Which variables should be measured at a road weather station – Artificial intelligence gives the answer

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ABSTRACT

The road weather stations (RWIS) are constructed to measure the conditions of the road. The sensor equipment normally consists of sensors for surface temperature, air temperature, relative humidity, wind speed, precipitation and type of precipitation. This study tries to answer which variables should be measured at an RWIS-station. This equipment has remained similar since 1979 when the RWIS-stations were first introduced. At a test site outside Göteborg some 100 climate variables, apart from the normal variables of an RWIS-station are measured. A neural network model is used to select the variables that give the best prediction of the surface temperature. Thereby recommendations of how to equip an RWIS-station can be made. Some climatic variables would be difficult to include in the RWIS-system because of high maintenance level, it may be practically impossible or simply too expensive. Results show that more temperature sensors in the ground help the neural network model predict the surface temperature. Ground heat flux and net radiation also improved the output of the model. The temperature predictions by the model were good when common variables were used as input and were improved when the additional variables were included. A forecast model from the Swedish meteorological office (SMHI) was also given as input for the neural network model. While the model from SMHI alone performed rather poorly, when combining it with the measured variables and the neural network model a very large improvement was achieved. The neural network had adapted and improved the output from the SMHI model to the site specific conditions. The analyzed time series was only two months long, so it was too short for the neural network model to learn how to predict occasions of special interest for road climate. A next step is to use a longer time series and more stations to improve the forecasts and so the model can learn to predict frost events. In the future the neural network model can be used as nowcasting system to improve the output from forecasting models, such as the one from SMHI.

Keywords: Neural Network, Forecast, Road climate.

1. INTRODUCTION

Road weather Information Systems (RWIS) were developed some 25 years ago in response to the demand from winter maintenance personal to have access to more precise information about road weather conditions in their surveillance area [1]. Since the start of the field station manufacturing the configuration of the stations and the type of sensors used has changed very little. More effect has been put into the development tools such as temperature forecast models, etc that use the data from the field stations [2-5]. This study tries to answer which variables should be measured at an RWIS-station to make the best road surface temperature (RST) forecasts. At a test site outside Göteborg, Sweden about 100 climate variables, apart from the normal variables of an RWIS-station were measured. An artificial intelligence model, in this case a neural network model (NNM) was used to select the variables that gave the best prediction of the surface temperature. Thereby recommendations of how to equip an RWIS-station could be made. Prior to letting the model choose a data set a first selection was made among the variables according to the following criterions:

1 The variables should be possible to measure at an RWIS-station and the equipment should not be too expensive. Examples of excluded variables are measurements taken lower than 30 cm above the surface, data from a sonic anemometer and from an IR gas analyser, etc.

2 The data set should include variables that represent physical processes, such as ground heat flux, radiation, sensible heat flux and latent heat flux. The ground heat flux was included by temperature gradients in the ground and by a heat flux plate in the ground. The radiation was represented by downwelling shortwave and longwave radiation and also by net radiation. The sensible and latent heat flux was represented by temperature and humidity gradients in the air.

Of the some 100 variables the NNM was given 21 variables to choose from. From these the best predictors were chosen to predict the future trend in the next three hours for the RST. This prediction was compared to a prediction of the NNM when just using the common variables normally available at the RWIS-stations and to a prediction from the Swedish Meteorological and Hydrological Institute (SMHI) forecast model.

The sensor equipment of an RWIS-station normally consists of sensors for surface temperature, air temperature, relative humidity, wind-speed, precipitation and type of precipitation. Air temperature and humidity sensors are placed at 2 m height. Assuming a road width of 20 m, the recommended sensor height, according to Oke [6] is 7 – 20 cm. If placed higher, the sensor will be affected by other surfaces than the road. Since the temperature and humidity sensors are placed at 2 m, the readings will be more representative of the surroundings than of the road. One could expect that the NNM would suggest that a sensor closer to the ground would be useful. However, in Almkvist et al. [7] it was shown that the air at 2 m in the vegetation surrounding the road was representative for the air column above the road down to about 10 cm. Since it is practically impossible to measure below this level at an RWIS-station a sensor between 2 m and 10 cm will not do much difference and the model may not find it useful. The only sensor of the RWIS-stations that actually represents the conditions of the road is the RST sensor. One would therefore expect the model to be dependant on this variable, not only because it is the one it is predicting.

The NNM has some advantages over a traditional forecast model based on physical equations. The NNM is better at adapting to a specific site. The model will learn from historical data how the variables at the site interact. The model will also adapt to any systematic errors in the instruments. This can be positive as long as the equipment is intact, but when a sensor is changed the model will have to learn how the new sensor behaves. A physical model can easier be adapted to different environments. When predicting the RST for road maintenance purposes, it is crucial to calibrate the RST sensor carefully. It is important to remember that the model will predict the sensor temperature and not the actual temperature. This is also true for the traditional forecast models since they are calibrated to the sensor temperature.

In this study the NNM is preferable to a physical model, since it is much easier to vary the number of input variables. The model will adapt automatically to the new variables. With a physical model the equations will have to be changed for each new input variable, which will be difficult and time consuming.

Fig. 1. The asphalt surface at Säve as seen from the north-west. The sensors in the asphalt are near the right tower towards the centre of the surface. The two towers carry most of the instrumentation used in the study. The road is seen as a grey line in the foreground.

2. SITE AND INSTRUMENTATION

The test site is situated at Säve Airport 10 km north of Göteborg. The measurement area consists of a 26x26 m asphalt surface in an open area along a two lane road. There is a 2 m wide ditch that separates the road from the asphalt area. Two masts with instrumentation are situated at the west side of the asphalt area (figure 1). There is a workmen's cabin at the east side of the surface while the south and western sides are fenced. The main wind direction is western, so the influence from the cabin is normally small, but the fence will cause extra turbulence. The asphalt surface was built up to be representative of a normal Swedish road. Hence it was constructed with a top layer of 7 cm asphalt followed by 70 cm of crushed rock. A geotextile was placed to separate the crushed rock from the clay soil below. All the variables measured at the test station are not listed in this paper, but the ones that were selected are presented in table 1. There were some additional variables measured that were not included in the table, but they are not used in this study. Some of the variables used in the study were calculated by combining different variables. This will be further explained in section 4. The measurements are described more in detail in Almkvist and Jansson [8].

3. THE NEURAL NETWORK MODEL

Using the NNM contains two stages, but it is only the second part of the NNM that uses a neural network training algorithm. The first part of the model is actually a powerful statistical method that uses a Feature Selection Algorithm to select which variables to use for the predictions. However, the first step is to choose the RST as the variable to predict. Then the Feature Selection Algorithm uses the Mutual Information (MI) of the variables to choose the most important predictors. MI is a good indicator for the relevance of a variable [9].

3.1 Feature Selection Algorithm

A good indicator for the relevance of a variable is to use the Mutual Information (MI) [9]. Battiti [10] formalized a greedy selection scheme to select n variables from all input predictors which maximizes MI. The scheme works in the following way: MI is calculated for pairs of each variable and the RST using several mathematical techniques [11-14]. The variable giving the highest MI is selected as the most important. The selected variable is then grouped with the RST to calculate MI for another variable. The variable with the highest MI gives the second most important variable. This is grouped with the RST and the first selected variable and the procedure is repeated until n variables have been selected.

3.2 Neural Network Predictor

Application of neural networks in time series forecasting [15-17] is based on the ability of neural networks to approximate nonlinear functions. A neural network is a computational model that is loosely based on the neuron cell structure of the biological nervous system. Given a training set of data, the neural network can learn the data with a learning algorithm; in this research, we used the most common algorithm, backpropagation together with the Extended Kalman Filtering (EKF) [18-19]. During the training phase, the neural network forms a mapping between inputs and desired outputs from the training set by altering weighted connections within the network. The neural network training phase can be expressed as a problem of finding the state estimate that minimizes the least square error, using all the previous measurements.

4. CASE STUDY

4.1 Selection of variables

As stated in section 1 the variables were selected according to their ability to represent physical processes and to make it practically possible to use them in an RWIS-station. Temperature and humidity gradients are calculated from differences between 5 m and 2 m and between 2 m and 0.3 m. These gradients represent sensible and latent heat flux, but as discussed in section 1, the height of 0.3 m is not sufficiently low to be representative for the road surface, so it is likely that the gradients reflect the conditions of the surroundings, rather than the road. The quality of the humidity sensors is especially important during hazardous conditions when there is risk for frost formation. Two different kinds of humidity sensors were studied. The Rotronic sensor is commonly used at the RWIS-station, whereas the Vaisala sensor is more expensive and normally used for research purposes. The cheaper sensors have recurring problems when the humidity is high, due to dew formation on the sensor. The more expensive sensor will heat the sensor when humidity is above a critical level and therefore avoid this problem. To see whether this had an impact on the RST forecast this comparison was made.

Variable	Symbol	Comment
Downward solar radiation	K_d [W/m2]	Pyranometer, Kipp & Zonen
Downward longwave radiation	L_d [W/m2]	Pyrgeometer, Kipp & Zonen
Net solar radiation	N_s [W/m2]	Pyrano/Pyrgeometer, Kipp & Zonen
Ground heat flux at the surface	Q_g [W/m2]	Hukseflux + RT gradient
Ground heat flux at 4 cm depth	$Q_{g\ 04}$[W/m2]	Hukseflux
Precipitation	R [mm]	Tipping bucket
Road surface temperature	RST [°C]	Pt-100
5 cm depth road temperature	RT_5 [°C]	Pt-100
Wind speed 10 m	W_s [m/s]	3-cup anemometer
Relative humidity 2 m	Rh [%]	Capacitive, Rotronic
Vapour pressure 2 m	E [Pa]	Capacitive, Rotronic
Relative humidity 2 m	Rh_{200} [%]	Capacitive, Vaisala HMP-243
Vapour pressure 2 m	E_{200} [Pa]	Capacitive, Vaisala HMP-243
RT gradient (0 cm and 5 cm depth)	$dTdz_{0\text{-}5}$ [°C/m]	Pt-100
Second spatial derivative of RT (0, 5 cm and 10 cm depth)	d_2Tdz_2 [°C2/m2]	Approximated by finite difference, Pt-100
Air temperature gradient (5 m and 2 m)	$dTdz_{5\text{-}2}$ [°C/m]	Pt-100
Air temperature gradient (2 m and 0.3 m)	$dTdz_{2\text{-}03}$ [°C/m]	Pt-100
Vapour pressure gradient (5 m and 2 m)	$dedz_{5\text{-}2}$ [Pa/m]	Capacitive
Vapour pressure gradient (2 m and 0.3 m)	$Dedz_{2\text{-}03}$ [Pa/m]	Capacitive
Air Pressure	P [Pa]	Environmental office
Air temperature 2m	T_a [°C]	Pt-100

Table 1: Meteorological variables used with the feature selection algorithm. RT is short for Road Temperature.

Rank	*Best predictors*	*Rank*	**Best predictors**
1	m_{RST} (t-3 Δt)	15	m_{d2Tdz2}(t-5 Δt)
2	m_{RST} (t-4 Δt)	16	m_{Qg}(t-4 Δt)
3	m_{RST} (t-5 Δt)	17	m_{Ns}(t-4 Δt)
4 *	m_{RST5} (t-3 Δt)	18	m_{Ns}(t-5 Δt)
5	m_{RST5} (t-4 Δt)	19	m_{Kd}(t-4 Δt)
6	m_{RST5} (t-5 Δt)	20	m_{Kd}(t-5 Δt)
7 *	m_{d2Tdz2}(t-3 Δt)	21	m_{Qg}(t-5 Δt)
8	m_{dTdz05}(t-4 Δt)	22 *	gm_{RST5}
9	m_{dTdz05}(t-3 Δt)	23	gm_{Ns}
10 *	m_{d2Tdz2}(t-4 Δt)	24	m_{Qg}(t-3 Δt)
11 *	m_{dTdz05}(t-5 Δt)	25	m_{Kd}(t-3 Δt)
12	m_{Qg4cm}(t-3 Δt)	26	gm_{RST}
13	m_{Qg4cm}(t-4 Δt)	27 *	gm_{d2Tdz2}
14	m_{Qg4cm}(t-5 Δt)	28 *	gm_{dTdz05}

Table 2: Best selected predictors. Asterisks (*) mark where the prediction improves the most.

4.2 Results and discussion

The system described in section 3 was applied to the data collected by the meteorological station at Säve. The measured meteorological variables are listed in table 1. The meteorological station sample frequency is ten minutes, but this was converted to 1 hour averages to reduce the amount of data. For each of the variables five delayed vectors were constructed as described in the following lines. Denote a vector containing the data of a particular variable collected by the meteorological station with **m**(t). Then the following vectors can be created: **m**(t-3Δt), **m**(t-4 Δt), **m**(t-5 Δt), [**m**(t-3 Δt)-**m**(t-4 Δt)] (**gm**) and **m**(t-24 Δt); in this case Δt is 1 hour. At the end of the process we arrive with a matrix **M** [*Nx5*] for each meteorological parameter. *N* is the number of samples in the database (1337), about 56 days. At this point the greedy selection algorithm was applied by setting:

$$\mathbf{F} = \left[\mathbf{M}_{Kd}\mathbf{M}_{Ld}\mathbf{M}_{Ns} .. \mathbf{M}_{Ta}\right], \quad (1)$$

where **F** is the full set of variables. This meant that globally a set of 105 possible predictors were to be scanned to find a subset of the most important variables. The algorithm was stopped when it had chosen the best 28 predictors. The results are summarized in table 2.

The feed-forward NNM was trained starting with 3 predictors up to 28, according to the rank order in table 2, to see which predictors, among the 28 selected, gave a real improvement for the road surface temperature prediction. It was seen that a major improvement in the prediction (*lower mean square error*) was achieved with the following input configurations: *4, 7, 10, 11, 22, 27* and *28* predictors. The predictors for which the improvements occur are marked in table 2. Using 11 predictors means that the RST, the second spatial derivative of RT, the RT at 5 cm depth and the temperature gradient between 0 cm and 5 cm depth are the key-features for the RST nowcasting. In the next level with 22 predictors the ground heat flux and radiative fluxes are included. Globally the NNM with 28 predictors gives the best result with a MSE of 5.7 $°C^2$ as illustrated in figure 8 a.

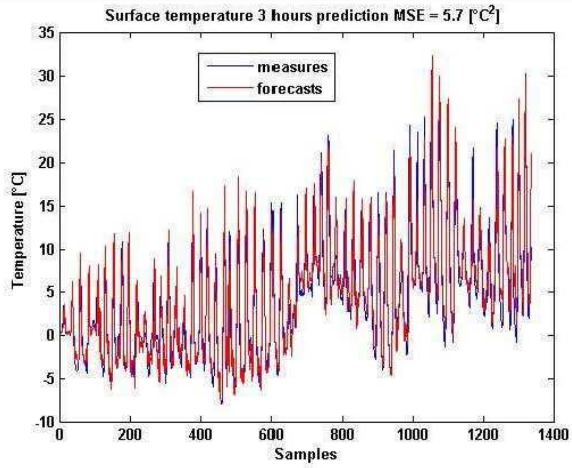

Fig. 8 a. RST prediction three hours ahead with 28 predictors.

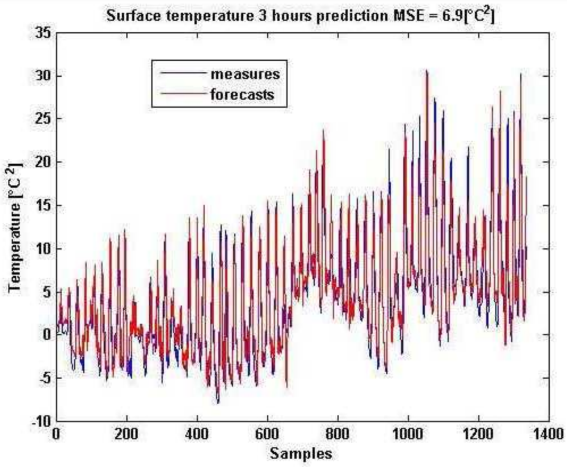

Fig. 8 b. RST prediction three hours ahead with common variables.

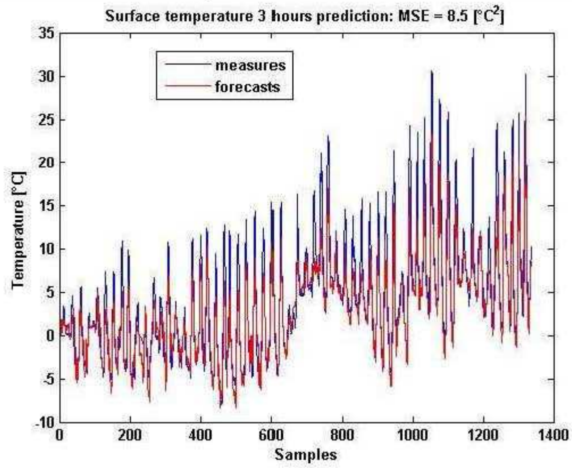

Fig. 8 c. SMHI RST prediction three hours ahead.

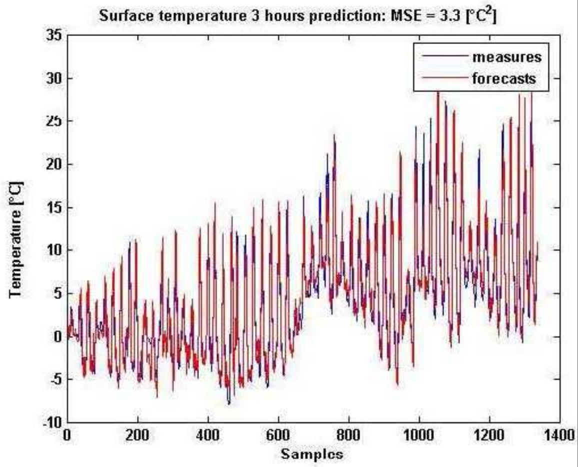

Fig. 8 d. RST prediction three hours ahead using selected predictors plus SMHI prognosis.

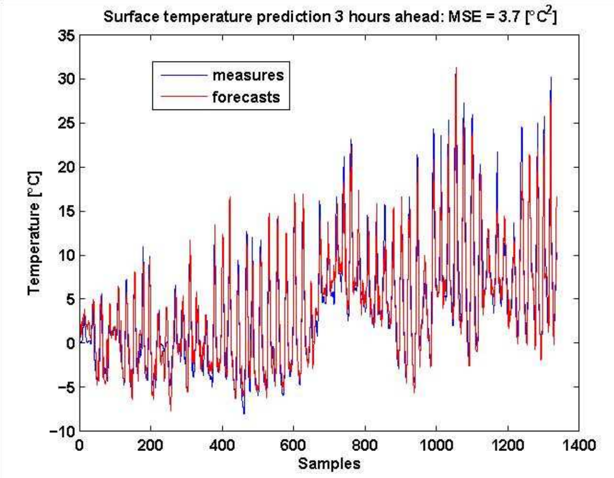

Figure 8 e: RST prediction three hours ahead using common variables plus SMHI prognosis.

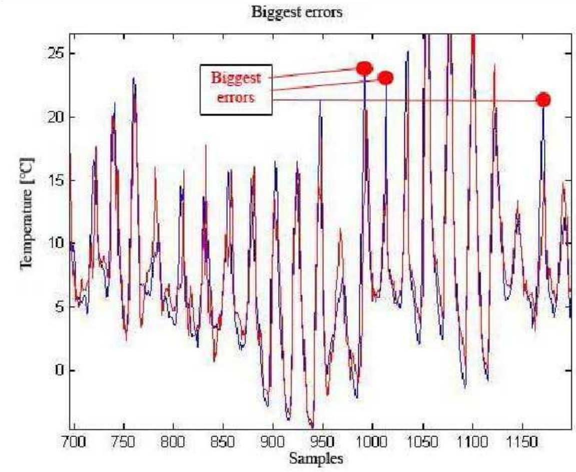

Figure 8 f: Zoom on the biggest errors from figure 8 a.

Figure 8 a-f: RST predictions using different sets of variables. The samples are from hour data taken during the period 11 February to 13 April.

Common RWIS-stations do not have all the predictors selected so the neural system was also tested using the main common variables as predictors: past values of RST, past values of air temperature, past values of relative humidity and past values of air pressure. With these inputs an MSE equal to 6.9 °C^2 was reached as illustrated in figure 8 b. It can be seen that the prediction with the predictors selected by the algorithm has a performance better than that using the common meteorological variables. Further it is found in figure 8 f that the biggest errors are at high temperature, which is in a range that is not dangerous for road conditions (*ice formation*). A closer look at figure 8 f shows that the largest errors actually occur when the maximum temperature of the day is reached.

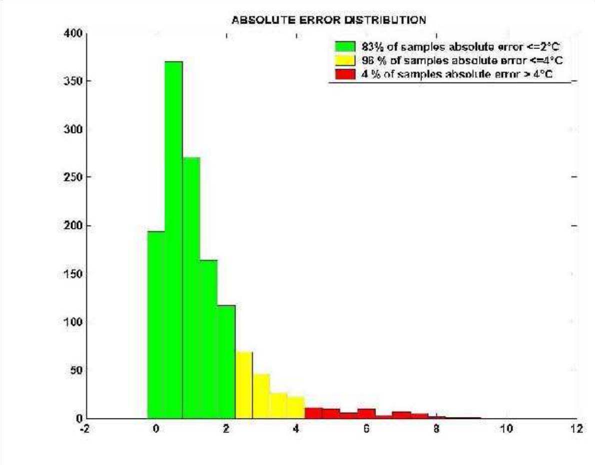

Figure 9 a: Absolute error distribution of the forecasts illustrated in figure 8 d.

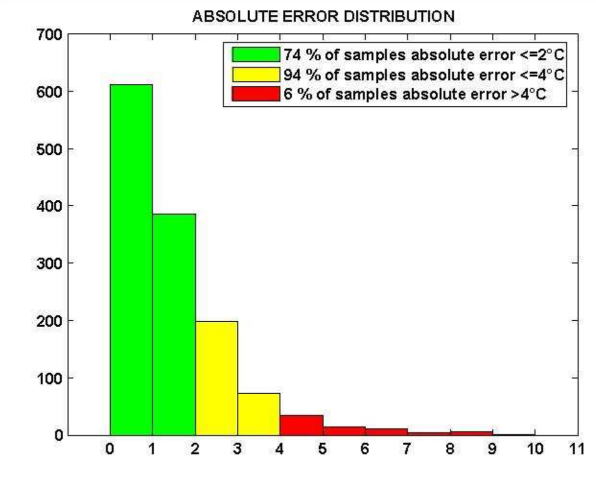

Figure 9 b: Absolute error distribution of the forecasts illustrated in figure 8 e.

Figure 9: Bar graphs of the error distribution.

In Sweden the SMHI (Swedish Meteorological and Hydrological Institute) provides prognosis of the RST for 1, 2, 3 and 4 hours at many sites of the country. It was decided to compare the results of our system to the SMHI 3 hour prognosis for the Säve station. The results can be seen in figure 8 c. It is evident that the neural system performance is better in both cases: with common and selected predictors. As the SMHI prognosis is available at many sites, an interesting idea was to add the 3 hour SMHI prognosis to the selected predictors for the NNM. By doing this experiment a major improvement of the system performance was accomplished. In fact the MSE was reduced to 3.3 °C^2 as seen in figure 8 d.

From the bar graph in figure 9 a it can be seen that even if the mean square error is 3.3 °C^2, in 83 % of samples the absolute error is less than or equal to 2°C, which is a good result. Furthermore the variance of the error distribution is 1.8 °C^2, a small value. This means that the majority of the errors are positioned very close to the mean error, i. e. ≈1.7 °C. Finally the NNM was trained with the common variables and the SMHI prediction, which resulted in an MSE equal to 3.7 °C^2 as shown in figure 8 e. From the error distribution graph (figure 9 b) we see that in 74 % of samples the absolute error is less than or equal to 2°C. This result is meaningful since, even with an RWIS-station equipped with common sensors, a big improvement compared to SMHI predictions was achieved.

5 CONCLUSIONS AND FUTURE PERSPECTIVES

Some findings in this paper are quite interesting. The NNM was shown to be a useful tool to select the most important variables for RST prediction. Furthermore it was shown that the best prediction was made using variables not included in the common sensor suite of an RWIS station, like the temperature sensor at 5 cm, 10 cm depth and the sensors to measure ground heat flux and radiation. The analyzed time series was too short for the neural network model to learn how to predict frost events or occasions that are of special interest for road climate, so factors like sensible and latent heat flux were not helpful for the model. Nevertheless it was shown that even if with the common variables good results can be reached. Finally evidence was given that combining the neural system with the SMHI prognosis, and in general with any kind of prognosis where they are available, gives a major improvement of the prediction. For future developments more data from the winter period should be collected in order to create an "ad hoc" database to train the system. This should improve the results and delete the big errors shown in figure 8 f. With more data the system could be tested as a forecasting model for frost events and perhaps in the future be used as a warning system for road maintenance people.

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