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Real-time computing of pavement conditions in cold regions: A large-scale application with road weather information system

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ABSTRACT

Pavement conditions including pavement temperatures, freezing and thawing depths, and the consequent mechanical performance are the key to the performance and longevity of the pavement. For example, thaw-weakening is a major cause of pavement damage in seasonally-frozen areas covering half of the U.S., leading to huge financial costs for taxpayers. In recent years, the damage has been lessened due to improved practices with Spring Load Restriction (SLR) policies. However, prevalent SLR date prediction methods/tools are still primitive from the perspective of information technology. Such methods/tools are obtained and/or implemented manually with small amounts of data, labor-intensive observations, and/or subjective experience. The paper reports what has been learned from a recent project supported by the Michigan Department of Transporation for the development of a web-based pavement condition prediction and SLR decision support tool: a web-based app called MDOTSLR. MDOTSLR enables access to much more data with little latency and automates data acquisition, processing, and decision making. In this paper, the data innovations and new models that support the functions of the tool will be first introduced. Followed will be the major functions (or services) of the app including software engineering details. Compared with traditional tools without web delivery, this web-based tool automates the acquisition and processing of weather data, GIS data, road weather information system data, and field measurements in real time and thus enables more accurate and convenient SLR predictions. The tool can be easily extended or modified for other road agencies for immediate financial savings in road maintenance and less disturbance to local transportation and economy.

1. Introduction

More than 4,071,000 miles (6,552,000 km) of roads form the arteries through which the U.S. economy pulses (Rosenberg, 2004; USDOT, 2016). Such a transportation infrastructure system links the essential components of modern society and directly impacts everyday life: producers to markets, workers to jobs, students to schools, and sick to hospitals. The highways account for a major portion (6%) of public spending (Shirley, 2017; Swenson, 1983). In 2014, federal, state, and local governments spent $165 billion on public highways and about 45% of the spending went toward operational costs such as winter road maintenance (Geddes and Madison, 2020; Reed et al., 2018; Shirley, 2017; Swenson, 1983), which heavily relied on the understanding of pavement conditions such as surface conditions (e.g., temperature, ice), freeze-thaw status (e.g., freezing and thawing depths), and consequent engineering behavior and maintenance policies (e.g., stiffness, drainage, spring load restrictions).

The practices adopted by most transportation agencies, e.g., county road commissions and state departments of transportation in the U.S., still mostly rely on simple calculations with models obtained with very general models (not site-specific) and limited data. For example, Spring Load Restriction (SLR) is a major winter maintenance practice adopted by road agencies. However, most county road engineers in the U.S. and many in other countries still use the FHWA model, which was developed in 1985 based on semi-synthetic data in the state of Washington. Besides, freezing and thawing depths – another pavement status indicator – only have very simple statistical/empirical models for their predictions. Such models were usually developed with limited data from specific

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sites and thus have difficulties in considering the variability in material properties. As a result, a model of this kind may exhibit very poor performance when being applied to a different location.

This condition of low data utilization conflicts with the fact that Governments have sensed the needs for data since the 1990s and have invested more and more in data acquisitions (Shahin et al., 2001; Shahin et al., 2008). The data in most engineering disciplines including infrastructure-related areas have been explosively increasing due to the advances in satellites, chips, audio and video devices, and low-cost sensors (Kitchin, 2014; Ma et al., 2015; Zaslavsky et al., 2013). For highway infrastructure, state Department of Transportations (DOTs) in the U.S. invested billions of dollars in data acquisition systems for weather, road information, and traffic (Maze et al., 2008). For example, Michigan DOT (or MDOT) established over 100 Road Weather Information System (RWIS) sites to collect data for road weather, pavement conditions, subsurface temperatures, and traffic images – such real-time data can easily reach hundreds of gigabytes. Despite the awareness of data's significance and increasing investments in data collection facilities/equipment, the utilization of such data for aiding in road operation and maintenance decision-making still far lags behind.

This study is performed to advance the road winter maintenance especially the spring load restriction practice in three different aspects. First, the acquisition, processing, and integration of the data in the context of model and software development are investigated. Second, new engineering models for assessing the status of the pavements including the forecast of pavements surface temperatures, calculation of measured freezing and thawing depths, and prediction of the freezing and thawing depths, and the start and end dates of the SLR period are presented. Third, details in a newly proposed web-based app including the enabling information technology are gathered. To introduce these new findings, the remainder of the paper is arranged as follows. First, background knowledge including the objectives of the project, methodology, and key concepts will be presented to offer a big picture and basics for understanding this large-scale application. Then, the data and models employed for the web-based tool will be introduced sequentially. This is followed by an explanation of the organization and functionality of the web-based road condition assessment and SLR decision support tool. Finally, conclusions are drawn as a summary of the whole paper.

2. Overview of this study

2.1. Objectives

The paper reports a lesson learned from a large-scale application for real-time computing of pavement conditions in cold regions via a project conducted with the Michigan Department of Transportation (MDOT) in the U.S. The objective of this project is to establish a web-based tool for predicting the status of pavements and supporting the decision-making for setting and removing SLR.

2.2. Methodology

As shown in Fig. 1, the major research and the corresponding research products consist of three components: data, models, and app. The app, mdotslr.org, is a major research product. To produce a functional and useful tool, the app needs to be running on models that guide the predictions of pavement conditions including SLR dates in a convenient and accurate way. As the SLR dates rely on the Freezing Depth (FD) and Thawing Depth (TD), models for the accurate predictions of FD and TD, forecast of pavement surface temperatures, and calculations of FD and TD based on subsurface temperatures are also needed. Due to this reason, models for all these predictions, forecasts, and calculations are sought to support the establishment and operation of the app. Data are needed for both the development and deployment of the models. Hence, data was another significant component of the research. By analogy, the app is the body, whereby an intelligent creature interacts with the environment and realizes its major functions; models are the brain, which determines how the body (app) interact with the environment; data are the food, which helps build up the brain (models). The app can become more and more robust as models are improved with more and more data, and the data can be obtained, processed, and managed by the app, leading to a closed-loop and a healthy research and development ecosystem. Such a concept has been rarely discussed in the existing cold regions and road infrastructure research but urgently needed in the advent of the data era.

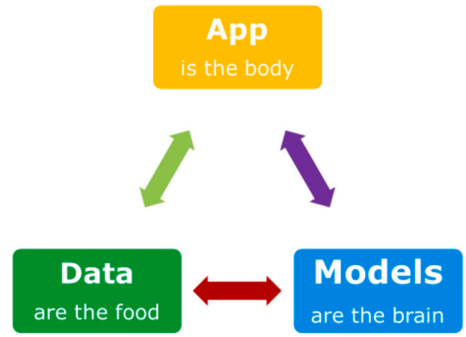

Fig. 1. Major components of the research and deliverables.

The target app, MDOTSLR (www.mdotslr.org) was developed based on the existing SLR practices in other states, a scientific understanding of the physical processes, existing models for freezing/thawing depth predictions, and available criteria and protocols for placing and lifting SLR. As shown in Fig. 2, the research consists of three layers, i.e., data, models, and app, which corresponds to the three major types of research products. In the data layer, four types of data, i.e., weather, RWIS, GIS, and field measurements (frost tube), were explored, based on which a correlation analysis was conducted to select data to be used in the next layer of models. In the model layer, two types of models were developed: a widely accepted SLR model, i.e., FHWA, and a newly proposed model, i.e., MDOT2019. The FHWA model comprises Freezing Index and Thawing Index (FI&TI) calculations and SLR date predictions, which are the major components of the FHWA model, and a new component for FD&TD predictions, which are proposed in this study to compare with the MDOT2019 model. The MDOT2019 model consists of five brand-new components, i.e., surface temperature prediction, FI&TI calculation, FD&TD calculations, FD&TD predictions, and SLR predictions. In the app layer, the two types of models were deployed based on data at selected sites for predictions covering the whole geographic region of Michigan. Five services were enabled: the forecast of pavement conditions including temperatures, FI/TI, SLR dates, mapping of freezing and thaw status including FI, TI, and a newly proposed concept to quantifying SLR status, i.e., degree of SLR, freezing statistics showing the distribution of the maximum FD contour in any given period, and a data portal for organizing and accessing data.

2.3. FHWA model vs. MDOT2019 model

The meaning of "model" is more complicated than usual in this study due to the scale of the application and the involvement of data and web-based apps. The following subsections are intended to offer more background information to clarify several concepts relevant to models to better introduce the research products.

This study covers the pavement conditions predictions in cold regions with a focus on the SLR application. For SLR models, the majority of the existing practices have been conducted based on the FHWA model or its variations. One leading effort is the SLR prediction model adopted by the Minnesota DOT in the U.S., which is possibly the only SLR application supported by a web-based app before this study (Asefzadeh et al., 2016). The SLR model was modified from the FHWA model with improved FI&TI predictions to allow for both solar irradiation and micro

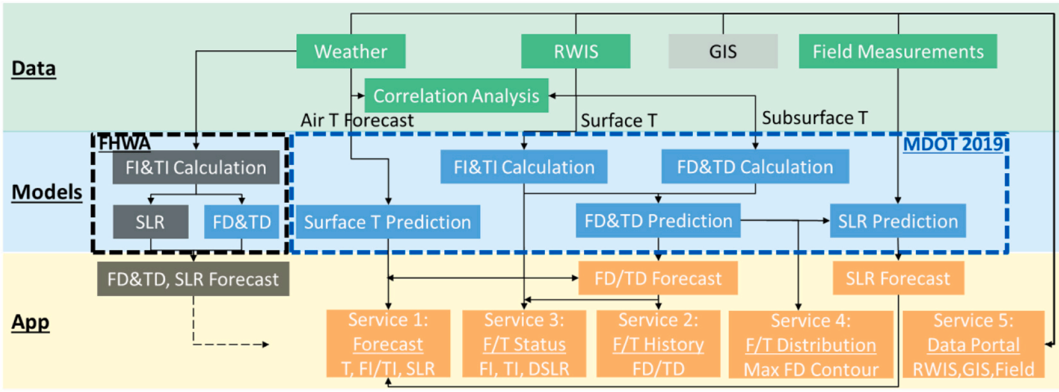

Fig. 2. Architecture and workflow of the research.

freeze-thaw cycles and with field measurements. The SLR practice adopted by the Manitoba Institute of Transportation in Canada was also modified from the FHWA model, with modified criteria for placing and removing SLR to better consider the local weather and geological conditions (Bradley et al. 2012). The model adopted by the South Dakota DOT improved the FHWA model by considering the influence of precipitation, i.e., total precipitation of the fall preceding the freeze-thaw season. Another variation of the FHWA model proposed by USDA/FS-NHDOT featured an improved procedure for calculating the reference temperature in the calculation of the FI and TI. In summary, most of such variations attempted to improve the FHWA model by better considering factors that can affect the SLR predictions, such as precipitation and solar irradiation, and such considerations were usually made by modifying the reference temperature for calculating the FI and TI and the criteria for placing and removing SLR.

The newly proposed MDOT2019 model adopted a philosophy distinct from that of the FHWA model and its variations. In the FHWA model and its variations, the SLR dates are predicted based on the air temperature only, and such predictions are made via the FI and TI calculated based on the air temperature. Thus, the procedure can be simplified as

Air Temperature➔FI/TI➔SLR Dates.

By contrast, in the MDOT2019 model, the procedure is more complicated. One major difference is that two extra elements, i.e., the surface temperature and FD/TD, were added to the procedure:

Air Temperature➔Surface Temperature➔FI/TI – ➔FD/TD➔SLR Dates.

One major reason for adding the two elements is that these elements can serve as bridges between the original three elements in the FHWA model. Instead of jumping from the air temperature to the SLR date prediction directly, the prediction of SLR dates with transitions via the surface temperature and FD/TD predictions could be much smoother, attributed to strong correlations between the new elements and its neighboring elements in the above procedure of the MDOT2019 model. The addition of such elements also allowed the MDOT2019 model to better assess the status of the pavements because the pavement surface temperature and FD/TD depths are two key factors in assessing the health status of pavement in cold regions. The surface temperature is needed for telling the road conditions for traffic and mobility while the FD and TD are a key in determining the structural integrity of the pavement under frost action. The MDOT2019 model contains (sub-)models for all the five elements.

2.4. Development of model vs. deployment of model

The development and deployment (use) of models are another point that needs to be explained to avoid confusion in understanding the work in this study. In traditional engineering research, the development and use of models are usually lumped together. In a simple way, the development of a model can be the acquisition of a new equation(s) via statistical or physics-based analysis, while the use of the model is to apply the model for analysis and application with new data. However, the use of models can be much more complicated as the development of a web-based app and the use of massive data are involved.

In this study, the development and use of models, especially MDOT2019, are two separate processes implemented by different parties at different locations with different sources of data. As shown in Fig. 3, the model was developed with surface and subsurface temperatures from the RWIS data at RWIS sites where adequate data is available. The data was used to construct (sub-)models for elements such as pavement surface temperatures. The constants in these equations reflect the local conditions such as geographical location, local weather, and material properties. The developments of such (sub-)models were conducted manually via statistical analysis. The use of the models was achieved by deploying such models in the web-based app. For example, the development and deployment phases can use different data sources. In the deployment phase, the surface temperatures, as the input, come from predictions made with the air temperature forecasts instead of RWIS measurements in the development phase, because RWIS can only provide measurements but no forecasts.

For deployment, it is also worthwhile to mention that interpolations were employed so that predictions at any given location can be made with models that were obtained at a limited number of RWIS sites. For the purpose, the concept of virtual RWIS (vRWIS), where input information such as weather and pavement conditions was obtained for calculations/predictions, was explored. Multiple techniques exist for extrapolating weather conditions from known locations to “virtual” sites: interpolation, climatological extrapolation, two-dimensional field analyses, and three-dimensional field analyses. This study adopts the interpolation technique. As shown in Fig. 4, the data at any given point can be obtained by interpolating the data at the three nearest valid RWIS sites with sufficient data. Such an interpolation was conducted based on the geographic locations of the sites in this study. For the purpose, the latitudes and longitudes of the sites are used to calculate the distance between any two sites. It is common to witness missing data caused by the misfunctioning or absence of sensors due to the heterogeneous

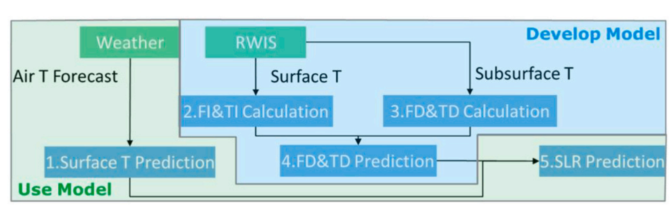

Fig. 3. Relationship between the development of deployment (use) of models.

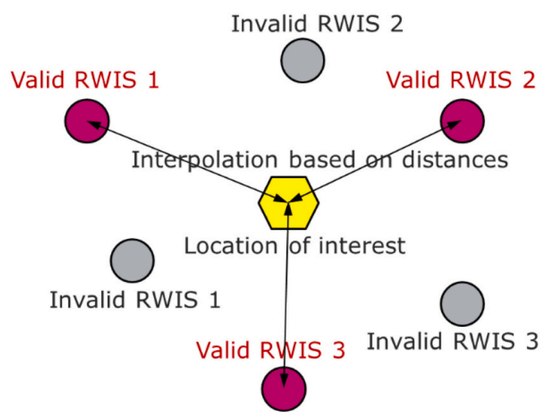

Fig. 4. Pavement temperature calculation with measurements from nearby RWIS sites.

sensor setup across the RWIS stations.

In addition to vRWIS, another type of mapping is introduced to enable site-specific predictions for not only any RWIS site, but also any county and zip code. In the app, the data was indexed by the RWIS site, county, and zip code. That is, the data for any location associated with any type of index can be converted to another index. The conversion can be done with pre-defined mappings. In the app, these mappings were achieved via tables. For example, the predictions for a given county can be obtained by averaging the predictions for the zip codes belonging to the county.

3. Data

This study features the utilization of data. Four types of data including weather, RWIS, GIS, and field measurements were tested or/ and adopted in the development and deployment stages of the project. As of now, weather and RWIS data has been implemented with data going back to 2013 while GIS soil data has been fully implemented. The weather and GIS data were collected and indexed for each zip code, RWIS data was acquired from each RWIS station, while field measurements, i.e., frost tube data, was fetched from each frost tube site. Shown in Fig. 5 are the locations of RWIS sites (blue) and sites with field measurements (green).

3.1. Weather data

Accurate air temperature information, both existing weather data and forecasts, can be obtained from various websites for free, though historical weather data can be hard to find at best and unreliable at worst. The initial weather database in MDOTSLR was created with a weather API from APIXU (https://www.apixu.com/) for data back to 2016 considering the low cost, good coverage, and excellent data integrity (no missing dates or regions). Other data APIs including those from NOAA were also tested at the beginning of the project. Most of these APIs exhibited issues in the above three aspects. For data before 2016, data were imported via the utilization of https://mesowest.org/api/, which was available for free and had a longer date range available but lacks complete coverage.

For forecast data, the Wunderground weather API at https://www.wunderground.com/weather/api/ is used considering its free ten-day forecasts. Forecasts extending over a longer period such as thirty days are also possible with APIs such as the one from http://www.accuweather.com/. However, long-range weather forecasts beyond one week a very questionable due to significantly reduced accuracy. In the latest version of the app, an API provided by Iteris (https://www.iteris.com/), who is the contractor for the MDOT MDSS system, was used to replace the APIXU weather data acquisition.

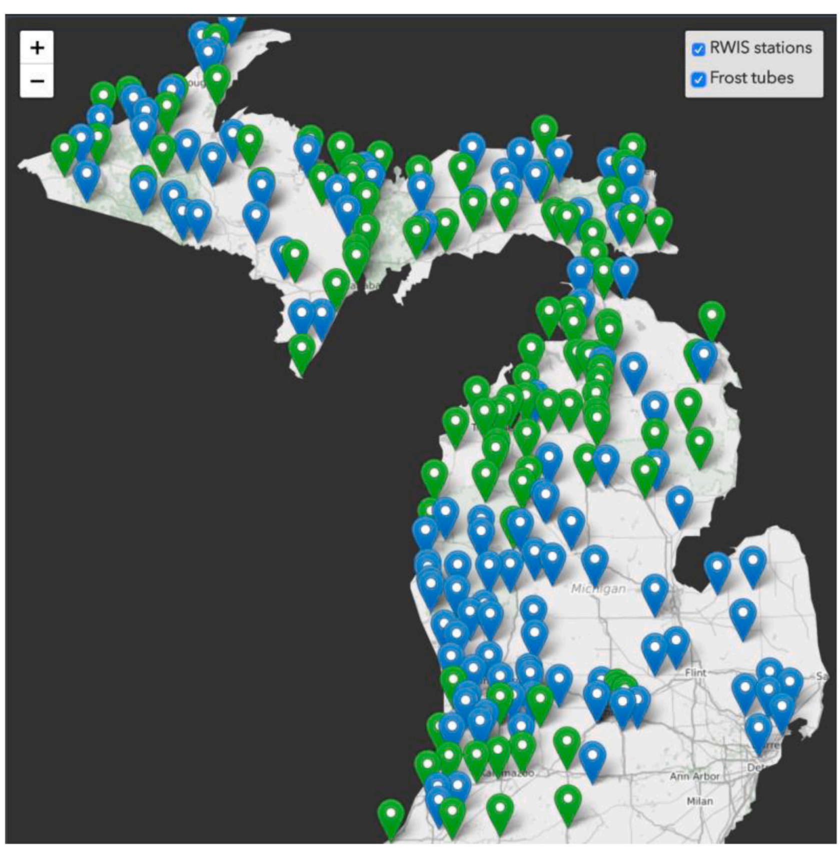

Fig. 5. RWIS stations and frost tube measurement sites in Michigan.

3.2. Acquisition of RWIS data

In early versions of the app, RWIS data were acquired via an API provided by the Vaisala corporation, the RWIS contractor of MDOT from December 2016 to June 2019. The data provided by Vaisala's API was expressed in fifteen-minute intervals. This presents two problems as 1) we were interested in the entire day in aggregate, not just in 15-min snapshots, and 2) we wanted a long date range of data, not just three days. To solve these problems, a script was developed and run at 1 a.m. every morning to capture and save the data from the API for the previous day into a MongoDB database. The script looks at all fifteen-minute periods over the past twenty-four hours, organizes all values into arrays that are representative of each data field and each sensor. These arrays then have their values averaged and that average is stored in the database as the value for that day. In the latest version of the app, PostgreSQL was used to replace MongoDB for managing the local database to facilitate data management considering the relational nature of the data.

RWIS data from 104 MDOT RWIS sites provides typical weather, road, and subsurface information. More sites will be built and added. The other source of RWIS data was historical data provided by Vaisala as csv and rpt files. The csv data has been fully imported to the local database in a fashion similar to that for data imported using the API. The rpt files unfortunately were proprietary and required some extra time to turn into csv's that could be imported.

3.3. Integration of GIS and soil data

GIS soil data is available for free from the USDA's soil mart database (https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm). Typical material properties for the top soil layers, i.e., six feet, can be obtained via the WebSoilSurvey API. All needed GIS data has been imported from the GIS site using an API. However, it is worthwhile to mention that the soil data was included to assist in the model development but is not being used in the operation of the models in the app. This is because most of the state highways managed by MDOT were built with excavation to depths more than six feet. That means, the base and subgrade material can be different from that in the GIS for the same location. Therefore, the GIS soil information, especially water content of the soil, the clay, silt and sand content of the soil, and the depth to the water table, was just used for reference when developing and assessing the models. Despite this fact, such GIS information may still be very useful for low volume and unpaved roads, which are laid over the natural soils. The GIS data can be utilized for more accurate site-specific models.

3.4. Data selection via correlation analysis

As introduced in the previous subsections, four categories of data were/are being obtained. In theory, any data can be employed for the predictions of FD/TD and SLR dates as long as the data is related. For example, in an initial assessment, the following data types were considered to be related to the intended predictions: 1. air temperature (freezing/thawing indices), 2. wind speed, 3. solar irradiation, 4. degree of saturation, 5. saturated thermal diffusivity 6. pavement type (cement and concrete) and thickness, and 7. thickness of the base (if any). However, it was found that it would be unrealistic to use all the information due to several reasons. First, some parameters such as pavement and soil information cannot be easily or/and accurately determined. Second, the establishment and use of a multivariate model with a lot of input variables are difficult and computationally expensive. Third, not all the parameters are equivalently relevant; as a result, the inclusion of some parameters in the model not only could be unworthy but also causes unexpected issues in both the development and the deployment of the models.

In the previous studies on freezing and thawing depth predictions and SLR date predictions, engineers usually assumed some parameters are significant, either based on observations or intuitions, and then constructed prediction models based on the assumption. This study attempted at establishing models using a more rational approach. That is, correlation analysis was conducted first to quantify the correlation between different types of data and predictions of interest such as FD and TD. Based on the results of the correlation analysis, the most relevant data types were selected as the input for the prediction models. The most common formula for correlation is Pearson's correlation formula.

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where X and Y are the two variables whose correlation is computed, cov (X, Y) is the covariance of X and Y, σ_X is the standard deviation of X, σ_Y is the standard deviation of Y. The covariance is calculated using the following equation:

$$cov(X,Y) = \mathrm{E}[(X-\mu_X)(Y-\mu_Y)] \tag{2}$$

where E is the expectation, μ_X is the mean of X, and μ_Y is the mean of Y.

Shown in Fig. 6 are the correlation analysis results for selected data types at a typical RWIS site. As can be seen, the correlation coefficient between any variable and itself is one. The correlation coefficients of interest in this study are those between FD&TD and other data types. It is not difficult to conclude that the pavement temperature has the highest correlation coefficient with both FD and TD in most cases, followed by the air temperature, FI, and TI. Due to this fact, the prediction models for FD&TD and SLR dates were built with freezing and thawing indices calculated with the pavement surface temperature. It is noted that precipitation, which was considered as a significant factor in some SLR models, exhibits a low correlation with the FD or TD in the RWIS data of this study. As a result, such data types, which may lead to insignificant improvements in the prediction accuracy but could increase the difficulty of statistical analysis significantly, were not adopted.

4. Model

4.1. Pavement surface temperature prediction

The surface temperature of pavement is a key factor in determining the driving conditions, i.e., roughness, cracks, snow and ice coverage, and salt concentration, and consequently the traffic condition. The correlation analysis introduced in the previous section also indicated that it has the strongest correlation with FD and TD. Therefore, the pavement surface temperature was selected for FD/TD and SLR predictions. This surface temperature is determined by the air temperature as well as other factors such as solar irradiation, precipitation, material properties, and geographical locations. While its strong correlation with the air temperature can be easily observed, models that can satisfactorily predict this parameter have not been reported. After extensive preliminary statistical analysis, it was found that predictions of the changes instead of the absolute value of the surface temperature exhibited much more promising results. The following relationship was found to be the one that can best predict the surface temperature changes:

$$\Delta\overline{T} = \mathrm{a} + \mathrm{b}\cdot\Delta T - \mathrm{c}\cdot\left(\overline{T} - T\right) \tag{3}$$

where $\Delta\overline{T}$ is the change in the pavement surface temperature over a given time Δt, ΔT is the change in the air temperature over that time, $\overline{T} - T$ is the difference between the present surface temperature and air temperature, and a, b, c are the fitting constants determined by the site-specific conditions. Given Δt=1 day, Eq. (3) can be reformulated to predict the surface temperature on Day $i + 1$ based on the known information on Day i:

$$\overline{T}_{i+1} = \overline{T}_i + \mathrm{a} + \mathrm{b}\cdot(T_{i+1} - T_i) - \mathrm{c}\cdot\left(\overline{T}_i - T_i\right) \tag{4}$$

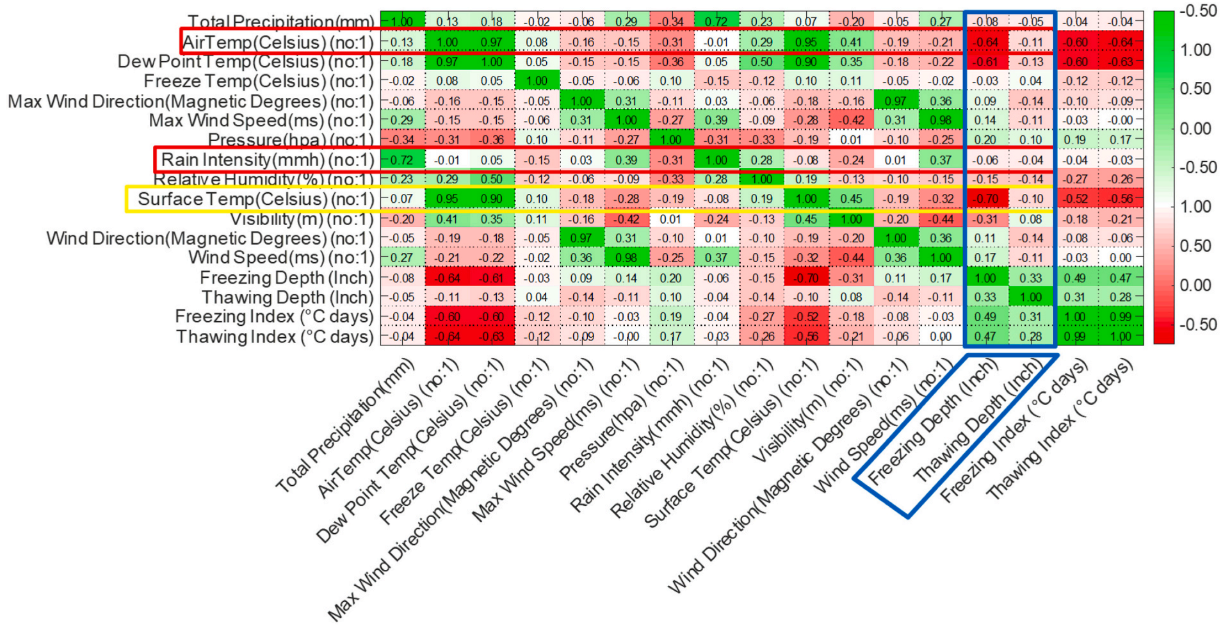

Fig. 6. Correlation analysis of different types of data of pavement.

Data from multiple RWIS stations were adopted to test the performance of the above equations. Fig. 7 demonstrates the performance of the above equations in fitting the measured data from two RWIS sites in Michigan, i.e., Calumet (a) and South Cadillac (b) in upper and lower Michigan, respectively. Most of the measured data illustrated by red dots are distributed in the vicinity of the blue plane representing the proposed function in Eq. (3).

The above results were obtained with a time increment of Δt=1 day. The agreement between predictions and measurements confirmed the effectiveness of the proposed function in formulating the relationship between the pavement surface temperature and air temperature. The above analyses yielded the following models for predicting the surface temperature when Δt=1 day:

$$\text{Calumet}: \Delta\overline{T} = 1.13663 + 0.69464 \cdot \Delta T - 0.23222 \cdot \left(\overline{T} - T\right) \tag{5}$$

$$\text{South Cadillac}: \Delta\overline{T} = 1.16592 + 0.68907 \cdot \Delta T - 0.24251 \cdot \left(\overline{T} - T\right) \tag{6}$$

The above equations are adequate for predicting the surface temperature on the following day based on the surface temperature and air temperature on the current day and the forecasted air temperature for the following day. However, predictions over a longer period are desired for long-range predictions and decision-making. For the purpose, the following iterative procedure was proposed.

1. The current day is Day (i), for which T_i and $\overline{T}$are known. T_{i+1} is available from the weather forecast. For example, with a 7-day air temperature forecast, T_{i+1} to T_{i+7} are known.
2. Calculate the change in the surface temperature from Day (i) to Day (i+1) using a model such as the one obtained for the South Cadillac site.

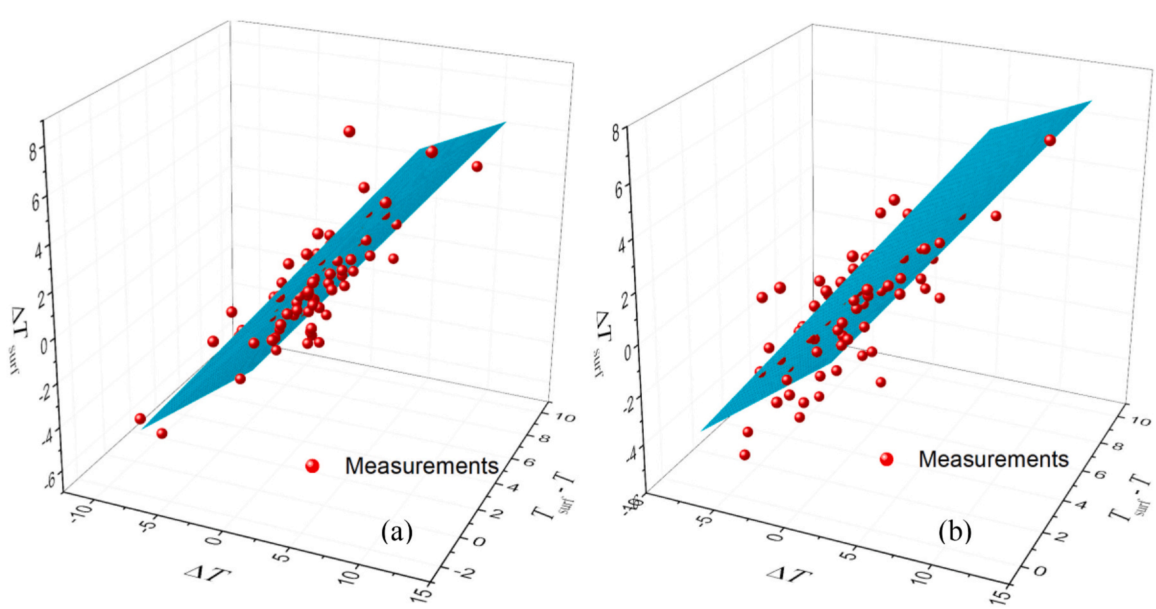

Fig. 7. Regression analysis of the proposed prediction model for pavement surface temperatures.

3. Calculate the surface temperature on Day (i+1) using Eq. 4.
4. Move to the next day and repeat the above steps until the intended forecast, e.g., 7 days, is finished.

The above procedure was adopted to predict the surface temperatures at various sites. It is surprising to find that the Calumet model and South Cadillac model gave out very similar predictions at most MDOT RWIS sites for data between January 15 and May 15 in different years, which covers most of the freeze-thaw periods in Michigan. Fig. 8 shows the forecast made with the South Cadillac model at the South Cadillac and Seney sites. The one-month forecast is much longer than the seven-day forecast needed for the app, but the Cadillac model still gives very good predictions at these two sites. Therefore, the south Cadillac model formulated by Eq. (6) was adopted as the state-wide model for pavement surface temperature predictions.

4.2. Freezing and thawing indices calculation

The concepts of FI and TI have been widely used in studies on the prediction of pavement conditions under frost action such as FD, TD, and SLR dates. The idea behind the FI and TI is to count the total amounts of freezing and thawing, respectively. As shown in Fig. 9, the temperature, e.g., usually the daily average air temperature, is split into two parts by a reference temperature such as the freezing point of bulk water. The area above the reference temperature reflects the amount of thawing cumulated over time while that below of the reference reflects the total amount of freezing.

In the FHWA model, *FI* and *TI* are calculated cumulatively over time using the following two equations.

$$FI = \sum_{i=1}^{M} (0 - T_i) \tag{7}$$

$$TI = \sum_{j=1}^{N} (T_j - T_{\text{ref}}) \tag{8}$$

$$T_{\text{ref}} = 29\ \text{F}\ (-1.67^{\circ}\text{C}) \tag{9}$$

where i and j are day numbers of the freezing day and thawing day, respectively, since the beginnings of the freezing freeze-thaw season, and T_i and T_j are the average temperatures of the ith freezing day and jth thawing day, respectively. Each day in a freeze-thaw cycle is either a freezing day or a thawing day, depending on which one of the above two equations is activated to calculate the corresponding temperature index. T_{ref} was originally proposed to account for the difference between the temperature of the pavement and that of the air, but later improved to consider other factors in different variations of the FHWA model.

The MDOT2019 model inherits the above equations for calculating the FI and TI. However, as mentioned, the daily average pavement surface temperature instead of the daily average air temperature was used, considering that the surface temperature has a higher correlation with the freezing status of the pavement. As a result, the obtained FI and TI values give out better quantifications of the total amounts of freezing and thawing in the pavement, respectively. Fig. 10 shows a typical comparison between FI values calculated with the FHWA and MDOT2019 models. As can be seen, the two models give out different FI values, both in terms of magnitudes and spatial distributions. FI values obtained in MDOT2019 are usually lower than those in the FHWA model, while the TI in MDOT2019 is greater than that in the FHWA model. Since the pavement surface temperature is much more reliable in reflecting the freeze-thaw status of pavement, the above differences especially those in the spatial distribution indicate that use of the FI and TI in the FHWA model may lead to FD/TD predictions that are much different from the actual values.

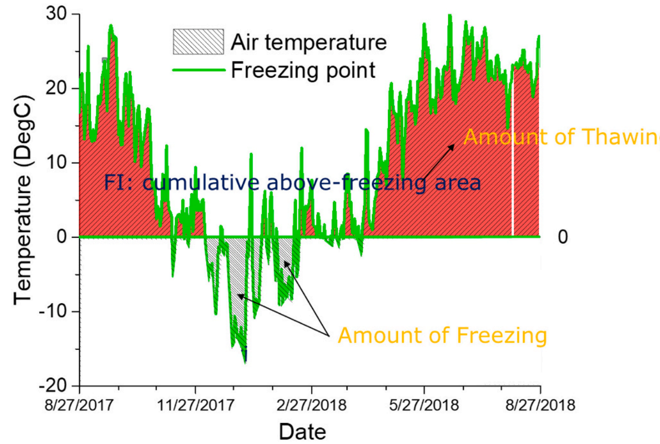

Fig. 9. Schematic of freezing and thawing indices.

4.3. Calculation of freezing and thawing depths

FD and TD are the two most significant types of data that are needed for the development and validation of FD/TD prediction models and SLR prediction models. Such data can be directly measured using frost tubes or other similar devices. However, frost tube measurements are not available at MDOT RWIS sites, which is possibly a very common situation in most RWIS systems. Frost tube measurements are only available for some sites at locations different from the RWIS sites and readings are only available on a few days when manual measurements are taken. The limited frost tube data is excluded in the current app and only used for validations of SLR date predictions and decision making. Considering the situation, an effort was made to calculate FD and TD based on subsurface temperatures. The calculated FD and TD can also be viewed as "measured" results as long as the calculation procedure presented in this subsection is credible.

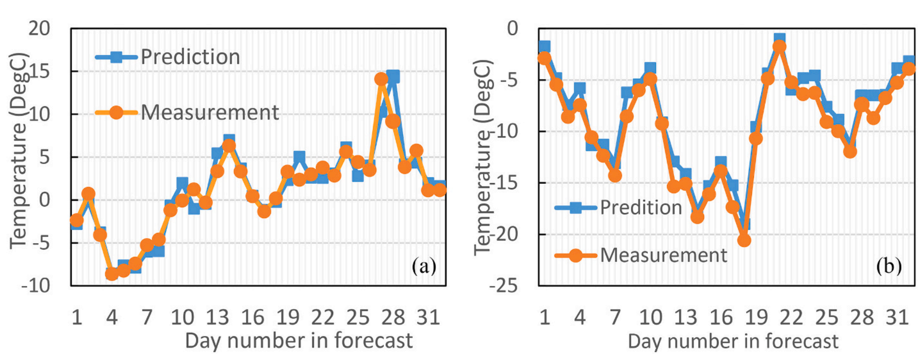

Fig. 8. Forecast of surface temperatures using the South Cadillac model at a) the Cadillac site for 3/1/2019–4/1/2019 and at b) the Seney site for data 3/1/2019–4/1/2019.

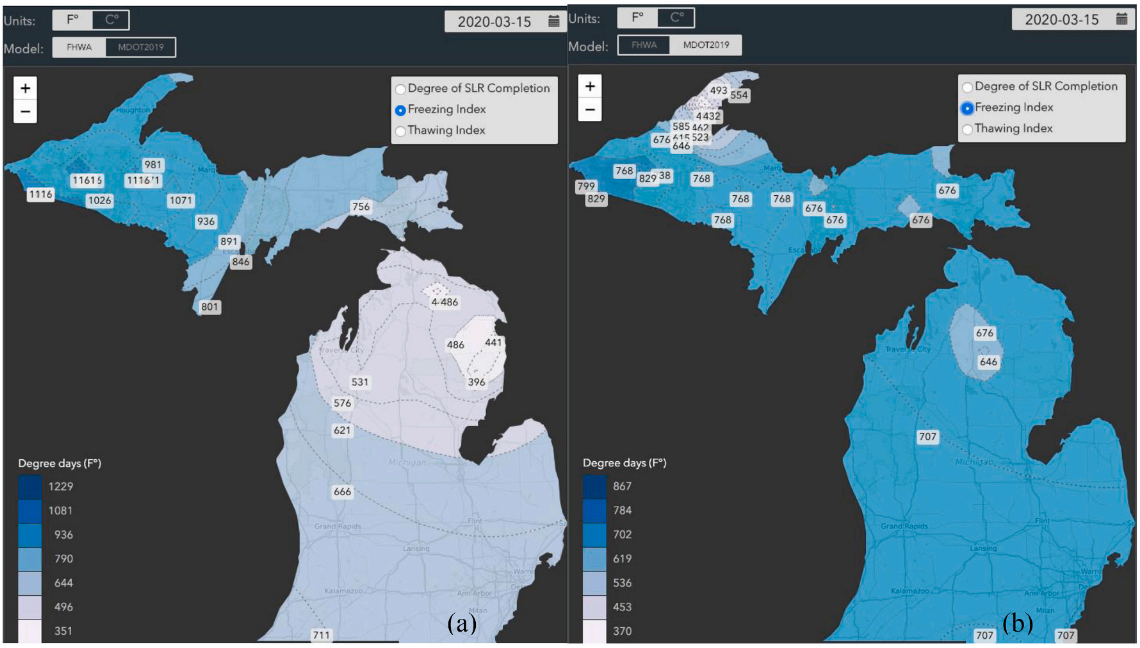

Fig. 10. Typical results of freezing index in 1) FHWA model and MDOT2019 model in MDOTSLR.

Fig. 11 is used to illustrate the way to calculate the FD and TD from subsurface temperatures. As illustrated, the rightmost curve represents a typical temperature distribution when the temperature at all the depths within the base and subgrade layers are above zero, e.g., a constant positive value. In early winter, the temperature decrease starts from the top, leading to the leftmost curve. The point of intersection between this curve and the freezing point curve corresponds to the freezing front. The depth of this point is FD. In spring, warm air temperatures trigger thawing from the top, which will bend the temperature curve into something like the middle curve. This curve intersects with the freezing point curve at two points. While the lower intersection point corresponds to FD, the upper intersection point marks TD. During calculation, these two curves can be differentiated by the change in the sign when passing the intersection point from top to bottom: a switch from the positive sign to the negative indicates TD whereas one from the negative to positive indicates FD. More than two points of intersection were observed in regions with several micro freeze-thaw cycles.

The FD and TD values calculated with measured subsurface temperatures at a typical site are presented in Fig. 12. As can be seen, FD first appeared in the middle of November 2017 and decreased significantly at the beginning of March 2018. During the freezing period, FD decreases somewhat, especially at the beginning of the freezing period. This is because there were several warm days to thaw the pavement base, leading to a decrease in FD. There a few TD points before March 2018 such as Point A.

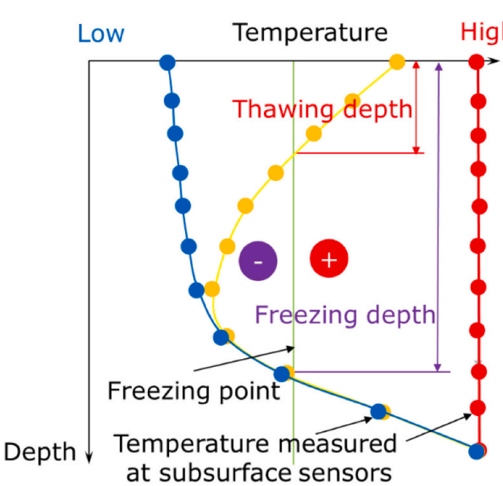

Fig. 11. Calculation of freezing and thawing depths based on subsurface temperature measurements.

4.4. Freezing and thawing depth predictions

The predictions of FD and TD are desired for assessing the status of pavement in cold regions for many relevant applications including SLR practices. The existing studies can be categorized into statistical/empirical models and physics-based models. Some statistical/empirical models were proposed based on physics, thus can be viewed as semi-empirical models from a strict point of view. Compared with statistical/empirical models, physics-based models can offer better predictions when accurate material properties and boundary conditions are available. But, unfortunately, easy access to such data is usually not the case. Besides, it requires much more effort to establish and implement such physics-based models. Due to this reason, statistical/empirical models are more widely used in practice.

However, evaluations of the existing statistical/empirical models in this study indicated that the existing models cannot satisfactorily describe the variation of FD with temperature or temperature indices. As shown in Fig. 13, the variation of FD with FI, which has been widely adopted for the prediction of FD, does not obey any basic mathematical functions as assumed by most of such models, and more significantly, the curve is not even smooth. The reason was revealed in this study when viewing the data from a higher-dimensional viewpoint. As illustrated in Fig. 13, when visualizing the data from a 3D viewpoint, the FD-FI curve seen from a 2D viewpoint is just the projection of the 3D curve on the FD-FI plane. at the beginning of each freeze-thaw cycle, the FD would increase from the origin if FI increases. On warm days within the freeze-thaw cycle, the TI increases while the FI remains the same, the curve then goes downhill and the FD decreases, which exhibits as a turning point in the 2D FD-FI curve such as Points 2 and 4. Based on this observation, it is assumed that each site has a unique surface in the FD-TI-FI space for FD predictions and another unique surface in the TD-TI-FI space for TD predictions. The shape of the surface is determined by the

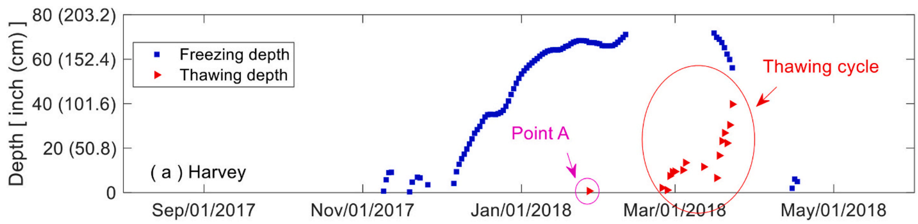

Fig. 12. Calculations of measured FDs and TDs for a typical RWIS site.

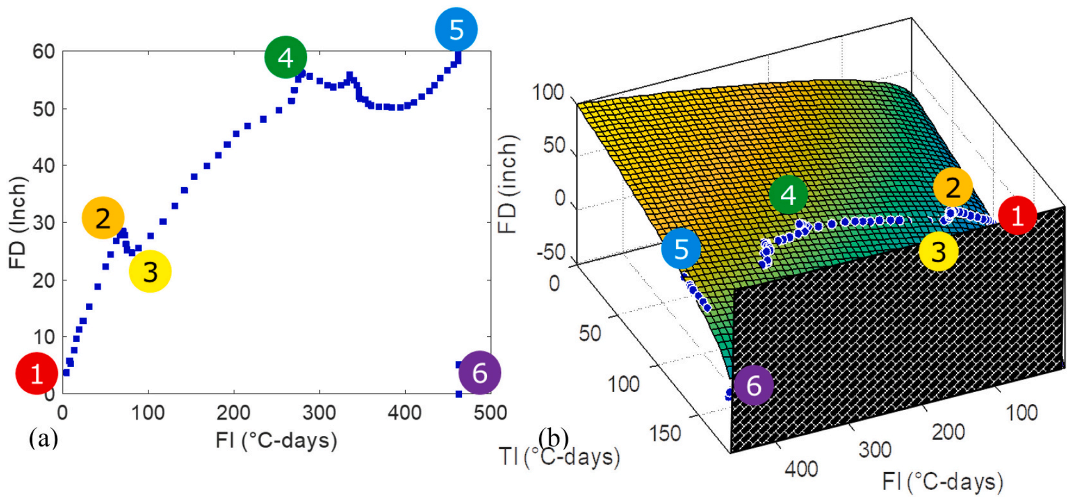

Fig. 13. From a) 2D models to b) 3D models.

field conditions of the site. Therefore, the goal of the model development for FD and TD predictions is to search for the mathematical function that can best formulate the surface for this site, which is called the FD and TD prediction models for this site.

Statistical analysis of the measured data at many RWIS sites indicated the following mathematical equations can best describe the surface in the FD-FI-TI space:

$$FD = a\sqrt{FI} + \sqrt{c - bTI} + d \tag{10}$$

where *a*, *b*, *c*, and *d* are fitting constants, in which the first three are always positive. A mainstream viewpoint is that freezing and thawing have similar processes, thus the mathematical formulations for TD and FD are similar,

$$TD = -e\sqrt{FIT} - \sqrt{g - fTI} + h \tag{11}$$

where *e*, *g*, *f*, and *h* are fitting constants, in which the first three are always positive. *FIT* is the cumulative freezing index in the thawing period only. Thus, the FI values cumulated before the start of the thawing period will be zeroed out in *FIT* calculations.

However, direct applications of the above equations may lead to unrealistic predictions or/and incompatible curve fitting results between FD and TD. To address the issues, constraints that better relate the above equations to the real conditions were added. The physical meanings of *c* and *d* in Eq. (10) were related to the pavement surface thickness. Before the freezing season starts, it is known that both FI and TI equal zero. Thus, Eq. (10) can be rewritten as

$$FD_{ini} = \sqrt{c} - d \tag{12}$$

where FD_{ini} is the initial freezing depth representing the pavement surface thickness. In Fig. 14, the base surface is the datum. FD starts from zero in the early freezing stage when FI is slightly greater than zero and TI is equal to zero. FD only occurs in the base and subgrade soils beneath

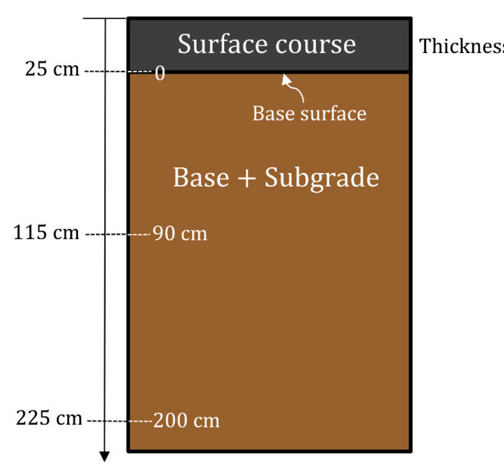

Fig. 14. Schematic of a test road pavement cross section.

the pavement surface. Under the condition of FI = TI = 0, FD_{ini} needs to be equal to an equivalent pavement thickness, which is assumed to be 25 cm in this study, such that realistic pavement structure conditions can be physically described using Eq. (10). Similarly, Eq. (11) for TD can be written as

$$TD_{ini} = -\sqrt{g} + h \tag{13}$$

At the same site, $FD_{ini} = TD_{ini}$ is required. The above explanations give out the physical meanings of all the fitting constants in the multivariate FD and TD prediction models (Eqs. (10) and (11)). This is different from the existing prediction models in which regression analyses were conducted without constraints, which may lead to problematic fitting constants ((Baïz et al., 2008) and Chapin et al. (2012)) .

Non-constrained nonlinear regression of measured data is widely used to find fitting constants in the FD/TD prediction models (Asefzadeh et al., 2016; Baïz et al., 2008; Marquis, 2008; Miller et al., 2012). However, non-constrained nonlinear regression cannot satisfy the requirements of Eqs. (12) and (13) in this study. We thus propose a new constrained optimization approach to satisfy such requirements. In theory, the minimum of a nonlinear multivariable function $f(\mathbf{x})$ can be expressed as (Bertsekas, 2014),

$$\min_{\mathbf{x}} f(\mathbf{x}) \text{ such that} \begin{cases} \mathbf{x} \geq 0 \\ ceq(\mathbf{x}) = 0 \end{cases} \tag{14}$$

where $\mathbf{x}$ is the fitting constant vector and $ceq(\mathbf{x})$ is the equality constraints that need to be satisfied. Take FD for example, $\mathbf{x}$ contains a, b, c, and d. $f(\mathbf{x})$ and $ceq(\mathbf{x})$ can be expressed as

$$\begin{cases} f(\mathbf{x}) = FD(\mathbf{x}) - g(\mathbf{x}) \\ ceq(\mathbf{x}) = \sqrt{c} - d - FD_{ini} \end{cases} \tag{15}$$

where $g(\mathbf{x})$ is the measured data vector. As mentioned, $FD_{ini} = TD_{ini} = -25$ is used. A negative sign is used here because the base surface is the datum. The sequential quadratic programming method (Gill and Wong, 2012) was adopted for the constrained nonlinear optimization. The randomly generated $\mathbf{x}$ was used to start the optimization process with a termination tolerance of 10^{-12}. Fig. 15 shows typical results of constrained nonlinear regression for obtaining models for two RWIS sites.

4.5. SLR predictions based on freezing/thawing depths

4.5.1. SLR criteria

In this study, the criteria for placing and removing SLR in the FHWA model were adopted from the original report of the FHWA model (for "thick Pavement"):

SLR placement : 25°F-days (22.2°C-days),

SLR removal : $TI = 0.3 \cdot FI$.

In the MDOT2019 model, the dates are determined by the predicted FD and TD instead of FI and TI. The date for placing the SLR is the time when the FD reaches 4 in.. The threshold FD value was selected to maintain a satisfactory level of conservativeness. The date for moving the SLR is the day when the FD meets the TD. In a few cases, both FD and TD drop below zero within one day, which can be caused by a sudden temperature rise. This day is also believed to the time to remove the SLR. Table 1 shows the typical SLR predictions with the MDOT2019 and FHWA model as well as the real SLR dates suggested by MDOT based on field observations.

4.5.2. Degree of SLR completion

Quantities that indicate the SLR status could be helpful in SLR practice but is missing in the existing studies. The SLR policymakers and operational engineers in MDOT expressed strong interest in such quantities especially one that can tell how much of the SLR has been accomplished or how far we are from the completion of the SLR. Such quantities can give both road engineers and road users a more intuitive way to visualize the SLR status and make plans. For the purpose, the following two equations were proposed as the degree of SLR completion in the MDOT2019 model and FHWA model, respectively.

$$\theta = \frac{TD}{FD} \tag{16}$$

$$\theta = \frac{FI}{0.3 \cdot TI} \tag{17}$$

It is not difficult to notice that the two definitions cannot be compared directly because they use different quantities, i.e., FD&TD in MDOT2019 and FI&TI in FHWA, in their definitions. Notwithstanding, it was found very helpful to assess the spatial distributions of the above quantities calculated in both models. Such distributions, which can be visualized using contour maps, show the freeze/thaw status of the whole region. Fig. 16 shows the degrees of SLR completion on a typical day in FHWA and MDOT2019 models. Again, we can see that the two models give out different predictions, both in terms of magnitudes and spatial distributions. Despite the difference, both models successfully captured the occurrence of the SLR, and the degrees of SLR completion are not far from each other, especially considering that it is common for the SLR dates predicted with the FHWA model to miss the actual SLR dates by several weeks.

5. App

5.1. Functions of the MDOTSLR tool

The tool aims to provide two modes for users: automatic and manual. In the automatic mode, the users do not need to provide input and they can receive an estimate based on the default values. In the manual mode, users can enter site-specific information such as the pavement type for a better prediction. As of now, the automatic mode has been finished while the manual mode is still under development.

As shown in Fig. 17, the web-based tool provides five main services including 1. Temperature, F/T indices & SLR prediction (status and forecast), 2. Freeze/thaw depths (freeze/thaw history), 3. Maps of freeze/thaw indices (freeze/thaw distribution), 4. Maximum freezing depth contour (historical maximum), and 5. Data portal (database for public). The five services can be accessed by clicking the corresponding button shown on the home page or via the quick access button on the right upper corner of any page. Fig. 17 shows the setup of the home page on a desktop. However, the responsive design of the tool endows it with user-friendliness in other electronic devices such as tablets and mobile phones.

Upon clicking the first service on the homepage, it transfers to a page illustrated in Fig. 18, on which users can enter a ZIP code or select a county to get the time series graphs of the temperature, freezing/thawing indices, and SLR prediction of a specific area in Michigan. The start date and unit of measure also can be chosen on this page. The SLR start and end dates in the selected time window, i.e., from the entered start date to the present, are marked with the corresponding SLR

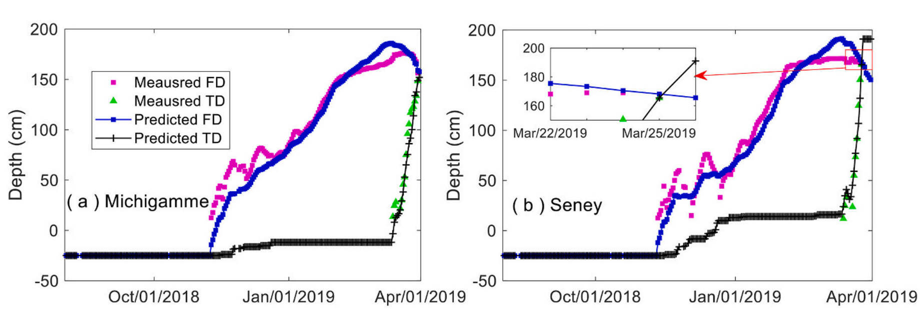

Fig. 15. Predictions of FD and TD with the measured data for Year Cycle 2018–2019.

Table 1
SLR dates predicted with MDOT2019 and FHWA and actual SLR dates.

Site	Year cycle	MDOT2019		FHWA		Actual SLR dates	
		SLR on	SLR off	SLR on	SLR off	SLR on	SLR off
Michigamme	2017–2018	2/28/2018	3/19/2018	2/26/2018	5/08/2018	2/26/2018	4/2/2018
49,861	2018–2019	3/13/2019	3/21/2019	3/13/2019	5/04/2019	3/12/2019	4/1/2019
Seney	2017–2018	2/27/2018	3/10/2018	1/20/2018	5/07/2018	2/23/2018	3/16/2018
49,883	2018–2019	3/17/2019	3/22/2019	11/25/2019	4/27/2019	3/13/2019	3/25/2019
Eastport	2017–2018	2/19/2018	2/28/2018	1/11/2018	4/23/2018	2/21/2018	3/1/2018
49,627	2018–2019	3/13/2019	3/22/2019	11/25/2019	4/20/2019	3/14/2019	3/25/2019

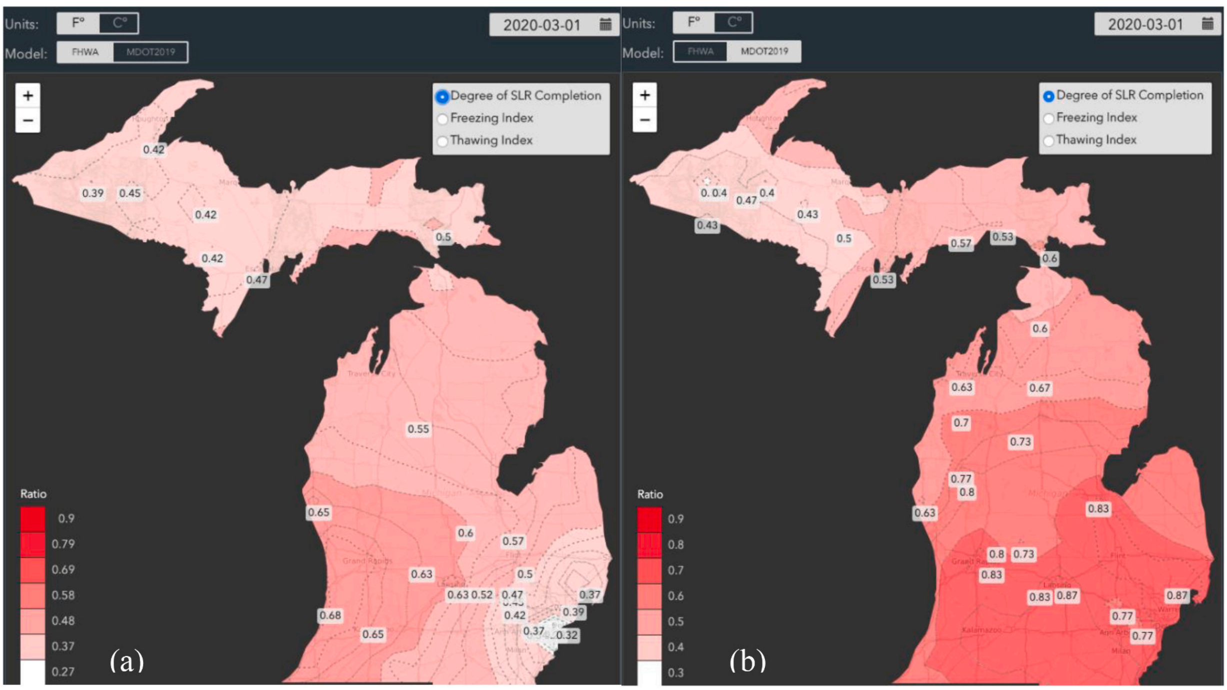

Fig. 16. Typical results of DLR completion in a) FHWA (left) and b) MDOT2019 models.

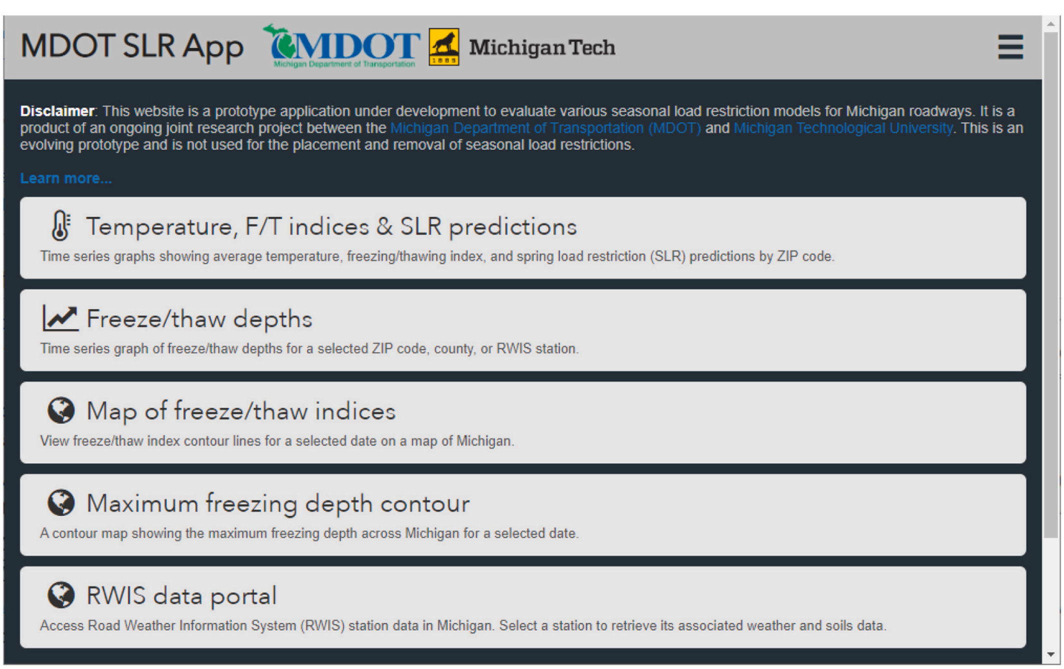

Fig. 17. Homepage of MDOT SLR App.

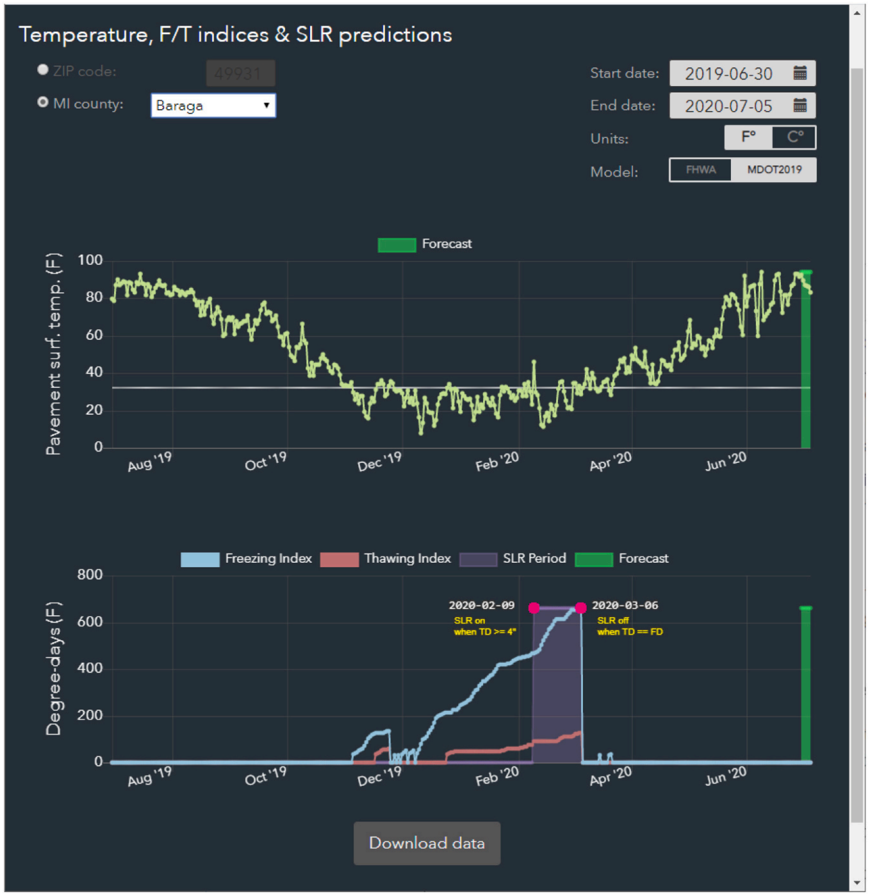

Fig. 18. Page of temperature, F/T indices & SLR prediction.

criteria. The green regions on the right ends of the two graphs represent the forecast (i.e., 7 days). All the data are downloadable via a "Download data" button at bottom of the web page, which is actually available in every service. This service is what road users and engineers need for making SLR-related decisions.

In the second service, the freeze/thaw history of any selected region, i.e., zip code, county, and RWIS station, can be checked in terms of the variations of FD and TD with time. As shown in Fig. 19, the MDOT2019 model predicts that freezing invades into the base and lower layers starting in December 2019 in the area with a zip code of 49,931. The thawing process appears about one week later. The two curves converge at the beginning of March in 2020, which marks the end of the SLR period. The two dropdown menus on the upper right Conner allow users to select any time window to check the freeze/thaw history. The two switches for units and models provide options for showing the results expressed in different units, i.e., ft. and m, and calculated with different models, i.e., FHWA and MDOT2019. It is noted that, if an RWIS station is selected, the FD and TD will be depths calculated with subsurface temperatures as explained in Section 4.3, which can be viewed as measurements instead of predictions.

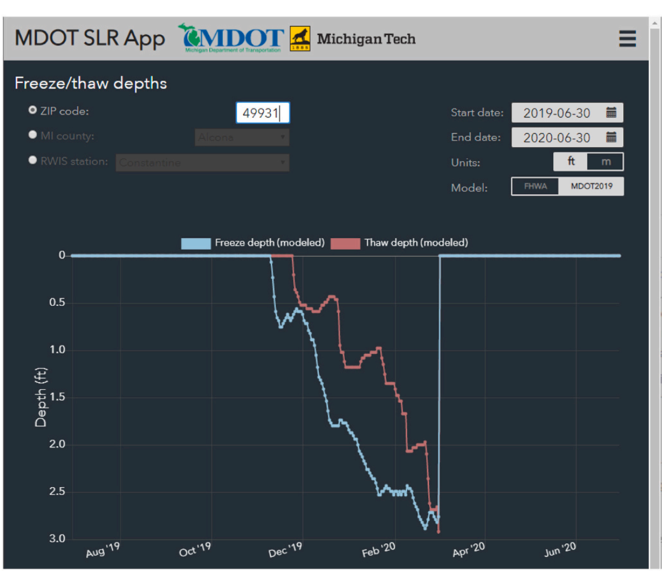

Fig. 19. Freeze/thaw history in terms of variations of freezing and thawing depths.

Service 4 shows the spatial distribution of freezing and thawing accumulations and SLR completion values in the whole state. The accumulation of freezing and thawing are quantified using the FI and TI values. Fig. 20 shows the distributions of FI calculated with the MDOT2019 model on a selected day. This feature is very helpful when people either want to get an overall idea of the freeze/thaw distributions in a region or want to check the status of the whole state on a specific day. In addition to FI and TI, the degree of completion can also be checked for its historical distributions. A typical degree of completion contour predicted with the two models is illustrated in Fig. 16.

The fourth service is designed for road engineers, who are especially interested in the maximum FD values over a given period. The maximum FD values are useful for the determination of the maximum excavation depth, which is one key parameter in determining the cost of the pavement construction. Also, a spatial distribution of such maximum FD values allows engineers to find areas that require special attention such

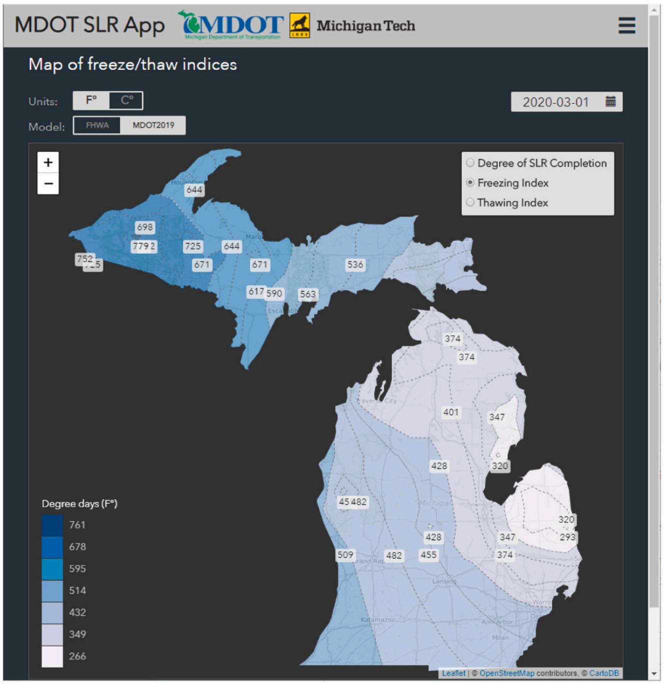

Fig. 20. Spatial distributions of freezing index, thawing index, and degree of SLR completion.

as those regions with abnormal freeze-thaw action. Such areas can be easily identified in an FD contour map as shown in Fig. 21. Users can specify the time window for calculating the maximum depth. Therefore, statistics for different design service life, e.g., twenty years, can be obtained from the maximum values of twenty years once enough data is available. The maximum depths delivered via this service include FD values predicted by FHWA and MDOT2019 as well as FD values from the RWIS measurements.

The fifth service is intended to provide convenient access to the database of the web-based tool. The GIS, RWIS, weather, and field

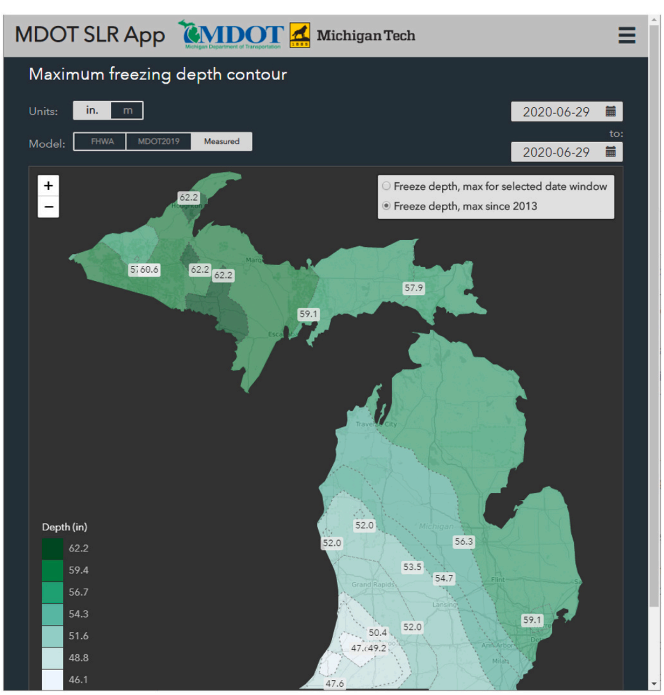

Fig. 21. Maximum freezing depths distributions.

measurement data associated with the stations marked in Fig. 5 can be displayed as tables once the corresponding station is clicked. For example, if a user clicks the green marker which represents the MI-02 Houghton Lake, the information of this station will be displayed.

Fig. 22 shows a table of daily weather and RWIS data including the parameters of average humidity, average temperature, average visibility, max wind speed, total precipitation, maximum air temperature, minimum air temperature, base temperatures at different depths, and chemical factor, and so on. The data can be downloaded as csv files for further analysis.

5.2. Development and use of the web-based app

The web-based app is essentially a dynamic website. For the front-end design, the web pages were written using HTML5 and CSS3 compiled from SASS. The responsive web design approach was adopted to make sure the website can be optimally accessed with all major types of electronic devices, i.e., desktops, tablets, and mobile phones. jQuery, a JavaScript library, was used to enhance the functionality and user-friendliness of the front-end pages. The mapping and location fetching was achieved with OpenStreetMap and Leaflet.js. Data transfer between the front-end and the server was performed via JSON. Nodejs (a JavaScript-based programming platform) was used to manage the retrieval of data from the weather and RWIS sites while MongoDB (replaced by PostgreSQL later) was used to store the data locally. For serving the app, Express, a Node.js website framework, was used to deliver HTML documents and data. The calculation process was programmed on the server side using Node.js to shorten the development cycle, though the calculations were developed using separate technologies. Weather and GIS information was obtained via APIs made available from the sources listed previously. The calculation results are shown as charts and tables on the web pages. This plotting functionality was developed using a free software charting library, Chart.js.

The app has been used in MDOT's SLR decisions. MDOT begins monitoring weather conditions and forecasts in January and uses existing tools such as MDOTSLR and pavement and drainage observations. These are then reported/discussed at a weekly meeting from February through May with the Central Office Permits Unit and representatives from the MDOT Regions. SLR decisions are communicated to MDOT leadership and partner agencies and stakeholders prior to implementation. However, it is worthwhile to reiterate that this is a decision-support tool; engineers' judgments and other information are still adopted for final decisions.

5.3. Features and benefits

Compared with traditional non-web SLR decision support tools, this web-based tool was confirmed to possess the following benefits in the testing stage.

- The tool can provide the users with much more accurate, convenient, and automated SLR decisions, which can effectively save the investment in repairing the road damage during the spring thaw season and effectively prolong the service life of the pavement.
- Since this data management and computing are automated, much less labor and expertise are required for assessing pavement conditions and making SLR decisions.
- The road users, especially those seriously affected by the SLR policy, such as trucking companies and industries that rely on hauling services, can also benefit from this tool.
- The tool has been changing the current practice in Michigan and enabled the SLR practice to be better guided by scientific and engineering principles and benefit from the digital infrastructure.
- This tool can also provide suggestions and information for future RWIS sites and help refine the pavement design so that it can better consider frost effects.

Daily Weather Data

ZIP code 48629 OWM data | RWIS station data

Date	Average humidity %	Average temp. C	Average visibility km	Max wind speed km/h	Total precipitation mm	Airtemp. [1] C	Basetemp. C	Basetemp. [depth:3] C	Basetemp. [depth:6] C	Basetemp. [depth:9] C	Basetemp. [depth:12] C	Basetemp. [depth:18] C	Basetemp. [depth:24] C	Basetemp. [depth:30] C	Basetemp. [depth:36] C	Basetemp. [depth:42] C	Basetemp. [depth:48] C	Basetemp. [depth:54] C	Basetemp. [depth:60] C	Basetemp. [depth:66] C	Basetemp. [depth:72] C	Chemical factor [2] %	Concentration [1] g/L	Concentration [2] g/L	Conductivity [1] S/m	Conductivity [2] S/m	Dew point
2018-07-28	67	20	19.3	12	1	18	--	24	24	24	24	24	24	23	23	23	23	22	22	22	21	--	--	0	--	0.0	13	--
2018-07-27	70	19	18.5	18	1	17	--	24	24	24	24	24	24	24	23	23	23	22	22	22	21	--	--	0	--	0.0	14	--
2018-07-26	72	20	18.2	17	1	20	--	25	25	25	25	25	24	24	23	23	23	22	22	22	21	--	--	0	--	0.0	15	--
2018-07-25	69	23	19.5	11	--	21	--	25	25	25	24	24	24	23	23	23	23	22	22	22	21	--	--	--	--	--	15	--
2018-07-24	79	23	16.3	11	10	21	--	24	24	24	24	24	24	24	23	23	23	23	22	22	21	--	--	--	--	--	18	--
2018-07-23	80	21	15.8	9	1	21	--	24	24	24	24	24	24	24	24	23	23	23	22	22	21	--	--	--	--	--	17	--
2018-07-22	76	21	12.8	18	8	20	--	23	23	23	23	24	24	24	24	24	23	23	22	22	21	--	--	0	--	0.0	18	--
2018-07-21	83	20	12.6	14	4	22	--	27	26	26	26	26	25	25	24	24	23	23	22	22	21	--	0	0	0.0	0.0	19	0.0
2018-07-20	71	23	17.5	19	1	22	--	28	27	27	26	26	25	25	24	24	23	23	22	21	21	--	--	--	--	--	15	--
2018-07-19	58	21	20.0	10	--	19	--	27	27	27	26	26	25	25	24	24	23	23	22	21	21	--	--	--	--	--	12	--
2018-07-18	59	20	20.0	13	--	17	--	27	27	27	26	26	25	25	24	24	23	23	22	21	21	--	--	--	--	--	10	--
2018-07-17	63	21	20.0	19	--	19	--	27	27	27	27	26	25	25	24	24	23	23	22	21	21	--	--	--	--	--	12	--
2018-07-16	75	24	16.1	13	3	25	--	28	27	27	26	26	25	24	24	24	23	22	22	21	20	--	--	--	--	--	20	--
2018-07-15	70	26	18.9	14	0	25	--	26	26	26	26	25	25	24	24	24	23	22	22	21	20	--	--	--	--	--	20	--
2018-07-14	70	25	14.9	9	22	23	--	26	26	26	26	26	25	25	24	24	23	22	22	21	20	--	0	0	0.0	0.0	21	0.0
2018-07-13	70	25	16.1	18	17	23	--	26	26	27	26	26	26	25	24	24	23	22	22	21	20	--	0	0	0.0	0.0	19	0.0
2018-07-12	59	25	19.8	16	1	21	--	29	28	28	27	26	26	25	24	23	23	22	21	21	20	--	--	--	--	--	12	--
2018-07-11	54	24	20.0	9	--	21	--	29	28	28	27	26	26	25	24	23	23	22	21	21	20	--	--	--	--	--	11	--
2018-07-10	60	24	19.2	11	--	24	--	29	28	28	27	26	25	24	24	23	22	22	21	20	20	--	--	--	--	--	13	--
2018-07-09	63	25	11.1	18	--	23	--	28	28	27	27	26	25	24	24	23	22	22	21	20	20	--	--	--	--	--	14	--
2018-07-08	57	24	10.0	16	--	22	--	28	27	27	27	26	25	24	24	23	22	22	21	20	19	--	--	--	--	--	11	--

Download data

Fig. 22. RWIS and weather data in the data portal.

- This tool can be easily extended or modified for most states in the U. S. as well as other places around the world. Its use could lead to an incalculable save in the budget of state DOTs, local road agencies, and road users.

6. Conclusion

The paper shares the lesson learned from a large-scale application for real-time computing of pavement conditions in cold regions. This study made research innovations involving data, model, and app to advance winter road maintenance and road condition monitoring and enable predictions and decision-making with a new computing infrastructure. A new MDOT2019 model consisting of new sub-models for road surface temperature predictions, freezing/thawing depth calculations with subsurface temperatures, predictions of freezing and thawing depths, prediction of the SLR dates, and acquisition of freezing/thawing status via the degree of SLR completion. Each of these (sub-)models advanced the corresponding topics in road engineering in cold regions. The study features the automated acquisition, processing, selection, and use of data for monitoring and predictions of road conditions in a state-of-the-art web delivery. Any other road agency can develop a similar tool by developing a web-based app after updating (or customizing) the MDOT2019 model (including all of its sub-models) with its own data, given that the agency has an RWIS or an equivalent data acquisition system.

In addition to the above innovations, the web-based tool, as an ensemble of the research products, showed unique benefits in the use of data, high level of automation, self-improvements over time, site-specific predictions, and customizable visualization and data access as well as other tangible socio-economic benefits. Due to the use of data, the study placed a cornerstone to move from the current model-driven winter road maintenance to the future data-driven road operation practices.

Declaration of Competing Interest

None.

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