University Transportation Research Center - Region 2

Final Report

Road Weather Information Systems for Winter Road Maintenance

Performing Organization: Rowan University

July 2018

Sponsor:
University Transportation Research Center - Region 2

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The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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16. Abstract

Road Weather Information System (RWIS) technology is a useful tool in evaluating road conditions in cold climates, and is helpful in optimizing the timing of salting/plowing procedures, as well as the quantity of salt used. RWIS technology is used as a means of improving the cost-effectiveness of winter road maintenance. Most agencies use RWIS data to predict winter storms that can justify snow and ice control, plowing, and chemical, salt, and sand operations. Agencies also use RWIS to predict weather for nighttime paving crews and also for legal issues when an operation is supposed to be done at a certain temperature. Using this information helps agencies to time out road repair jobs accordingly so that the job can be done in the least amount of time and also in the correct conditions for the materials to be applied in. Two models that are being analyzed are the Model of the Environment and Temperature of the Roads (METRo) and statistical models based on field data from long-term pavement performance (LTPP) database. These models are used mostly because of their capability of predicting pavement surface temperature.

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Road Weather Information Systems for Winter Road Maintenance

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Abstract

Road Weather Information System (RWIS) technology is a useful tool in evaluating road conditions in cold climates, and is helpful in optimizing the timing of salting/plowing procedures, as well as the quantity of salt to be used. RWIS technology is used as a means of improving the cost-effectiveness of winter road maintenance. Most agencies use RWIS data to predict winter storms that can justify snow and ice control, plowing, and chemical, salt, and sand operations. Agencies also use RWIS to predict weather for nighttime paving crews and also for legal issues when an operation is supposed to be done at a certain temperature. Using this information helps agencies to time out road repair jobs accordingly so that the job can be done in the least amount of time and also in the correct conditions for the materials to be applied in. Two models that are being analyzed are the Model of the Environment and Temperature of the Roads (METRo) and statistical models based on field data. These models are used mostly because of their capability of predicting pavement surface temperature.

Objectives

The objective of this project was to evaluate two different road forecasting models, t the Model of the Environment and Temperature of the Roads (METRo) and statistical models based on field data. Through analysis, the better model of the two would be chosen to be further analyzed and download. A more thorough analysis would be done on the corresponding program using RWIS data and comparing the programs forecasted output to the actual observed data.

Introduction

The Road Weather Information System is currently being used by DOTs in multiple states. Road Weather Information Systems (RWIS) is an effective system to help winter maintenance operations by recording weather and pavement data at selected locations. RWIS is composed of weather, pavement sensors, data processing units, and data transmission equipment, Figure 1. RWIS uses different types of sensors such as a thermometer, anemometer, wind vane, and rain gauge. These sensors along with others collect data such as temperature, wind speed, wind direction, fog and smoke, precipitation. RWIS also has another integrated feature that can measure pavement and subbase temperature of a road by connecting a probe and embedding it into the respective layers of the area of interest, Figure 1.

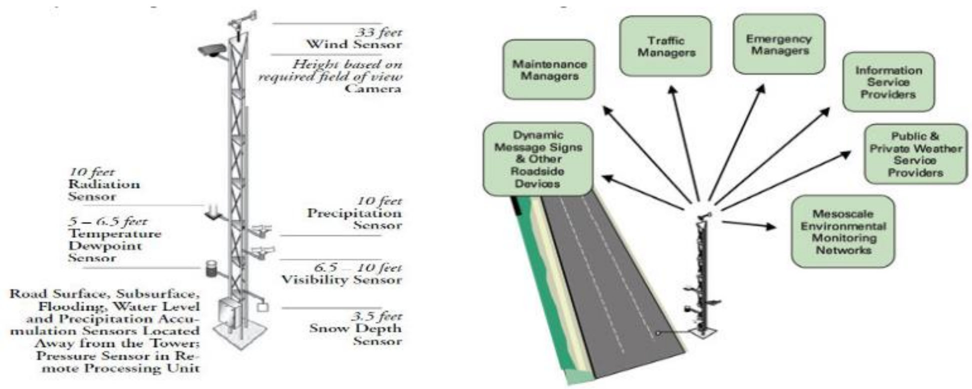


Figure 1: a) Environmental Sensor System (ESS) for RWIS (After Rall 2010) and (b) Application of RWIS Data

The road weather information system (RWIS) network is a collection of environmental sensor stations (ESS), which gives state DOTs unprecedented access to detailed, accurate, timely, and roadway-relevant weather information to effectively and efficiently promote safety, mobility and productivity in the face of weather-related challenges. RWIS network of ESSs currently installed across the State of New Jersey are providing valuable road weather data to the NJDOT, Figure 2-a. These stations have been applied to assist maintenance managers about road treatments, such as salting, plowing, or a combination of approaches, Figure 2-b. Based on the RWIS, decision support systems have been developed to recommend actions given forecasted conditions to promote safety and efficiency.

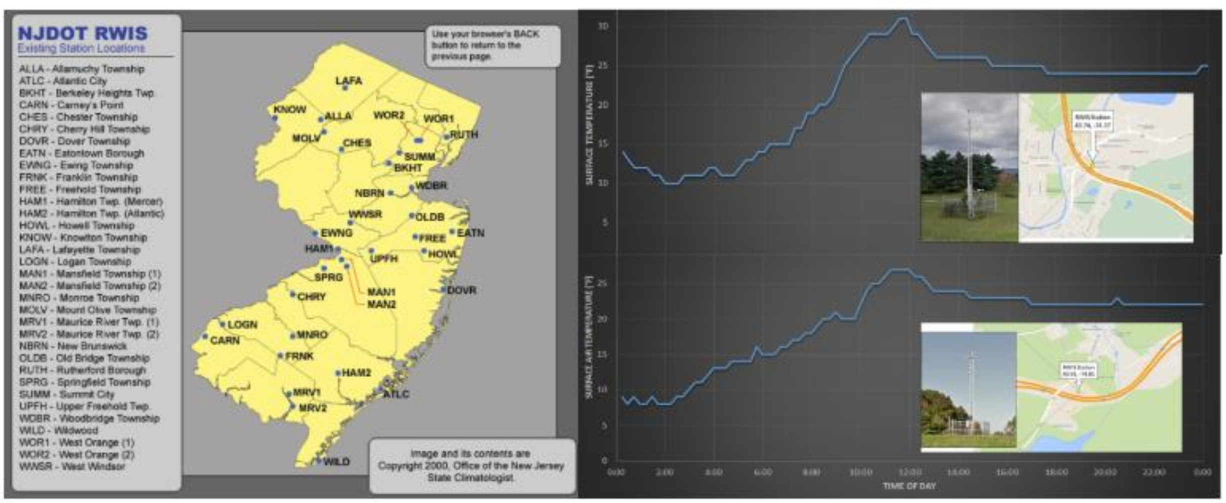


Figure 2: a) NJ RWIS Stations b) Road surface temperature from RWIS station Summit and Allamuchy, NJ

Winter conditions cause for unsafe roads and lots of time and money trying to make the roads safe again for the users. Every year, state highway agencies spend approximately 1.5 billion dollars clearing roadways in order to be safely used by its travelers. Currently there are two methods being implemented to keep road safe for travelers: anti-icing and deicing. [10]

Anti-icing is a strategy that prevents snow and ice from sticking to the roadway. It involves putting down a chemical solution on the roadway beforehand to keep the snow from sticking to the asphalt by lowering the temperature at which water freezes at. This causes the snow to become slushier instead of icy allowing motorists to have more control of their vehicle while driving. However, anti-icing is a strategy that has to start before or as the storm is starting which means that models need to predict where the storm will be so that the agencies can pinpoint when and where to begin the process. This makes RWIS data very important since the data that is recorded is needed in the models in order to predict the storm. Models such as empirical models and METRo can be used to get this prediction to implement the strategy, at the right time, with the right amount of anti-icing solution. Anti-icing strategies have proven to help keep roads safe for travelers, reduce the environmental impact of winter operations, and make post-storm clean-up easier. The anti-icing chemicals that are being used are liquid calcium magnesium acetate, liquid calcium chloride, liquid magnesium chloride, liquid sodium chloride, liquid potassium acetate, and solid sodium chloride. [10]

Deicing is another strategy to help clear roads during winter storms. This is the tradition strategy for winter storms which includes plowing, salting, and sanding. These operations all involve breaking the bond between the pavement and the snow on its surface. Although it has been proven to be effective over the years, it has proven to not always be the most efficient. The lack of site-specific, detailed weather information results in highway agencies waiting until the storm hits to send out their crews. By the time crews are sent out, the storm already has the advantage and the crews struggle to keep up with the storm and keep the roads clear and safe for motorists to operate their vehicles. [10]

In 1995, 15 states started participating in the Federal Highway Administration's (FHWA) test and evaluation to determine the effectiveness of the anti-icing operations. The results from each of the 15 states are being used to determine the conditions that anti-icing is most effective, as well as the strategies and techniques that are successful in the broad range of topographic, climatic, and traffic conditions. The anti-icing operation comes down to knowing which chemical to use, at what time, and amount. Different locations have different answers as to each step which depend on the sites conditions such as weather, geography, and traffic. Determining this information depends on real-time, localized weather information as well as accurate forecasts for specific corridors. The results found from this test included; a reduction in the amount of chemicals needed, the prevention of black ice or frost on bridge decks when liquid chemicals are periodically applied, required less effort to return the pavement to a bare condition at the end of the storm, and the reduction in the amount of abrasive used on the road. [10]

Literature Review

Enhanced Integrated Climatic Model (EICM)
The Enhanced Integrated Climatic Model is used in order to predict and simulate internal pavement temperature, moisture, and freeze-thaw conditions as a function of time from climatic data. The climatic data that is needed for this model are conditions such as air temperature, precipitation, wind speed, percentage sunshine, and relative humidity

Another input that affects the pavement temperature is the solar reflectivity. This value differs according to pavement type and pavement age. For rigid pavements the value increases as the concrete ages and darkens while flexible pavements the value decreases with time as the pavement lightens in color. EICM allows the user to enter the number of increments for each layer and it will generate the temperatures for specified nodes at the certain depths.

EICM uses three models to collect and get its data from that is used to simulate pavement conditions. The three models are:

- Climatic-Materials-Structures (CMS) model, developed at the University of Illinois.
- Infiltration and Drainage (ID) model, developed at the Texas Transportation Institute.
- Frost Heave and Thaw Settlement Model, developed by the CRREL.

The Climatic-Materials-Structures (CMS) model simulates field conditions by accounting for the differences in climatic data due to the differences in geographical location. The climatic model that is incorporated in the CMS program takes material and climatic inputs and calculated temperature and moisture profiles that vary with time. The program uses this climatic data and the profiles to determine the materials model. The materials model calculates the asphalt base, subbase, and subgrade stiffness. Lastly the output of both climatic and material data can be combined with load data that can be put into structure analysis and performance models.

The Infiltration and Drainage (ID) model simulates the permeability of the pavement base and subgrade. This model accounts for the amount of water that is penetrating the asphalt through cracks and joints. This method consists of five (5) parts: (1) Estimation of the amount of rainfall that falls each day, (2) The infiltration of water through the cracks and joints in the pavement, (3) Computing the simultaneous drainage of water into the subgrade and into the lateral drains, (4) The dry and wet probabilities of a pavement, and (5) Effect of water saturation on load-carrying capacity of base course and subgrade. Infiltration through pavement cracks and joints used either Ridgeway’s rate of infiltration of water through cracks and joints or Dempsey and Robnett’s regression equations that were developed from field measurements that estimated the amount of free water that was entering the pavement base course.

The Frost Heave and Thaw Settlement model is a one-dimensional representation of vertical heat and moisture flux and is based on a numerical solution technique termed the nodal domain integration method. This model is used to predict the amount of moisture in the system to better understand the freeze-thaw in the system. This model is primarily being used for non-cohesive soils with a grain size varying from silts to dirty gravel. When this model was used with cohesive soil, clays, the results have not been validated. When using this model a soil of uniform horizontal stratified soils can be viewed in 3 layers: fully frozen, fully unfrozen, and zone of freezing. The zone of freezing is importing fully unfrozen soil and exporting fully frozen soil to the extent that the volume of the exported is greater than the imported, which causes the soil to heave. When the soil freezes with more volume than previously it wants to move upwards which gives the soil no place to go but upwards and creates bumps and cracks in the roadway [13].

Figure 3. In this figure soil heaves have created bumps and cracks in the roadway.

Performance Assessment EICM

In 2003 a comparison of the EICM model and field measurements were conducted by Zubair Ahmed, Ivana Marukic, Sameh Zaghloul, and Nick Vitillo. The data used was from New Jersey in the months January, July, September, and December which typically depict the four seasons. Since EICM needs specific inputs of data for the model to be calculated they started with a sensitivity test of the biggest changing factors. Test runs were also conducted to see how well generated data from EICM would match to actual field measurements.

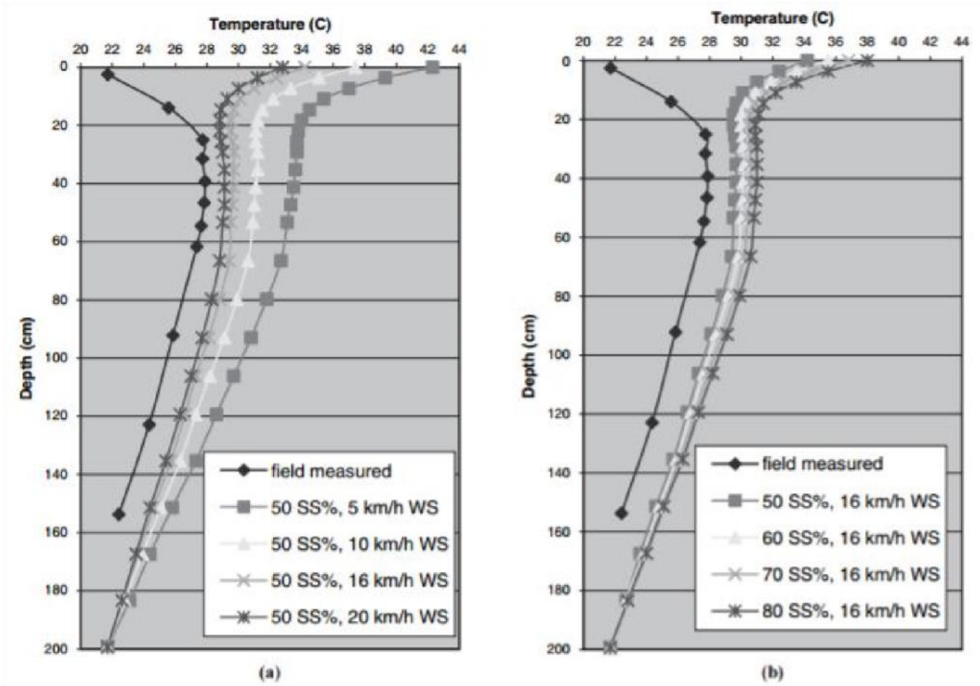


Figure 4. Temperature sensitivity analysis results on July 10, 2003. (a) wind speed sensitivity (b) percentage of sunshine sensitivity.

In Figure 4 the sensitivity tests shows that the EICM is highly sensitive to the wind speed. The predicted temperature curve has a greater variation to it as the wind speed increases. This test shows that the greater the wind speed at the same percentage of sunshine the lower the temperature will be on the asphalt surface. EICM also predicts a temperature that varies greatly due to wind speed below the surface 150 cm. The sensitivity of the percentage of sunshine on the asphalt surface does not vary significantly from an increase of sunshine percentage.

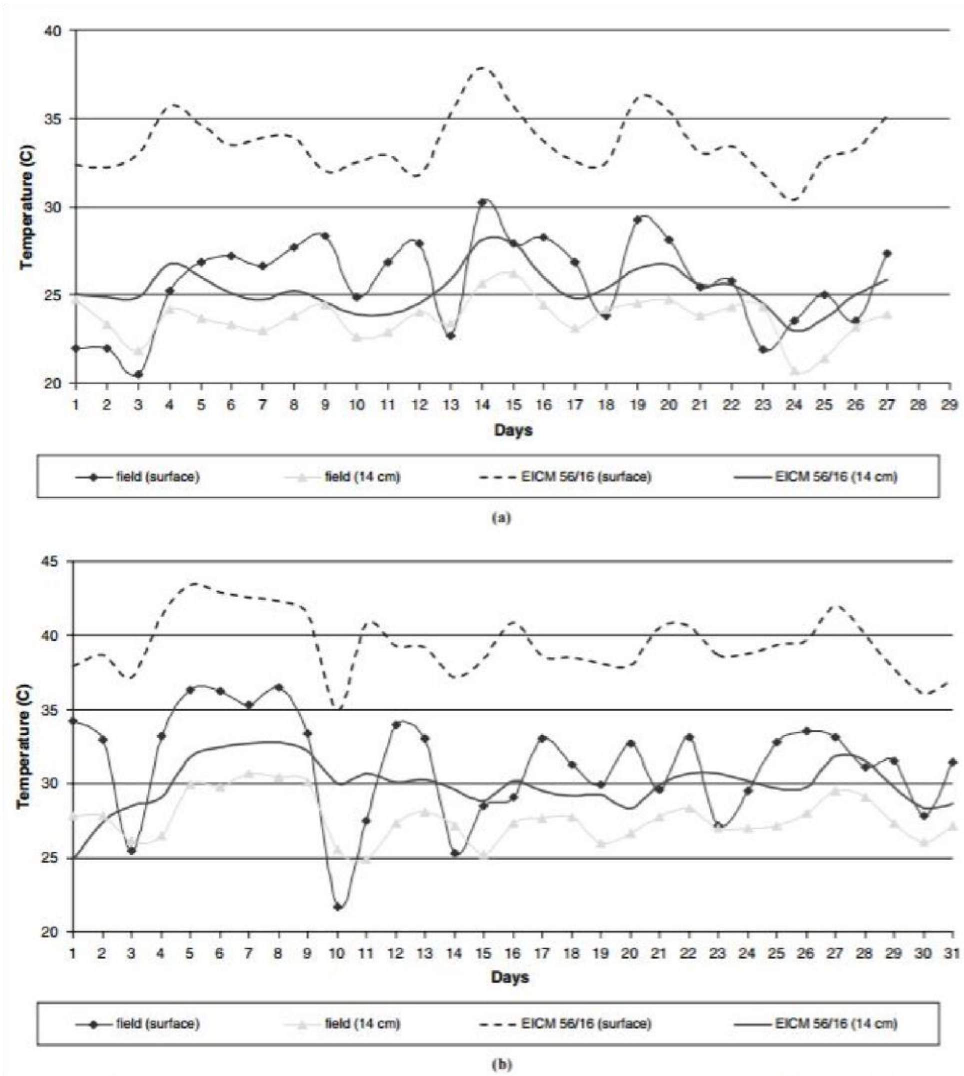
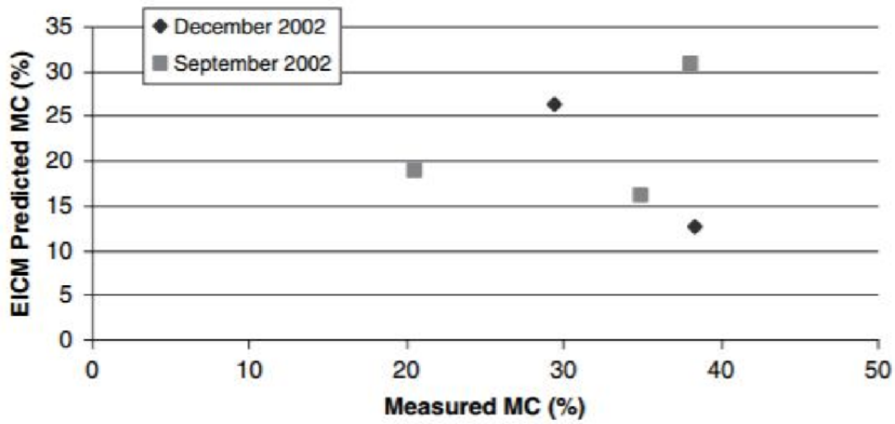


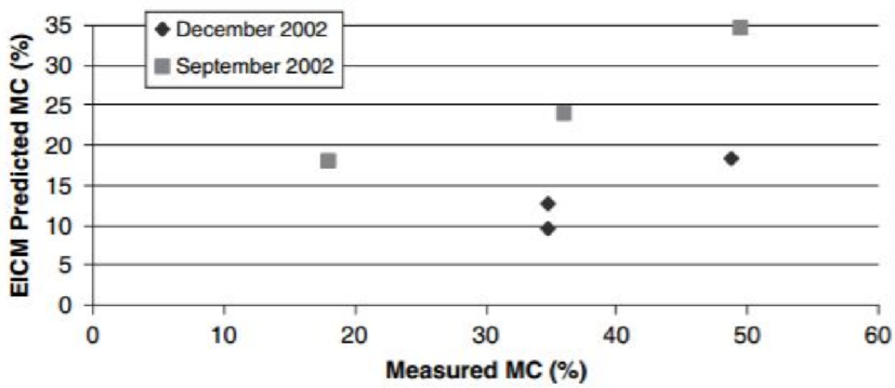
Figure 5 Difference in measured versus predicted temperature in asphalt surface later, (a) September 2003 and (b) July 2003.

Figure 5 shows field measured temperatures versus EICM generated temperatures of the surface of the asphalt. The figure shows that EICM generate temperatures are always higher than what is really recorded but follow the overall trend of the temperature pretty well.

From the results of this test if we use this model to predict temperature for winter operations the model will generate a higher temperature than it will really be outside. This causes for an issue where the EICM could predict a given day to be 6 degrees Celsius but the actual temperature could be 0 degrees Celsius which is freezing. The problem with temperatures being greater than the actual temperature is that the winter operations crew will calculate the winter weather preparation incorrectly and may cause for the roads to become frozen in areas and unsafe.



(a)



(b)

Figure 6. Correlation analysis for moisture content for (a) LTPP Site 5E and (b) LTPP Site 9C.

Figure 6 shows EICM predicted versus measured moisture content at two different test sites in New Jersey. From the graph there is no correlation between the two. The generated value and actual measured value vary too much to see a correlation between EICM and actual conditions. Without proper moisture content the program will not be able to accurately predict freeze thaw conditions that need to be remediated so that the soil does not heave or crack. If the model is incorrect the DOT will be misguided in their findings for soil heaves and cracks due to subbase moisture freezing. From the study that was conducted with New Jersey weather information has proven to have false data that has an error percentage that is too high to use for Winter Weather Road Operations. The data will provide misguided results and will cause in unsafe, and improper usages of materials for Winter Weather Operations.

Methodology

A deeper look was taken into METRo and the corresponding files that make it run properly. Once the files were analyzed, METRo could be properly installed and the METRo self test could be run successfully. Once METRo was installed, the data would be formatted correctly based off of new configured standards that were found. This data collected for the observation would be from 2013 January to December 2014 for the Forecast and Observation data. The data set into METRo however, for the observation data was set from January 2013 to the end of the year in December of 2014. The Forecast data was set from June 2013 to June 2014 so that it overlapped with the Observation data. Thus METRo would produce an output from January 2014 to June 2014 which was then compared against the collected observation data of 2014. This allowed for the error and accuracy of METRo to be analyzed. Furthermore, a GUI was created for ease of use so the user does not have to use the command line every time. Later on, the implementation of METRo in windows was analyzed.

Model of the Environment and Temperature of the Roads (METRo)

The METRo model is used to forecast local pavement temperatures and road conditions, by using weather forecasts coupled with road surface observations. Using this coupled data, the METRo system is able to predict the evolution of pavement temperatures, as well as the accumulation of liquid (rain), snow, and ice.

The METRo model consists of 3 parts: an energy balance module for the road surface, a heat conduction module for the road material, and a module that deals with water, ice, and snow accumulation.

1. Energy Balance Module

Correct evaluation of energy fluxes within the road surface is crucial to obtaining accurate forecasts in road conditions. The following formula is used in determining the energy fluxes at the road surface:

$$R = (1-\alpha)S + \varepsilon I - \varepsilon\sigma T_s - H + L_a E \pm L_f P + A$$

where R is the sum of net solar radiation flux, S is the incoming flux, ⍰ is the albedo (amount of radiation reflected by the road surface), εI is the absorbed incoming infrared radiation flux, σ is the Stefan-Boltzmann constant, T_s is the road temperature, H is the sensible turbulent heat flux, L⍰E is the latent heat flux, $\pm L_f P$ is the flux associated with phase changes of precipitating water, and A is anthropogenic flux. In future models, a variable for shading will be incorporated to account for sunlight exposure.

The METRo technology is able to calculate all of these incoming radiation fluxes, and use correction factors to compensate for discrepancies between forecasted values, and observed values during the coupling phase.

2. Heat Conduction Module for Road Material

The evolution of the temperature profile in road material is found using the following one-dimensional heat diffusion formula:

$$C(z)\frac{\delta T(z,t)}{\delta t} = -\frac{\delta G(z,t)}{\delta z}$$

Where *C* is heat capacity, and *G* is the ground heat flux. The ground heat flux value is calculated by the following formula:

$$G(z,t) = -k(z)\frac{\delta T(z,t)}{\delta z}$$

Where *k* is the heat conductivity. *C* and *k* values vary with different road materials, therefore the values will be different depending on depth, *z,* in the road profile. A numerical grid is coupled with the formulae for METRo's use. There are two different numerical grids currently available: a variable-resolution grid for normal roads resting on soil, and a uniform-resolution grid for use on bridges and overpasses, which are suspended in midair [3].

3. Surface Water/Ice Accumulation Model

The METRo model is able to predict the accumulation of water, ice, and snow on the road surface by calculating precipitation, evaporation, runoff, etc. The system also has the ability to make assumptions about snow cleared off the road by traffic [3]. A system of two reservoirs is used to simulate the accumulation of water, snow, and ice on the road. Only one of the reservoirs is to be assumed nonempty at any time t, except during a phase transition, where one reservoir's contents are transferred to the other. The change in the amount of substance on the road surface can be quantified by the following formulae:

$$\frac{dW_t}{dt} = P - E + \frac{R - G_1}{L_f} - r$$
$$\frac{dW_s}{dt} = P - E - \frac{R - G_1}{L_f} - r$$

Where W_t is the evolution of water, W_s is the evolution of ice and snow, G_1 is the downward heat flux between the first and second layers in the road, r is the runoff, P is the precipitation, E is the evaporation, and $(R-G_1)/L_f$ is a transfer term only active at 0^oC [3].

The process of predicting road surface characteristics is separated into the 4 parts: the atmospheric forcing phase, initialization phase, coupling phase, and forecast phase. During the atmospheric forcing phase, weather forecast are either provided completely automatically, or by meteorologists. For both instances, METRo is linked to the "SCRIBE" system, which is an expert system able to predict any type of weather forecast based on two sets of matrices, each containing different weather elements such as NWP output, statistical guidance from PP models, UMOS models, models of other analyses, and climatology data [13]. The SCRIBE matrices are decoded by regional weather centers, and the weather elements are fed to a forecast generator. The forecasts include road condition forecasts from METRo. The atmospheric forcing stage of the METRo software can be run automatically, or operated and modified manually by meteorologists.

For the automatic mode of atmospheric forcing, METRo inputs are taken from the SCRIBE matrices, one with regular weather conditions, and one with radiative fluxes. A benefit of the automated mode is its easiness of use. Being that all variables needed for forecasts are included in the SCRIBE matrices, no manual intervention is required, and METRo runs completely automatically.

For the manual mode, meteorologists can use the SCRIBE interface to modify the forecast of the variables (temperature, humidity, wind, precipitation amount and type, and cloud cover). For time's sake, the meteorologist can modify variable at only one site, and the same atmospheric forcing can be implemented at all sites in the area, but with METRo forecasts respective to those sites. Challenges arise in the manual mode when meteorologists are seldom trained to modify these forecasted values for infrared and radiative fluxes. These variable cannot be used in manual mode because of meteorologists modifying the forecasts, which makes the variables obsolete. Therefore, instead of using given variables for radiative fluxes, METRo must use parameterization developed from statistical analysis of previous radiative fluxes.

For the initialization phase, initial road temperature profiles are needed for each forecast. Therefore, METRo uses road temperature observations over a 2-day period to force the heat conduction model. The road profile produced at the end of this period is what will be used as the initial condition in the following period- the coupling phase [3].

In the coupling phase, METRo adjusts the forecasted road temperature values to coincide with actual observations from local weather stations. The previously mentioned SCRIBE forecasts are provided to the METRo model every 12 hours, while RWIS forecasts are issued at various points throughout the day. Within the coupling period, METRo can perform short-term road temperature forecasts during delays between the beginning of the most recent atmospheric forecast period and the time when METRo forecasts are issued.

After the coupling period, it is noted that values retained during atmospheric forcing may still differ from forecasts from the 12-hourly provided SCRIBE matrices. Therefore, in the forecasting phase, the atmospheric forcing values may be modified to reflect the initial discrepancies between forecasts, and actual observations. To do this, METRo is initialized with the most recent forecasts available, and is then forced with both initial observations and original forecasted values.

METRo Challenges, Limitations, and Shortcomings

A major challenge that is faced when implementing METRo technology is the necessity for a profile of the road's surface and subsurface. If the previously mentioned 2 day observations are not carried out prior to the coupling phase, the METRo device will be unable to couple previous observations to predictions.

Another potential drawback with METRo software is that it takes approximately 2 seconds to generate a 48-hour forecast, which is rather long compared to the 0.2 seconds it takes to generate the same forecast for SNTHERM software, which only evaluates snow cover [8].

Moreover, the METRo appears to consistently perform poorly during the summer time. This issue can be mostly attributed to the fact that the METRo software was created for the purpose of analyzing roads in winter conditions. In past analyses, the METRo software has forecasted road temperatures that are up to 20°C higher than the actual temperature [9].

There are areas noted that could be improved upon within the METRo model, where there are shortcomings in the model's performance. While METRo is able to predict pavement temperature based off of snow and precipitation buildup on the road surface, it is currently unable to predict buildup of snow, ice, and rain on the road surface based on weather forecasts. Another shortcoming of the METRo software is its inability to evaluate the roadway's exposure to sunlight when predicting its surface temperature. Projected sunlight exposure is a key factor in the increase or decrease in pavement temperature, therefore it is crucial to use software able to factor in the amount of sun on the roadway's surface.

Statistical Models

Since physical model building is complex to simulate accurately, to apply in larger network, statistical approaches have been adopted for pavement temperature estimation. Sherif and Hassan (2004) developed a multi-linear regression model to predict pavement surface temperature by considering air temperature and dew point as independent variables (*10*). The model further included time-lag-dependent variables to eliminate autocorrelation for improvement. The models are well fitted by high R-square values above 0.90; however, the prediction accuracy would have been clear if the estimation errors and standard deviations were provided for model validation.

Krsmanc et al. (2013) proposed a linear regression model based on stepwise selection method and cross validation process (*11*). The final models were compared with a physical model METRo, and the result showed that statistical models are significantly better than METRo in terms of accuracy. Hosseini et al. (2015) developed a multi linear regression model and a neutral network model to forecast pavement surface temperature in parking lots with low traffic volume (*12*). The pavement surface temperature outputs of two multi linear regression models are hourly and daily based. The linear regression models show low R-square values. The study also developed Artificial Neural Network model to detect the complex relationships within variables. However, more detailed evaluations are needed to prove the acceptable accuracy of the models.

The BELLS equations developed using LTPP data are widely used in practice for in-depth temperature prediction within flexible pavement structure. The input data using BELLS include pavement surface temperature, average air temperature of one day earlier, depth below surface, and the time of day of testing (*7*). However, the pavement surface temperature need to be known first, which still relies on temperature sensors or manually measured at test locations.

Mohseni (1998) proposed the low and high pavement temperature models using data from LTPP Seasonal Monitoring Program (SMP) for the purpose of improving asphalt binder selection procedure in SUPERPAVE (*1*). The LTPP-SMP includes 30 test sites throughout the North America, collecting average hourly air temperature and pavement temperature of top 5 sensors. The low temperature regression model developed using SMP data include variables of air temperature, latitude of the section, and depth to surface.

Work Performed - METRo

METRo Case Study- Boulder, Colorado

A 2-day performance assessment was carried out starting on 7 July, 2006, in Boulder, Colorado in which METRo software was tested alongside the Fast All-season Soil Strength (FASST) model, to find a sufficient replacement technology for the aforementioned SNTHERM software. Several case studies were performed to compare road temperature predictions from FASST, SNTHERM, and METRo to observed road temperatures for an Environmental Sensor Station. For each case, two types of analyses were completed: one where road temperature predictions were generated using forecast atmospheric data, and another where predictions were generated using actual road surface/subsurface observations (perfect prognosis, or perfprog)

The case study began on 7 July 2006. The weather was warm and rainy. However, a "summer cold front" came across Colorado and rain ensued as predicted, dropping the temperature to the mid 60s. For the forecast driven road temperatures, SNTHERM and FASST respond well to the reduction in solar insolation associated with the predicted onset of rain. The METRo forecast on the first day reflects a clear cloud cover forecast, and it is closer to the peak road temperature than the SNTHERM and FASST. However, METRo does not respond well to the predicted rain. This data is reflected in the figure 7 below.

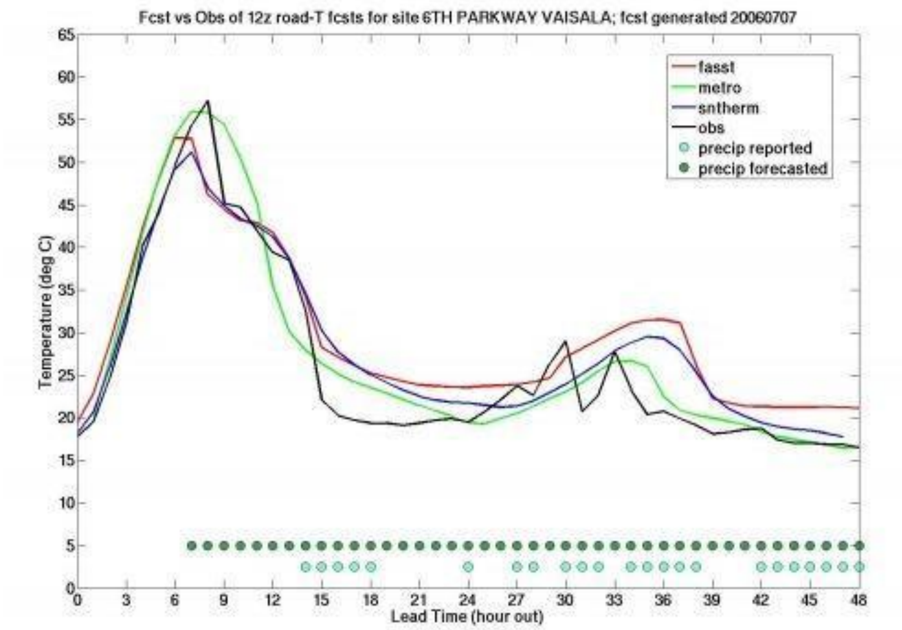


Figure 7. Comparison of predicted precipitation by model

For the perfect prognosis analysis, METRo showed the best overall road temperature forecast of the 3 systems when observed radiation values were considered, while FASST and SNTHERM underestimate road temperatures. METRo performs well in this test during the overnight phase, however, fails to outperform SNTHERM the next day. METRo software was unable to detect the differences between using observed cloud cover to derive solar radiation, and using observed radiation for temperature predictions. However, METRo was still able to predict accurate temperatures late into the afternoon and evening of the second day. Resulting data from perfprog analysis is shown in the figure 8 below.

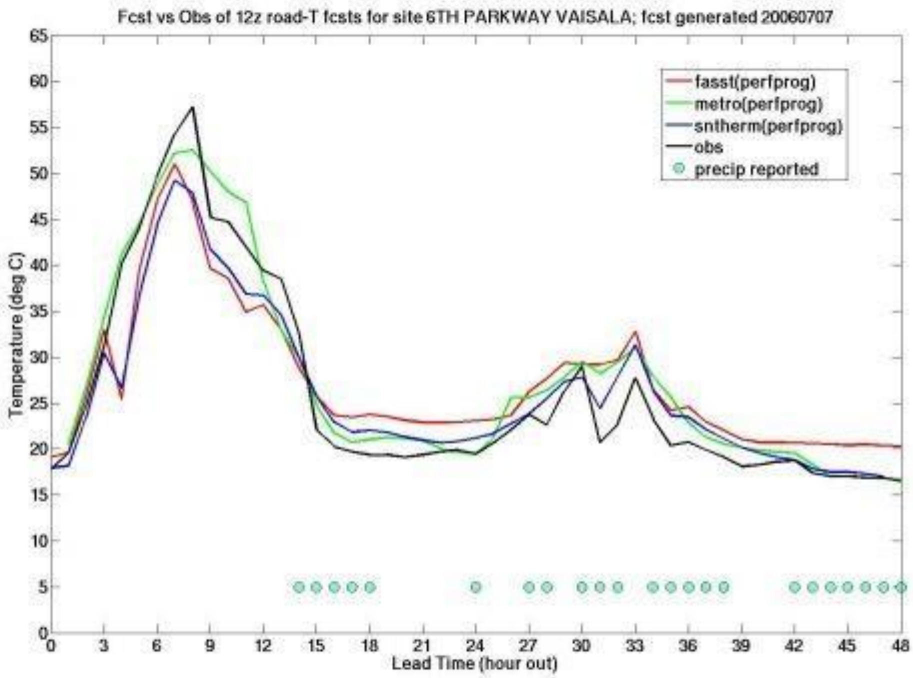


Figure 8. Comparison of predicted temperature by model

The study was continued on November 8 2006, with a record high temperature of 80^{o}F. For the forecast driven predictions, METRo's predictions are the closest to the observed road temperatures, while FASST and SNTHERM both underestimate the peak in road temperature. The following day (November 9) a weak, unexpected cold front, lead to an inaccurate weather forecast, which consequently led to poor predictions by all three technologies. METRo, FASST, and SNTHERM all overestimated the road surface temperatures, as shown by the figure 9.

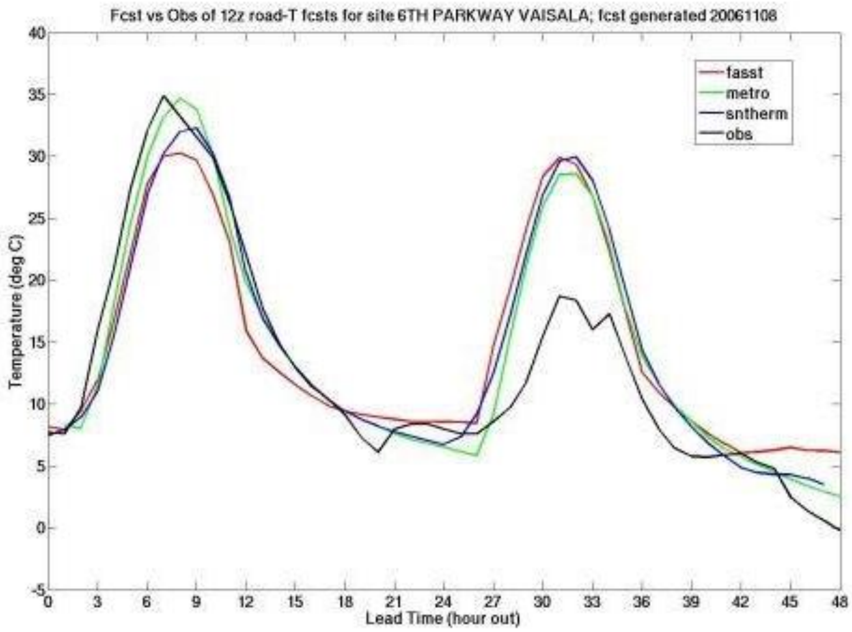


Figure 9. Comparison of predicted road surface temperature by model

The same two-day study was analyzed with perfect prognosis. The perfprog results showed that the METRo software provided the best forecast. It is noted that METRo does well with emulating the increase and decrease in pavement temperatures during the morning and afternoon, respectively, and also does well in predicting overnight pavement temperatures. On the following day, the 3 technologies were not misled by the unexpected cold front, and METRo again shows the most accurate forecast. METRo and FASST overestimate the pavement temperature on the second night, while SNTHERM underestimates, as it did the first night. The aforementioned results are shown in the Figure 10.

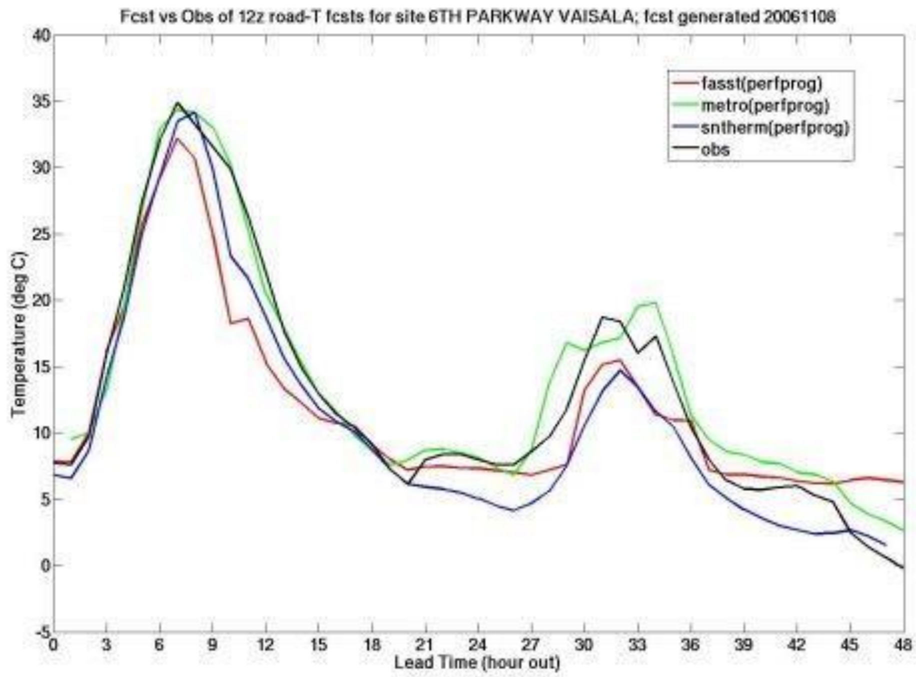


Figure 10. Comparison of predicted road surface temperature by model

The case study was continued, and finalized, on November 28 2006, with 5 to 6 inches of snowfall that began falling at 5PM. On the first day, the forecast driven predictions show all three models do well in predicting pavement temperatures. However, METRo provided superior forecasts in the afternoon, with FASST overestimating, and SNTHERM under predicting. METRo also does notably well in predicting pavement temperatures upon snowfall, with only a slight cold bias during day 2, and a slight warm bias through the second night see figure 11.

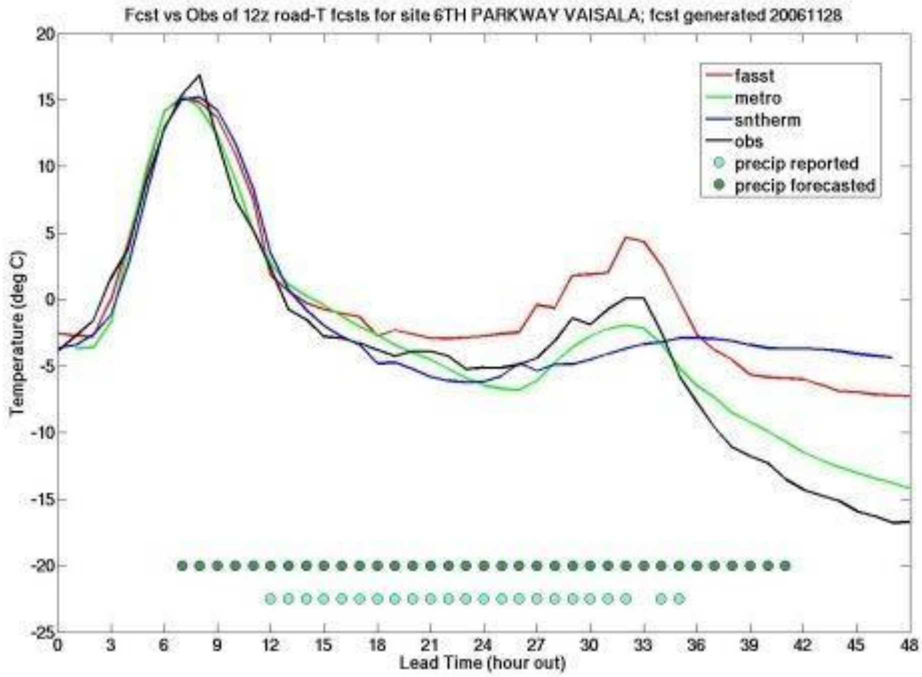


Figure 11. Comparison of predicted road surface temperature by model with snowfall

In the perfprog analysis, results are similar to the forecast driven test results. While all three models underestimate the peak road temperature, METRo does well in predicting the decrease in road temperature throughout the afternoon, while temperature decreases by FASST and SNTHERM are predicted too early. Throughout the night of November 28, METRo remains the most accurate forecast, while FASST and SNTHERM predict temperatures too cold and too warm, respectively. Day two forecasts show an underestimation of the increase in pavement temperature upon sunrise by the METRo model. The predictions by FASST after sunrise are accurate, but predictions are overestimated throughout the day. SNTHERM showed poor results due to the buildup of snow, causing for inaccurate forecasts by the model. These results are shown in the figure 12 [8].

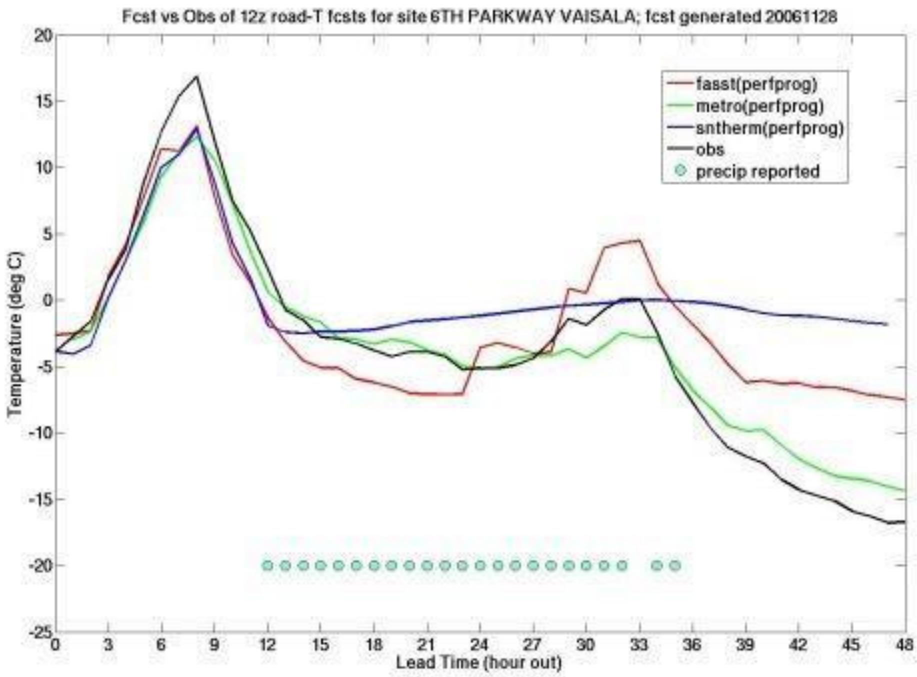


Figure 12. Comparison of predicted road surface temperature by model with snowfall

METRo Case Study- Ames, Iowa

A 28 day study was conducted on Interstate Highway 35 in Ames, Iowa, to further analyze the precision and accuracy of the METRo software in forecasting pavement temperatures. A 2 month calibration validation test was conducted using the METRo model in order to validate the results given by the model in relation to observed phenomena. The station observed for calibration validation was station RAMI4, located on I-35 where it overpasses East 13th Street in Ames, Iowa. For this calibration validation, METRo required 3 separate input schema: RWIS Station Observations, Atmospheric Forecasts, and RWIS Station Configuration. The station was analyzed for archived data from January 3, 2014 to January 31, 2014.

METRo Data Format

METRo is able to accurately predict the road conditions in an area based off of the observed road conditions, predicted forecast and station location details. These files must be in an .xml format or else METRo will not be able to run. Additionally, the observed conditions must overlap with the predicted forecast so that METRo has a baseline as to how the road will act against the given forecasted data. The forecasted data must be in an hourly format and it is advised that the observation is also in an hourly format. This is because METRo needs the observation and forecast data array length to be the same size. If the data is not the same size, METRo will automatically cut the data until the array lengths the same size. Thus, in order to not lose any data, the data sets should both be in an hourly format and be the same array size.

The observation, station, forecast and output roadcast files each have their own parameters which define them. Table 1 describes the parameters that make up the observation data set. The element names describe how the xml file should abbreviate each field description. If this is not setup correctly with the correct units, METRo will either produce a fatal error or output the wrong data.

Table 1: Required Data Format for the Observation data file

Field Description	**Element Name**	**Unit**
Date and time of observation	observation-time	ISO 8601
Air temperature	at	Celsius
Dew point	td	Celsius
Presence of precipitation	pi	0: No -- 1: Yes
Wind speed	ws	km/h
Road condition	sc	SSI code
Road surface temperature	st	Celsius
Road subsurface temperature (40 cm)	sst	Celsius

Atmospheric forecasts are needed for the METRo model to formulate accurate pavement temperature forecasts based upon atmospheric conditions. Phenomena such as cloud cover, wind speed, air temperature, and dew point temperature are prominent in affecting the temperature of pavement. Table 2 shows atmospheric forecasts inputs needed by the METRo model.

Table 2: Required Data Format for the Forecast data set

Field Description	**Element Name**	**Unit**
Date and time of forecasted elements	forecast-time	ISO 8601
Air temperature (1.5 m)	at	Celsius

Dew point (1.5 m)	td	Celsius
Rain precipitation quantity since the beginning of the forecast	ra	mm
Snow precipitation quantity since the beginning of the forecast	sn	cm
Wind speed (10 m)	ws	km/h
Surface pressure (at the station height)	ap	mb
Octal cloud coverage (0-8)	cc	octal

The Station Configuration input schema is a configuration of the RWIS station being analyzed for its data output. For this study, station RAMI4 in Ames Iowa, located on Interstate 35. Table 3 shows the configuration of station RAMI4.

Table 3: RAMI4 Station Configuration format

Field Description	**Element Name**
Version number	version
Date of creation	production-date
Time zones of station	time-zone
Latitude and longitude	coordinate + latitude, longitude
Station type	station-type

One of the variables produced by the roadcast output file is the road condition, or rc. Table 4 shows the different variables and their respective road conditions as produced by METRo.

Table 4: Different Road Conditions with METRo Values

Description of Road Condition	**METRo Value**
Dry Road	1
Wet Road	2
Ice/Snow on the Road	3
Mix Water/Snow on Road	4
Dew	5
Melting Snow	6
Frost	7
Icing Rain	8

Results and Discussion

Installation of METRo is a tough and tedious process when installed on Ubuntu, this is due to the fact that METRo relies on a lot of dependencies as runs code in python, C++ and FORTRAN. FORTRAN is an old language and should eventually be replaced by a more robust and current language. Additionally, the steps for proper installation on the METRo wiki often did not work and required someone with advanced knowledge in Linux to navigate around these problems. A test was completed on another Linux distribution, CentOS in which the installation of METRo was attempted. The installation of METRo took a fraction of the time then it did on Ubuntu, thus future work on this project should be completed on the CentOS distribution for ease of installation and use. In order to make the process of using METRo easier, a GUI was created that allowed for METRo to be accessed independently of the command line. This GUI was operational in both Linux and Windows, Figure 14. This means that the user of METRo does not have to be proficient in the command line in order to run METRo.

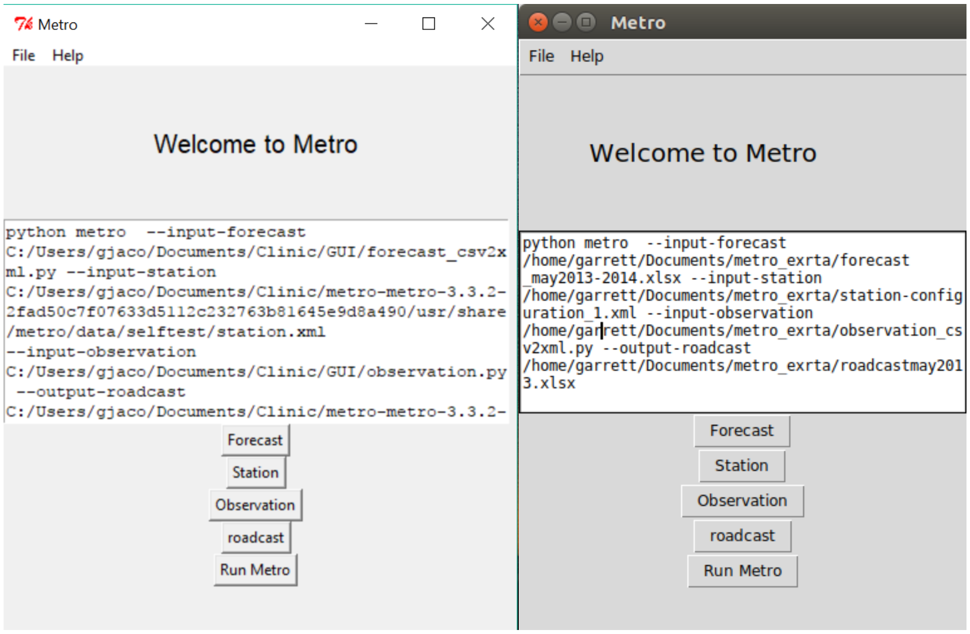


Figure 14. GUI implementation in Windows (left) and Linux (right)

Data manipulation was a huge part of getting METRo to work as once the installation was successfully completed, the data needs to be properly formatted as stated above or else METRo will not be operational. This data can be downloaded from https://mesonet.agron.iastate.edu/RWIS/ which will give the observation data and https://gis.ncdc.noaa.gov/maps/ncei/lcd which is where the forecasted data is located. The data was manipulated in excel which allowed large amount of data to be altered at one time. This process was limited to the processing power of the computer as altering large amounts of data takes a vast amount of time. For ease of use in the future, the data should be manipulated in a more robust program like MATLAB. The data was converted from csv file to xml format using a python script. Thus, setting up the data in the correct format in the excel file was imperative.

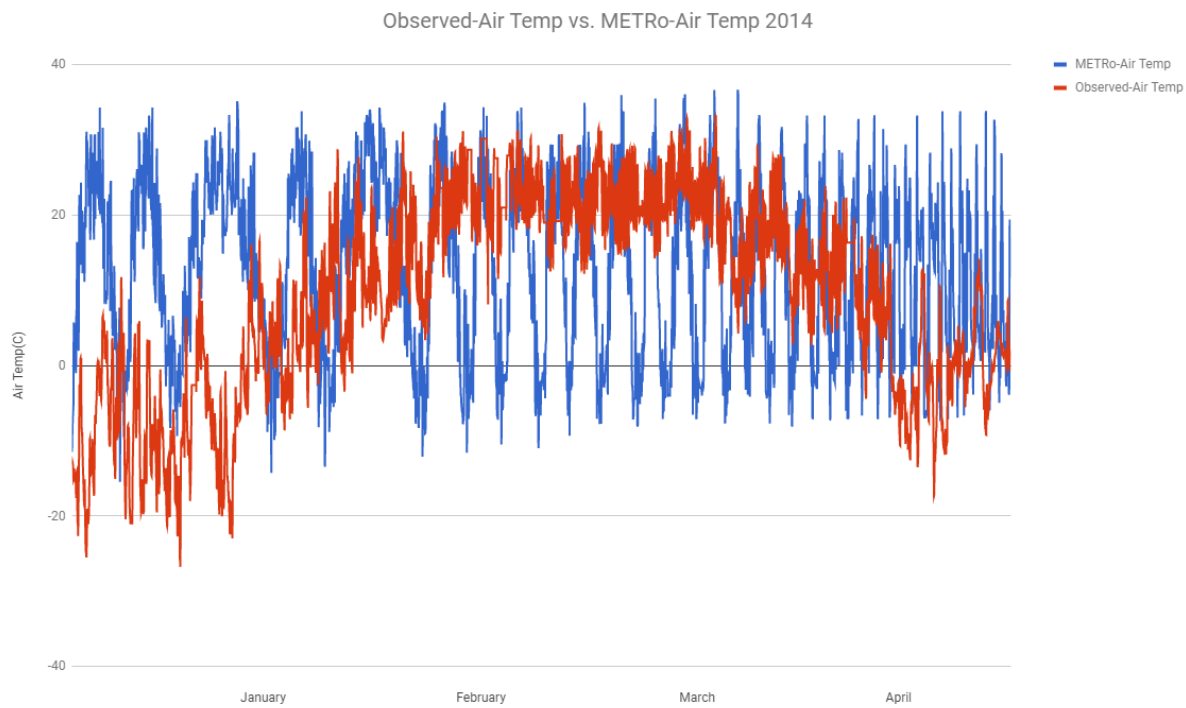


Figure 15. METRo air temp vs predicted air temp over 4 months

The graph above shows the difference between the observed air temperatures to the output of METRo's air temperature, figure 15. The blue lines are for METRo while the red is for the observed. The reason being that METRo is off in the graph above is because one of its faults is failure to be compatible with summer temperatures. This is why the readings are much higher than the actual given readings from the observed air temperature. This shown to be true because once it reaches the month of April it is severely higher. As said previously in the report METRo is meant primarily for colder conditions and not warmer temperatures.

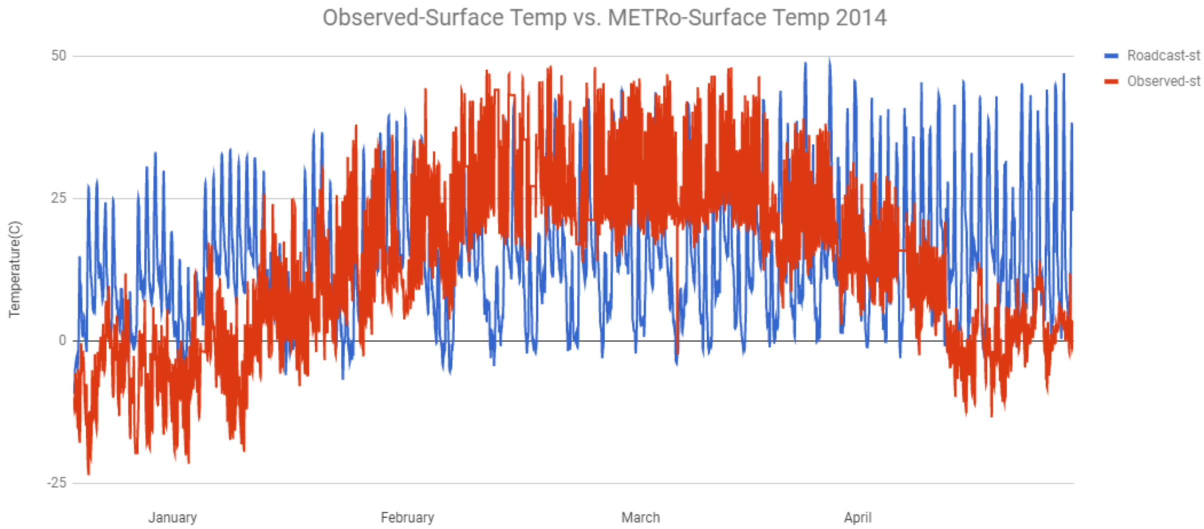


Figure 16. METRo surface temp vs predicted surface temp over 4 months

The graph in figure 16 demonstrates METRo's surface temperature to the observed surface temperature. This is the predicted weather given by METRo; as it is seen above METRo is very off compared to actual readings from the observed. This is due to METRo taking in readings from the overall day in frequency of hourly intervals. This will have it estimating the overall weather predictions to a close approximation for the day, which will vary from actual data taken by the station for observation.

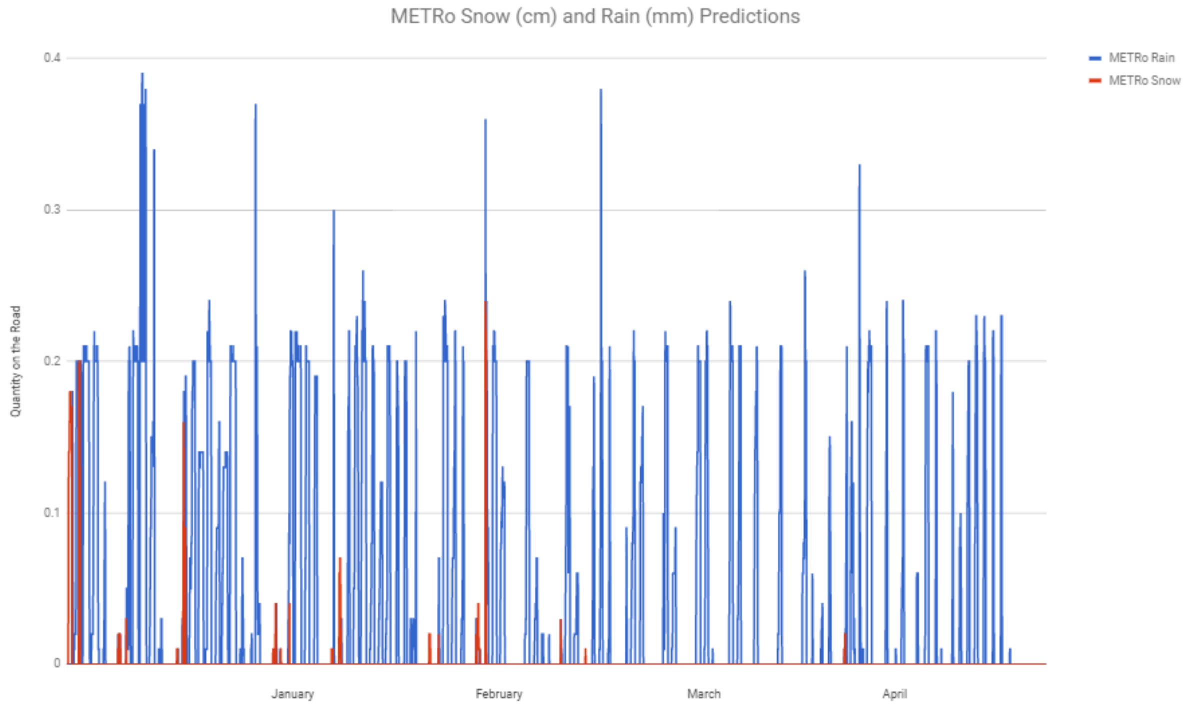


Figure 17. METRo rain and snow predictions

The graph above shows the rain and snow predictions given by METRo. Although METRo managed to predict the snow for January and most of February, there is much more rain than snow in the months that approach warmer temperatures. This can help with road maintenance because the salt trucks will know how much salt is required for the roads depending on the amount of snow on the road. Likewise, predicting the amount of rain will help cities figure out ways to avoid flooding on the streets and highways. This is one of the many benefits that METRo will have when it is finally perfected and ready to be launched.

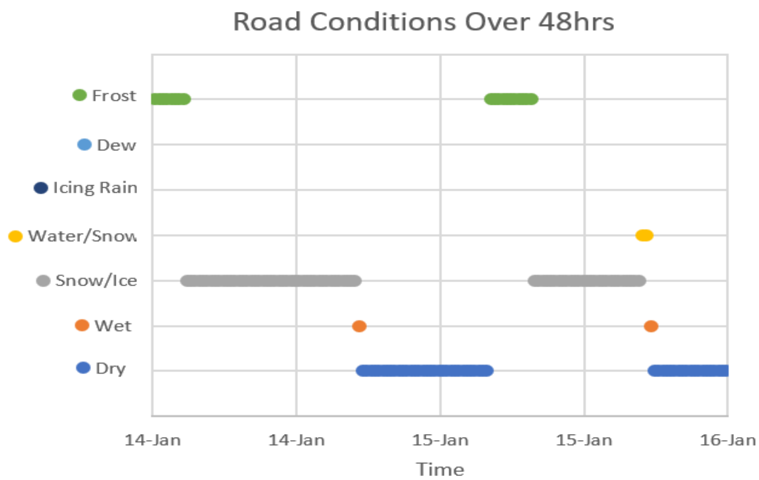


Figure 18. 48 Hour Road Conditions

A follow up to the study done on the RWIS station in Ames, Iowa was conducted in order to reduce the amount of noise in the data. This was completed by shortening the span of time of METRo's output from four months down to 28 days. METRo should ideally be used for shorter periods of time and mostly in the winter as these are the conditions where METRo is the most beneficial. METRo's output of the road conditions in the roadcast file were plotted in figure 18 to show the several different road conditions forecasted over a two day period from January 14, 2014 to January 16, 2014. Several different road conditions were observed over the two day period. Having accurately predicted road conditions is important in preparing for winter storm maintenance because maintenance crews need to know if snow or icy conditions will persist on the roads in order to prepare salt trucks.

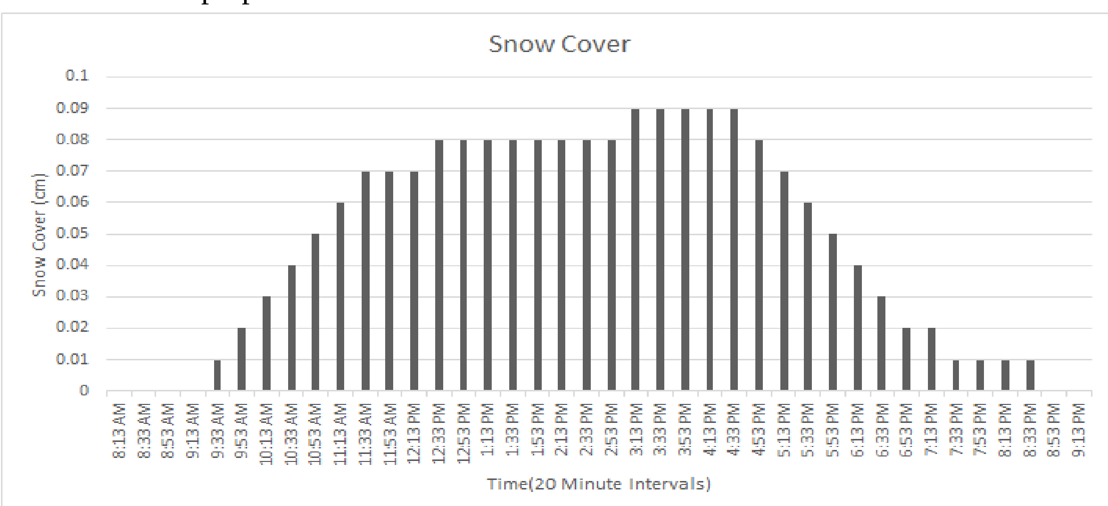


Figure 19. Snow Accumulation on Road

Ease of Access

Another look was taken at the GUI displayed in Figure 14 and improvements were made in order to make it easier to use. The GUI was written in python with the use of tkinter which allows the user to make a GUI. This was completed by re-imaging the entire layout of the GUI for a more aesthetic look. With the selection of each button, a file drop down menu appears where the user can select the resected file. Normally, the user would have to type in the location of their files in the command line. However, with the use of a button, when the user selects the file that they want to add, the code will automatically be generated for the location of that file and the file name will also be added to the command line. Additionally, when using the old GUI, there was no way for the user to clear their input into METRo unless they restarted the GUI. Thus a clear button was added to the GUI so if the user made a mistake on selecting their files, they can easily clear the input code without having to restart the program. Furthermore, the help button will now direct the user to the METRo wiki, where they can find more detailed information on METRo.

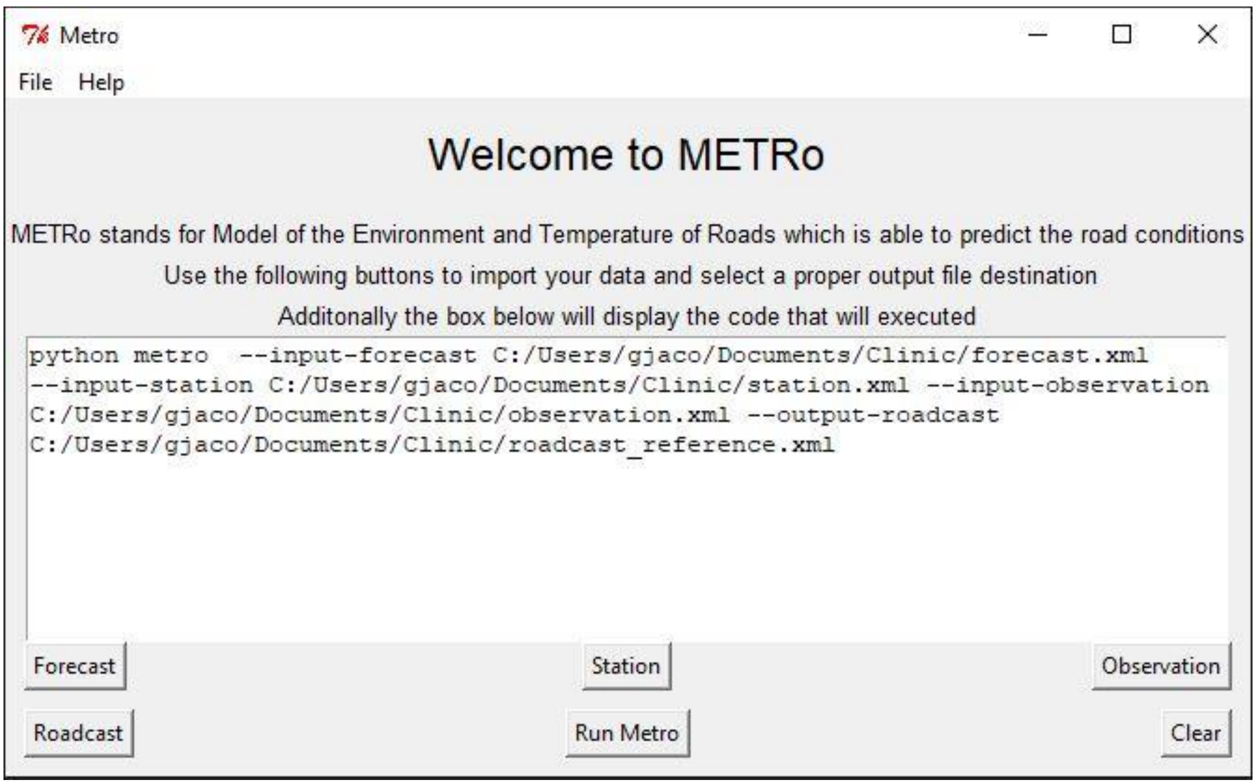


Figure 20. Updated GUI

Proper instillation of this GUI is key in order to for it to work properly with METRo. The GUI files can first be downloaded off of GitHub with the link to the GitHub location is found on Dr. Nazari’s webpage. Once the file is downloaded, it should be placed in the following location: “/usr/local/metro/metro/usr/bin”. This is where the metro.py file is located, which is the location that the user of METRo would normally have to go to if they were to run METRo. After the file is placed in the according directory, a shortcut should be made of the file and placed on the desktop.

When the user accesses the shortcut on their desktop, the shortcut will act like a normal program desktop shortcut and launch the GUI. The user is now fully setup to use the GUI to run METRo. Additionally, when working with METRo, the inputs to METRo have to be in xml format. However, when working with the forecast and observation parameters, the data is in csv and xlsx. In order to easily transfer the files to xml file format, two different python scripts were created that takes in a csv file and output the proper xml format for METRo. A script for the forecast file and observation file were created and can be located on the GITHub page for the METRo GUI. When using the scripts, the user should place the scripts in the same location as the file that they are trying to convert. Additionally, the user should go into the python scripts and change the file name and the output file name respectively. This will make more sense when looking at the python file and is further detailed in the python script itself. The user can call the script with the the python command in the command line.

Conclusion

In conclusion, it was found that METRo's ideal usage should be for short periods of time. Using a shorter period of time allows METRo to produce a more accurate forecast. When implemented by different companies, METRo should mainly be used in the winter time, as this is when METRo's road condition or snow accumulation output can be utilized the most. A GUI was also created to make METRo more accessible to users, providing ease of access and reducing the time it would normally take to input data, making Road Weather Information Systems technology more practical for implementation into industry.

Work Performed – Statistical Models

LTPP DATA COLLECTION AND PREPARATION

Data Collection

The data used in this study were collected from the Federal Highway Administration's (FHWA) Long-Term Pavement Performance (LTPP) Program at INFOPAVE. The integration of pavement surface temperature from falling weight deflectometer (FWD) test data and metrological data from MERRA provide sufficient information to accomplish the objectives of this study. Modern-Era Retrospective Analysis for Research and Applications (MERRA), Version 2, supported by NASA, is recently released by LTPP database. It provides hourly based weather and climate information world-wide beginning in 1980.

From literature review, the most important variable in statistical regression model is air temperature; other variables help to explain the variation of pavement surface temperature are solar radiation, wind velocity, and dew point (*1, 10, 12*). To evaluate the contribution from possible meteorological variables in the regression model, we collected five meteorological variables and three variables the day before from MERRA data sets. The meteorological variables are wind velocity, precipitation, surface shortwave radiation, cloud cover, humidity, total solar radiation the day before, average air temperature the day before, and the average humidity the day before. In addition, pavement type, surface layer thickness, air temperature and pavement surface temperature are extracted from data set of “FWD Data without Drop Data” under “Data Selection and Download”.

Since this study is interested in the temperature response of rigid pavement surface under cold weather conditions, only states in cold region were considered. In further data screening steps, the states of Iowa are selected because it has fairly large amount of road surface temperature data during cold months. The test time of the selected data is from 1990 to 2010. Noted that year selection is not an impact factor of the analysis, the primary intention of time period selection is to collect sufficient data points in cold seasons.

Interpolation with Linear Approximation

The biggest obstacle of collected data is the unmatched time of observations from two different data sets. Variables of pavement type, surface layer thickness, air temperature, and pavement surface temperature extracted from FWD tests have uneven time spaces varying from one minute to hours depending on the test date and time. On the other hand, meteorological variables collected from MERRA data sets are hourly based data at time of integral points.

To optimize the use of available data without compromising the accuracy of meteorological variables, locally weighted variables using linear approximation for data smoothing is introduced. With this process, the resolution of meteorological variables collected from MERRA data sets will change from hourly based to minute based. Since the time intervals are small, the assumption is the relationship of meteorological variables between two hours is linear and can be approximately reproduced from data given by MERRA data set. Equation 1 shows a unique linear function passing through two neighboring data points of (t_m,$f(t_m)$) and (t_{m+1},$f(t_{m+1})$). Finally, the estimated meteorological variables were matched according to the SHRP_ID and test time from FWD data set.

$$f(t) = \frac{t-t_{m+1}}{t_m-t_{m+1}}\, f(t_m) + \frac{t-t_m}{t_{m+1}+t_m}\, f(t_{m+1}) \qquad (1)$$

$$t_m \le t \le t_{m+1}, \qquad m \in [0,1,2,3,\ldots,23]$$

Where, t equals to the time between two integral time points corresponding to the time of dependent variable collected from FWD tests; $f(t)$equals to the reproduced meteorological values at time t; and m equals to integral time from morning (0) to midnight (23).

Statistical Summary

Table 1 show the statistical summary of dependent and independent variables. The number of observation is 455. The minimum value of pavement surface temperature is -5.2℃, the maximum is 29℃, and the average is 11.08℃. Amount all the independent variables, air temperature is most closely related to pavement surface temperature. Figure 1 plots pavement surface temperatures versus air temperatures that were used in the analysis. It is obvious that there is a positive correlation between pavement surface temperature and air temperature. However, the relationship between pavement surface temperature and air temperature may not be fully captured in a simple linear relationship.

Table 1 Statistics Summary of Dependent and Independent Variables (Number of Observations 455)

Variable Description	Label	Unit	Mean	Std Dev	Minimum	Maximum
Pavement Surface Temperature	T_PVMT_C	℃	11.08	7.26	-5.20	29.00
Air Temperature	T_AIR_C	℃	10.40	7.23	-9.60	20.90
Wind Velocity	W	m s-1	10.73	4.70	0.00	24.61
Could Cover	C	%	0.52	0.38	0.00	1.00
Shortwave Surface	SO	W m-2	489.72	230.13	9.10	980.20
Precipitation	P	mm	0.01	0.02	0.00	0.20
Relative Humidity	H	%	55.77	14.56	28.00	88.00
Total Surface Shortwave Radiation the Day Before	S_1	W m-2	4358	1606	1013	8311
Average Relative Humidity the Day Before	H_1	%	71.87	10.93	45.00	94.00
Average Air Temperature the Day Before	T_1	℃	7.66	7.86	-9.30	22.50
Latitude	LAT	Degree	41.88	0.36	41.56	42.62
Pavement Thickness	TH	mm	33.12	12.10	11.70	52.60

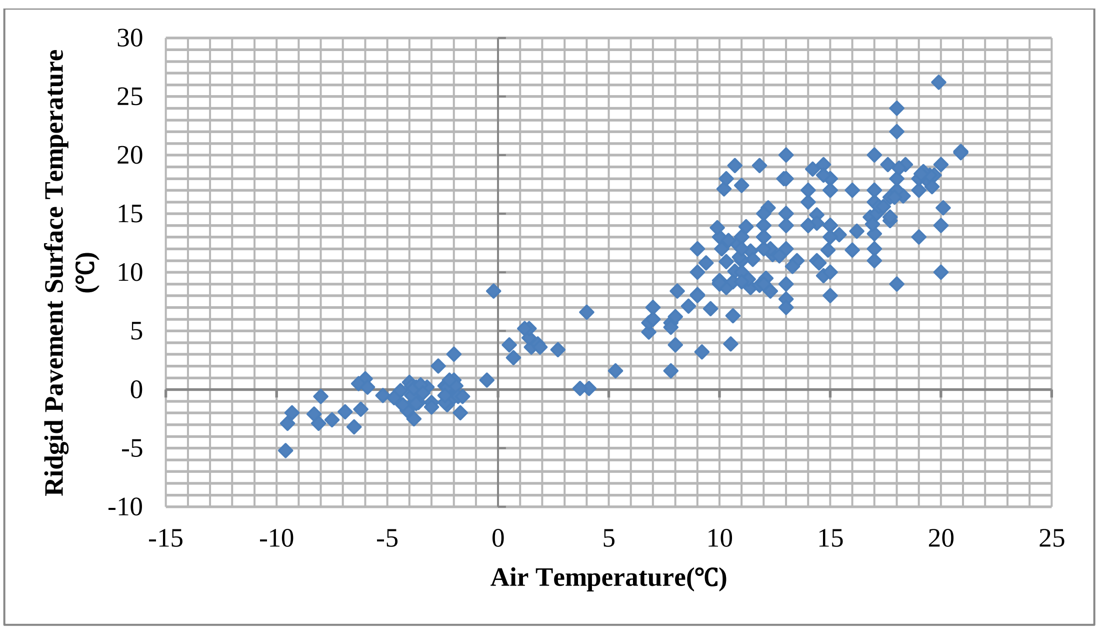


Figure 1 Rigid Pavement Surface Temperature v.s. air temperature

MODEL DEVELOPMENT

Variables Selection

In order to develop a statistical multiple linear regression model using meteorological variables and pavement properties to predict pavement surface temperature under cold weather condition, the model construction uses stepwise selection process to include the most appropriate independent variables.

Stepwise regression algorithm is one of the most popular processes among model selection-type procedures. It is a combination of forward and backward selection methods; when it adds a variable the process it also considers dropping any of the variables in the model that are insignificant at level alpha (*13*). Since a variable added in the earlier steps might be unnecessary because the relationship between it and other repressors are changed in each step. The cutoff values for entering and dropping variable are alphas at 0.05, which means all coefficient estimates have to be significant between 0 to 0.05 levels.

After running a preliminary stepwise regression using all variables shown in Table 1 to predict pavement surface temperature, a common type of model inadequacy has been detected through plots of residuals. Figure 2 shows the predicted value against residual. The ideal graph would be where points are in a horizontal band and departure from that indicates model defects; however, a u-shape has been shown which suggests that relationship is not linear and more x variables are needed. After adding other important plots of residuals against each regressor, a similar trend of u-shape had been found specific to the variable of air temperature as shown in Figure 3. We decided to incorporate a square term of air temperature in the model which later has been proved to significantly improve the model adequacy. In addition, the transformation of logarithm with the base of 10 has been applied to the variable of Total Surface Shortwave Radiation the Day Before as to avoid the extremely small coefficient of that variable.

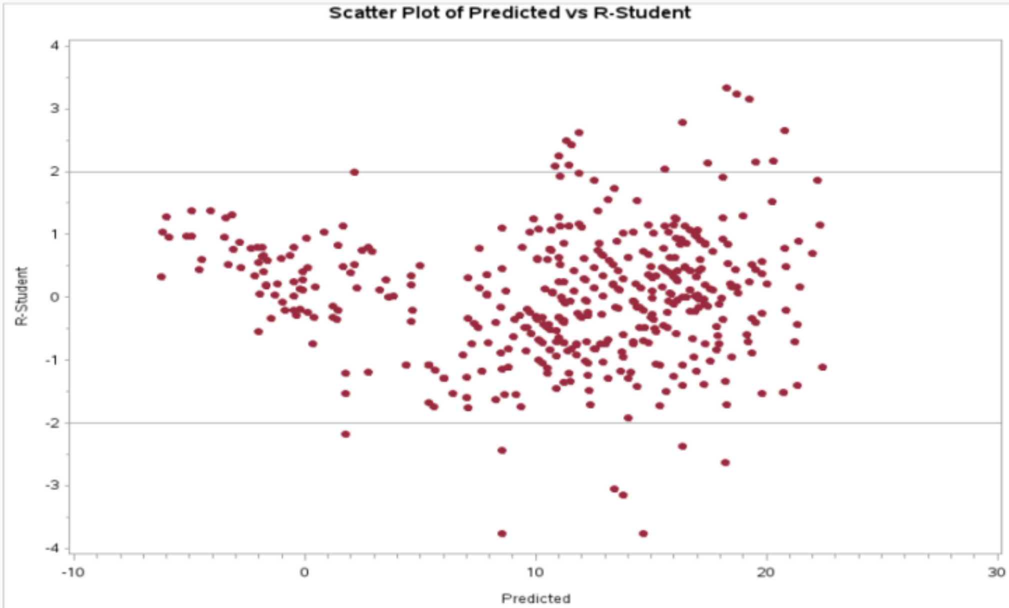


Figure 2 Plot of Predicted Value against Residual

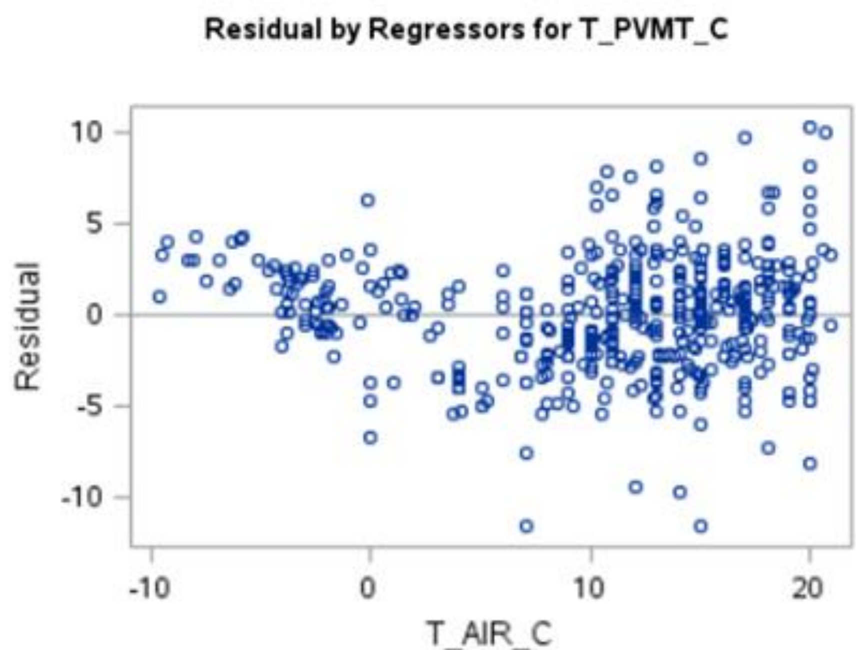


Figure 3 Plot of Residuals against the Regressor of Air Temperature

Table 2 shows the summary of stepwise variables selection process in predicting pavement surface temperatures for concrete surface. The prediction model includes variables of air temperature, a square term of air temperature, the product of air temperature and pavement thickness, average humidity the day before, and total surface shortwave radiation the day before. Each variable are significant at 5% level and the final model is overall significant with very low P-value close to zero. In addition, the final step has a small Mallow's C (p) value of 6.80 which is very close to numbers of parameters of 5, indicating that it is the most desirable selection of subset parameters among other regression models. When Mallow's C (p) value is far deviated from value of the numbers of parameter in the model, there is bias with the regression equations. Mallow's C(p) value is related to mean square error of a fitted value, as shown in Equation 2 (*13*).

$$E\,[\hat{y}_i - E(y_i)]^2 = E\,[\hat{y}_i - E(y_i)]^2 + Var\,(\hat{y}_i) \tag{2}$$

Where, $\hat{y}_i$ is the predicted value, and $y_i$is the observed value.

Table 2 Summary of Stepwise Selection

Summary of Stepwise Selection									
Step	Variable Entered	Variable Removed	Label	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	T_AIR_C		T_AIR_C	1	0.7941	0.7941	88.9700	1747.49	<.0001
2	T_AIR_C_2		T_AIR_C_2	2	0.0138	0.8079	54.8907	32.36	<.0001
3	T_AIR_TH		T_AIR_TH	3	0.0100	0.8179	30.7246	24.70	<.0001
4	H_1		H_1	4	0.0047	0.8225	20.4654	11.85	0.0006
5	LOG_S_1		LOG_S_1	5	0.0060	0.8285	6.7987	15.64	<.0001

Instead of depending on the stepwise variable selection process, it is also desirable to consider regression models with all possible combinations of the independent variables and compared with the result generated by stepwise process. In this case, there are thirteen independent variables available, which means 8192 (2^{13}) models are possible for examination. In the output generated by SAS, the first three potential winning models with a ranking of the highest Adjust R-square were compared.

Table 3 Top 3 models with the highest Adjusted R-Square

Number in Model	Adjusted R-Square	R-Square	C(p)	AIC	BIC	MSE	SSE	Variables in Model
5	0.8266	0.8285	4.6734	1013.0985	1015.2944	9.14760	4107.27043	T_AIR_C_2 T_AIR_C LOG_S_1 H_1 T_AIR_TH
6	0.8264	0.8287	6.1951	1014.6121	1016.8559	9.15822	4102.88208	T_AIR_C_2 T_AIR_C LAT LOG_S_1 H_1 T_AIR_TH
6	0.8263	0.8286	6.4813	1014.9032	1017.1379	9.16408	4105.50771	T_AIR_C_2 T_AIR_C LOG_S_1 SO H_1 T_AIR_TH

From Table 3, the first model with 5 variables is the same with the result using stepwise selection, and the three models have very similar performance in most criteria such as Adjust R-square, R-square and MSE. Although the second and the third model have one additional variable in the model, comparing the first model, it shows that the introduction of variables of latitude and shortwave radiation to the surface does not increase the adjusted R-square value. Hence, the variable of latitude and shortwave radiation brings similar information with other variables or provide little improvement to the model. One of the possible explanations would be latitude within a single state fails to significantly alter pavement surface temperature although it might has a superior impact within a larger geographic extent, for example, in national-wide. At the same time, the variable of shortwave radiation provides less information to explain the variable of the change of pavement surface temperature as compared to the total surface shortwave radiation the day before. By evaluating all possible combinations of the independent variables, the variable selection of Stepwise process has been reinforced.

Detection and Examination of Outliers

One of the assumptions in building multiple linear regression models it that the errors should be normally distributed with mean 0 and constant variance. Since the violations of the basic multiple linear regression assumptions might lead to an extreme deviation of expected performance of the model, the assumptions should be tested and effectively corrected whenever necessary. It is noted that the above sections of variables selection are global model properties which do not guarantee model adequacy, thus the examination of outliers to diagnose the violations of the basic regression assumptions are necessary.

To evaluate and detect the potential outliers of the 455 observations of asphalt pavement based on the model selected by stepwise process, two methods of Cook's Distance and Studentized Residual for residuals scaling are chosen. Cook (1979) has suggested a way to measure the influence of a point on the estimated values of $\beta's$. The measure of the squared distance between the least-squares estimate based on all n pints $\hat{\beta}$ and the estimate obtained by deleting the ith point $\widehat{\beta_1}$ (*14*). Another way to interpret Cook's distance is that the vector of fitted values moves when the i^{th} observation is deleted. Studentized Residual improves the residual scaling by dividing the prediction error by the exact standard deviation of the i^{th} residual. The violations of model assumptions are more likely at remote points which drag the regression model towards it as to reduce the large error. Studentized Residual larger or equal to 3 are suspect for the outliers; Cook's D equal or larger than 4/n (n is the number of observations) is the widely accepted cut-off values for highly influential points.

By computing Cook's Distance and Studentized Residual for each observation, 38 data points exceeding the threshold values are filtered out. Most of the outliers are data points concentrate in 1990, 1992 and 1993. The possible causes would be measurement errors due to sensor malfunction, extreme weather conditions, regional climate difference, changes of traffic conditions, or changes of landscaping such as new plants and high raised buildings. Such observations might create confusions in model building process. As a result, the data points were deleted as suspected measurement errors although the alarm of high Cook's Distance is worth further examination in the future analysis.

Model Reconstruction

With the removal of outliers, the number of observations changes from 455 to 417, the model structure changed responding to the new data set. Some of the independent variables selected from previous model building process using original data set might not be insignificant at the moment. Thus model reconstruction is necessary to find the best fit with new set of data. The selection method will be stepwise process with cutoff values for entering and dropping variables at 5% significant level as well as considering regression models with all possible combinations of the independent variables.

The best model structure from stepwise analysis of pavement surface temperature prediction remain the same, including air temperature, a square term of air temperature, the product of air temperature and pavement thickness, average humidity the day before, and total surface shortwave radiation the day before. At the same time, the adjust R square is 0.8893 which is higher than the previous model structure with 0.8266. Another significant improvement would be the reduction of MSE from 9.15 degree Celsius to 5.33 degree Celsius, indicating the accuracy of the prediction has improved. The increased accuracy can be shown from the comparison of two scatter plots of predicted value verses observations of pavement surface temperature. The scatter plot on the left (a) in Figure 4 is from regression model with original data set, and scatter plot on the right (b) is from regression model without outliers. It is obvious that predicted pavement surface temperature on (b) plot is more concentrated and fall near the line of predicted value equals to observations.

$$Rigid\ Pavement\ Surface\ Temperautre\ [℃] = (-)11.863 + 0.0151 * T\_AIR\_C^2 + 0.815 * T\_AIR\_C + 0.046 * H\_1 + 2.897 * LOG\_S\_1 - 0.048 * T\_AIR\_TH/10 \quad (3)$$

Where, T_AIR_C is Air Temperature in ℃; H_1 is average humidity the day before in the unit of percentage; S_1 is total surface shortwave radiation the day before in W m^{-2}; T_AIR_TH is the product of air temperature in ℃ and pavement thickness in mm.

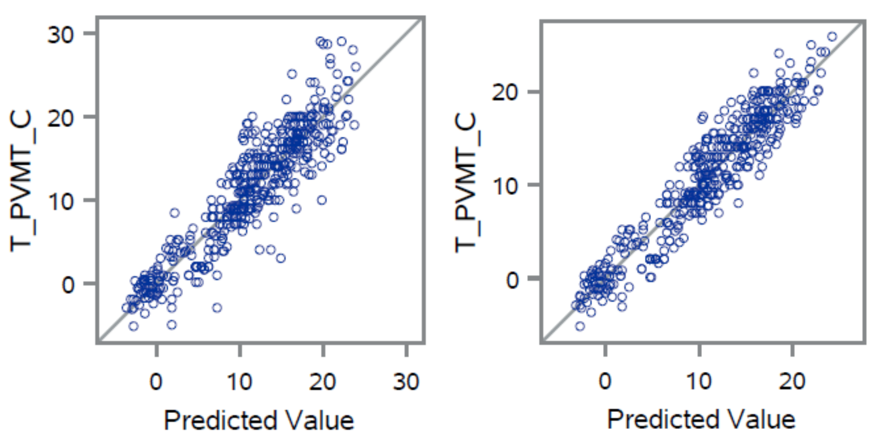


Figure 4 Scatter plots of predicted value verses observations of asphalt pavement surface temperature (degree Celsius): (a) regression model with original data set; (b) regression model without outliers

MODEL EVALUATION

Cross-Validation

Picard and Cook (1984) pointed out that when a winning model is chosen using a particular set of data, the ability of prediction of future observations with the model is not likely to be the same as one would expect (*15*). The dilemma of difference between sample and population is persistent. Ideally, a good model requires evaluation from future data to get a sufficient estimator of MSE although it is impracticable during model construction process. To accelerate this process, part of the present data can be reserved for model validation. Thus, the predictive ability of a model could be expected by its ability to predict the data of the hold-out sample. At the same time, the predictive ability of a model is reflected by statistical properties of the difference between the observed and predicted dependent variables$(Y_i - \hat{Y}_i)$ (*15*).

This study uses k-fold random cross validation for holdout process. Figure 5 shows the working principle of k-fold cross validation. The data is roughly split into 5 equal-sized parts. The observation is randomly chosen using binomial distribution with assigned p=0.8 and (1-p) =0.2. The training process consists of k-1 folds of data using method of least squares estimation, and 1 fold of data is holding out for validation purpose. The fitted models from the training process are used to calculate the predicted residual sum of squares on the validation part. As a result, estimated prediction error denoted by CVPRESS can be obtained from the sum of k predicted residual sum of squares.

Root Mean Square Error and CVPRESS are widely used measures of model performance in cross validation. The results show that Root Mean Square Error is 2.308 degree Celsius for pavement prediction model the CVPRESS is 2259 from the five-fold cross validation, indicating the standard deviation of the difference between the predicted values from the model and the real observations of pavement surface temperature is about 2 degree Celsius. Hence the selected model is validated and the accuracy to predict concrete pavement surface temperature is within 2.3 degree Celsius.

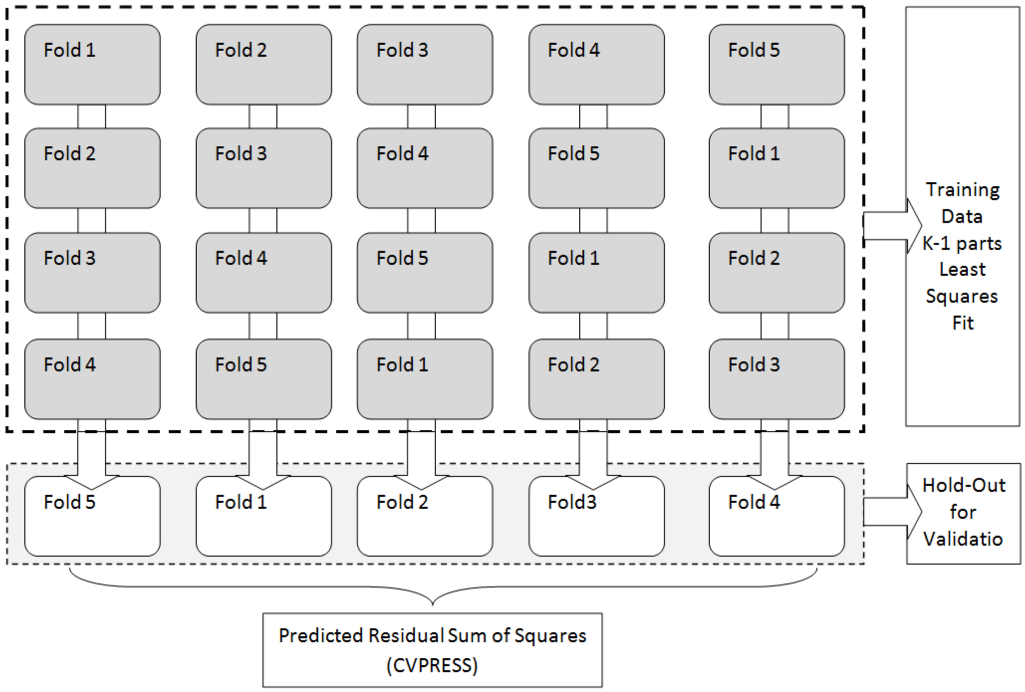


Figure 5 Applying k-fold cross validation (k=5)

DISCUSSION & CONCLUSION

This study developed and validated statistical regression models for rigid pavement surface temperature prediction to facilitate winter road maintenance. Compared to physical model for pavement temperature prediction, the inputs of the proposed model only require basic pavement information and easily assessable weather forecasting data. Moreover, the proposed model reaches the ideal situation when variable coefficients are physically logical and the selected model is in a good statistical performance.

After data collection and preparation, a range of statistical analyses were conducted to develop multiple-linear regression model for rigid pavement surface temperature prediction under cold weather conditions. Variables included in the model are air temperature, a square term of air temperature, the product of air temperature and pavement thickness, average humidity the day before, and total surface shortwave radiation the day before. Each variable and the final models are significant at level of 0.05. With an internal five-fold cross validation applied to validate the predictive ability of the model for future observations, the proposed model can accurately predict rigid pavement surface temperature having errors within 2.3℃.

Improvements of the regression model might include the variables of traffic conditions. External data for model evaluations might increase the reliability of the developed models. Moreover, spatial analysis of pavement surface temperature prediction incorporating with Geographic information system (GIS) in the network level would be expected to facilitate winter maintenance planning and decision making.

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APPENDIX:

1: List of Deliverables

1. Poster for Rowan University's annual STEM Symposium
2. Poster for Rowan University's Engineering Clinic Showcase
3. Quarterly Report submitted to University Transportation Research Center (UTRC)

2: Graphs

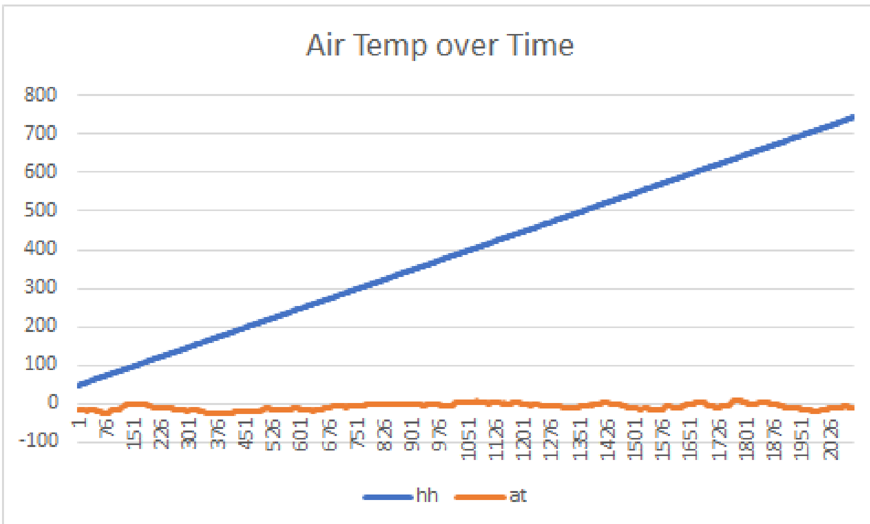

Figure A1: Air temperature over time

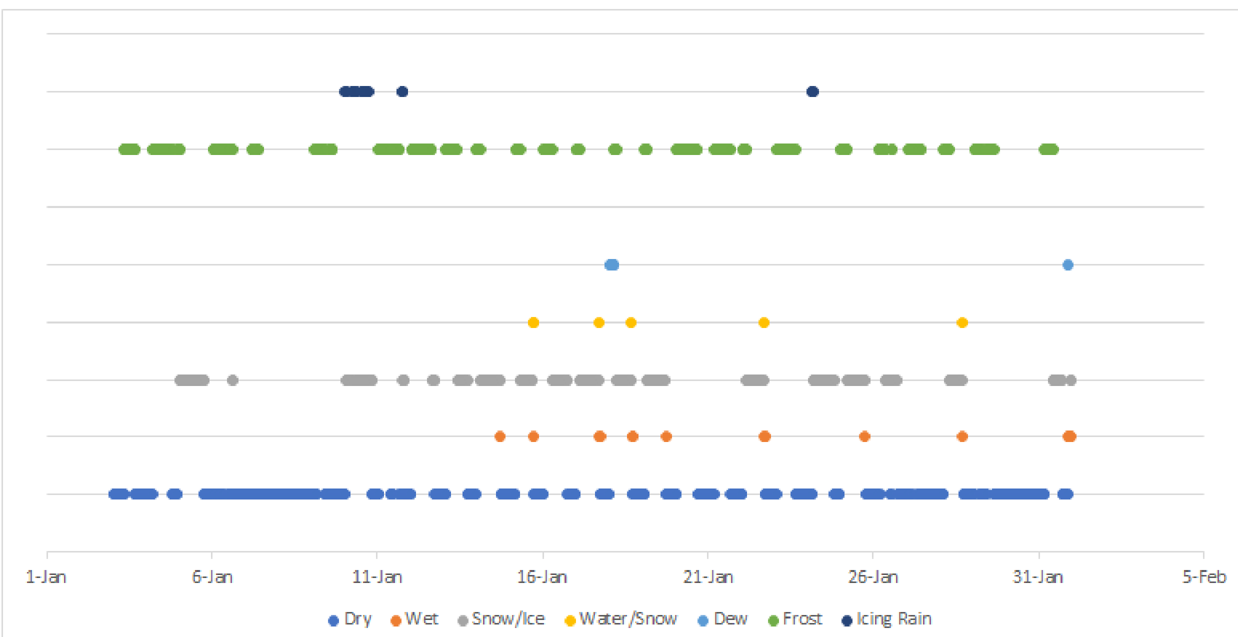

Figure A2: Road conditions over time

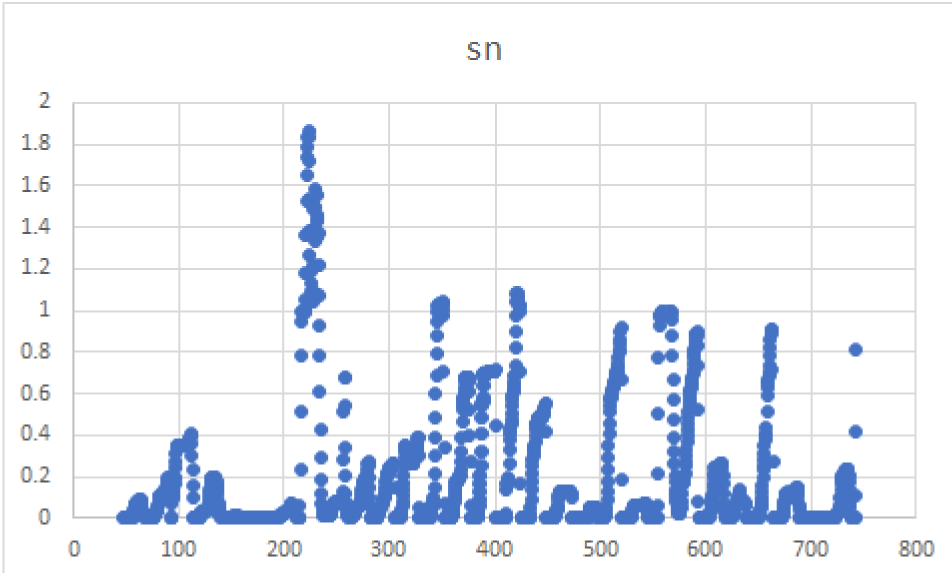

Figure A3: Snow cover over time

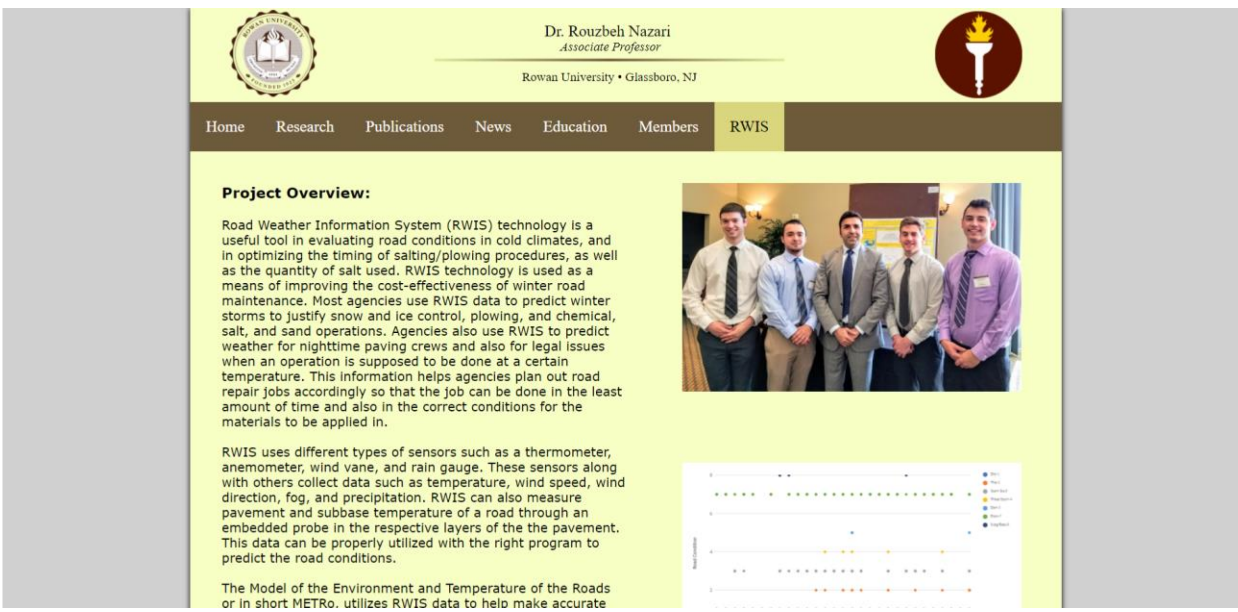

Figure A4: Dr. Nazari’s updated website

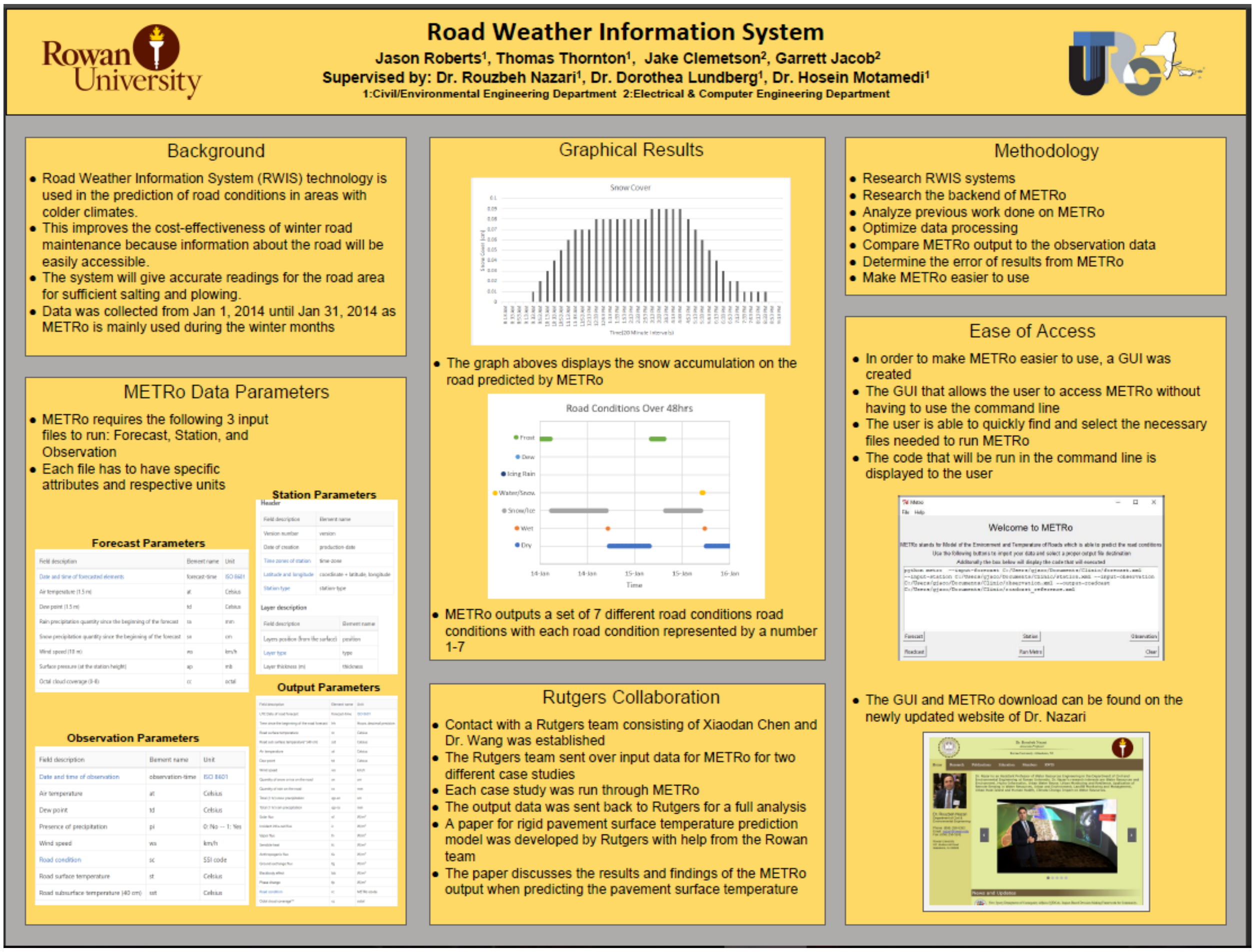

Figure A5: Road Weather Information System poster

3: Links

1. METRo Wiki: https://framagit.org/metroprojects/metro/wikis/METRo
2. Dr. Nazari's Website: http://users.rowan.edu/~nazari/RWIS.html
3. Github: https://github.com/jacobg0/METRo-GUI
4. METRo Download: https://framagit.org/metroprojects/metro
5. Observation Data: https://mesonet.agron.iastate.edu/RWIS/
6. Forecast Data: https://gis.ncdc.noaa.gov/maps/ncei/lcd

4: GUI Source Code

```
# GUI

from Tkinter import *
import os
import webbrowser
import tkFileDialog, Tkconstants, Tkinter
```

```
from tkFileDialog import askopenfilename
from tkFileDialog import asksaveasfile

root = Tk()
root.title("METRo")
#root.configure(background = 808080)

# grab length of the array then subtract the length of the array
# vary code for each variable then add together



class Application(Frame):
   # declaring global variables
   global code0
   global code
   global code1
   global code2
   global code3
   code0 = ""
   code = ""
   code1 = ""
   code2 = ""
   code3 = ""



   global Metro_wiki
   Metro_wiki = 'https://framagit.org/metroprojects/metro/wikis/METRo'


   # defining classes
   def __init__(self, master):
       Frame.__init__(self, master)
       self.grid()
       self.create_label()
       self.btn_forecast()
       self.btn_station()
       self.btn_observation()
       self.btn_roadcast()
       self.create_widget()
       self.run_metro()
       self.Metro_def()
       self.Explination()
       self.Explain_code()
       self.result()
       self.btn_clear()

   # Label for text, background color(bg), font color, font style and size, heigth and
width of the label


   def create_label(self):
```

```
        self.label = Label(self, text="Welcome to METRo", fg="black", font=(None, 18), height=2, width=0)
        self.label.grid(row =0,column=2)

    def Metro_def(self):
        self.label = Label(self,
                           text="METRo stands for Model of the Environment and Temperature of Roads which is able to predict the road conditions", fg="black", font=(None, 10))
        self.label.grid(row=1, column=0, columnspan=5)

    def Explination(self):
        self.label = Label(self,
                           text=" Use the following buttons to import your data and select a proper output file destination",
                           fg="black", font=(None, 10))
        self.label.grid(row=2, column=0, columnspan=5)

    def Explain_code(self):
        self.label = Label(self,
                           text="Additonally the box below will display the code that will executed",
                           fg="black", font=(None, 10))
        self.label.grid(row=7, column=0, columnspan=5)



    # define all of the possible input buttons
    def btn_forecast(self):
        self.button = Button(root, text="Forecast", command=self.forecast, justify='center')
        self.button.grid(row=2, column=0, padx =10,sticky = W)


    def btn_station(self):
        self.button = Button(root, text="Station", command=self.station)
        self.button.grid(row=2, column=0, padx = 10)

    def btn_observation(self):
        self.button = Button(root, text="Observation", command=self.observation)
        self.button.grid(row=2, column=0, padx =10,sticky = E)

    def btn_roadcast(self):
        self.button = Button(root, text="Roadcast", command=self.roadcast)
        self.button.grid(row=3, column=0, padx = 10, sticky =  W )


    def btn_clear(self):
        self.button = Button(root, text = "Clear", command = self.clear)
        self.button.grid(row=3, column=0, padx = 10, sticky =  E )


    # defines the forecast button
```

```
    def forecast(self):
        global code
        global code0

        code0 = "cd /usr/local/metro/metro/usr/bin python metro"


        code += " --input-forecast "
        forecast = tkFileDialog.askopenfilename(filetypes=(("All files", "*.*"), ("XML",
"*.xml")))
        code += forecast

        self.result.delete(0.0, END)
        self.result.insert(0.0,code0+ code)


        # box where metro code is displayed
    def result(self):

        self.result = Text(self, width=80, height=10, wrap=WORD)
        self.result.grid(row= 20, column=2)

    # defines the station button
    def station(self):
        global code1
        # global stat

        code1 += " --input-station "
        stat  =  tkFileDialog.askopenfilename(filetypes=(("All  files",  "*.*"),  ("XML",
"*.xml")))
        code1 += stat

        self.result.delete(0.0, END)
        self.result.insert(0.0, code0+code+code1)

    # defines the observation button
    def observation(self):
        global code2

        code2 += " --input-observation "
        observation  =  tkFileDialog.askopenfilename(filetypes=(("All  files",  "*.*"),
("XML", "*.xml")))
        code2 += observation

        self.result.delete(0.0, END)
        self.result.insert(0.0, code0+code+code1+code2)

    # defines the roadcast button
    def roadcast(self):
        global code3

        code3 += " --output-roadcast "
        roadcast = tkFileDialog.askopenfilename(filetypes=(("All files", "*.*"), ("XML",
```

```
"*.xml")))
        code3 += roadcast

        self.result.delete(0.0, END)
        self.result.insert(0.0, code0+code+code1+code2+code3)

    # defines the run Metro button
    def create_widget(self):
        self.button = Button(root, text="Run Metro", command=self.run_metro)
        self.button.grid(row=3, column=0, pady=10)

    # defines what run button actually does
    def run_metro(self):
        global code0
        global code
        global code1
        global code2
        global code3
        global observation

        # os.system(fore)
        print(code0+code+code1+code2+code3)
        os.system(code0+code+code1+code2+code3)

    def clear(self):
        global code0
        global code
        global code1
        global code2
        global code3

       # del code
      #  code = False
       # code = None

        code0 =""
        code=""
        code1 =""
        code2=""
        code3=""

        self.result.delete(0.0, 'end')


        #command = root.quit()

        #os.system('python GUI.0.py')




# Defining a top bar menu
def NewFile():
```

```python
    print ""


def OpenFile():
    name = askopenfilename()
    print name


def About():
    webbrowser.open(Metro_wiki, 2)
    print "You are being redirected to the Metro Wiki"



# create a sub window where the user can select a file to convert from CSV to xml
def csv_xml():
    win2 =Toplevel()
    win2.title('Convert CSV to XML')
    win2.geometry("400x200")




    create_label= Label(win2, text="Using the buttons below, selct the file to convert
and the output file", fg="black", font=(None, 10))
    create_label.grid(row=0, column=2)



    def inputfile():
        global csvfile

        csvfile = tkFileDialog.askopenfilename(filetypes=(("All files", "*.*"), ("XML",
"*.xml")))

    btn_input = Button(win2, text= "select the file to input", command =inputfile )
    btn_input.grid(row=1,column=1)




    #def lift_win1():
    #    win2.lift(aboveThis=root)

    #btn_lift = Button(win2, text="Lift win1", command=lift_win1)
   # btn_lift.pack(padx=30, pady=5)






      # self.button = button(root, text = "Select your file that you want to convert")
```

```python
    def create_button(self):
        self.button    =    Button(root,    text="Convert    CSV    Forecast    to    XML",
command=self.forecast_conversion,
                            justify='center')

    def forecast_conversion(self):
        forecast_conversion   =   tkFileDialog.askopenfilename(filetypes=(("All   files",
"*.*"), ("XML", "*.xml")))
        forecast_conversion = fore_csy.py

    def btn_observation(self):
        self.button = Button(root, text="Observation", command=self.observation)
        self.button.grid(row=2, column=0, padx =10,sticky = E)




# Defining a file menu
menu = Menu(root)
root.config(menu=menu)
filemenu = Menu(menu)
menu.add_cascade(label="File", menu=filemenu)
#filemenu.add_command(label="New XML file", command=NewFile())
#command=csv_xml)
#filemenu.add_command(label="Open", command=OpenFile)
filemenu.add_command(label="Convert CSV to XML", command=csv_xml)

filemenu.add_separator()
filemenu.add_command(label="Exit", command=root.quit)

# Defining a help Menu
helpmenu = Menu(menu)
menu.add_cascade(label="Help", menu=helpmenu)
helpmenu.add_command(label="Metro Wiki", command=About)

#root.geometry("410x500")


app = Application(root)

root.mainloop()
```

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