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Roadway Friction Modeling: Improving the Use of Friction Measurements in State DOTs

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Aurora Project 2020-04

Final Report
January 2023

About Aurora

The Aurora program is a partnership of highway agencies that collaborate on research, development, and deployment of road weather information to improve the efficiency, safety, and reliability of surface transportation. The program is administered by the Center for Weather Impacts on Mobility and Safety (CWIMS), which is housed under the Institute for Transportation at Iowa State University. The mission of Aurora and its members is to seek to implement advanced road weather information systems (RWIS) that fully integrate state-of-the-art roadway and weather forecasting technologies with coordinated, multi-agency weather monitoring infrastructures.

The preparation of this report was financed in part through funds provided by the Iowa Department of Transportation through its "Second Revised Agreement for the Management of Research Conducted by Iowa State University for the Iowa Department of Transportation" and its amendments.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
Aurora Project 2020-04		

4. Title and Subtitle	5. Report Date
Roadway Friction Modeling: Improving the Use of Friction Measurements in State DOTs	January 2023
	6. Performing Organization Code
7. Author(s)	**8. Performing Organization Report No.**
Gerry Wiener, Laura Fay, Tom Brummet, Scott Landolt, Justin Lentz, Seth Linden, and Bill Petzke	
9. Performing Organization Name and Address	**10. Work Unit No. (TRAIS)**
National Center for Atmospheric Research P.O. Box 3000 Boulder, CO 80307 Western Transportation Institute Montana State University P.O. Box 174250 Bozeman, MT 59717	**11. Contract or Grant No.**
12. Sponsoring Organization Name and Address	**13. Type of Report and Period Covered**
Aurora Program Iowa Department of Transportation 800 Lincoln Way Ames, IA 50010 Federal Highway Administration 1200 New Jersey Avenue, SE Washington, DC 20590	Final Report **14. Sponsoring Agency Code** Part of TPF-5(435) and Federal SPR Part II, CFDA 20.205

15. Supplementary Notes

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16. Abstract

The objectives of this project were to determine the relationship between weather conditions and roadway friction measurements as observed in the laboratory, determine whether it is possible to standardize friction measurements coming from multiple friction sensors for identical weather conditions and roadway pavement types, determine whether the relationship between weather and roadway friction found in the laboratory is analogous to the relationship between weather and pavement friction found in practice on highways, and model roadway friction using weather conditions to predict it at sites where friction measurements may not be available.

The objectives were accomplished through cold laboratory testing of stationary friction sensors, standardizing friction measurements from multiple stationary and mobile friction sensors, using meteorological measurements from Colorado and Minnesota to infer road friction conditions, and conducting a friction wheel measurement analysis using data from Sweden.

Key findings from this effort include the following:

- Machine learning models can be created using data from friction sensors in the cold laboratory that exhibit a good mean absolute error in predicting the laboratory friction response to meteorological conditions set in the laboratory, but the models have a higher mean absolute error when applied to data from the field. For this reason, the researchers do not recommend using the model developed in the laboratory with field data.
- Collocated road weather information system (RWIS) and stationary friction sensor data can be used to develop state-specific friction models using machine learning techniques. These models can then be used to provide a synthetic friction estimate at RWIS sites that are not equipped with stationary friction sensors. The accuracy of the predictions can be determined at sites where friction sensors are available. The accuracy is improved when water thickness and/or snow thickness are available.
- RWIS measurements including air temperature, surface temperature, dew point temperature, relative humidity, and road condition measurements including road state, water thickness, and snow thickness can be used to derive an accurate friction model that targets observed friction values.
- Friction values from multiple sensor types are close in magnitude when friction is high, but when friction values drop, agreement among sensors is variable. To standardize the measurements from multiple friction sensors, friction values from multiple sensors can either be averaged or associated with a set of friction categories.

17. Key Words	18. Distribution Statement
roadway friction measurements—roadway pavement types—tire grip—winter highway safety—winter roadway conditions	No restrictions.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified.	Unclassified.	72	NA

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

ROADWAY FRICTION MODELING: IMPROVING THE USE OF FRICTION MEASUREMENTS IN STATE DOTS

Final Report
January 2023

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Sponsored by
Federal Highway Administration Aurora Program
Transportation Pooled Fund
(TPF-5(435))

Preparation of this report was financed in part
through funds provided by the Iowa Department of Transportation
through its Research Management Agreement with the
Institute for Transportation

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ACKNOWLEDGMENTS

This research was conducted under the Federal Highway Administration (FHWA) Transportation Pooled Fund Aurora Program. The authors would like to acknowledge the FHWA, the Aurora Program partners, and the Iowa Department of Transportation (DOT), which is the lead state for the program, for their financial support and technical assistance.

This research would not have been possible without the support of the Aurora Pooled Fund technical advisory committee members: Zach Hans, Neal Hawkins, Jamie Yount, Jason Norville, Dale Kirmer, Mike Adams, Kevin Duby, Steve Hancock, James Roath, Jon Bjorkquist, Paul Denkler, Richard “Todd” Miller, Colby Fortier-Brown, Aidan Neeley, and Iowa DOT representative Tina Greenfield Huitt.

The researchers would like to acknowledge the following organizations and individuals for sharing data and expertise: the Colorado DOT and Maine DOT; Clear Roads and SRF Consulting Group, which shared data collected as a part of their Mobile Technologies for Assessment of Winter Road Conditions project; Dan Eriksson from the Swedish Transport Administration (Trafikverket); and Johan Casselgren from Luleå University of Technology. Additional thanks go to Alex Sydney, Greg Waidley, Khyle Clute, Natalie Villwock-Witte, Karalyn Clouser, Matthew Bell, Dana May, Anna Price, and Curtis Walker.

EXECUTIVE SUMMARY

The objective of this project was to determine the relationship between weather conditions and friction measurements as observed in the laboratory, determine whether it is possible to standardize friction measurements received from multiple friction sensors monitoring identical weather conditions and pavement types, determine whether the relationship between weather and friction found in the laboratory is analogous to the relationship between weather and friction found in the field, and use weather conditions to model and predict road friction at sites where friction measurements may not be available.

The following tasks were performed to meet these objectives.

Cold Laboratory Testing of Stationary Friction Sensors

The project team installed stationary friction sensors from Vaisala and High Sierra in a cold laboratory and spent one week testing the sensors by simulating different meteorological and road conditions. The team was not able to get the High Sierra sensor to produce friction measurements during the test, so all reported data are from the Vaisala sensor. The team analyzed the laboratory-based friction data and determined how the sensors responded to the differing simulated weather and road conditions. The Vaisala friction sensor did signal a response to the different weather conditions but was not able to differentiate light, moderate, and heavy snow conditions since it produced friction measurements near 0.4 on a 0.0 to 1.0 friction scale for all the snow conditions (0.0 represents no friction and 1.0 excellent road friction).

The team then modeled the Vaisala friction based on predictors such as air temperature, surface temperature, dew point temperature, relative humidity, water thickness, snow thickness, and ice thickness. The team was able to get an accurate prediction of surface friction (mean absolute error [MAE] of 0.0043) using all the measurements and a decent prediction (MAE of 0.15) when water, snow, and ice thickness were excluded.

Standardizing Friction Measurements from Multiple Friction Sensors

The project team attempted to standardize collocated meteorological and friction measurements using data from two previous studies:

- Mobile friction sensor and associated meteorological data from a Clear Roads study performed in 2018 in Minnesota (Minge et al. 2019)
- Stationary friction and road weather information system (RWIS) data collected at a site in Etna, Maine, in 2021 by the Maine Department of Transportation (MaineDOT) (Hans et al. 2022)

The project team determined that the different sensors are generally in close agreement when friction values are greater than 0.7. During a lower friction event, the sensors (whether mobile or stationary) will typically sense the event in tandem but will differ on the magnitude. For example, some sensors may register an event as “moderate” and others register the same event as “low to moderate” or “low.” In both studies, the friction sensors could deviate in magnitude significantly during such events, with friction measurements from one sensor significantly higher or significantly lower than measurements from another.

Using Meteorological Measurements to Infer Road Friction Conditions

In working on this task, the team collected data from four different environments:

- Colorado Department of Transportation (CDOT) RWIS and optical friction data
- Cold laboratory RWIS and optical friction data (collected by the research team at the National Center for Atmospheric Research [NCAR] Cold Laboratory)
- Clear Roads Minnesota mobile optical friction data collected in a Clear Roads study (Minge et al. 2019)
- Minneapolis-St. Paul International Airport (MSP) RWIS and friction wheel data

The project team collected CDOT RWIS and optical friction data over a 1.5-year period to target Colorado surface friction conditions using machine learning (ML). The team also used models based on the MSP data and the cold laboratory data to target the Colorado surface friction. The model using the CDOT RWIS and optical friction data had the best performance among the various models in predicting the Colorado friction magnitudes, which illustrates that the results of ML focused on the data of a particular environment typically outperform the results of models based on data sets obtained in similar but different environments.

Adding road state, water thickness, or snow thickness to the list of predictor variables improved performance of the Colorado ML friction model significantly. Thus, these variables were significantly correlated with the road friction measurement. The project team determined that it is extremely important to perform the ML training using a balanced set of friction values and avoid training using predominantly 0.82 friction values.

Friction Wheel Measurement Analysis

Finally, the project team analyzed friction wheel measurements and collocated RWIS data from Trafikverket, the Swedish Transportation Administration. The main goal was to determine the benefit of incorporating data from a friction wheel to either standardize friction measurements or predict friction. The team determined that there is correlation between precipitation events and road friction as measured by the friction wheel, though friction events measured using the friction wheel were not necessarily close to the RWIS sites, so there was a lack of data characterizing the relationship between RWIS and nearby friction wheel measurements.

Key Findings

- ML models can be created using data from friction sensors in the cold laboratory that exhibit a good MAE (0.15) when predicting the laboratory friction response to meteorological conditions set in the laboratory. These models have a higher MAE (0.27) when applied to data from the field. Note that 0.27 is a sizable error in a 0.0 to 1.0 friction scale. For this reason, we do not recommend using the laboratory-developed model on field data.
- Collocated RWIS and stationary friction sensor data can be used to develop state-specific friction models using ML techniques. These models can then be used to provide a synthetic friction estimate at RWIS sites that are not equipped with stationary friction sensors. The accuracy of the predictions can be determined at sites where friction sensors are available and can be improved when water thickness and/or snow thickness are also available.
- RWIS measurements including air temperature, surface temperature, dew point temperature, relative humidity, and road condition measurements, including road state, water thickness, and snow thickness, can be used to derive an accurate friction model that targets observed friction values.
- Friction values from multiple sensor types are close in magnitude when friction is high (0.7 to 1.0), but agreement among sensors is variable when friction values drop below 0.6. To standardize the measurements from multiple friction sensors, friction values can either be averaged or associated with a set of friction categories.

INTRODUCTION

The roadway friction modeling study presented in this report had the following major objectives:

1. Determine whether road friction can be effectively modeled using stationary sensor equipment in a cold laboratory.
    a. If so, can the models developed for the cold laboratory be applied to field data to estimate the road friction associated with a variety of simulated weather conditions?
2. Determine whether road friction models developed for particular states/environments can be effectively applied in a new state.
3. Ascertain the performance of a road friction model implemented using data from a particular state. Ancillary questions include the following:
    a. What meteorological and surface condition fields should be used as friction model predictors?
    b. What is the comparative importance of the various meteorological and surface condition fields in predicting friction?

The subsequent chapters of this report provide detailed descriptions of the data sources and data processing methods used, the machine learning (ML) techniques applied, the models developed, and the models' performance.

COLD LABORATORY TESTING

Objectives

The goal of laboratory testing multiple sensors commonly used by transportation agencies to obtain road weather information and surface conditions was to collect data in a controlled environment.

Methods

Laboratory testing was conducted at the National Center for Atmospheric Research (NCAR) cold laboratory facility in Boulder, Colorado. The experiments described in this chapter were designed to capture data for various storm scenarios: light, moderate, and heavy snow events; black ice and thicker ice; and a storm coming in warm then ending cold with ice and snow present (Table 1).

Each test condition was conducted on asphalt made in the Colorado Department of Transportation (CDOT) asphalt laboratory and concrete pavements made to Montana Department of Transportation (MDT) specifications in the Montana State University (MSU) Structures Laboratory.

Table 1. Design of experiments used in the cold laboratory testing

Test Number	Storm Definition	Surface State: Snow/Ice	Surface State: Depth	Pavement Type	Air Temp
1	Light	Snow	0.1–0.5 in. per hr	Asphalt	<20°F
2					25–30°F
3					31–36°F
4				Concrete	<20°F
5					25–30°F
6					31–36°F
7	Moderate	Snow	0.5–1 in. per hr	Asphalt	<20°F
8					25–30°F
9					31–36°F
10				Concrete	<20°F
11					25–30°F
12					31–36°F
13	Heavy	Snow	1–2 in. per hr	Asphalt	<20°F
14					25–30°F
15					31–36°F
16				Concrete	<20°F
17					25–30°F
18					31–36°F
19	Warm to Cold	Ice then Snow	0.04–0.08 in. (1–2 mm) ice then 1–2 in. snow	Asphalt	36°F to <20°F
20					
21					
22				Concrete	
23					
24					
25	Black Ice	Ice	0.04–0.08 in. (1–2 mm)	Asphalt	25–32°F
26					<32°F
27				Concrete	25–32°F
28					<32°F
29	Ice	Ice	0.2+ in. (5+ mm)	Asphalt	<25°F
30					30–32°F
31				Concrete	<25°F
32					30–32°F

Parameters/Setup of the Cold Room

The NCAR cold room consists of two chambers: an inner chamber that measures approximately 10 ft x 10 ft x 10 ft and an outer, connected chamber that measures approximately 20 ft x10 ft x 10 ft for a combined volume of 3,000 ft^3. Both chambers were used during testing, with the sensors deployed near the ceiling of the outer chamber and aimed at the test surfaces located on the floor of the inner chamber (with approximately 25 ft of distance between them). The cold chambers have the ability to cool to -20°F, though most of the testing was done at temperatures near 0°F. Six-second and one-minute observations of temperature and relative humidity were collected in the cold chambers independent of the other sensors throughout the testing period.

Making Snow

The NCAR artificial snow generation "snow machine" system was created under funding from the Federal Aviation Administration (FAA) with a goal of testing aircraft deicing and anti-icing fluids in a laboratory environment (Landolt et al. 2018). The snow machine can also support a wide variety of testing for other purposes, including snow on pavement samples. The snow machine operates by shaving ice from ice cylinders fed into rotating Forstner bits located at the top of the machine (Figure 1).

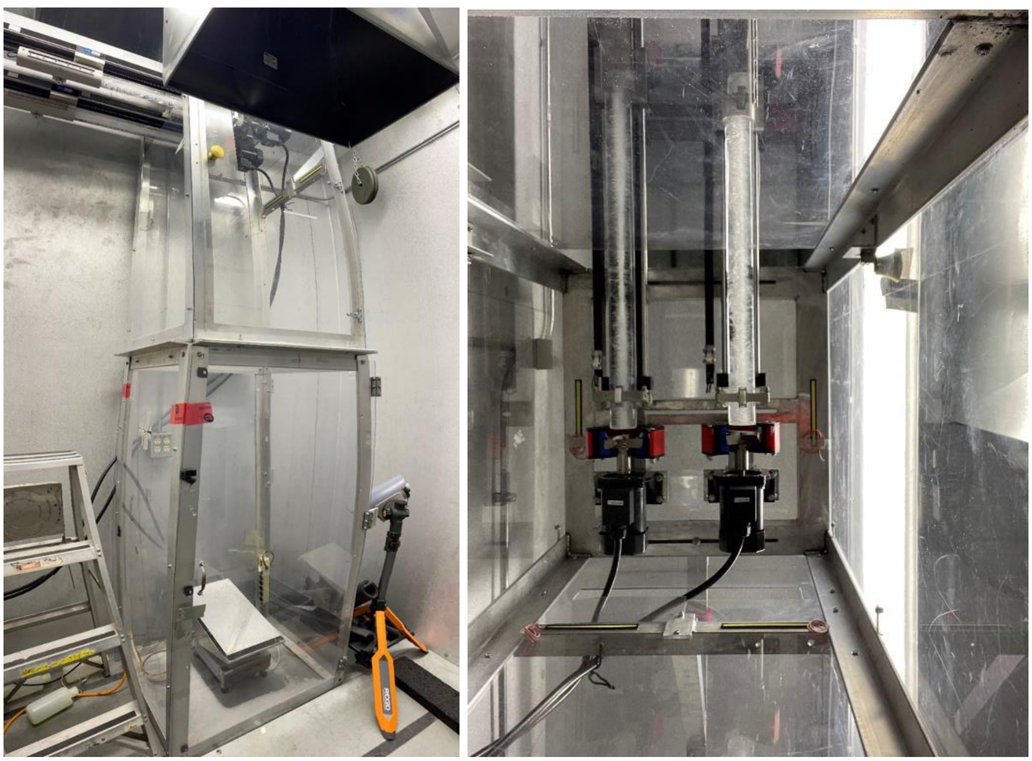


Figure 1. Snow machine in cold chamber (left) and ice cylinders mounted in the machine used to make snow (right)

While the shaved ice particles do not have the same crystalline structure as natural snow, the density and size distribution of the particles match natural snowfall conditions. The rotational speed of the Forstner bits can also be adjusted to change the characteristics of the ice shavings. Slowing the turn rate will result in larger flakes and increasing the turn rate will result in smaller flakes, allowing testing to take place on a wide range of snowfall sizes. The speed at which the ice cylinders are fed into the Forstner bits can also be modified, resulting in adjustable real-time rates ranging from very light to heavy snowfall intensities. Asphalt and pavement samples were placed inside the machine, and snow fell onto the samples to create three conditions: light, moderate, and heavy snow (Figure 2), as defined in Table 1.

Figure 2. Snow on asphalt pavement samples showing light (left), moderate (middle), and heavy (right) snow

Making Ice Layers

To create ice layers, a spray bottle was used to create a thin and even layer of water on the pavement surface to mimic black ice conditions on roadways. The depth of water/ice was validated by measurement using a metric ruler and targeted 1 to 2 mm of water thickness. To create a thicker ice layer, water was poured onto the pavement surface to a depth of up to 5 mm. The water was retained on the pavement surface by applying a layer of silicon caulking around the outer perimeter of the pavement sample (Figure 3).

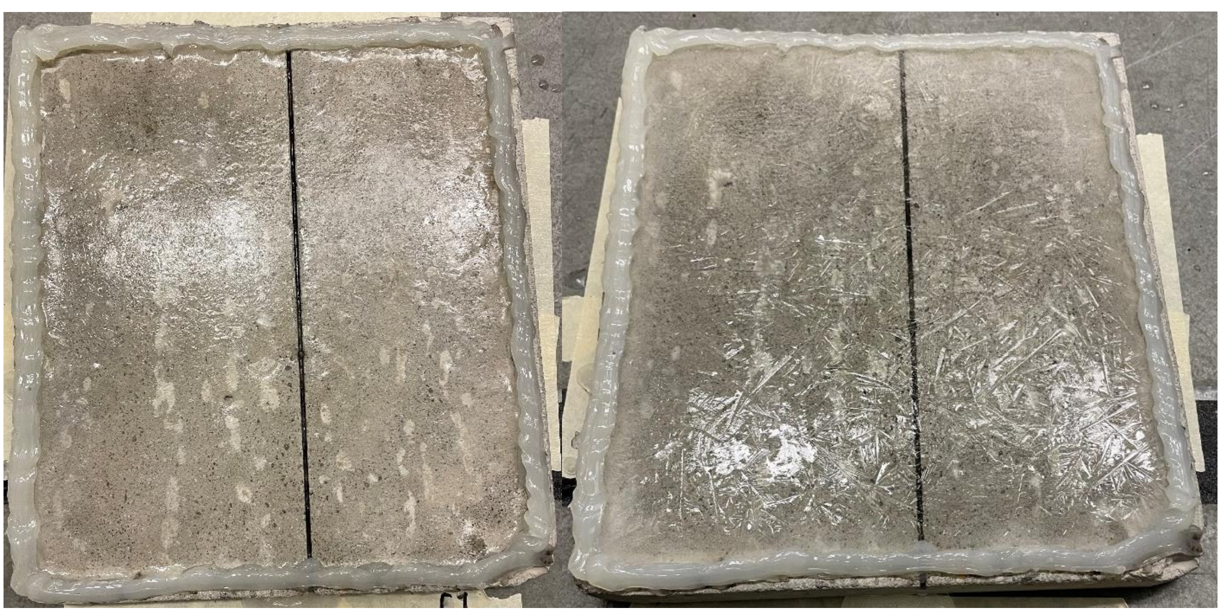


Figure 3. Concrete sample with a thin black ice layer (left) and a thicker ice layer (right)

A third testing scenario was used to mimic a storm environment that starts warm and gradually cools, where initially wet pavement turns to icy pavement then is covered by snowfall. This scenario was created by applying a light mist of water to the pavement surface using a spray bottle, then applying snow to the pavement surface (Figure 4), as defined in Table 1.

Figure 4. Warm to cold storm scenario showing dry pavement above freezing (above 32°F, left), wet pavement at freezing temperatures (below 32°F, middle), and snow on icy pavement with temperatures well below freezing (below 32°F, right)

Sensors

Data were collected from two sensors: the Vaisala DSC111 and DSC211 in series and the High Sierra IceSight. The data elements measured and reported by each sensor are provided in Table 2.

Table 2. Summary table of sensors and the data elements measured and reported

Data Elements Measured/Reported	Sensor		
	Ice Sight	**DSC111**	**DSC211**
Air temperature (°C)	x	x	x
Surface temperature (°C)	x	x	x
Relative Humidity (%)	x	x	
Dew Point		x	
Friction Value	x		x
Friction Category	x		
Surface state/condition			x
Water thickness (mm)			x
Ice thickness (mm)			x
Snow thickness (mm)			x

Note that all data elements were collected, with the exception of road condition and friction (grip), from the IceSight sensor. Every attempt was made to collect the road condition and grip data from the IceSight sensor, including contact with the technical support group at High Sierra, but the data values failed to change during testing, so the road condition and grip data from this sensor could not be assessed.

The sensors were mounted to the ceiling of the cold laboratory by an aluminum welded frame and aimed at the location of the samples on the floor (Figure 5).

Figure 5. Sensor mounting configuration in the NCAR cold laboratory

Applying Machine Learning Methods to the Laboratory Data

The friction tests were performed during the week of December 13, 2021, at the NCAR cold laboratory. However, as noted above, the project team was unable to get the IceSight friction sensor to work correctly at that time. The friction values registered by the IceSight sensor were consistently 0.0, and as a result the project team was unable to standardize the friction measurements for multiple laboratory sensors because the only valid laboratory friction values came from the DSC211 sensor. Therefore, the project focused on modeling the DSC211 friction data based on different sets of predictors:

- Basic predictor set (BP): air temperature, dew point temperature, relative humidity, surface temperature
- BP + water thickness (BPW)
- BP + water thickness + snow thickness + ice thickness (BPWSI)

Results

Cold Laboratory Friction Measurement Analysis

Table 1 outlines the variety of test cases performed in the cold laboratory. In ideal circumstances, friction sensor measurements should detect differences in friction during simulations of various weather scenarios. For example, one would expect differences in measured friction between light, moderate, and heavy snow scenarios. One would also expect the friction measured during a snow event to be greater than that on ice. Figure 6 shows that tests performed between 16:00 and 20:00 on December 15, 2021, which included tests of light, moderate, and heavy snow, generally reported a friction value of 0.4.

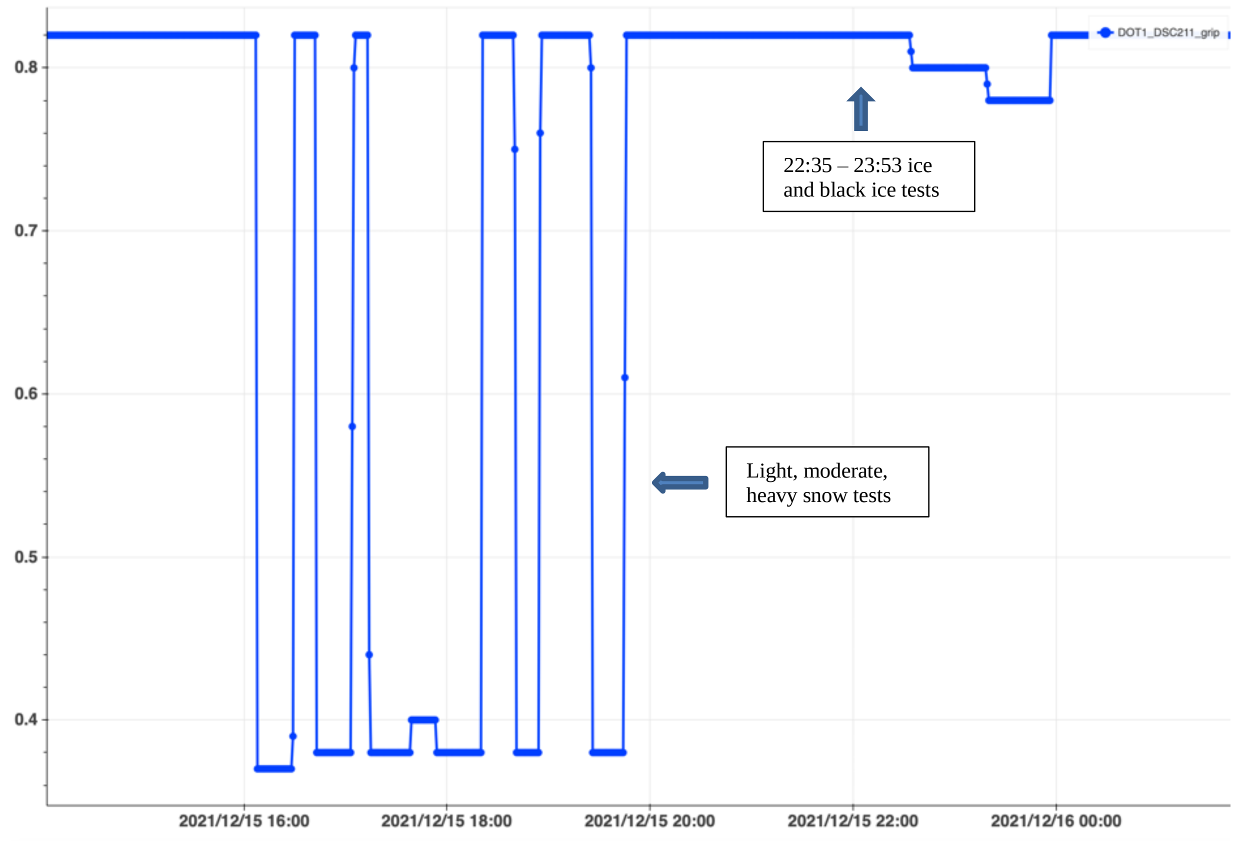


Figure 6. Laboratory friction recorded for different simulated weather scenarios on December 15, 2021

Ice and black ice tests were performed at the end of December 15, 2021, right before December 16, 2021. At the time, the friction measurements exhibited only small deviations from 0.8, so it appears that the DSC211 was not measuring a significant loss in friction during the ice simulations. Additional ice and black ice tests were performed on December 16, 2021, and the friction recorded during these tests held steady at 0.82 or decreased to slightly below 0.8. Some of the moderate and heavy snow tests performed on December 16, 2021, between 16:00 and 19:00 recorded friction values from 0.4 to 0.55. These can be seen in Figure 7.

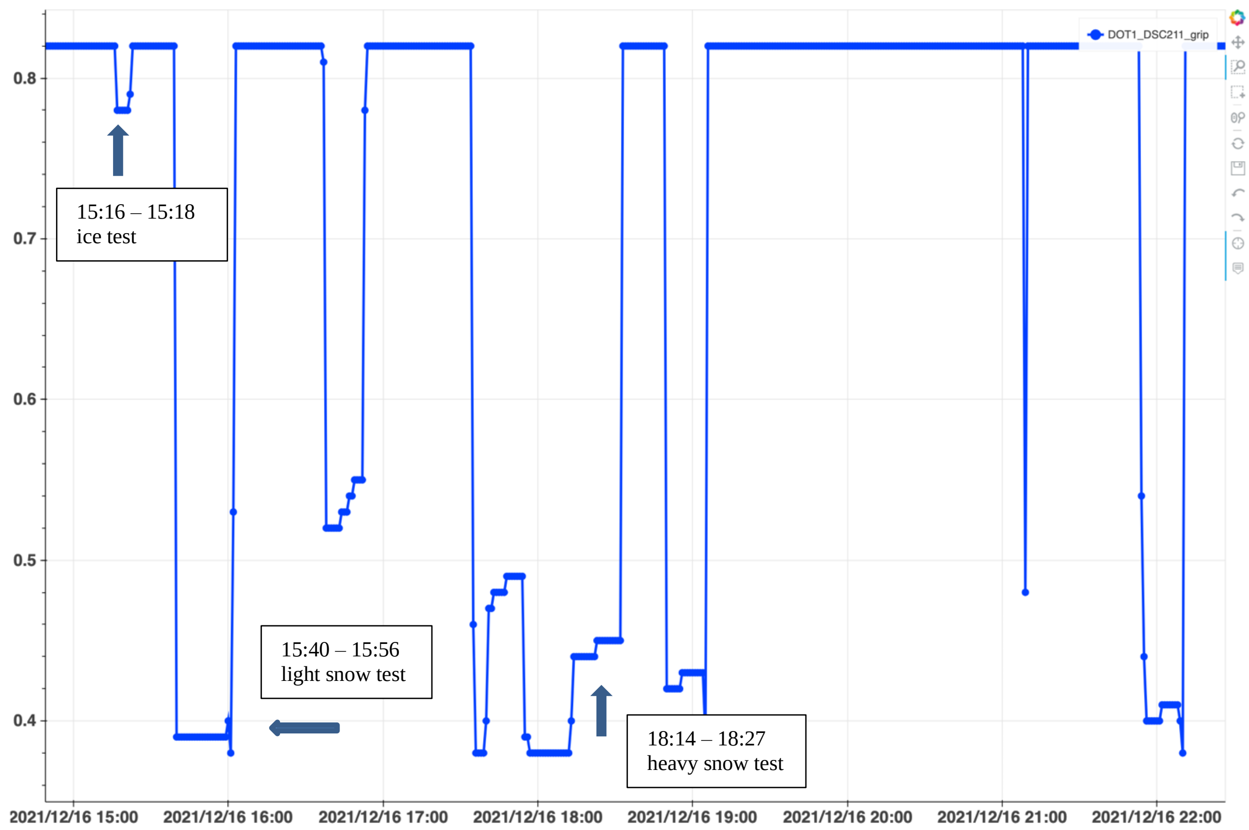


Figure 7. Laboratory friction recorded for different simulated weather scenarios on December 16, 2021

One potential source of error was the method used to ensure that the sensors were collecting data from the pavement samples. Before each test, a laser was used to site the location and area where the samples should be placed (based on manufacturer guidelines). It is possible that the area within view of the sensor included a small section that was not the pavement sample, which in this case was the concrete floor. To avoid the potential for this issue in future laboratory testing, larger samples (3 x 3 ft) are recommended.

Cold Laboratory Friction Measurement Machine Learning

The project team preprocessed the cold laboratory data set gathered from December 13, 2022, through December 17, 2022, prior to performing ML. This involved removing all records where friction values were precisely 0.82, because that value was typically recorded at times when no tests were being performed. (A friction value of 0.82 from the Vaisala DSC211 is the default highest [best] friction value that will be reported.) The data set, consisting of 745 records, was then split into a training set and test set, where the dates and times of all records in the training set were required to precede those in the test set (i.e., all test set records are in the training set's future). Approximately 80% of the laboratory test records were placed in the training set and 20% of the records were placed in the test set. Default settings were used for the random forest (RF) and gradient-boosted tree algorithms except the parameter n_estimators, which was set to

1,000 for the RF. The mean absolute error (MAE) results of using different friction predictor sets can be found in Table 3.

Table 3. Results from the prediction of cold laboratory friction using different predictor sets

Predictor Set	RF MAE	Gradient-Boosted Tree MAE
BP	**0.15**	0.21
BPW	**0.12**	0.16
BPWSI	0.0043	**0.0034**

Note that the lower the MAE the better the result and that prediction improves as more DSC211 sensor variables are used.

Figure 8 depicts a histogram of the DSC211 laboratory friction values.

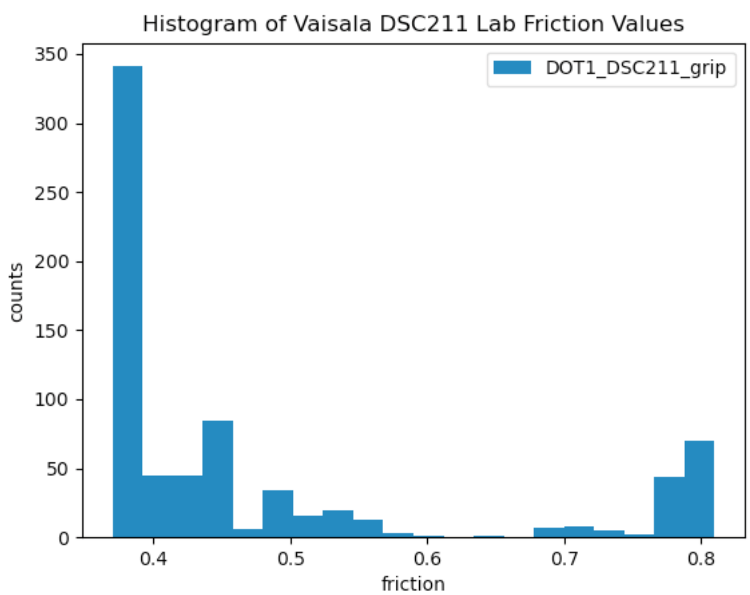


Figure 8. DSC211 laboratory friction values

Note that the histogram shows that the underlying laboratory ML data set is biased toward a lower friction environment. This makes sense given that the majority of the laboratory tests were recording low friction events.

Figure 9 through Figure 14 illustrate the importance of each friction predictor, as determined by the RF and gradient-boosted tree algorithms.

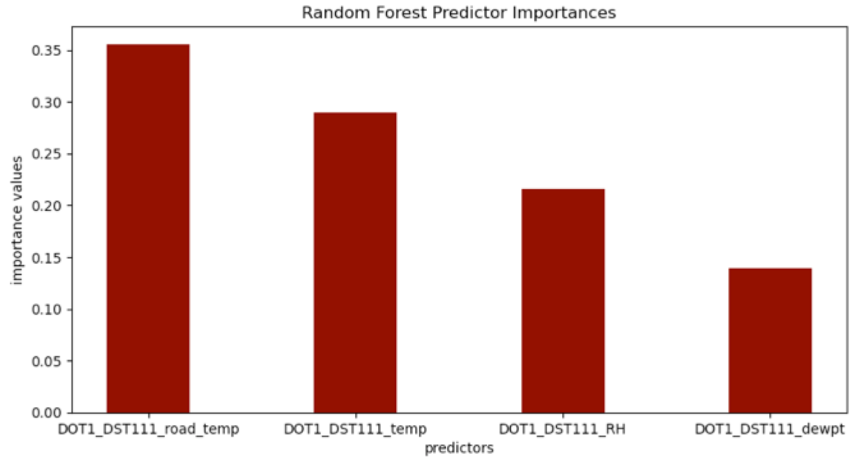


Figure 9. RF predictor importance for BP

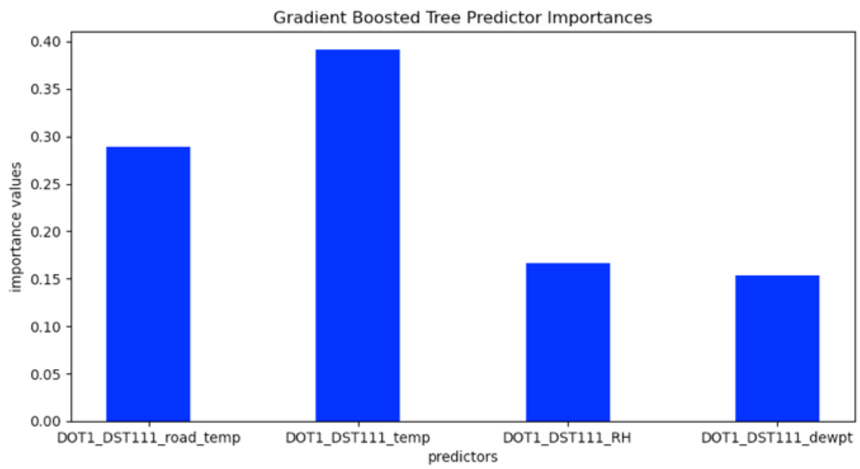


Figure 10. Gradient-boosted tree predictor importance for BP

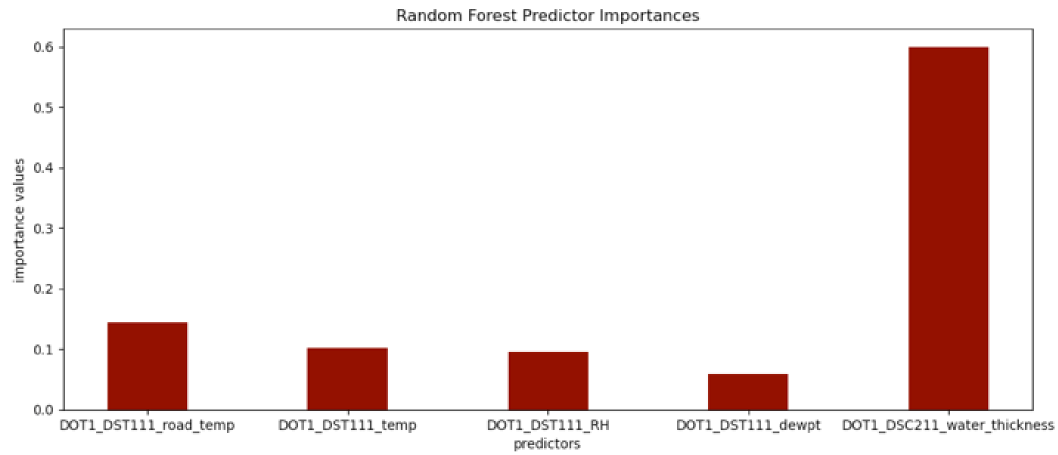


Figure 11. RF predictor importance for BPW

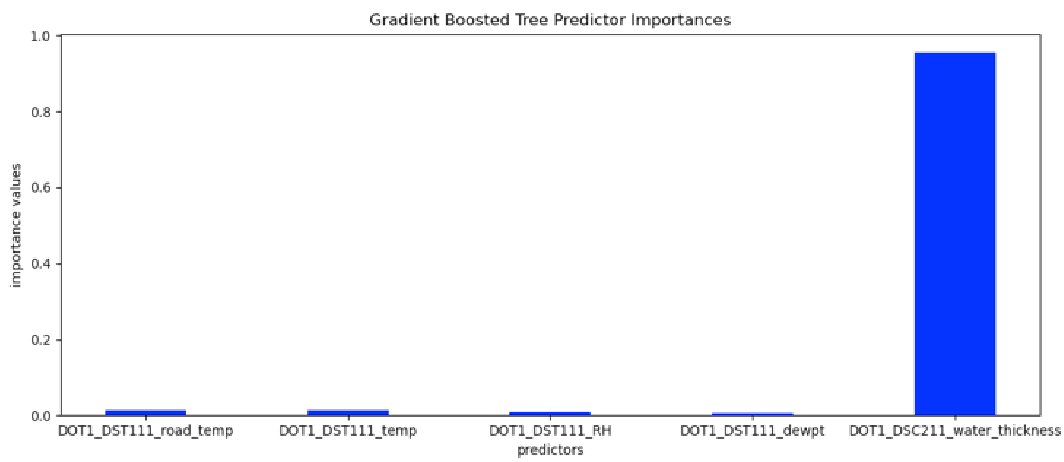


Figure 12. Gradient-boosted tree predictor importance for BPW

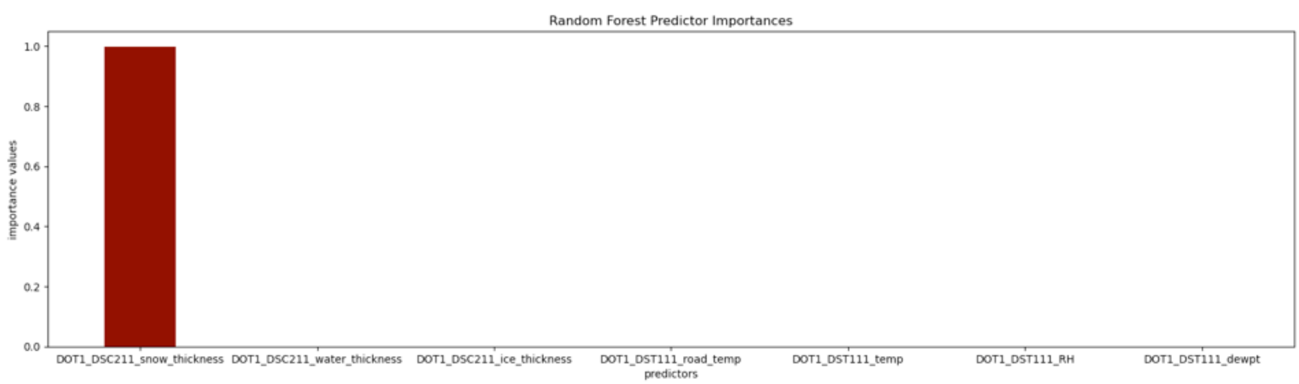


Figure 13. RF predictor importance for BPWSI

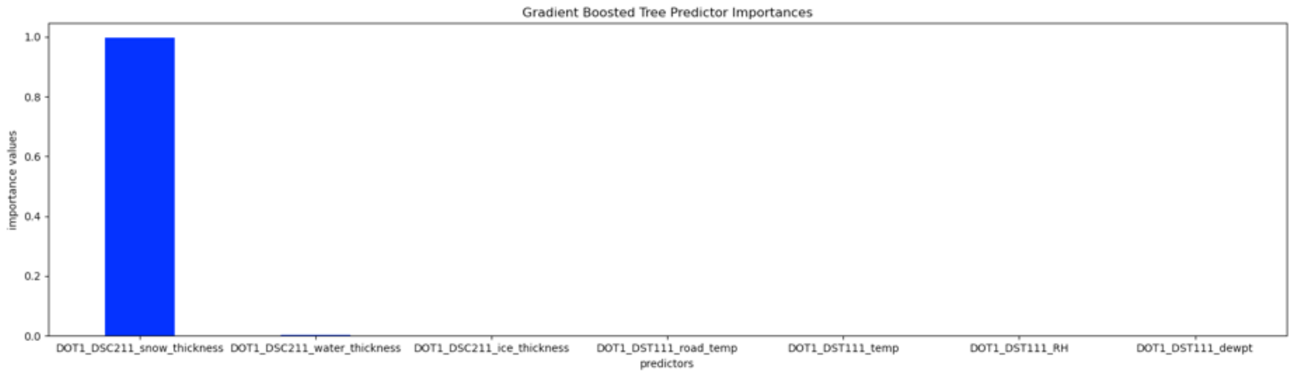


Figure 14. Gradient-boosted tree predictor importance for BPWSI

Note the slight difference in predictor importance for the BP predictor set; road temperature was the most important predictor in the RF algorithm, whereas air temperature was found to be the most important predictor for the gradient-boosted tree algorithm. When water thickness is added, it becomes the most important predictor, as can be seen in Figure 11 and Figure 12. If snow thickness is available, all the other predictors are determined to have minimal importance, as can be seen in Figure 13 and Figure 14.

Conclusions

Analysis of the cold laboratory test data demonstrated the following:

- The light, moderate, and heavy snow simulations produced similar friction values, which were typically in the neighborhood of 0.4. Thus, the Vaisala DSC211 was not able to distinguish friction differences between snow types in the cold laboratory.
- The friction values for the black ice and ice simulations were close to 0.8. Thus, the Vaisala DSC211 sensor did not register low friction for ice in the cold laboratory.

The cold laboratory ML results illustrate that standard meteorological measurements such as road temperature, air temperature, relative humidity, and dew point temperature can be used to approximate Vaisala-derived road friction in the laboratory. However, knowing the water thickness and, especially, snow thickness is of key importance in achieving an accurate assessment of the Vaisala-derived road friction in simulated winter conditions.

STANDARDIZING FRICTION MEASUREMENTS

Objectives

A goal of the project was to investigate how to standardize friction measurements recorded by different friction sensors, thus determining how measurements from one sensor correspond to those of another. Over time, state departments of transportation (DOTs) may own sensors made by multiple manufacturers and, after getting accustomed to utilizing the measurements from one sensor, be unsure how to adapt to another.

Methods

The project examined two different data sets while investigating the feasibility of standardizing friction measurements:

- Mobile friction sensor and associated meteorological data from a Clear Roads study performed in 2018 in Minnesota (Minge et al. 2019)
- Stationary friction and road weather information system (RWIS) data collected at a site in Etna, Maine, in 2021 by the Maine DOT (MaineDOT) (Hans et al. 2022)

Initially, time series plots of data from the different sensors were created to determine whether consistent trends between sensor measurements could be observed. For example, were friction values from one sensor consistently greater in magnitude than the values from another? Were the values from different sensors consistently close in magnitude?

The different mobile friction sensors also provide road state information in the following categories:

- Dry
- Damp
- Wet
- Ice
- Snow
- Slush

In the process of investigating how to standardize the measurements from the different sensors, the project team became interested in determining whether the sensors generally agreed on the categorization of road friction.

Results

Clear Roads Study

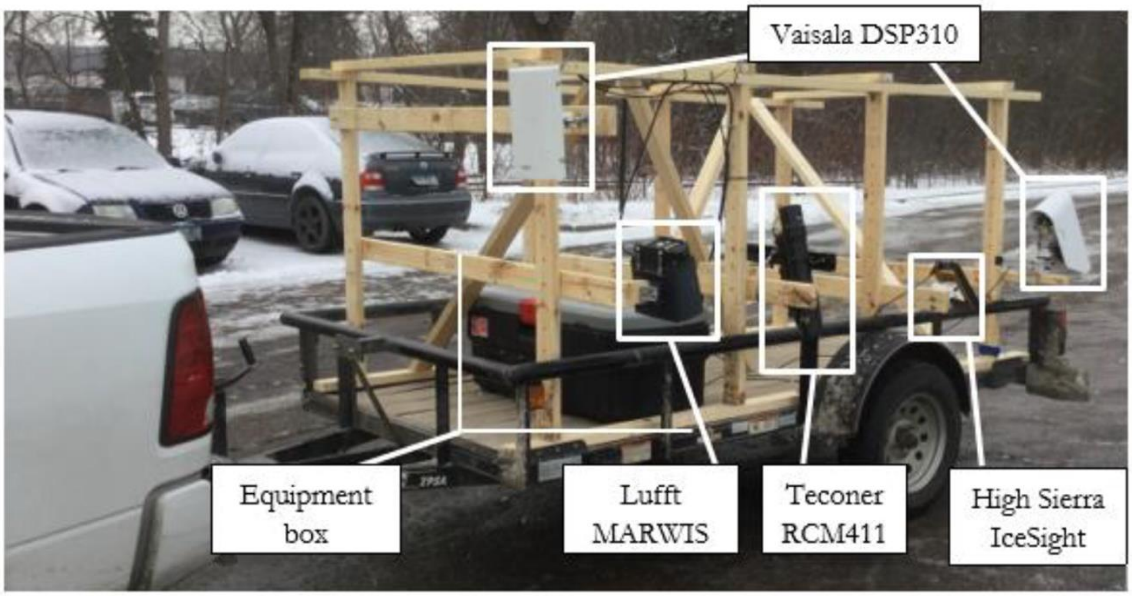
The team investigated mobile friction sensor data that had been gathered in a Clear Roads study performed in Minnesota (Minge et al. 2019) and subsequently shared with this research effort.

The Clear Roads study evaluated the performance of four mobile friction sensors:

- Lufft MARWIS
- Teconer RCM411
- High Sierra Mobile IceSight
- Vaisala DSP310

The data set was gathered on a variety of Minnesota road surfaces, under varying weather conditions, on 20 different days between January 15, 2018, and April 16, 2018. Note that the winter road conditions in the study did not reflect average winter road conditions in Minnesota, as is described in more detail in Minge et al. (2019). Data collection was conducted in two phases: (1) sensor comparison tests performed on the MnROAD Test Facility and (2) sensor tests conducted in live traffic on Minnesota highways. Additional details can be found in Minge et al. (2019).

During the study, the mobile friction sensors were mounted on a trailer, as can be seen Figure 15. Note that each sensor viewed the same line along the road, so one would expect the individual friction sensor measurements to be in general agreement.



Minge et al. 2019, Clear Roads TPF

Figure 15. Mobile friction sensors mounted for the Clear Roads study

Clear Roads Plot Analysis

The friction data plots in this section illustrate the challenges of standardizing mobile friction measurements from different sensor types.

In Figure 16, after 14:20, notice how the Teconer, Lufft, and Vaisala sensor friction values are in general agreement between 0.7 and 0.8. However, there are short transitions to lower friction values, and during these transitions the friction magnitudes vary considerably. In particular, the High Sierra sensor was rarely in agreement with the other sensors.

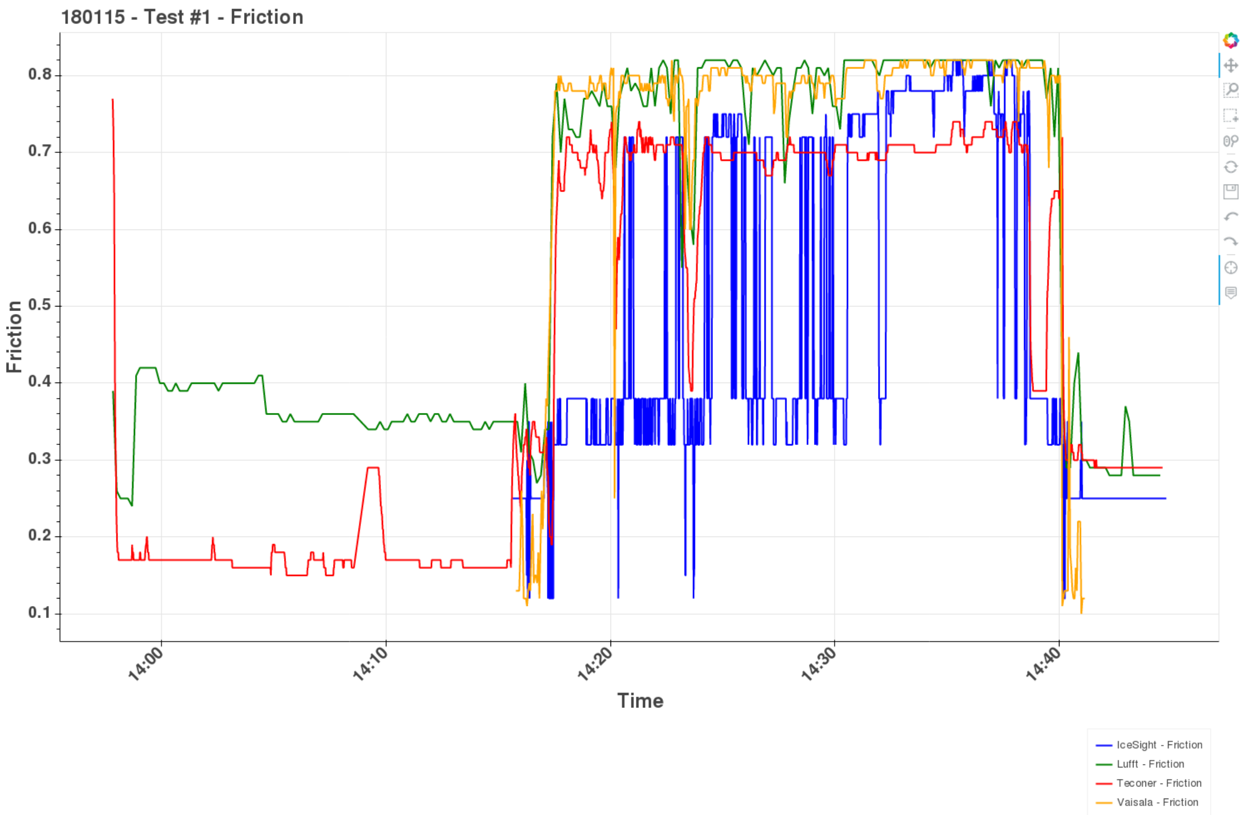


Figure 16. January 15, 2018, Clear Roads friction sensor plot

In Figure 17, note how the High Sierra IceSight and Teconer sensor values are in general agreement and consistently fall within a low friction category, though the IceSight values tend to jump between 0.1 and 0.3.

Figure 17. First January 22, 2018, Clear Roads friction sensor plot

The Vaisala and Lufft values also share some agreement, although these values generally fall within a higher friction range of 0.4 to 0.7. There is one interval, between 13:50 and 14:00, where almost all sensor values fall between 0.1 and 0.4.

In Figure 18, note how the friction values recorded by the different sensors generally disagree in this low friction case.

Figure 18. Second January 22, 2018, Clear Roads friction sensor plot

The Vaisala sensor exhibits values in the 0.1 to 0.3 range, whereas the Lufft sensor exhibits values between 0.35 and 0.4. The Teconer and High Sierra sensors are in general agreement in the 0.25 to 0.3 range. Note how the Vaisala sensor reports the lowest friction in Figure 18 but the highest in the previous plot (Figure 17), while the Lufft sensor reports low to moderate friction and the other sensors differ.

In Figure 19, note how the friction values from the various sensors are in general agreement in this high friction case. They fall in the range of 0.7 to 0.8, with the exception of the IceSight sensor.

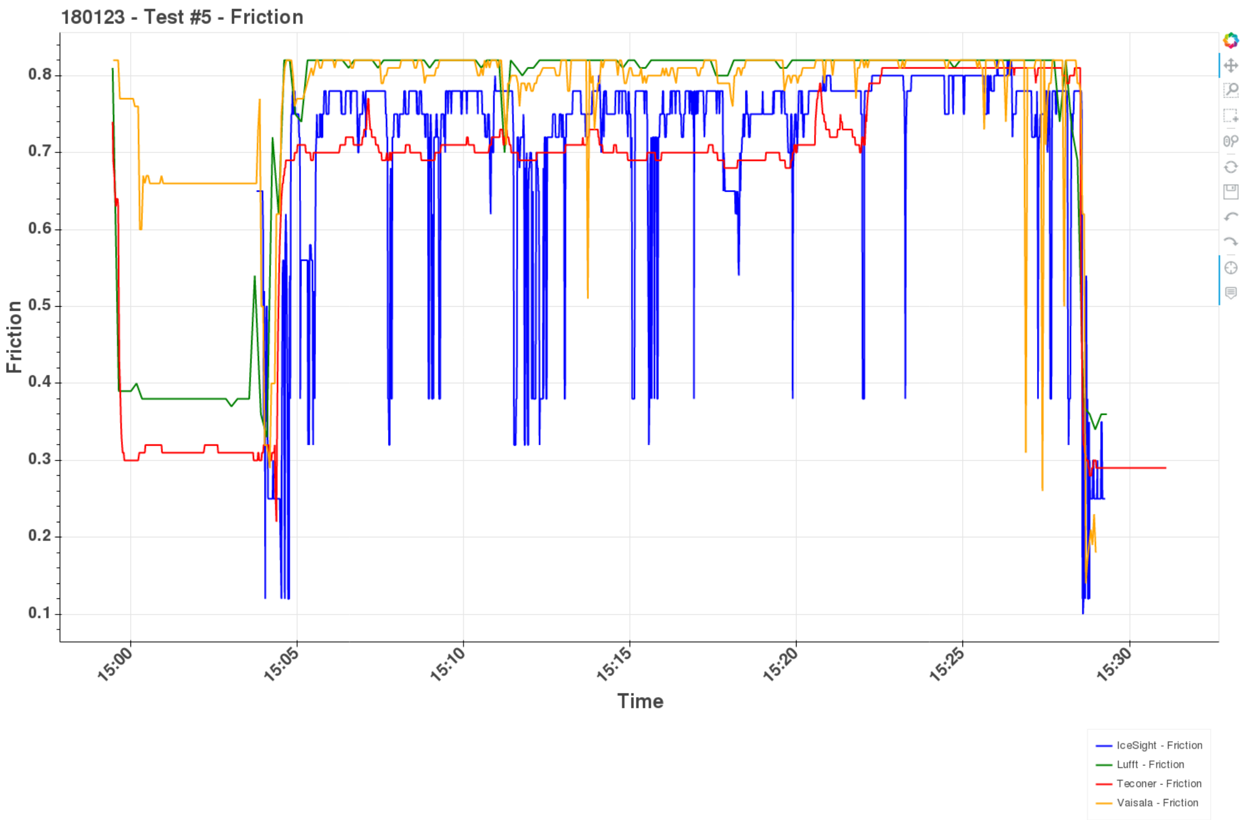


Figure 19. January 23, 2018, Clear Roads friction sensor plot

In Figure 20, note how the friction values vary between the different sensors in this low friction case.

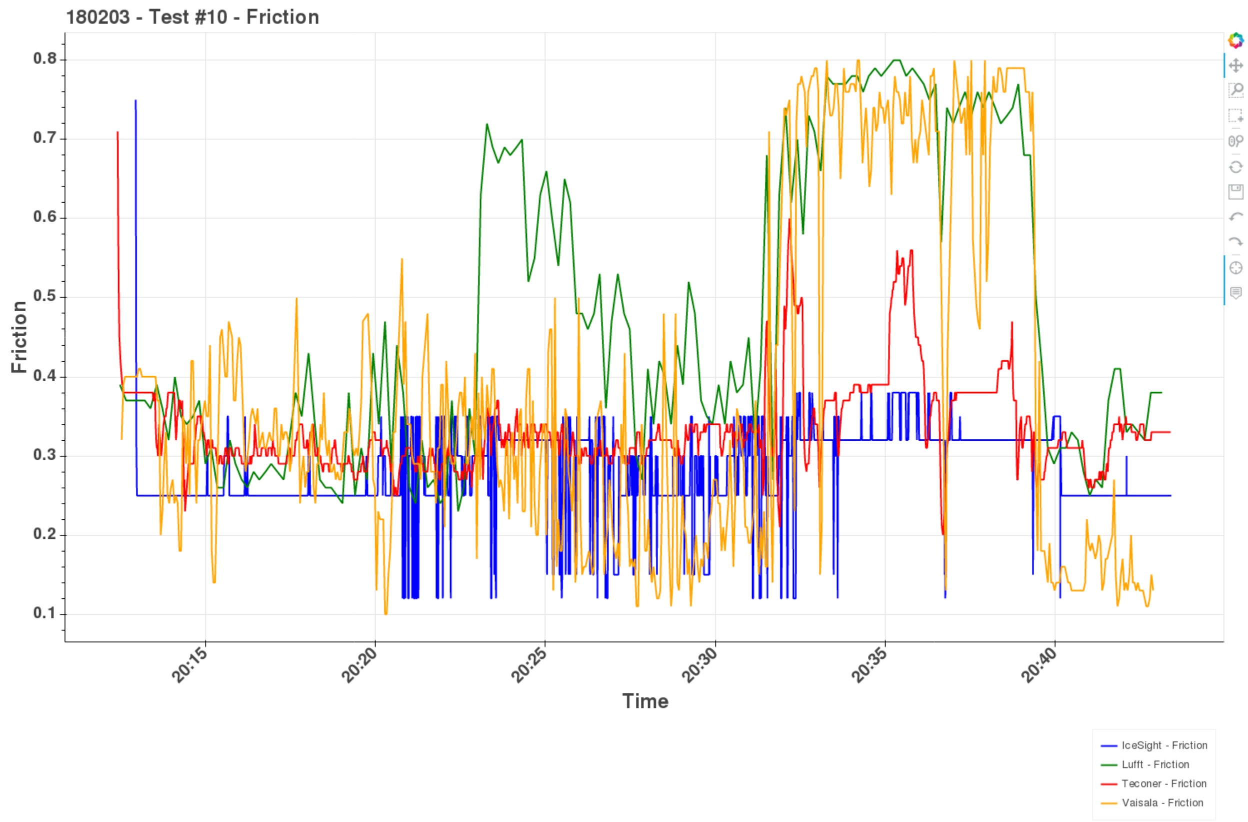


Figure 20. First February 3, 2018, Clear Roads friction sensor plot

Sometimes the Vaisala sensor friction values are among the lowest and sometimes they are among the highest. There are significant differences between the Vaisala/Lufft sensors and Teconer/High Sierra sensors from 20:35 to 20:40, where the Vaisala/Lufft sensor values are generally between 0.7 and 0.8 and the Teconer/High Sierra sensor values are largely between 0.3 and 0.4.

In Figure 21, note how the friction values vary between the different sensors in this low friction case.

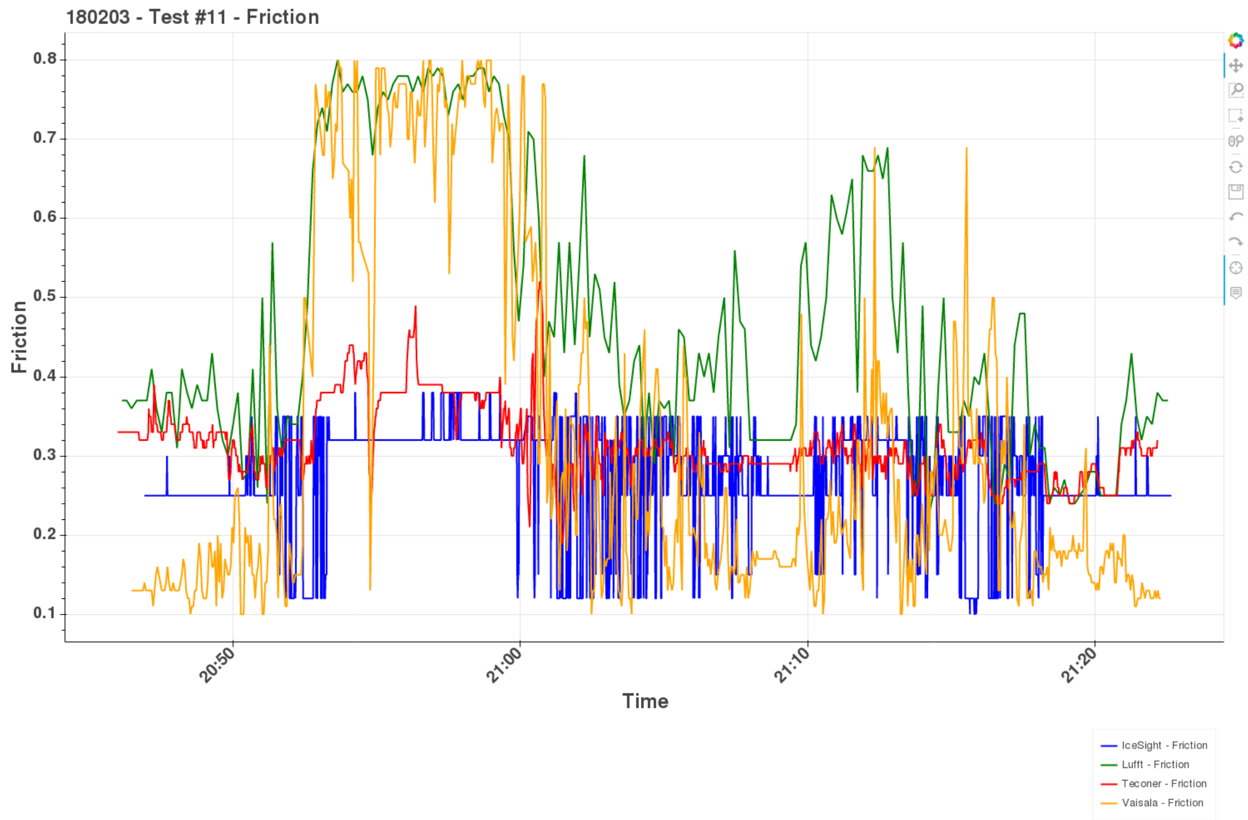


Figure 21. Second February 3, 2018, Clear Roads friction sensor plot

Sometimes the Vaisala sensor friction values are among the lowest and sometimes they are among the highest. There are significant differences between Vaisala/Lufft sensors and the Teconer/High Sierra sensors between 20:50 and 21:00, where the Vaisala/Lufft sensor values are generally between 0.7 and 0.8 and the Teconer/High Sierra sensor values are largely between 0.3 and 0.4. Such categorical differences make friction standardization challenging.

Conclusions on the Analysis of Clear Roads Data

The Clear Roads study data illustrate the value of having collocated friction measurements from multiple mobile sensors focusing on the same line of locations along the road. There were insufficient data in the 20 tests to create a statistically reasonable standardization of the friction values from the different sensors. Therefore, the project team recommends gathering at least one to two full winter seasons of data representing a variety of friction events. Here are some initial conclusions from the present study:

- The Clear Roads mobile friction sensor measurements tend to have closer agreement during high friction conditions.
- There can be significant differences in friction measurements and friction categorization during low friction events.

Maine Friction Data

The RWIS and stationary friction data gathered by MaineDOT were collected from January through March 2021 at an RWIS site in Etna, Maine (see Figure 22).

Figure 22. Friction sensors mounted at the Etna, Maine, site

The Etna RWIS site is the location of Maine’s most frequent and dangerous black-ice-related crashes. Four grip sensors were situated at the site during the data collection period. Three of the sensors, a Lufft sensor, a Boschung sensor, and a Vaisala sensor (Vaisala 1), were connected to a Campbell datalogger. A second Vaisala sensor (Vaisala 2) was connected to a Vaisala RPU on an older pole directly behind the front pole. At the time, the Lufft and Boschung sensors were less than a year old. The Vaisala sensors had seen long-term usage, and the measurements from the Vaisala 2 sensor were considered suspect by MaineDOT due to the age of the sensor.

Maine Friction Data Plot Analysis

Figure 23 presents an overview of all the friction data gathered from January through April 2021 at the Etna RWIS site in Maine.

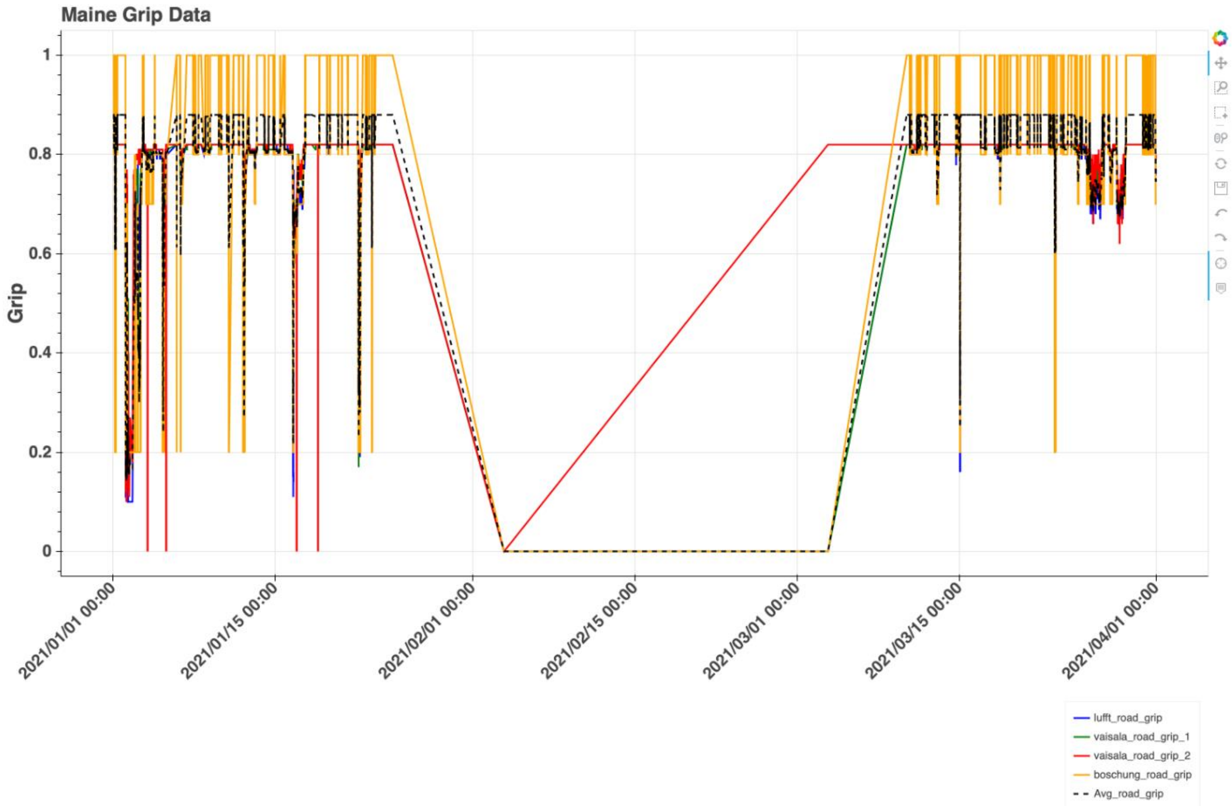


Figure 23. Plot of the entire Winter 2021 friction data set at the Etna, Maine, RWIS site

Unfortunately, a significant period of data is missing between February and mid-March. Three significant friction events were captured in the data:

1. January 1–2: low friction values
2. January 16: low and medium friction values
3. March 25–30: friction values near 0.7

Note that the isolated spikes in the Boschung (yellow line, Figure 23) and Vaisala 2 (red line, Figure 23) sensor data suggest data quality issues.

The time series plots in Figure 24 illustrate a low friction event on January 2, 2021.

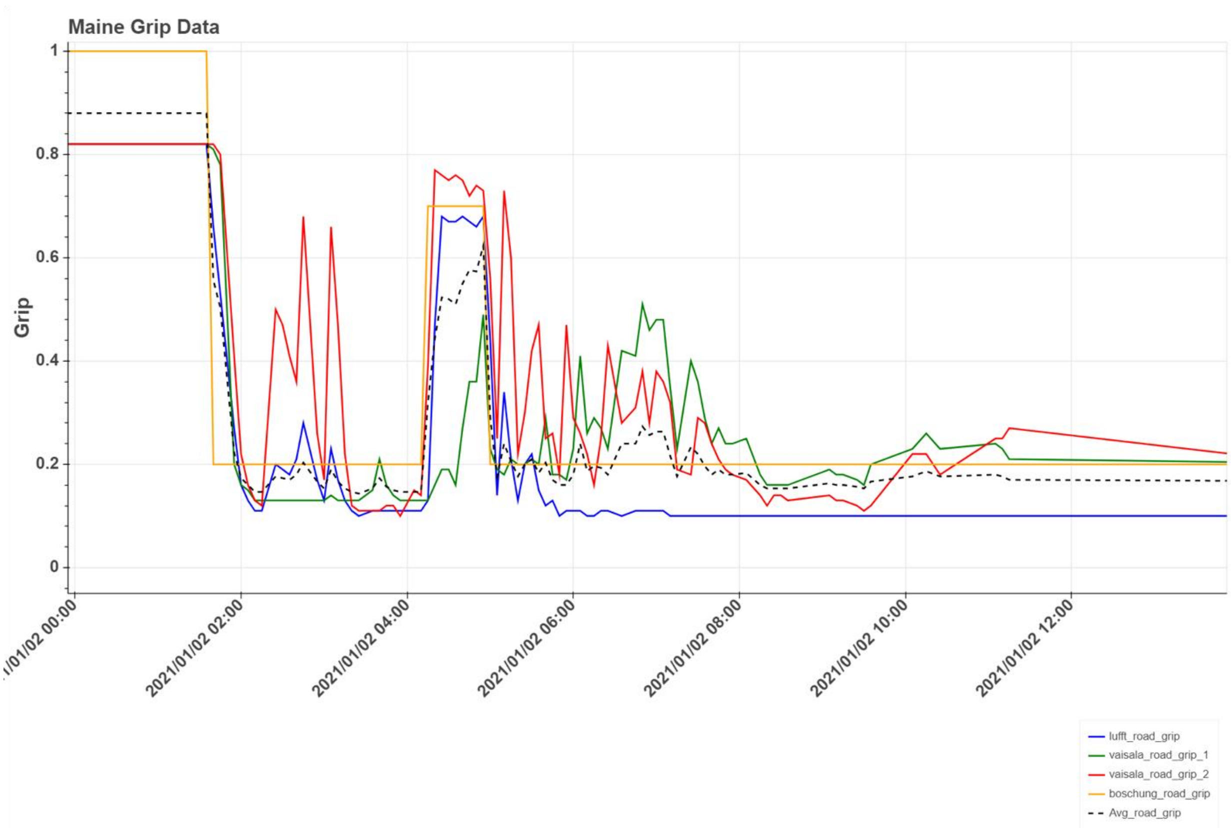


Figure 24. Plot of January 2, 2021, friction data at the Etna, Maine, RWIS site

Agreement between the Lufft and Boschung sensor data is good, with notable periods where the Vaisala sensor values disagree with each other and with the Lufft/Boschung time series data. For example, the Vaisala 2 sensor is significantly different from the other three sensors between 2021/01/02 02:00 and 2021/01/02 03:00. Between 2021/01/02 04:00 and 2021/01/02 05:00 the Vaisala 1 sensor has values significantly lower than those of the other sensors.

The time series plots in Figure 25 illustrate a low friction event on January 16, 2021.

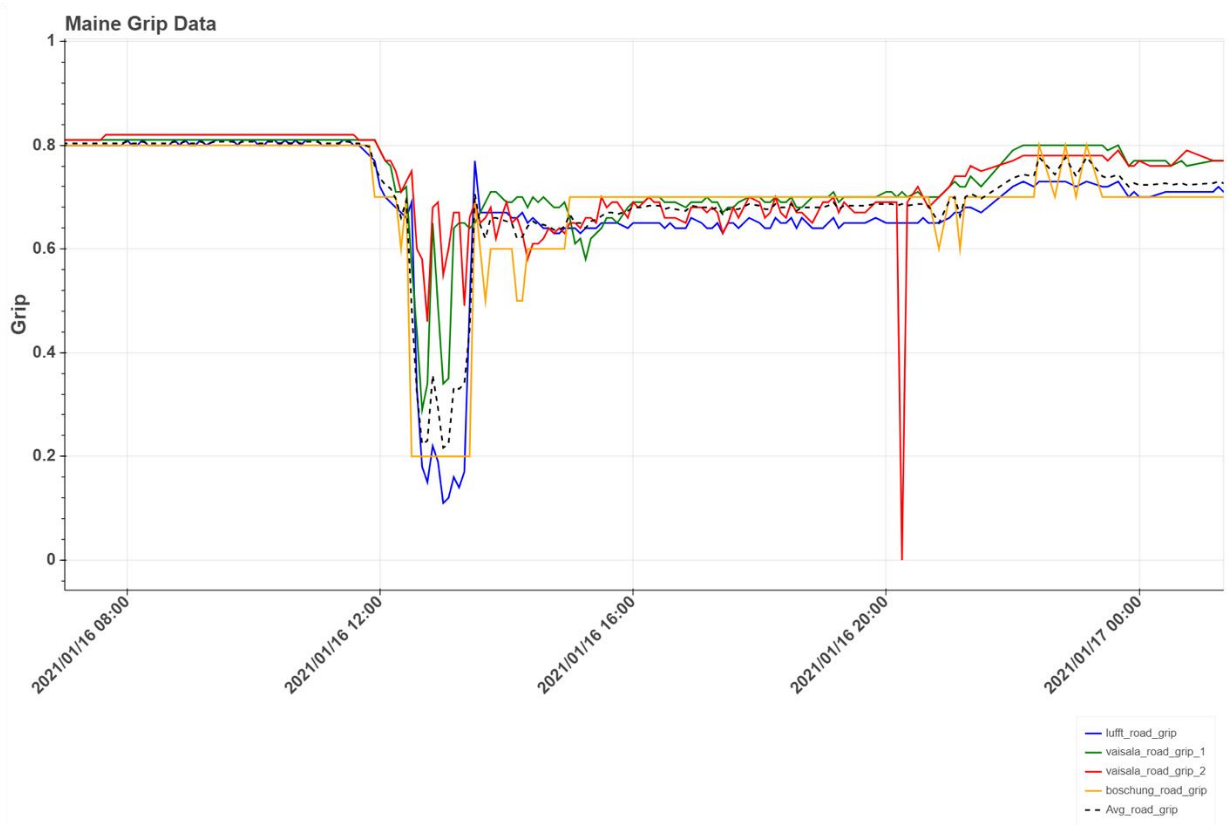


Figure 25. Plot of January 16, 2021, friction data at the Etna, Maine, RWIS site

Agreement is good among all sensors when friction values are near 0.8 (high road friction). As the low friction event is entered after 12:00 on January 16, the Lufft and Boschung sensors are in good agreement. However, the two Vaisala sensors detect the low friction event but assign higher friction values, and the Vaisala 2 sensor does not register the event as strongly as the other sensors. As the road friction improves, the sensor values come into closer agreement. Note that the spike from the Vaisala 2 sensor just after 2021/01/16 20:00 (red line, Figure 25) suggests an incorrect friction value.

The time series plots in Figure 26 illustrate a low friction event on January 22, 2021.

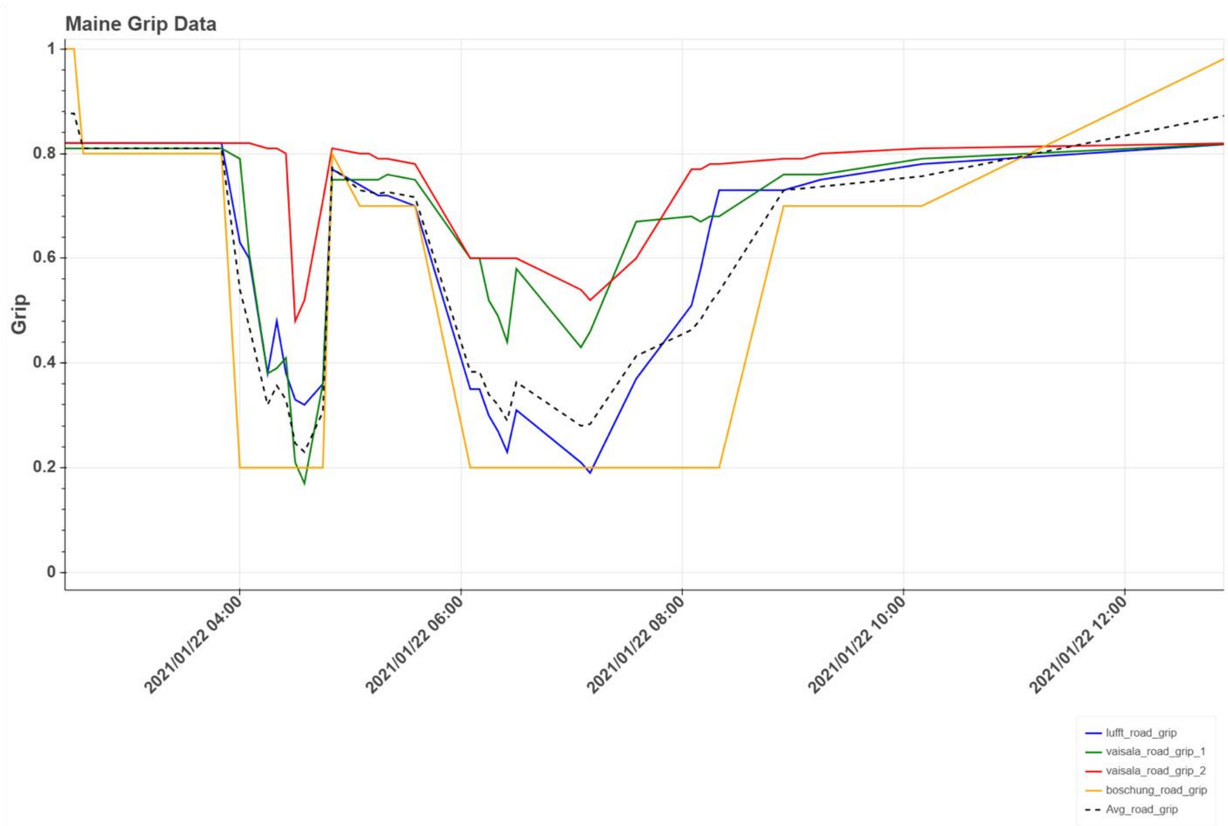


Figure 26. Plot of January 22, 2021, friction data at the Etna, Maine, RWIS site

The agreement between the Lufft and Boschung sensors is not quite as good as in the previous figures. All the sensors pick up on the event but register different friction values and ranges.

In Figure 27, the friction values from the suite of sensors are all greater than or equal to 0.7.

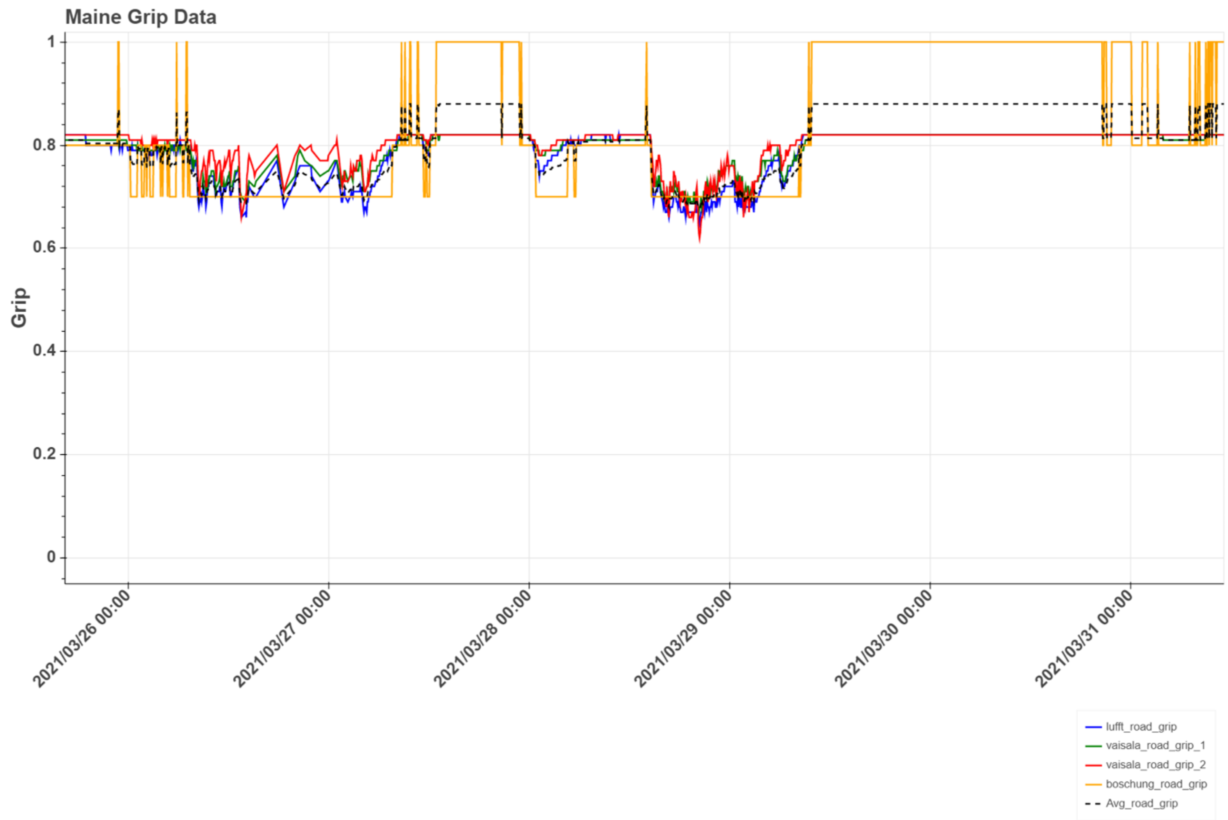


Figure 27. Plot of March 25, 2021, friction data at the Etna, Maine, RWIS site

This figure illustrates good agreement between the friction values from the different sensors, except for the Boschung sensor, which exhibits spiky behavior.

Conclusions on the Analysis of Maine Friction Data

The Maine data illustrate the value of having collocated friction measurements from multiple sensors. The sensors are all viewing the same location except for the Vaisala 2 sensor, which is a little down the road from the others. There are insufficient data to create a statistically reasonable standardization of the friction values from the different sensors. To do so, the project team recommends gathering at least one to two full winter seasons of data representing a variety of friction events. Here are some initial conclusions from the present study:

- The Etna friction sensor measurements tend to have closer agreement when the friction magnitudes are higher (> 0.6).
- There can be significant differences in friction measurements when transitioning from higher friction to lower friction or vice versa.
- There can be significant differences in friction measurement magnitudes after transitioning to a low friction environment.
- It was helpful to have the Lufft, Boschung, and Vaisala 1 sensors mounted on the same pole and pointing at the same spot on the road.

- Even though there is a difference in friction magnitudes between the different sensors, they are generally in agreement with regard to signaling lower friction events.

Methods for Standardizing Friction Measurements

Two methods for standardizing friction measurements are discussed below.

Averaging Measurements from Different Sensors

All of the mobile and stationary friction devices considered in this study offer competing measurements for road friction, so, lacking a friction wheel to provide a standard measurement of actual road friction, the simplest technique for estimating actual friction from competing stationary friction sensor measurements is to calculate a weighted average of all the measurements. The weights would be proportional to the estimated quality of the different sensor measurements. If the quality of the sensors is unknown, the weights can all be initialized to 1.0. The procedure would be as follows:

1. Identify and perform quality control on erroneous measurements.
2. Form a weighted average of the non-erroneous measurements.

The average can then be used as an approximation of the actual friction.

Breaking Friction Measurements into Ranges/Categories

Another approach to standardizing friction measurements from different sensors is to categorize the friction values into different ranges. For example, divide the 0 to 1.0 friction range into intervals such as the following:

1. 0.8 and above (high friction)
2. 0.6 to 0.8 (moderate friction)
3. 0.4 to 0.6 (low to moderate friction)
4. below 0.4 (low friction)

By mapping the values from each sensor into the ranges mentioned above, one can determine sensor accuracy in terms of whether the sensor correctly identifies the friction range or category that is mostly agreed upon.

Conclusions

- The friction sensors in the individual Clear Roads and Maine studies are generally in close agreement during high friction conditions (> 0.6).

- The friction sensors are generally in agreement when signaling a lower friction event but can disagree on the magnitude. For example, some sensors may register an event as a “moderate” friction event and others register the same event as “low to moderate” or “low.”
- When transitioning into or out of a low friction environment, the friction sensors can deviate in magnitude significantly.
- It is important to have sufficient data to determine statistically relevant patterns in the friction measurements from different sensor types.
- It can be challenging to properly collocate and configure multiple friction sensors for one or more winter seasons and thus gather a sufficiently robust friction data set.
- Friction measurements from one sensor can be either significantly higher or significantly lower than measurements from another.

USING METEOROLOGICAL MEASUREMENTS TO INFER ROAD FRICTION CONDITIONS

Objective

One of the major goals of the project was to investigate the relationship between meteorological and surface conditions as measured by RWIS and road friction sensors. For more information, see Minge et al. (2019), Juga et al. (2013), and Siril et al. (2004). For example, freezing, wet conditions can cause ice to form on roads, which lowers road surface friction. The research team was specifically interested in investigating whether supervised ML techniques can be used effectively to model these relationships and provide insight into friction conditions at sites where only non-friction RWIS measurements are available. To verify the performance of the ML techniques, the project focused on RWIS sites where friction measurements are available. Note, however, that the actual friction measurements were never included in the set of predictors.

The project team was also interested in determining whether friction models developed in the laboratory or in particular states could be effectively applied in a new location. This could potentially lead to a low-cost method for estimating road friction without having to perform a custom study.

Methods

Data Sets

To perform the investigation, the project team identified the following data sets:

- Colorado RWIS and optical friction data
- Cold laboratory meteorological and optical friction data (collected by the research team)
- Clear Roads Minnesota mobile optical friction data
- Minneapolis-St. Paul International Airport (MSP) meteorological and friction wheel data

Colorado RWIS and Optical Friction Data

The Colorado RWIS and optical friction data were gathered over a period of approximately 1.5 years from September 9, 2019, through March 4, 2021, and consist of atmospheric and surface variables. Atmospheric measurements are measurements of conditions above the surface and include temperature, relative humidity, wind speed, and precipitation, while surface measurements include road surface temperature, road state water depth, and road friction. Optical road friction sensor measurements are not uniformly available at all Colorado RWIS sites, so the project team restricted attention to 102 sites where road friction data were available from Vaisala DSC211 sensors. The ML experiments restricted the data set to winter months (October through March). Since the Colorado friction data are unbalanced, with too many 0.82 friction values (note that the Vaisala sensors had a default value of 0.82 for good friction), all

0.82 friction values were removed prior to ML. The project team identified predictors from the following RWIS measurements and then evaluated ML model performance using the friction measurements from the Vaisala DSC211 sensors:

- Air temperature
- Dew point temperature
- Precipitation intensity (categorical)
- Precipitation status (categorical)
- Relative humidity
- Road state
- Surface temperature
- Water depth
- Wind speed
- 10-minute precipitation accumulation

Cold Laboratory RWIS and Friction Data

This data set is described in detail in the Cold Laboratory Testing chapter.

Clear Roads Minnesota Mobile Optical Friction Data

The Clear Roads Minnesota mobile optical friction data came from a Clear Roads study performed in 2018 (Minge et al. 2019). The data set is described in detail in the Clear Roads Study section. This study evaluated the performance of four different mobile friction sensors:

- Vaisala DSP310
- Lufft MARWIS
- Teconer RCM411
- High Sierra Mobile IceSight

The data set was gathered on a variety of Minnesota road surfaces, under varying weather conditions, on 20 different days between January 15, 2018, and April 16, 2018. Note that the winter road conditions in the study do not reflect average winter road conditions in Minnesota.

Since Colorado uses the stationary Vaisala DSC211 optical friction sensor, the team selected the Vaisala DSP310 sensor data to create the Clear Roads ML model. The Vaisala DSP310 sensor consists of the DSC111 surface state sensor, the DSP101 pavement temperature sensor, and the HMP155 humidity and temperature probe. The ML experiments identified predictors from the following measurements:

- Air temperature
- Dew point temperature
- Relative humidity

- Road state (raw or remapped)
- Surface temperature
- Water depth

The target for the Clear Roads model was to match either the Vaisala DSP310 friction coefficient or a friction category (low, medium, high) based on the Vaisala DSP310 friction coefficient.

MSP Surface Station and Friction Wheel Data

The MSP data set consists of data gathered from a Halliday friction wheel and from surface stations at MSP. Models targeting the friction wheel measurements used the following predictors:

1. Surface temperature
2. Relative humidity
3. Wind speed
4. Solar zenith angle
5. Most severe weather state in the previous three hours (using precipitation type and intensity)

Colorado RWIS Data Preparation

The following steps were involved in the preparation of the Colorado RWIS data for machine learning:

1. Perform quality control on the RWIS measurements by removing missing values and out-of-range values.
2. Merge atmospheric and surface RWIS data files with the same date/time. (The underlying files are created every 10 minutes.)
3. Remove duplicate measurements (measurements taken at the same date/time and having the same values).
4. If there are multiple surface temperature values at a single site, calculate the mean.
5. If there are multiple road state values at a single site, calculate the mode.
6. If there are multiple water depth values at a single site, calculate the mean.
7. If there are multiple ice percentage values at a single site, calculate the mean.
8. Format the data for the application of ML algorithms.

One of the goals of this project was to determine whether the relationship between weather conditions and friction found in the laboratory was similar to the relationship between weather conditions and friction found on highways. The Vaisala DSC111 and DSC211 sensors used in the laboratory study were also used at numerous RWIS locations in Colorado, so their measurements, both in the laboratory and out in the field, were used in this investigation. The research team was interested in whether supervised ML techniques could be used to effectively model the relationships between meteorological conditions and friction and whether models developed for predicting friction found in the laboratory could be used out in the field.

Machine Learning Approaches

Different ML modeling approaches were used to predict friction in Colorado. One of the approaches involved training different ML algorithms on Colorado RWIS training data and targeting road friction measured at Colorado RWIS sites. Other approaches involved using data sets from other states or from the cold laboratory to model friction. So, for example, the project team created friction models using RWIS and friction data gathered in Minnesota. These models were then applied to the RWIS data gathered in Colorado to predict friction at Colorado RWIS sites.

The project team used two approaches when assessing ML model performance:

1. MAE, where the absolute value of the difference between the model forecast and the observed friction value is calculated for many test cases. The errors are then averaged to produce an MAE value.
2. Hit rate, where the observed friction values ranging from 0.0 to 1.0 are first divided into three ranges:
    a. values ≤ 0.35
    b. 0.35 < values ≤ 0.45
    c. 0.45 ≤ values

    The forecast is then checked to see whether it is in the same range as the observation or whether it is at least reasonably close to that range. Finally, the forecast is checked to see whether it is within a certain distance of the observation. If it passes the check, it is a hit, and if does not pass the check, it is a miss. A full description of the hit rate algorithm is provided in Appendix A.

After randomly choosing one-third of the Colorado RWIS friction sites for the Colorado test data set, the different approaches were evaluated as follows:

- Model the Colorado RWIS and friction data at RWIS sites that are not included in the test set. Apply the resulting model to the data in the Colorado test data set.
- Model the cold laboratory data targeting road surface friction and then apply the resulting model to the Colorado test data set.
- Model the Minnesota Clear Roads data targeting road surface friction and then apply the resulting model to the Colorado test data set.
- Model the MSP data targeting runway surface friction and then apply the resulting model to the Colorado test data set.

Colorado Machine Learning Model Description

The project team was interested in determining whether an ML model developed using Colorado RWIS data would outperform ML models developed using data sets from other environments such as Minnesota or the cold laboratory. Here is a description of how ML models were developed using the Colorado RWIS and friction data:

1. For each experiment, randomly split the Colorado RWIS sites into a training group and a testing group. Two-thirds of the RWIS sites with friction sensors were used for training, and one-third of the sites were held back for testing.
2. Fit an RF regressor model to the training data and set the parameter n_estimators (the number of trees in the RF model) to 10.
3. Evaluate the performance of the RF regressor model on the test data.
4. Repeat steps 1, 2, and 3 N times to calculate an average MAE for all runs.

Note that the experiments described below use different fields for predictors. The target values are always friction values from a set of sites held back for testing.

Cold Laboratory Model Description

RF models were trained on the laboratory data set (747 valid points with non-missing data) with the parameter n_estimators set to 10. This model was subsequently applied to the Colorado RWIS data. Note that the size of the cold laboratory data set is exceedingly small compared to the Colorado RWIS data set (700,000+ data points). The average laboratory friction value (0.48) is much lower than the average Colorado RWIS friction value (0.70) since the majority of Colorado friction data are 0.81.

Clear Roads Vaisala Model Description

An RF model was trained on the Clear Roads Vaisala data set (10,591 valid points with non-missing data). This model was subsequently applied to the Colorado RWIS data. The average Clear Roads friction value (0.54) is much lower than the average Colorado RWIS friction value (0.70) since the majority of Colorado RWIS friction data are 0.81. The parameter n_estimators was set to 10.

Minneapolis-St. Paul International Airport Model Description

An RF model was trained on the MSP data set (1,454 valid points with non-missing data). This model was subsequently applied to the Colorado RWIS data. The average MSP friction value (0.35) is much lower than the average Colorado RWIS friction value (0.70) since the majority of CDOT friction data are 0.81. The parameter n_estimators was set to 10.

Results

The project team explored different data sets in the creation of ML models and then applied the resulting ML models to the Colorado RWIS data.

The RF regression model was used extensively while modeling the data sets, including the Clear Roads, MSP, cold laboratory, and CDOT RWIS data sets. In some cases, the project team explored the use of other ML models, such as gradient-boosted regression, cubist, and C5.

Experiment 1: Generic Machine Learning Results

This experiment was performed to assess ML model performance using a basic set of predictors targeting the measured road friction in Colorado. The basic predictor set (BPS) used to train the model is air temperature, dew point temperature, relative humidity, and surface temperature.

To avoid creating models that consistently predict high friction, the project team removed data records where the friction values were equal to 0.82, the most common friction value.

The Colorado RWIS model has the lowest error and best performance in Experiment 1 (Table 4).

Table 4. Generic ML results for forecasting road friction using the BPS

Model	BPS MAE	BPS Hit Rate
Colorado RWIS (friction <0.82)	**0.15**	**73% (bolded results are best results)**
Cold Lab	0.27	42%
Clear Roads	0.23	60%
MSP	0.26	53%

Experiment 2: Machine Learning Results Adding Road State from the Vaisala DSC211 Friction Sensor

The chosen predictor sets used for training in Experiment 2 are BPS (air temperature, dew point temperature, relative humidity, surface temperature) and RS211, which is BPS plus road state from the Vaisala DSC211 friction sensor.

The fact that the MSP errors are high and the hit rate is low is likely because the MSP training set primarily contains data records with low friction values (Table 5). Adding road state to the predictor set had a positive effect on reducing error and improving hit rate.

Table 5. ML results for forecasting road friction using the BPS plus RS211 road state

Model	BPS MAE	RS211 MAE	BPS Hit Rate	RS211 Hit Rate
Colorado RWIS (friction <0.82)	0.14	**0.073**	75%	**86%**
MSP (friction < 0.82)	0.27	0.27	49%	46%

Experiment 3: Machine Learning Results Using Road State from the Vaisala DSC211 Friction Sensor Versus Road State from the Vaisala DSC111 Road State Sensor

The chosen predictor sets used for training in Experiment 3 are BPS (air temperature, dew point temperature, relative humidity, surface temperature), RS211 (BPS plus road state from the

Vaisala DSC211 friction sensor), and RS111, which is BPS plus road state from a non-friction sensor (Vaisala DSC111).

The Colorado RWIS MAE and hit rate results for the two ML models, RS211 and RS111, are similar (Table 6). Note that the data set for the Vaisala DSC111 sensor was significantly smaller than that of the Vaisala DSC211 sensor.

Table 6. ML results for forecasting road friction using road state from different sensors

Model	RS211 MAE	RS111 MAE	RS211 Hit Rate	RS111 Hit Rate
Colorado RWIS (friction < 0.82)	**0.078**	0.091	**90%**	88%
MSP (friction < 0.82)	0.31	0.177	43%	43%

Experiment 4: Machine Learning Results Using Three-Hour Precipitation Weather State Versus Road State

Experiment 4 was performed to identify the value of using a three-hour precipitation weather state parameter in place of road state when predicting road friction. The three-hour precipitation weather state is defined as the most severe precipitation weather state in the past three hours.

The chosen predictor sets used for training in Experiment 4 are BPS (air temperature, dew point temperature, relative humidity, surface temperature), RS211 (BPS plus road state from the Vaisala DSC211 friction sensor), and PBPS, which is BPS plus precipitation weather state.

Experiment 4 suggests that utilizing a precipitation state parameter in the Colorado RWIS models does not offer much improvement in comparison to not using it (Table 7).

Table 7. ML results for forecasting road friction using BPS, road state, and precipitation

Model	BPS MAE	RS211 MAE	PBPS MAE	BPS Hit Rate	RS211 Hit Rate	PBPS Hit Rate
Colorado RWIS (friction <0.82)	0.14	**0.073**	0.14	75%	**86%**	73%
MSP (friction <0.82)	0.27	0.27	0.26	49%	46%	50%

Experiment 5: Machine Learning Results Using Wind Speed

This experiment was performed to identify whether wind speed is helpful in predicting road friction when combined with BPS (air temperature, dew point temperature, relative humidity, surface temperature) in a parameter set called WPS, which is BPS plus wind speed.

Experiment 5 suggests that adding wind speed has minimal impact on predicting road friction (Table 8).

Table 8. Generic ML results for forecasting road friction using BPS and wind speed

Model	BPS MAE	WPS MAE	BPS Hit Rate	WPS Hit Rate
Colorado RWIS (friction <0.82)	0.15	0.15	73%	73%

Conclusions

- The Colorado model trained on Colorado RWIS data, which targets Colorado RWIS friction measurements, had better performance than models that were trained using the cold laboratory data or data from other states.
- Adding road state to the list of predictor variables improved performance significantly. This is not surprising since road state is closely aligned with road friction.
- Adding wind speed did not improve the performance of the Colorado friction model.
- Adding a three-hour precipitation weather state parameter was not helpful. (However, additional work should be performed to determine how precipitation influences road state.)
- Models transferred from the laboratory or other states demonstrated good performance in targeting Colorado friction, but their performance was not as good as the performance achieved in their original environments.
- Friction data sets are often unbalanced and include a majority of benign friction values of 0.82. When estimating the friction experienced in low friction events, it is important to establish an appropriate mix of friction and corresponding meteorological measurements.

Based on these conclusions, the following recommendations can be made:

- Treatment has an obvious effect on road state, so it will be important to obtain digital treatment data and integrate that into the friction prediction system.
- The creation of friction ML models based on friction data collected during storm event days should be investigated. This would involve the following:
  - Identify storm event periods.
  - Gather data prior to the storm event, during the storm event, and for a period of time after the storm event.
  - Use the data collected for model training and testing.

FRICTION WHEEL MEASUREMENT ANALYSIS

Objective

A friction wheel may be used to provide a benchmark road friction measurement for a specific tire type. Mobile and stationary friction sensors typically use lasers or LEDs and optical sensors to identify road water, snow, ice, and friction based on spectral differences in the sensed light returned. The project team was particularly interested in analyzing the relationship between RWIS data and nearby friction wheel measurements designed to serve as a baseline for standardized stationary friction sensor measurements.

Methods

The project team was able utilize a set of Swedish friction wheel measurements and nearby RWIS measurements collected by Trafikverket, the Swedish Transportation Administration (Figure 28).

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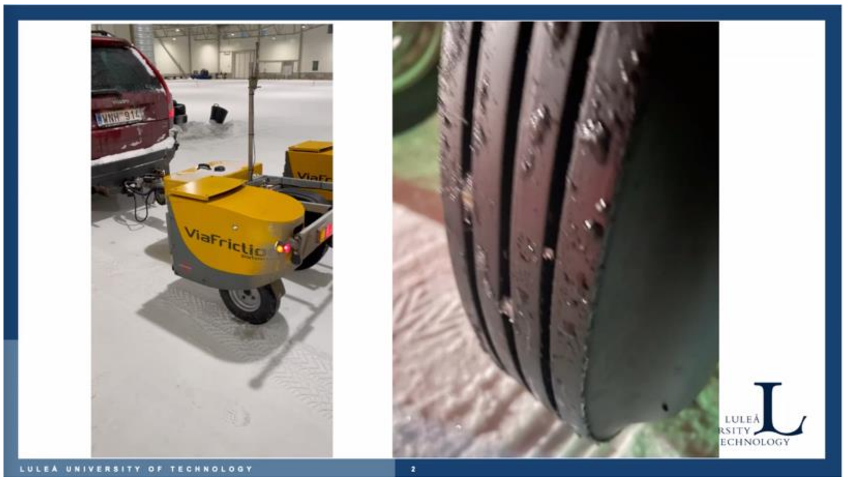
Figure 28. Location of the friction case studies in Luleå, Sweden

The measurements were gathered for several case studies during the 2020–2021 and 2021–2022 winter seasons. Figure 29 shows the trailer setup and actual friction wheel used in the case studies.



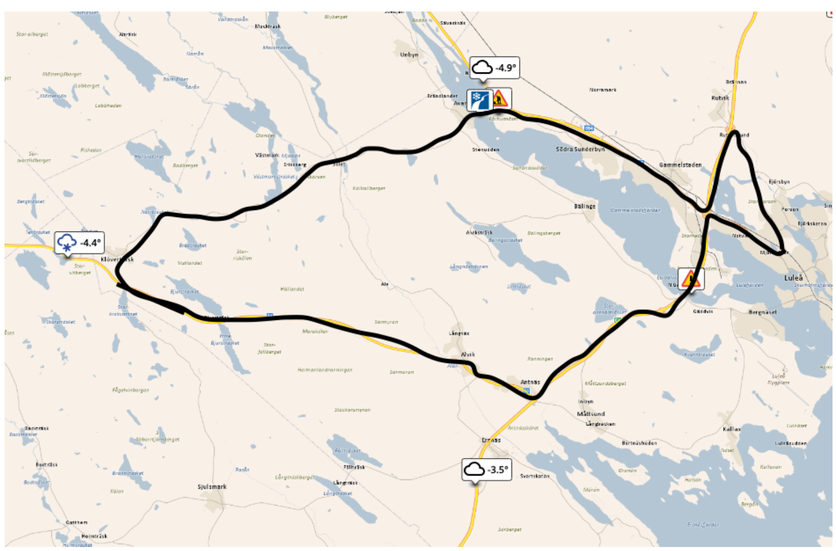
Provided by Johan Casselgren, © Luleå University of Technology

Figure 29. Trailer (left) and friction wheel (right) used in the Trafikverket case studies

Since the data set provided by Trafikverket consisted of approximately 25 case studies, each covering a period of a few hours, the project team concluded that there were not enough cases for a statistically meaningful application of ML techniques to investigate the relationship between the RWIS data and friction wheel measurements. The project team then decided to visualize the cases in a preliminary investigation of the relationship between RWIS precipitation and friction wheel measurement.

Results

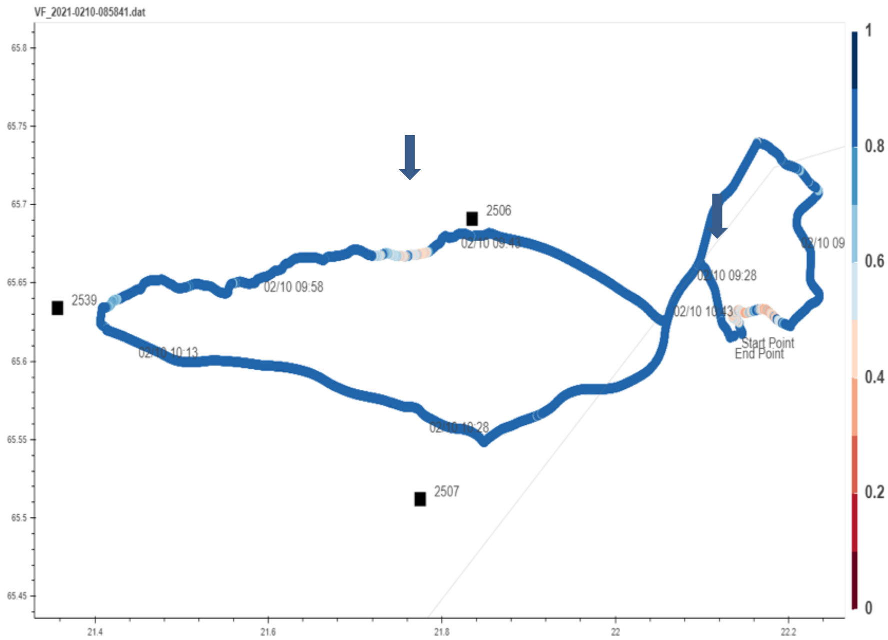
Figure 30 shows the route traveled while collecting the friction measurements for all of the case studies and the locations of the three RWIS sites in this area of Sweden.



Provided by Johan Casselgren

Figure 30. Trafikverket friction data collection route

For the case study on February 10, 2021, observed friction values are plotted in Figure 31 with key dates and times.

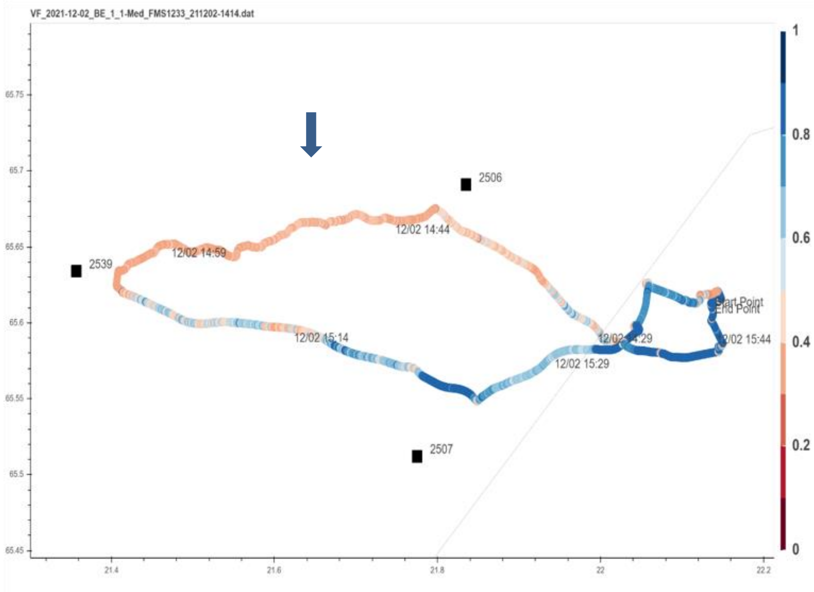


Created by NCAR research team

Figure 31. Route traversed in Luleå, Sweden, with observed friction values for the February 10, 2021, case study

The three RWIS stations are represented by black rectangles and the RWIS identifiers 2506, 2507, or 2539. Latitudes are labeled along the y-axis and longitudes along the x-axis. Notice the high friction values of 0.7 and above through most of the event, though there are a few periods where lower friction was measured, just after the start of the route at 09:28 and then again shortly after 09:43. There was no record of precipitation at the three RWIS stations within the three hours prior to or during the case study. However, data for RWIS station 2506 were not consistently available.

Figure 32 depicts the December 2, 2021, case study, where high friction values were observed from 14:29 to 15:14 and RWIS stations 2539 and 2507 both reported snow (Precip Type 4) during the entire time period (Figure 33). RWIS station 2539 reported the highest snow quantities during the period, which correspond well with the friction readings depicted near station 2539.



Created by NCAR research team

Figure 32. Route traversed in Luleå, Sweden, with observed friction values for the December 2, 2021, case study

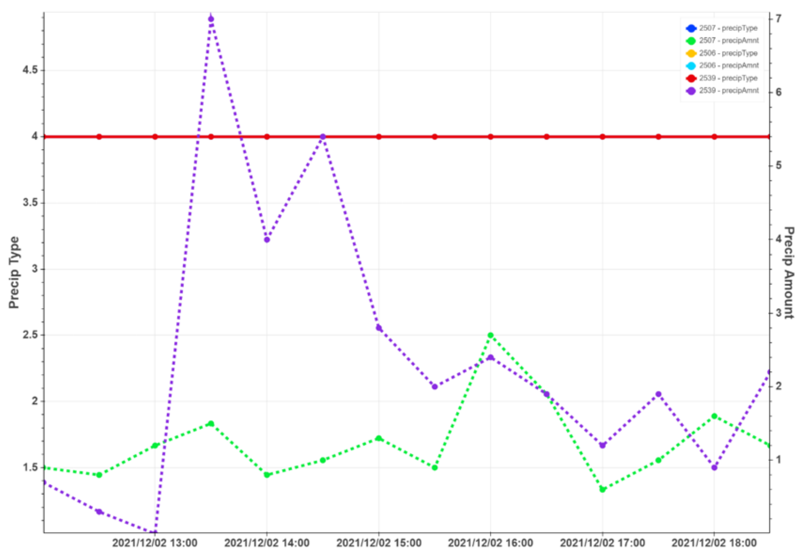
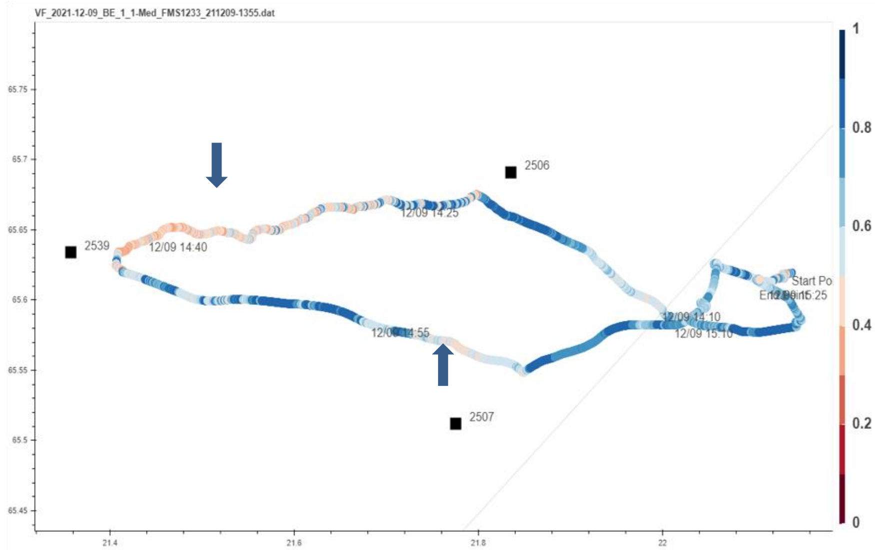


Figure 33. Precipitation for the December 2, 2021, case study

In Figure 34, road friction was observed from approximately 14:25 through 14:40 in the vicinity of RWIS station 2539 on December 9, 2021. Friction was also observed near RWIS station 2507 after 14:55. RWIS stations 2539 and 2507 both reported snow (Precip Type 4) during the entire time period (Figure 35).



Created by NCAR research team

Figure 34. Route traversed in Luleå, Sweden, with observed friction values for the December 9, 2021, case study

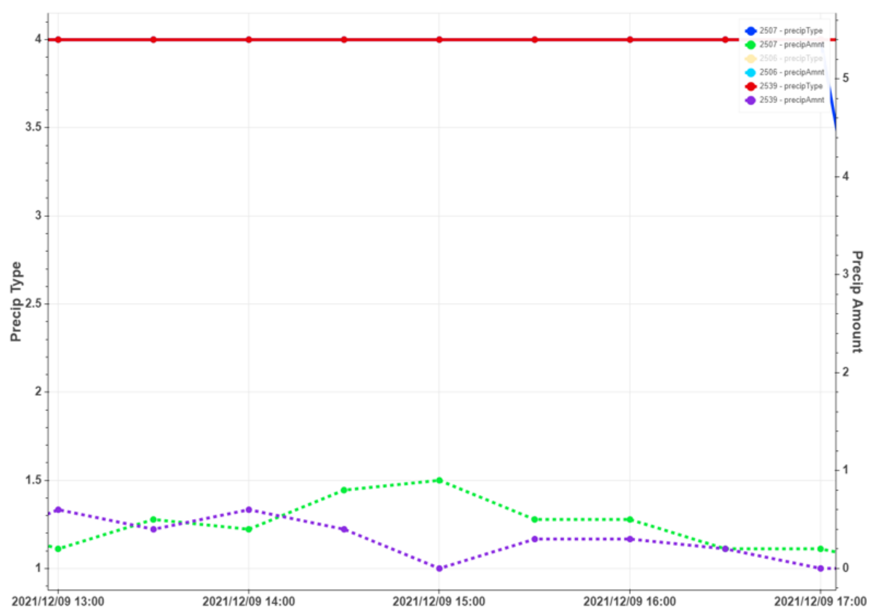


Figure 35. Precipitation for the December 9, 2021, case study

Conclusions

- There is correlation between precipitation events recorded at the RWIS stations and road friction measured by the friction wheel.
- There were times when road friction was low but there were no recent precipitation measurements. Note that one of the RWIS sites, 2506, was often missing data, so this could be the cause.

- The RWIS sites were not necessarily close to where the friction wheel measurements were taken. This could affect modeling of the relationship between RWIS measurements and friction measurements. Localized weather could also mask the relationship between RWIS measurements and nearby friction measurements.
- More data are needed to effectively model the relationship between RWIS measurements and nearby friction measurements.
- Friction measurements are affected by road type, and the road types where the tests were performed differ considerably in makeup.

RESULTS AND DISCUSSION

Can Laboratory Testing Be Used as a Proxy for Field Data Collection in Friction Modeling?

It is unlikely that laboratory results can be used as a proxy for field data collection. To obtain the best friction model performance, it is important to calibrate the friction sensor equipment properly and then gather field data while mirroring the expected environment and conditions as closely as possible. As detailed in this report, different sensor types can record different sensor measurements for the same road conditions at a site. Therefore, it is important that the sensor type of interest is installed in the field, ideally at multiple locations that reflect the various weather environments characterizing the weather in the state. For example, moderate snow friction measurements on a non-shaded highway in Denver, Colorado, may be significantly different from moderate snow friction measurements on a shaded highway in the mountains near Vail, Colorado.

If No Friction Data Are Collected, What Variables Are Most Important to Collect for Use in a Friction Model?

Air temperature, dew point temperature, relative humidity, and surface temperature are important to collect and make up a basic predictor set. If available, road state, water thickness, and snow thickness can potentially improve friction prediction performance significantly.

Which Model Works Best and Why?

Both the RF and gradient-boosted tree algorithms exhibited similar performance in this analysis. More important was the set of predictors chosen and the identification of reasonable training and test sets. Some predictors, such as wind speed and precipitation, did not offer improvement in tests when compared with air temperature, dew point temperature, relative humidity, and surface temperature. The training and test sets should be a balance of high, moderate, and low friction types. Training on data sets that consist of predominantly high friction measurements is not advisable.

Can Multiple Friction Data Sources Be Used by a State Department of Transportation? If So, How Can They Be Made Comparable?

Combining multiple friction sensors is not ideal, and care should be taken if multiple friction sources are used. One can make them comparable by taking an average or weighted average and establishing error statistics against the average. A second approach is to assign friction measurements from different sensors to categories (high, moderate, low to moderate, low) and then identify the predominant categories from the sensor suite. Note that measurements from different sensors can confuse users since the friction categories suggested by the sensor measurements may differ. The sensors may also be of different qualities and ages and may behave differently under the same environmental conditions. All these issues present challenges when comparing data from different sensors.

Is a Friction Wheel/Skid Trailer Needed to Validate Friction Data Accuracy?

If a state wishes to pursue the use of a variety of friction sensors, this report recommends that a comparison study be performed of the optical friction sensor measurements (stationary or mobile) versus friction wheel measurements. A friction wheel establishes a measurement baseline against which the optical friction sensors can be compared.

Key Findings

- ML models can be created using cold laboratory data that exhibit a good MAE (0.15) in predicting the friction response to meteorological conditions set in the laboratory. These models have a higher MAE (0.27) when applied to data from the field. Note that 0.27 is a sizable error in a 0.0 to 1.0 friction scale. For this reason, this report does not recommend using the laboratory-developed model on field data.
- Collocated RWIS and stationary friction sensor data can be used to develop state-specific friction models using ML techniques. These models can then be used to provide a synthetic friction estimate at RWIS sites that are not equipped with stationary friction sensors. The accuracy of the predictions can be determined at sites where friction sensors are available, and accuracy is improved when water thickness and/or snow thickness are also available.
- RWIS measurements including air temperature, surface temperature, dew point temperature, relative humidity, and road condition measurements, including road state, water thickness, and snow thickness, can be used to derive an accurate friction model that targets observed friction values.
- Friction values from multiple sensor types are close in magnitude when friction is high (0.7 to 1.0), but agreement among sensors is variable when friction values drop below 0.6. To standardize the measurements from multiple friction sensors, perform the following:
    - Take the weighted average of friction values from multiple sensors.
    - Map friction values to categories such as high, moderate, low to moderate, and low. The most agreed-upon value can be selected as the standardized value.

RECOMMENDATIONS

Incorporating Friction Diagnoses and Predictions in a State Maintenance Decision Support System

Winter maintenance decision support system (MDSS) algorithms typically diagnose and predict categorical road conditions such as dry, light snow, moderate snow, heavy snow, etc. To add precision to MDSS implementations, estimates of road friction would, based on their accuracy, enable a more quantitative approach to road treatments and the establishment of variable speed limits. A key outcome of this project is the creation of ML models that predict road friction measurements from sensors that are in actual use in a state. The advantage of this approach is that the friction predictions are tailored to approximate the friction measurements that DOT maintenance personnel are already accustomed to using. A clear requirement for adopting this approach is that state road maintenance personnel are already collecting good friction measurements in their road maintenance workflow. In states where this is true, the project recommends the following:

- Augment the MDSS by incorporating friction diagnosis and prediction.
- Perform a study involving DOT staff using the MDSS friction diagnoses and predictions during a winter season.
- Assess the benefit of using the friction diagnoses and predictions.
- Validate the friction diagnoses and predictions at sites where friction sensors are available.

Whether to Utilize a Friction Model Developed for Another State

If a state, State B, is interested in using a friction model that was developed for another state, State A, State B should consider several issues:

- Is State B using the same friction sensor type as State A? If not, there could be significant differences in predicted friction.
- Are the geography and weather in State B similar to those in State A? For example, is State B flat and State A mountainous? Does State B have similar winter weather to State A?
- Is the road composition in areas of interest in State B similar to that in State A?
- Are the types of RWIS measurements used in modeling friction in State A also available in State B? For example, if road state and/or water thickness are used in modeling friction in State A, are road state and/or water thickness also available in State B?
- Is the friction model for State A performing well?

If these issues have been addressed satisfactorily, it would be feasible for State B to try using the friction model developed for State A. Still, based on what was discovered in this project, a best practice would be for State B to gather relevant RWIS and friction data and then model State B’s friction data based on State B’s RWIS data.

Steps for Creating Friction Models for a State Department of Transportation

If a state uses a number of friction sensors at different RWIS locations, the state should collect the collocated RWIS and friction data over a minimum of one to two winter seasons to integrate friction prediction into the state's winter MDSS. It is important that the winter seasons have a sufficient number and variety of winter storm events so that the modeling can be performed on a robust data set. If the state is also interested in friction prediction in the spring, summer, and fall seasons, the corresponding RWIS and friction data should be collected during these seasons as well. ML models can then be created based on the fields mentioned in this report.

As mentioned in Using Meteorological Measurements to Infer Road Friction Conditions, the following steps should be performed:

1. Perform quality control on the RWIS measurements by removing missing values and out-of-range values. As part of RWIS data quality control, it is important that the RWIS and friction sensors are regularly maintained so that quality measurements are recorded.
2. Merge atmospheric and surface RWIS data and index data records by date/time.
3. Remove duplicate measurements (measurements taken at the same date/time and having the same values).
4. If there are multiple scalar values, such as surface temperature, at a single site, calculate the mean.
5. If there are multiple categorical values, such as road state, at a single site, calculate the mode.
6. Format the data for the application of ML algorithms.
7. Select algorithms such as RF or gradient-boosted trees for ML.
   a. Using automated ML techniques may also prove beneficial. Such techniques allow for the automatic testing of a variety of different ML algorithms.
8. Ensure that the training and test sets have balanced friction values of different magnitudes. The data sets should not be overweighted with good (read: high) road friction values such as 0.82.

FUTURE WORK AND REARCH NEEDS

State-Based Road Friction Modeling Using Road Weather Information System Data

As mentioned in the Recommendations chapter, it is helpful to determine how friction measurements, diagnoses, and predictions are actively used by state DOTs. However, doing so will require close collaboration between the friction model developers and DOT users to allow for refinement of the friction models and the formulation and presentation of products.

Testing and Refining Friction Models and Incorporating Treatment Data

The Colorado friction models were trained using measurements from a subset of the friction sensor sites and were then tested on measurements from the friction sensor sites held back for testing. Another training/testing paradigm is to train on data from all friction sites over a winter season but hold out the last month of the season for testing. This approach would support the incremental modeling of road friction in a state (e.g., retraining the friction model once per week and then evaluating its performance over the next week).

How Can Road Treatments Be Optimized Using Friction Diagnoses and Predictions?

Road treatment information is not incorporated into the current friction models developed for this project. However, road treatments have a direct effect on road friction and will be important to incorporate in the future. Therefore, the digital acquisition of near-real-time road treatment information will be necessary.

Once friction modeling has been implemented for a state, it is important to understand how road treatment scheduling can be optimized with friction measurements, diagnoses, and predictions. It is also important to get feedback on the accuracy of the friction measurements and predictions from plow drivers.

Testing the Accuracy of Friction Models in Rural or Remote Locations with Limited Data

A direct method of testing the accuracy of friction models in rural or remote locations is to install suitable sensors at those locations. Given that installation can be costly, however, one can instead get an idea of friction model accuracy by identifying current friction sensor sites that have similar geographic features and climatic conditions to the rural or remote locations of interest. One can then estimate the accuracy at the rural or remote sites by calculating the accuracy at the known sites.

Using Image Recognition and Speed Data in Friction Modeling

Camera image recognition and collocated speed data can potentially be used to improve road friction modeling and categorization.

Using Road Friction Estimation When Setting Virtual Speed Limits

One significant application of road friction measurements and short-term friction prediction is in the setting of virtual speed limits. If current friction measurements are the only input in virtual speed limits and future friction trends are not taken into account, there is a risk that the speed limits will be adjusted from higher to lower speeds (or vice versa) too frequently.

Using Connected Vehicle, Automated Vehicle, and/or Crowd-Sourced Data in Friction Modeling

The use of friction data from connected and/or automated vehicles and crowd-sourced data could, especially when compared to friction wheel data, improve road friction modeling.

Friction Data Archiving

In the course of this project, it has become apparent that there is a need for the proactive archiving of friction data. Meaningful and accurate ML is dependent on the collection of suitable data sets. There is also a need for the transportation ML community to reach out to state DOTs and encourage well-organized data archival efforts.

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APPENDIX A. DATA DICTIONARIES

Cold Laboratory Data Dictionary

Field	Description
TIME	NA
DOT1_CMP_1min_temp	NA
DOT1_CMP_1min_rh	NA
DOT1_ICESIGHT_y_voltage	NA
DOT1_ICESIGHT_x_voltage	NA
DOT1_ICESIGHT_voltage_ratio	NA
DOT1_ICESIGHT_air_temp_secondary	NA
DOT1_ICESIGHT_surface_temp	NA
DOT1_ICESIGHT_displayed_condition_code	NA
DOT1_ICESIGHT_measured_condition_code	NA
DOT1_ICESIGHT_displayed_condition_text	NA
DOT1_ICESIGHT_measured_condition_text	NA
DOT1_ICESIGHT_displayed_friction_code	NA
DOT1_ICESIGHT_measured_friction_code	NA
DOT1_ICESIGHT_displayed_friction_code_value	NA
DOT1_ICESIGHT_measured_friction_code_value	NA
DOT1_ICESIGHT_dirty_lens	NA
DOT1_ICESIGHT_grip	NA
DOT1_ICESIGHT_rh	NA
DOT1_ICESIGHT_air_temp_primary	NA
DOT1_ICESIGHT_air_temp_tertiary	NA
DOT1_ICESIGHT_legacy_code	NA
DOT1_DSC211_temp,DOT1_DSC211_voltage	NA
DOT1_DSC211_surf_state	surface state code: 0, 1, 2, 3, 6, 9, 106, 109, 206. Similar to Vaisala codes where 106 = "warning + snowy" and 206 = "alarm + snowy"
DOT1_DSC211_grip	Surface friction between 0.0 and 1.0
DOT1_DSC211_status	NA, 0.0, 4.0. Probably related to the status of the sensor. It was 0.0 approximately 73% of the time.
DOT1_DSC211_water_thickness	water thickness in mm
DOT1_DSC211_ice_thickness	ice thickness in mm
DOT1_DSC211_snow_thickness	snow thickness in mm
DOT1_DST111_temp	air temperature in Celsius
DOT1_DST111_RH	relative humidity %
DOT1_DST111_dewpt	dew point temperature in Celsius
DOT1_DST111_voltage	NA
DOT1_DST111_road_temp	road temperature in Celsius
DOT1_DST111_status	NA

Colorado Data Dictionary

Field	Description
DateTime	yyyy-mm-dd hh:mm:ss+00:00
SITE_ID_NUM	site identifier
SENSOR_ID_NUM	integer specifying the sensor at the site.
Friction	friction value between 0.0 and 1.0
Surface_status_num_mode	most common surface status code from the reporting sensors (using SENSOR_ID_NUM)
Surface_status_fric_sensor	surface_status reported by the sensor (SENSOR_ID_NUM) that reported friction
SurfTemp_mean	mean of surface temperatures at site
SurfTemp_fric_sensor	surface temperature in Celsius from friction sensor
Water_depth_mean	mean of water depths at site
Water_depth_fric_sensor	water depth reported by the sensor that reported friction; units = mm
ice_pct_mean	mean of ice percentages
ice_pct_fric_sensor	ice percentage from the sensor that reported friction
ESS_AIR_TEMPERATURE_NUM	air temperature in Celsius
ESS_RELATIVE_HUMIDITY_NUM	%
ESS_DEW_POINT_TEMP_NUM	dew point in Celsius

Clear Roads Data Dictionary

Field	Description
AirTemp_C	air temperature Celsius
Altitude	?
DSC111 Status	NA
DSP101 Status	NA
DateTime	mm/dd/yy
Dewpt	dew point temperature Celsius
Friction	0.0–1.0
HMP155 Status	NA
Ice [mm]	ice thickness mm
Interface Unit Status	NA
Latitude	degrees
Longitude	degrees west
RH	relative humidity %
RawRoadState	?
RoadStateRemapped	?
Satellites	?
Sensor	sensor name like Vaisala
Snow [mm],	snow thickness mm
State	?
Surface_C	surface temperature Celsius
Test	test number
Water [mm]	water thickness mm

Maine Data Dictionary

The project team combined Maine friction data and RWIS data from the Etna site into a single file for ease of processing.

Field Name	Description
Date	yyyy-mm-dd hh:mm:ss
boschung_road_condition	code value: 0, 2, 3, 4, 5, 7, 9, 13
lufft_road_condition	code value: integers 0 through10
lufft_road_grip	(friction value between 0.0 and 1.0) * 100.
lufft_water_film_in	surface water thickness in inches
vaisala_road_condition_1	numeric code
vaisala_road_condition_2	numeric code
vaisala_road_grip_1	(friction value between 0.0 and 1.0) * 100.
vaisala_road_grip_2	(friction value between 0.0 and 1.0) * 100.
boschung_road_grip	(friction value between 0.0 and 1.0) * 100.
vaisala_water_film_1_in	inches
boschung_road_grip_scaled	(friction value between 0.0 and 1.0) * 100.
Relative Humidity	%
Wind Gust Direction	degrees true north
Precip Situation	numeric code
Air Temperature	degF
Atmospheric Pressure	kPa
Subsurface Temperature	degF
Visibility	mi
Wind Average Speed	mph
Wind Gust Speed	mph
Dew Point	degF

Sweden Data Dictionaries

Two separate CSV files were used to store the friction and RWIS data from Sweden.

Sweden Friction Data Dictionary

Field Name	Description
Tid [ms]	time value in milliseconds
fric_V	longitudinal friction between 0 and 1.0
fric_H	lateral friction between 0 and 1.0
v_MW_V [km/t]	likely km/h
v_MW_H [km/t]	likely km/h
v_TW [km/t]	likely km/h
Slip_V [%]	longitudinal slip percent
Slip_H [%]	lateral slip percent
TotalDist [m]	distance in meters
Lat [°]	latitude in degrees
Long [°]	longitude in degrees
Veg []	not used
Parsell []	not used
MeterVal [m]	not used
Usikker []	not used
Merke []	not used
Grenseverdi []	not used
OmT [°C]	not used
OvT [°C]	not used
Date	yyyy-mm-dd hh:mm:ss.SSS

Sweden RWIS Data Dictionary

Field	Description
station	station identifier
Date	yyyy-mm-dd hh:mm:ss.SSS
SurfT	Celsius
FarrT	not used
AirT	Celsius
humidity	%
dewpt	Celsius
precipType	numeric code
precipAmnt	likely cm
windMax	likely m/s
windSpeed	likely m/s
windDir	(N = north, O = east, S = south, V = west). values like NO, O, V, SV, NV, S
windMean30min	likely m/s
Varsel	not used
status	not used
error	not used

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