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Statistical approach for forecasting road surface temperature

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ABSTRACT: Snow and ice make road conditions and use difficult and represent a major challenge for the winter road maintenance service. Optimizing winter maintenance service and safety thus requires accurate short-term forecasts of the meteorological state of the roads. The most common approach to forecasting road conditions is an energy balance model based on a one-dimensional diffusion equation. Physical models can predict the road surface temperature, which is the most important parameter for determining the road surface condition (e.g. dry, wet, ice, snow). However, such models can show a large degree of error at sites where physical processes are too complex to be simulated correctly. To solve this problem, physical models are often combined with statistical approaches. This paper proposes a purely statistical method for forecasting road surface temperature based on stepwise linear regression analysis with appropriate selection of the input parameters and separate models for different time intervals. The method is tested on data from several Slovenian road weather stations. Its accuracy is comparable to or better than that of physical models.

KEY WORDS stepwise linear regression; prediction models; road weather station (RWS); road weather information systems (RWIS)

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1. Introduction

During the period from late autumn to early spring, many countries experience severe winter conditions such as snow, ice and frost. Such conditions make the road conditions and use difficult and present several challenges for the winter maintenance service. Optimizing winter maintenance decisions (treatment locations, timing, types and rates) will have an important impact on the roadway efficiency and the possible risk of accidents. An accurate prediction of road weather conditions is important for providing safer roads (Fridstrøm *et al*., 1995; Norrman *et al*., 2000), minimizing the environmental damage from over-salting (Ramakrishna and Viraraghavan, 2005) and for cutting the winter road maintenance costs. For example, Chapman *et al*. (2001b) report that the total budget for winter road maintenance in the United Kingdom is more than 140 million pounds every year, with salt corrosion causing a further 100 million pounds of damage each year to vehicles and structures.

Numerous models for predicting meteorological conditions on the road have been introduced and accepted by winter maintenance personnel for effective winter road maintenance decisions. These prediction models are a part of advanced systems known as the road weather information systems (RWIS) and maintenance decision support systems (MDSS). There are many reports about savings from the use of such systems. The State of Wisconsin, U.S., reports saving US$75 500 and reducing the salt usage by 2500 tons during a single winter storm (Shao, 1998). Implementation of the MDSS in the State of Indiana resulted in saving about US$11 million, 188 000 tons of salt (36% saving) and 42 000 work hours (20% saving) in the winter of 2008–2009 compared to the previous season (McClellan *et al*., 2009).

In contrast to the widely used physical models based on a one-dimensional diffusion equation, this paper proposes a purely statistical approach in the form of linear regression models fitted on past data. To cope with non-linear interactions between variables and with the unobserved properties of locations, separate models are constructed for individual locations and hours, and then partially merged to increase their robustness.

The paper is organized as follows. The next two sections review the existing methods and the available data used in the study. Description of the proposed method is followed by a section in which the method is evaluated on testing data and compared with a physical model.

2. Existing methods

Road surface temperature (RST) is influenced by numerous meteorological, geographical and road parameters, which can produce vast temperature variations across the road section (Thornes *et al*., 2005; Chapman and Thornes, 2008). One such example is shown in Figure 1, with temperatures varying from below 0 °C (dark) to above 20 °C (bright). The most important factors are: air temperature, radiation fluxes, humidity, precipitation, wind, topography, properties of the road materials and traffic. Their influence on the road is studied in detail in literature (e.g. Thornes, 1991; Kawashima *et al*., 2000; Chapman *et al*., 2001a; Weller and Thornes, 2001).

Classical weather forecasts are inadequate for road condition forecasting since they are based on data from weather stations that can be far from the road system and do not necessarily reflect the weather conditions on the road.

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Figure 1. Thermal image showing a variation of the surface temperature on the road section near Ravbarkomanda in the southwestern part of Slovenia. (Source: Articon d.o.o.). This figure is available in colour online at wileyonlinelibrary.com/journal/met

The most common approach to forecasting road conditions is though a physical energy balance model. Several such models with reasonably high accuracy have been developed in the last decades (e.g. Sass, 1992; Shao and Lister, 1996; Sass and Lister, 1997; Crevier and Delage, 2001; Korotenko, 2002; Takahashi *et al*., 2006). These models take weather forecasts and measurements of the road weather stations as inputs and predict RST using the energy balance equation. The initial temperature profile is interpolated using the measurements from the road weather stations at the surface and at different depths. The lower boundary condition is treated as a constant temperature at some depth. The upper boundary condition between the atmosphere and the road surface is expressed by an energy balance equation. The road surface condition, such as dry, wet, frost or ice, is then predicted from the RST value and the amount of moisture or water on the road surface.

A widely used physical model for forecasting RST and road conditions is METRo (Crevier and Delage, 2001; Linden and Drobot, 2010) which was first implemented in 1999 at the Ottawa Regional Centre in Canada. METRo is composed of three modules:

- the energy balance of the road surface model which describes the energy fluxes at the road surface:

$$R = (1-\alpha)S + \varepsilon I - \varepsilon\sigma T_s^4 - H - L_a E \pm L_f P + A \quad (1)$$

where R is net radiation flux, α albedo, S incoming solar flux, ε emissivity, I incoming infrared flux, σ Stefan–Boltzmann constant, T_s temperature of the road, H latent heat flux, L_a vaporization or sublimation heat, E water vapour flux, L_f heat of fusion of water, P precipitation rate, and A anthropogenic flux,

- a heat-conduction module for the road material which can predict the RST based on a one-dimensional diffusion equation:

$$\frac{\partial q}{\partial t} = -K\frac{\partial^2 q}{\partial x^2} \quad (2)$$

  where q is heat flux in the road, t time, x depth and K heat capacity of the road, and,
- a surface water/ice accumulation model.

Physical models still show a large degree of error for places at which physical processes are too complex to be simulated correctly. To solve this problem, they can be improved with further parameterizations of the relevant phenomena (Shao and Lister, 1995; Takahashi *et al*., 2006) or combined with statistical approaches to improve the quality of input or output variables (Shao, 1998; Pasero and Moniaci, 2006). Purely statistical approaches have also been used. Berrocal *et al*. (2010) propose two statistical methods for forecasting the probability of ice formation. Sherif and Hassan (2004) study the relationship between RST and weather variables with statistical models that can be also used for forecasting RST.

3. Data

Slovenia lies in a meteorologically diverse European territory between the western Alps, northern Adriatic and Pannonian Plain. Its surface encompasses 20 273 km^2, 63% of which is covered by forests. Forty eight percent of the land lies at an altitude higher than 500 m (Figure 2(a)). Average temperatures in the coldest months do not drop below $-3\,^\circ$C, and at least 4 months have an average temperature above $10\,^\circ$C. Average annual minimum daily temperatures are below $2\,^\circ$C in the high-elevation parts, around $8\,^\circ$C near the sea and around $5\,^\circ$C in the other parts.

Slovenia has more than 38 000 km of public and 13 000 km of forest roads. Frequent daily and seasonal variations in temperatures and precipitation cause rapid changes in road conditions and require frequent and quick responses from the winter maintenance service. There are nearly 90 road weather stations (RWSs) on Slovenian roads, situated mostly on motorways and regional roads. All of them are equipped with embedded or remote road sensors and meteorological sensors. The most common measurements on RWSs are: road temperature on the surface and at different depths, thickness of water film on the road, salt concentration, road condition, air temperature and humidity, dew point, air pressure, amount and type of precipitation, visibility, and speed and direction of the wind.

The data used in this study were collected by three RWSs that were selected as representatives of different kinds of environments. RWS Jeprca is situated between the central and northwestern part of Slovenia on a straight regional road. Terrain around the station is very flat and the nearest buildings and forest patches are 200 m away. RWS Mislinja (Figure 2(b)) is situated in northern Slovenia in a small valley on an ascending and winding regional road. The station is surrounded by trees and nearby objects. RWS Črmošnjice is situated at the beginning of a small village in the southeastern part of Slovenia. The nature of the moderate terrain is between those of the other two stations. All three stations are regularly maintained and

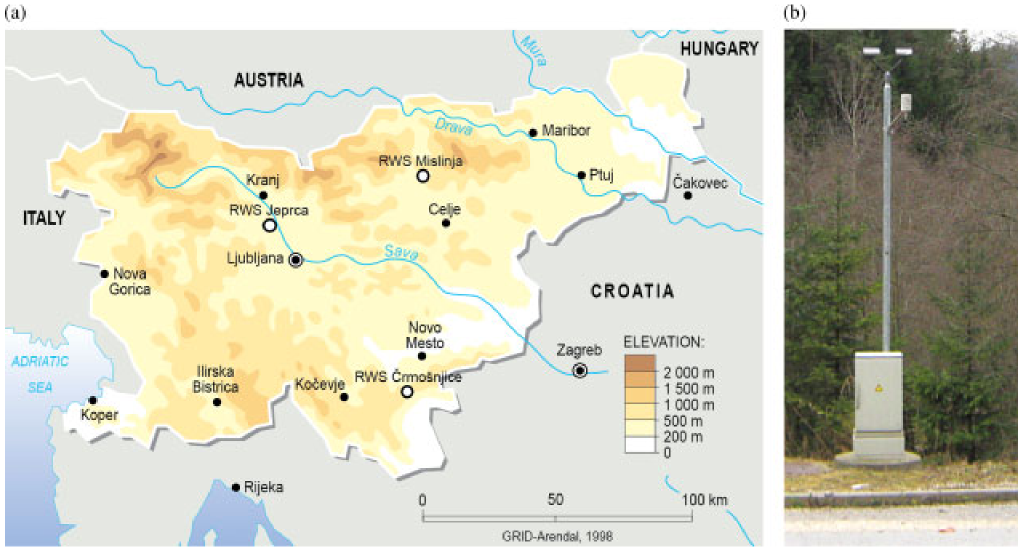

Figure 2. Map of Slovenia (source: Philippe Rekacewicz, Emmanuelle Bournay, UNEP/GRID-Arendal) with the locations of the RWSs used in this study (a) and RWS Mislinja (b). This figure is available in colour online at wileyonlinelibrary.com/journal/met

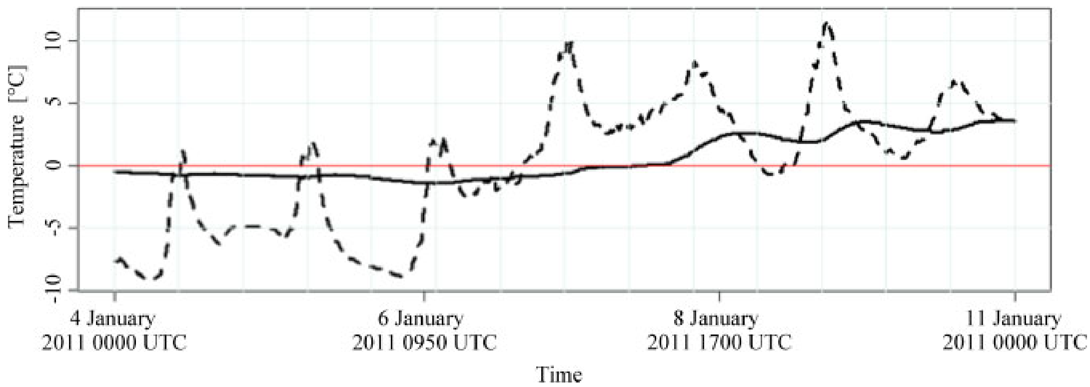

Figure 3. Road surface (dashed line) and subsurface (solid line) temperature measurements on RWS Mislinja from 4 to 11 January 2011. This figure is available in colour online at wileyonlinelibrary.com/journal/met

provide continuous measurements without any major losses. For illustration, Figure 3 shows data for two temperature measurements for eight consecutive days (4–11 January 2011) on RWS Mislinja.

Another important data source is weather forecasts by the INCA (Integrated Nowcasting through Comprehensive Analysis) system, which has been developed primarily for providing improved numerical forecast products in the nowcasting with very short time range (up to 12 h) and good spatial resolution of 1 km (Haiden *et al.*, 2011). INCA analysis and nowcasting data include temperature, humidity, wind and the amounts and types of precipitation. The model proposed in this paper also uses predictions of radiation fluxes, pressure and cloudiness data from ALADIN numerical weather prediction model with a coarser spatial resolution of 9.5 km.

The available data of appropriate quality currently covers the period of the last two winters. For a realistic testing of the method, the data collected in winter 2009/2010 (1 December 2009 to 1 April 2010) are used for fitting the model, and the available data from the second winter (1 October 2010 to 1 February 2011) are used for testing.

The input parameters to the modelling procedure are hourly measurements from the selected Slovenian RWSs and the meteorological data from INCA/ALADIN weather forecasts for the locations of the RWSs (Table 1). All input parameters are scaled by subtracting the mean and dividing by two standard deviations.

Table 1. Input parameters and abbreviations.

Abbreviation	Meaning
RWS measurements (first letter M)	
MA	Air temperature
MR	Road surface temperature
MD	Road subsurface temperature (30 cm)
MH	Air humidity
MF	Thickness of water film
Weather forecasts for 6 h (first letter F)	
FA_3	3 h air temperature forecast
FA_6	6 h air temperature forecast
FH	Air humidity
FW	Wind speed
FP	Precipitation amount
FL	Longwave radiation
FS	Shortwave radiation
FC	Cloudiness

4. Method

The proposed purely statistical approach for forecasting RST is based on stepwise linear regression analysis with appropriate selection of the input parameters. The classical linear regression model can be written in matrix notation as: $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$, where $\mathbf{y}$ is a $n \times 1$ vector of response variable, $\mathbf{X}$ is an $n \times p$ matrix of observable variables, $\boldsymbol{\beta}$ is a $p \times 1$ vector of parameters and $\mathbf{e}$ is an $n \times 1$ random error vector (errors are assumed to have independent normal distributions with a mean of 0 and standard deviation σ); p is the number of parameters and n is the number of data instances. The least squares estimate of $\boldsymbol{\beta}$ that minimizes the sum of squared errors, $\sum_{i=1}^{n}(y_i - X_i\hat{\boldsymbol{\beta}})^2$, is computed as $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$, where $'$ denotes matrix transposition.

Stepwise regression is a form of regression modelling which selects a subset of parameters, for instance by using the Akaike information criterion (Akaike, 1974): $AIC = 2v - 2\log(L)$, where v represents the number of variables in the fitted model and L is the likelihood of the model. Stepwise regression finds and uses a subset of variables that minimizes AIC.

The model construction does not include any data on physical properties of the locations. This decision is intentional since it is difficult to measure or assess such properties and also to include them properly in the model. This may represent a major source of inaccuracy in physical models. As a consequence, a single, general linear regression model encompassing all stations and times of the day would assume that the effects of the variables (the co-efficients $\hat{\boldsymbol{\beta}}$) are independent of time and of a location's properties. To cope with this, separate linear models are first constructed for each station and each hour. In this way, the unobserved properties of locations are implicitly included through differences in co-efficients of different models. According to the bias-variance decomposition of error, these partial models have smaller bias but high variance due to the small sample sizes used for fitting them. To enhance them by decreasing the variance part of the error without (significantly) increasing the bias, similar models for different times of the day are merged as described below. In the same fashion, it would be possible to merge models for similar stations if data on more weather stations were available.

Let $M_0, M_1, \ldots, M_{23}$ be a list of models for each hour of the day and let $D_0, D_1, \ldots, D_{23}$ be sets of data instances used for fitting these models. Let E_i be the root mean square (RMS) error of M_i computed using cross-validation on the training data set. To determine which pair of models to merge, a new set of models $M_{0,1}, M_{1,2}, \ldots, M_{22,23}, M_{23,0}$ is constructed from the unions of consecutive data sets $D_0 \cup D_1, D_1 \cup D_2 \ldots, D_{22} \cup D_{23}, D_{23} \cup D_0$. The error of each merged model, denoted by $E_{i,i+1}$ is compared with the weighted average error of the two separate models:

$$E'_{i,i+1} = \frac{E_i \cdot |S_i| + E_{i+1} \cdot |S_{i+1}|}{|S_i| + |S_{i+1}|} \quad (3)$$

where $|S_i|$ is the number of elements of the training set S_i for the model M_i, and with summation by modulo 24, e.g. $23 + 1 = 0$.

The pair of models whose merging increases the error the least (or even decreases it), as measured by $E_{i,i+1} - E'_{i,i+1}$, is replaced by the merged model. The whole procedure is repeated until there is only a single model left (see Figure 4 for an illustration).

The difference $E_{i,i+1} - E'_{i,i+1}$ for the selected pair is expected to be negative in the first few steps (merging increases the accuracy), while in the later steps the error will start increasing. The overall error as the function of the number of models is shown at the bottom of charts in Figure 4. After the procedure is finished, the number of models that will actually be used for making predictions is determined based on the expected errors. A suitable robust criterion is to use the last local minimum (that is, the local minimum with the smallest number of models) at which the RMS error does not exceed the smallest average RMS error by more than 0.5 °C. For instance, for RWS Jeprca such a minimum occurs in four models, as shown at the bottom of Figure 4(a).

The procedure is generally expected to yield two main models, one for daytime and another for night time, possibly with some intermediate models for transition periods. On the other hand, solutions that end up with multiple models covering short time intervals are unreliable and should be avoided.

5. Evaluation

The main goal set forth in this study is to predict the RST for 6 h in advance. Models are constructed as described in Section 4 on the training data from winter 2009–2010 and tested on data from winter 2010–2011. The selection of parameters used in the model for each location and hour is based on the Akaike information criterion, as described in Section 4.

Figure 4 visualizes the models for each location. The left part shows the absolute importance of individual parameters (columns) for hourly models (rows); darker colours denote larger co-efficients in the linear model, with white meaning that the parameter is not used and black signifying co-efficients of absolute value 5 or more (see Table 2 for the exact numerical values of co-efficients in the final models). The dendrogram on the right-hand side shows how the models were merged, and the plot under it shows the corresponding RMS errors. The cut-off point that gives the final models is represented by the vertical dashed line. Horizontal dashed lines separate the corresponding final models.

The absolute importance of parameters for a particular RWS can be assessed by observing their values across the hourly models. Parameters with mostly high values (e.g. above 2) can be considered as more important and *vice versa*. Figure 4 shows some general similarities between the stations. The merging procedure proposed, as expected, two large models for each RWS, one for daytime when the shortwave radiation is important and the overall average temperature (intercept) is higher (columns FS and IN), and another for night time when the shortwave radiation is unimportant and the intercept is low. Between these two there are models that cover 1–3 h and smoothen the transition.

Table 2 shows the numerical values of co-efficients in the final, merged model. Some input parameters are important most of the time, in particular, air temperature measurements and forecasts (MA, FA_3 and FA_6), RST measurements (MR) and road subsurface temperature (MD). The latter is more important for RWSs Mislinja and Črmošnjice than for RWS Jeprca; the main reasons may be differences in road construction and the topography in the vicinity of the RWS. Particular characteristics of locations (e.g. road materials, topography, anthropogenic influences) are reflected in different co-efficient values for each RWS and with different boundaries of time intervals. For example, at the location of RWS Mislinja the late afternoon solar flux is screened by some high trees on the western side. As a result, the transition to the night time model begins 2 h earlier than at the other two stations.

Table 3 shows RMS errors for the final models for each location (columns marked as 'S'). Four models are used for

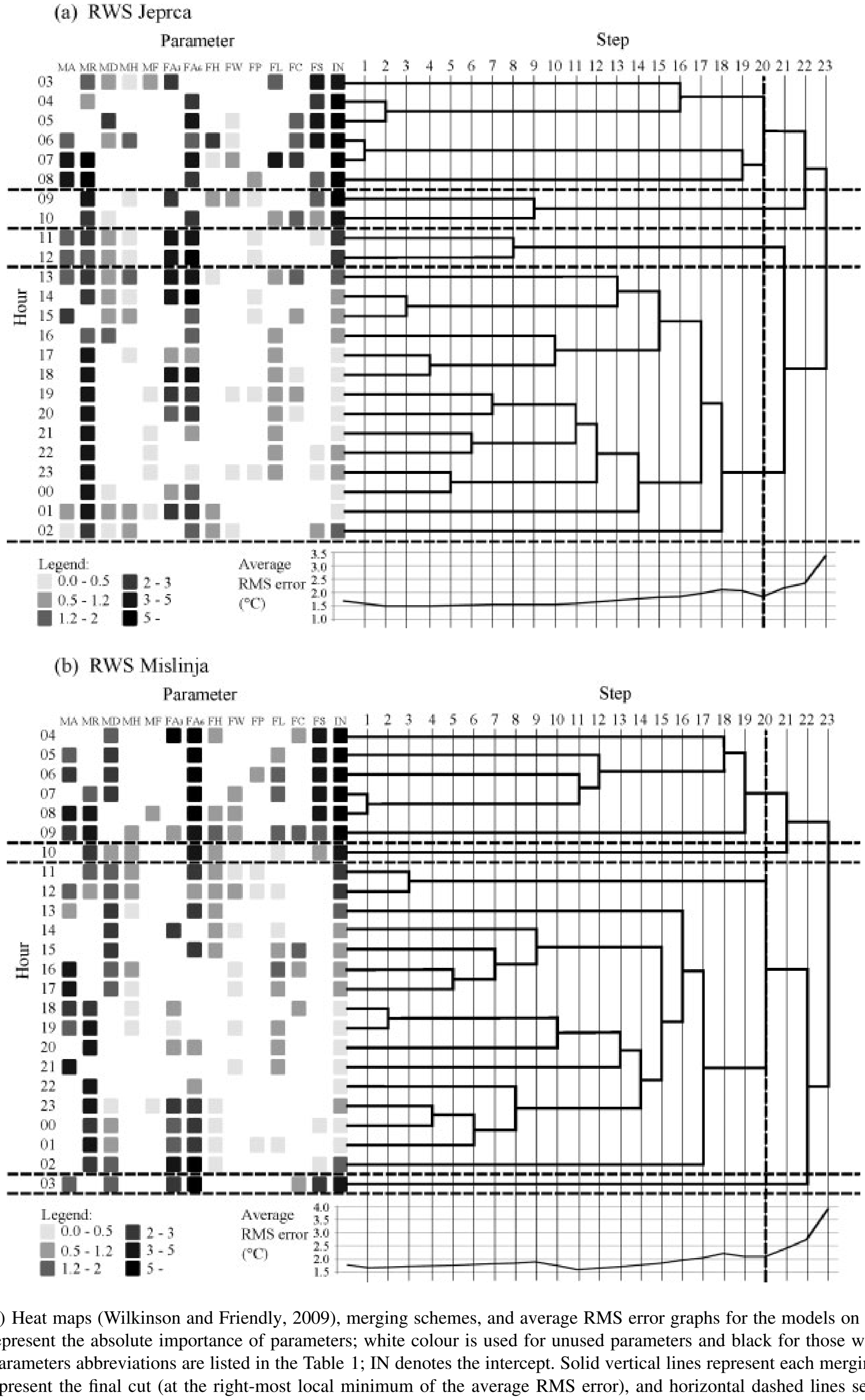

Figure 4. (a,b,c) Heat maps (Wilkinson and Friendly, 2009), merging schemes, and average RMS error graphs for the models on selected RWSs. Heat squares represent the absolute importance of parameters; white colour is used for unused parameters and black for those with co-efficients of 5 or more. Parameters abbreviations are listed in the Table 1; IN denotes the intercept. Solid vertical lines represent each merging step, vertical dashed lines represent the final cut (at the right-most local minimum of the average RMS error), and horizontal dashed lines separate the final models for each location. Hours are in UTC and represent the time of making the 6 h prediction (e.g. 09 denotes the prediction for temperature at 1500 UTC made at 0900 UTC).

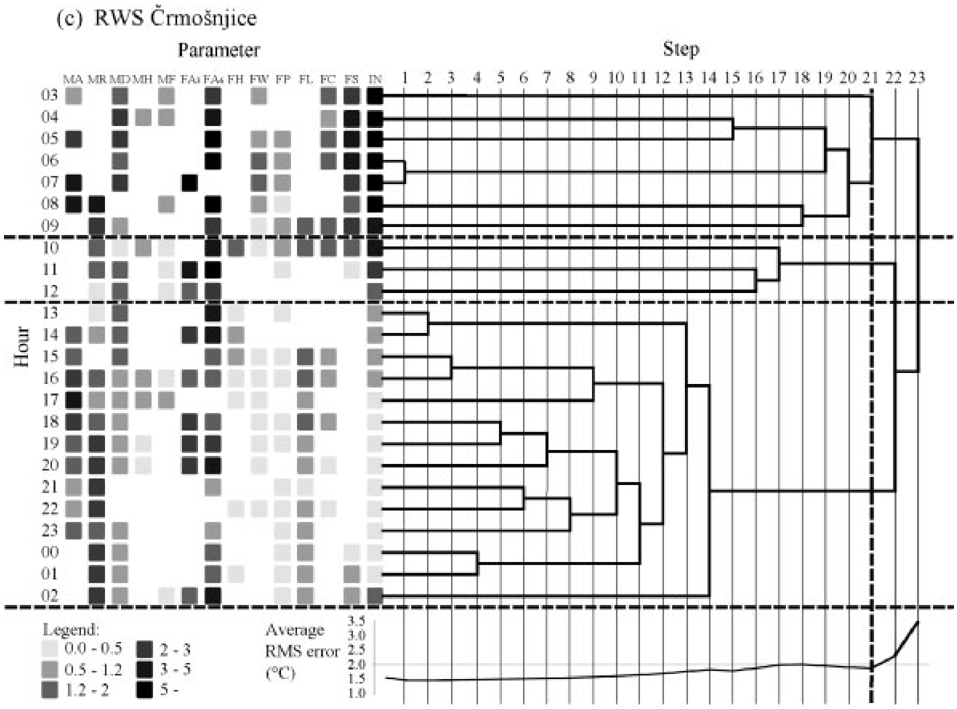

Figure 4. (*Continued*).

Table 2. Selected input parameters with co-efficient values for final models.

RWS	Parameter / Model	MA	MR	MD	MH	MF	FA_3	FA_6	FH	FW	FP	FL	FC	FS	IN
Jeprca	From 0300 to 0800	−2.1	2.6	0.7	0.7	0.1	2.8	1.5	−1.2	−0.6	−0.4	−1.2	1.4	2.1	5.9
	From 0900 to 1000	1.2	3.1	0.8	0.4	–	−3.4	2.2	−0.4	−0.4	−0.3	0.3	−0.3	1.4	4.8
	From 1100 to 1200	0.9	2.1	0.7	0.4	–	−3.1	5.0	–	−0.2	−0.3	–	–	0.3	2.6
	From 1300 to 0200	–	2.4	–	0.2	–	–	4.2	–	–	−0.1	–	–	–	0.4
Mislinja	0300	1.4	2.6	1.3	−0.6	–	−3.0	6.0	0.7	–	−0.6	0.6	1.1	2.4	3.5
	From 0400 to 0900	−3.6	2.1	1.4	–	–	−2.3	5.7	0.4	–	–	−0.3	–	2.7	6.8
	1000	1.4	1.0	0.9	–	–	–	3.1	–	–	–	–	–	0.5	4.0
	From 1100 to 0200	–	–	1.6	–	–	–	3.3	–	–	–	–	–	–	0.6
Črmošnjice	From 0300 to 0900	−2.9	1.2	1.6	0.3	0.2	3.0	3.2	0.2	−0.9	−0.5	0.6	0.5	2.4	6.0
	From 1000 to 1200	1.8	1.4	1.2	–	0.2	−2.7	5.7	0.2	0.1	−0.4	–	0.2	0.9	2.6
	From 1300 to 0200	–	1.1	1.1	–	0.2	−2.1	3.0	–	–	−0.2	–	–	0.3	0.3

Parameter abbreviations are given in the Table 1. Empty cells correspond to unused parameters.

making predictions at RWS Jeprca. Only the model for hours from 0300 to 0800 has a significant proportion of the prediction error larger than 4 °C (15%) which may be considered too high. As these predictions correspond to daytime when temperatures typically increase, this does not represent a substantial road safety problem. The model predicting temperatures in the more critical time frame covering the late afternoon and night (from 1300 to 0200) has a high predictive accuracy. Similar observations can be made for the other two stations: daytime models make somewhat larger errors, while the evening and night time predictions are quite accurate.

Predictions made for the transitional periods are also sufficiently accurate, even for RWS Mislinja, in which they cover only single-hour intervals, so much smaller data samples were used for fitting them.

Deeper analysis of the daytime model errors at RWS Mislinja show that errors mostly occur when RST rises faster than predicted, which is not as critical for the road safety as would be the opposite type of error, underestimating the decrease of temperature in the evening or at night). However, RST can be still near the critical range around 0 °C. Large prediction errors typically occur when shortwave radiation and cloudiness variability are high. This could be explained by inaccurate weather forecasts, especially for the shortwave radiation, which is particularly important for model from 0400 to 0900. Unfortunately, RWSs are not equipped with shortwave radiation sensors so it was not possible to verify directly the correlation between the prediction error and the difference between the forecast and the actual shortwave radiation. However, a small positive correlation ($R^2 = 0.22$) between the model's errors and air temperature forecast errors (Figure 5) offers a weak indirect indication that the RST prediction error may be related to weather forecast errors.

Such post hoc analyses are however speculative and more data would be needed to support them.

The usefulness of the proposed merging procedure is tested by comparing the resulting models by linear models for entire days, that is, a single linear model constructed for each RWS.

Table 3. Errors of 6 h RST predictions for statistical approach (S) and for METRo physical model (P).

RWS	Model time frame (UTC hours of the beginning of the prediction)	RMS error on test set		Percent of the predictions on test set with error larger than 2 °C		Percent of the predictions on test set with error larger than 4 °C	
		S	P	S	P	S	P
Jeprca	From 0300 to 0800	2.86	3.42	43	69	15	32
	From 0900 to 1000	1.63	1.53	22	16	2	4
	From 1100 to 1200	1.41	2.46	16	48	0	12
	From 1300 to 0200	1.55	2.86	20	56	0	20
	From 0000 to 2300 (average)	1.88	2.86	26	55	4	21
Mislinja	0300	1.99	3.00	30	64	5	23
	From 0400 to 0900	3.21	3.09	48	56	21	26
	1000	1.70	2.23	24	48	1	6
	From 1100 to 0200	1.33	3.26	13	73	0	26
	From 0000 to 2300 (average)	1.84	3.16	23	67	6	25
Črmošnjice	From 0300 to 0900	2.65	3.29	42	66	15	31
	From 1000 to 1200	1.49	1.46	17	17	1	3
	From 1300 to 0200	1.30	2.37	12	41	0	10
	From 0000 to 2300 (average)	1.72	2.52	21	45	5	15

Average errors for every RWS are weighted by the sizes of time intervals.

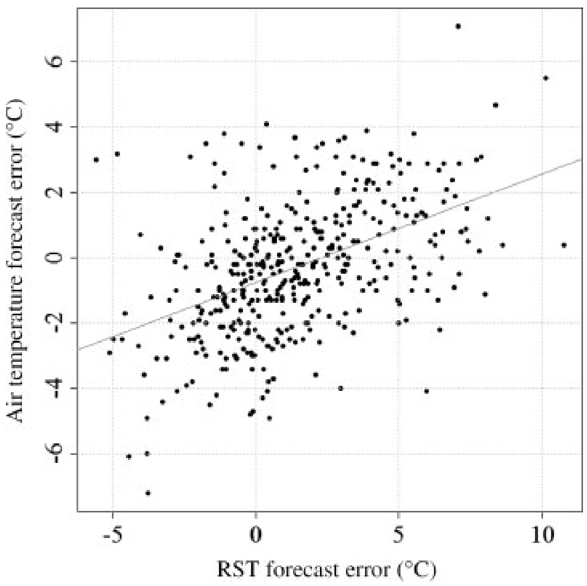

Figure 5. Small positive correlation between RST prediction errors (axis x) and air temperature forecast errors (axis y) on RWS Mislinja for hours between 0400 and 0900. Each point represents a prediction for a specific hour and day.

The RMS errors of these models on test data, 3.37, 3.92 and 3.45 for RWS Jeprca, Mislinja and Črmošnjice, respectively, are about two times higher than the average errors of the proposed method.

Finally, the proposed approach was compared with a physical model METRo tested on the data from the same winter (2010–2011) and using the same forecasts (INCA/ALADIN with 1 km/9.5 km horizontal resolution). The specific road construction parameters that would require coring the road were not available, so standard road construction profiles from the road data bank were used. This may put METRo at a disadvantage, yet it reflects the common practice in which METRo is used with imperfect data since coring is not feasible due to practical and cost issues. The authors are not aware of any study about the effect of imprecise data on the accuracy of the METRos predictions.

Despite this, the METRos performance on the three Slovenian locations is similar to that reported by Crevier and Delage (2001) for Canada: about one half of daytime temperature predictions of METRo are within the ±2 K error range. Crevier and Delage also report that night time RMS error is about 2 K; results of METRo for Slovenian RWSs are somewhat worse (2.46, 3.26 and 2.37 for RWSs Jeprca, Mislinja and Črmošnjice, respectively).

METRo's results, split into the same intervals as used for the statistical model, are shown in Table 3, in columns marked by 'P'. The METRo physical model shows marginally better accuracies in some of the shorter transitional intervals, while other errors are generally higher. The only larger interval for which the physical model slightly outperforms the statistical one is the daytime model for RWS Mislinja, which has already been scrutinized above.

The Wilcoxon signed rank test (Wilcoxon, 1945) on absolute errors for both approaches gives very low p-values for all three RWSs, so the statistical approach significantly outperforms the METRo physical model.

6. Discussion and conclusions

This paper proposes a novel approach for construction of models for predicting the RST based on purely statistical modelling. A standard multivariate linear regression model is used for its simplicity and robustness. To consider the varying importance of individual factors over the day, multiple models are constructed for different time intervals. The number of intervals and their boundaries is governed by the data themselves. The method merges the models to minimize the number of models and the predictive error on the training set at the same time. Comparison between the accuracy of a single model for the entire day and the composite model showed the advantage of the latter approach.

Physical models are set up using the data about each location, which may be difficult, error-prone and can cause large predictive errors. The premise of this research is that this can be avoided by using the past measurements and constructing a separate set of models for each location. Experiments confirm this hypothesis and show that the statistical model mostly outperforms the physical one in the given experimental setup.

A restriction of the proposed approach is that it needs at least one harsh winter to have sufficient data for proper fitting of the model. On the other hand, the model can be continuously improved as new data are gathered. The physical model can be used with just a few hours of historical data for the coupling phase but cannot be, in its basic form, improved by measurements from RWSs.

It is encouraging that even with the rather small amount of available data (a single winter worth of data was used for fitting the model), the study already showed very promising results. Due to the simplicity of their construction and application, this makes statistical models a suitable alternative to physical models of road surface temperature and conditions.

Recent research (Chapman and Thornes, 2011) considers geomatics to help in creating a detailed geographical database along the road system (considering latitude, longitude, altitude, sky-view factor, topography, road construction, traffic, land use). Appropriate weather forecasts are then used to interpolate the RST and road surface condition across the entire road network with high spatial and temporal resolutions. The point-based approach to predicting RST on the RWS location, as proposed here, could provide the necessary reference points to compute route-based RST predictions and thus achieve a complete coverage of the road system needed for safe but cost-efficient winter road maintenance service.

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