Otherwise, the analysis could display a non-meteorological bias of higher frequency over populated areas. However, there is still a need to capture spatial variability in the durations of each precipitation type. To accommodate these requirements, the hexagonal cells were sized to an area of approximately 34,500 sq. km (about 13,000 sq. mi) and filtered using a weighted discrete kernel smoother covering seven cells, a center cell and its six neighbors. This acts to remove most artifacts due to population centers while preserving meaningful information about spatial variability.

For the purposes of these analyses, each observation is assumed to have a lifetime of one hour within the clock hour of the report submission. For instance, an observation of snow at 15 minutes past the hour counted as snow for the preceding 15 min and following 45 min. An observation of snow submitted at 59 past the hour is assumed to be valid for the preceding 59 min and the following 1 min. Under the assumption that observations arrive at random times during the hour, this is as good as any other method of counting "hours of precipitation."

Analyses are performed for snow, ice pellets, and freezing rain using the combined mPING and ASOS/AWOS data. Monthly averages were derived for the five months November, December, January, February and March. While winter precipitation occurs outside of these months, such instances are rare. In all cases, the combined data result in more overall hours of a given precipitation type than either data source alone. Since there are so few observations of ice pellets from the ASOS/AWOS, the ice pellet analysis depicts mPING reports. The standard surface observation systems do a relatively good job of observing snow, although mPING observations add about 15% to the total number of snow hours. However, the combined mPING and ASOS/AWOS surface data yield almost double the number of hours of freezing rain in some areas than either system alone.

4.3 Annual Duration of Winter Precipitation

Results of this analysis procedure are shown in Figure 4.1. This indicates several hundred hours of snow on average with a steady increase in the number of hours as you move north. In fact, the northern portion of the state observes snow at more than double the frequency as the southern portion of the state. A few dozen hours of freezing rain and ice pellets are observed on average across state with subtle variations, generally increasing as you move north and east. These plots provide an overall summary of the analysis, however more detailed information (monthly averages, observation locations) is available athttp://weather.eaps.purdue.edu/winter/.

4.4 Comparison to Previous Work

These analyses can be considered an update of a recent Clear Roads pooled fund study (Mewes, 2012) where detailed maps of average annual durations of winter precipitation (snow, blowing snow, and freezing rain) along with annual snowfall were produced across the United States. An overall winter severity index was developed that combined the parameters, and high-resolution gridded datasets were generated. Mewes (2012) combined standard airport weather observations with NAM model winter precipitation type diagnostics (see section 2.3). Examples of the annual hours of snow and freezing rain are shown in Figure 4.2

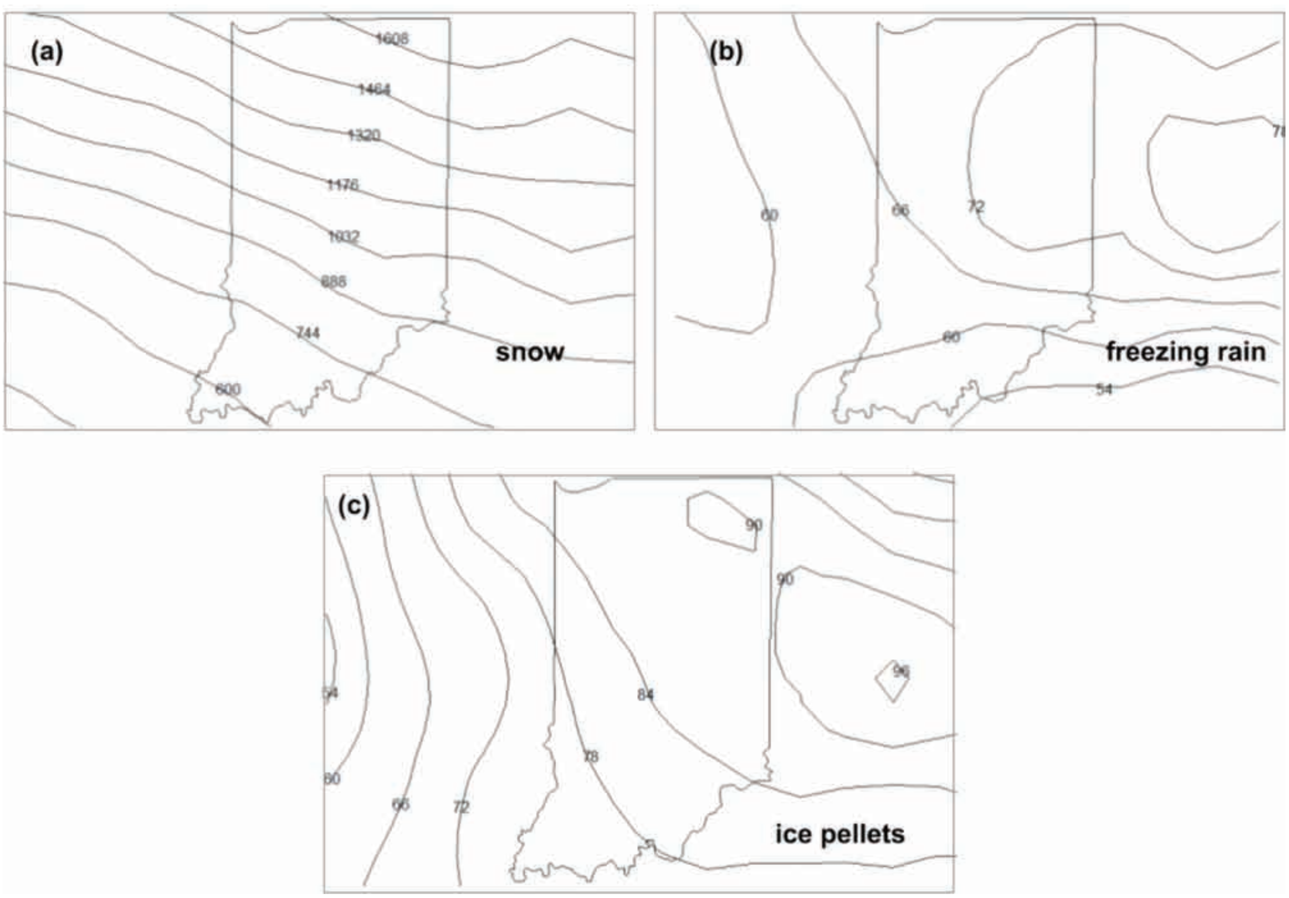

Figure 4.1 Average annual duration (hours) of snow (a), freezing rain (b), and ice pellets (c) from merged mPING/ASOS/AWOS Jan 2013–Mar 2018.

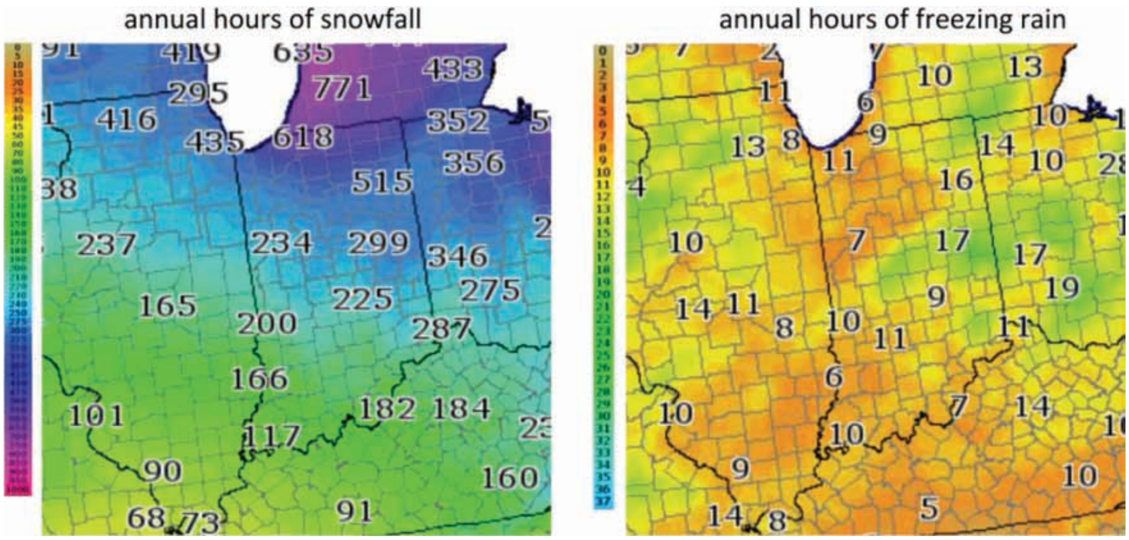

Figure 4.2 Examples of analyses of annual duration of snow and freezing rain (hours) from Clear Roads study. (Source: Mewes, 2012.)

(Mewes, 2012), indicating significant discrepancies between our updated analyses and this previous study. The previous study indicates annual durations that are a factor of four to five times lower than our current analyses. These discrepancies are partially due to the different data sources that were used; the additional mPING observations used in this project should tend to increase the number of observations of winter precipitation. No minimum threshold of precipitation rates or visibility reductions were used in this work, while Mewes (2012) did set such thresholds, which may have substantially increased the number of observations counted in this project.

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About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at: http://docs.lib.purdue.edu/jtrp

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The recommended citation for this publication is:

Baldwin, M. E., Burris, K. D., & Elmore, K. L. (2018). A*utomated estimation of winter driving conditions* (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2018/22). West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284316867