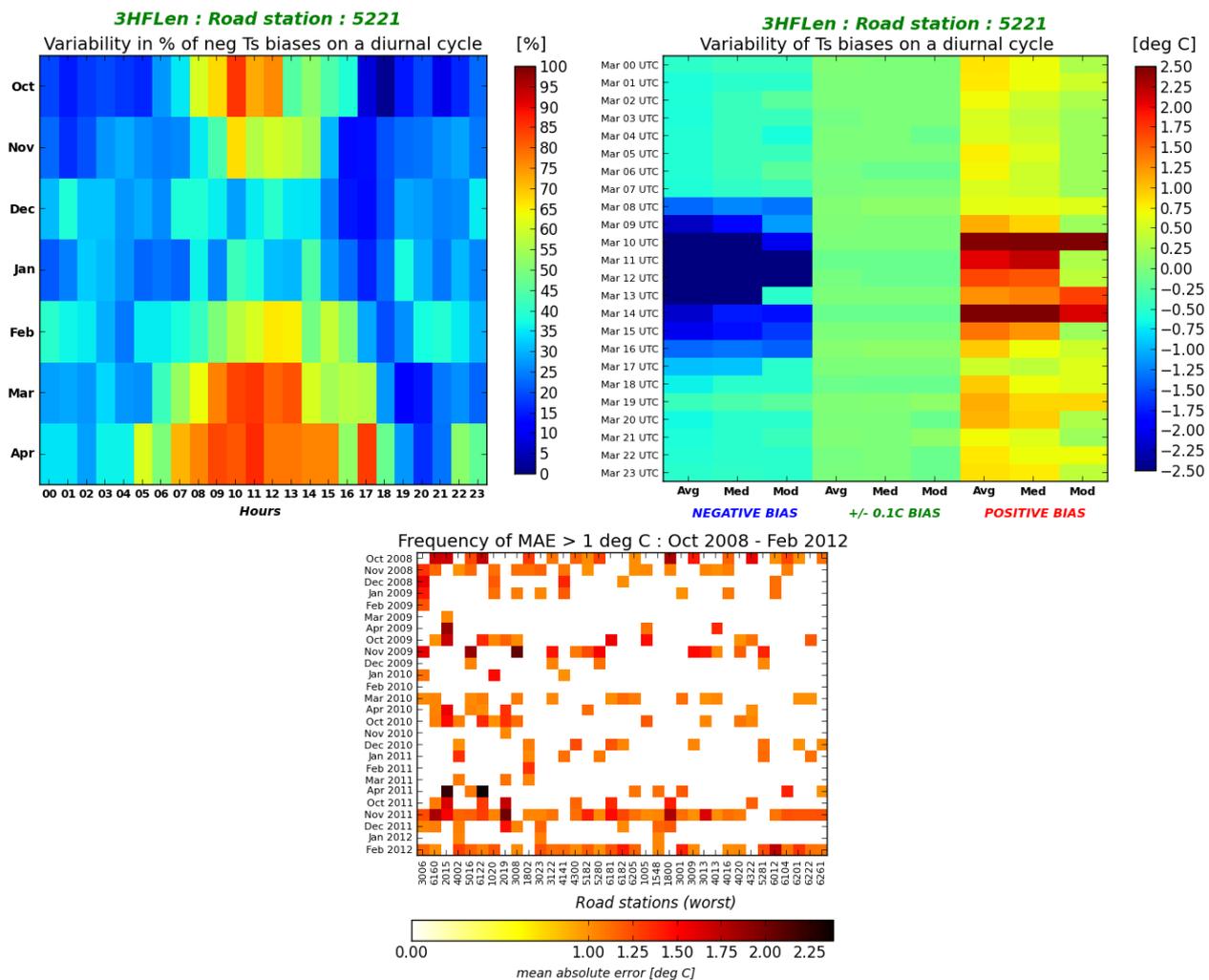




## Scientific Report 12-05

# Approaches to Statistical Correction of the Road Weather Model Forecasts

*Alexander Mahura, Claus Petersen, Bent H. Sass*





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## Abstract

The approach for statistical correction of the road surface temperature ( $T_s$ ) for the first 5 hours forecast lengths was developed. It is based on a statistics of  $T_s$  bias variability (within three intervals: negative,  $\pm 0.1^\circ\text{C}$ , and positive) considering average, median and mode values of the bias. Hierarchy of importance of forecasted meteorological parameters (cloud cover, wind speed and direction, road, air and dew temperatures differences) is used for selection of correction value. All these meteorological parameters are calculated for the same intervals for each forecast length (1-5), road station (395), month (Oct-Apr), and hour (00-23) on a diurnal cycle.

At first, the method developed was tested and verified for a group of road stations in the Nordjylland region of Denmark (winter 2011), and then for the entire road network (Oct 2011 – Feb 2012). It showed better performance when the multi-year dataset is used to calculate statistics.

## Resumé

En metode til statistisk korrektion af vejtemperatur for prognoser op til 5 timer er blevet udviklet. Metoden er baseret på en statistisk analyse af bias i vejtemperaturen (opdelt i 3 intervaller: negativ,  $\pm 0.1$  grader celsius og positiv) hvor bias er enten middel, median eller mest hyppige. Forskellige meteorologiske parameter (skydække, vindhastighed, vindretning, vejtemperatur, forskel mellem luft- og dugpunktstemperatur) bliver anvendt som indikator for hvilken korrektion der skal anvendes. Alle parameterne er beregnet for samme intervaller for hver prognoselængde (1-5), vejstation (395), måned (oktober-april) og time (00-23) på daglig basis.

Metoden blev først testet og verificeret for en gruppe af vejstationer i Nordjylland (vinter 2011) og derefter for hele vejnettet (oktober 2011 - februar 2012). Performance var bedst når flerårig dataset blev anvendt til at beregne statistikken.

# 1. Introduction

The **road surface temperature** ( $T_s$ ) is a key meteorological parameters predicted for the roads maintenance carried out by the national road services. In Denmark, the Danish Road Directorate (DRD) in cooperation with the local commune services is responsible to keep roads safe and always available for traffic. The most critical issue is to know in time information about slippery road conditions which may lead to accidental situations in traffic. For that the DRD is working in a close collaboration with the Danish Meteorological Institute (DMI). DMI operates the Road Weather Modelling System (RWMS) which is composed of the road observational network (about 400 road stations), Numerical Weather Prediction (NWP) model and Road Conditions Model (RCM). Output of the NWP model is used further for the RCM model forecasts of selected meteorological parameters, including the road surface temperature. Every hour, these forecasts of the road conditions are provided for the DRD and customers/ end-users. Once the forecasts are known, the maintenance of the roads and traffic conditions is taking place. If needed, the salting of the road surfaces is carried out. It is done in order to reduce danger at driving, to select optimal driving speed, to minimize environmental impact, etc.

As any forecast the  $T_s$  forecast is not always perfect. As for any forecasted parameter the deviations of forecasts from observations might exist. Although errors in forecast might be different in nature, but a systematic error is one of the errors which might be possible to correct. In general, the quality of forecast can be estimated through analysis of the mean error and the mean absolute error. Minimization of these both parameters will show improvement of the forecast. From one side, improvement of the forecast can be done through changes in the model's physics and dynamics, through refining existing parameterizations or elaborating new ones, through tuning model parameters or applying advanced numerical methods, etc. From the other side, improvement of the forecast can be done through post-processing of operational forecasts after the model run completed. For example, it can be done by applying statistical post-processing of the model output.

The **main goal** of this study is to develop, test and verify approach for improvement of the road surface temperature forecasts based on application of the statistical correction factor.

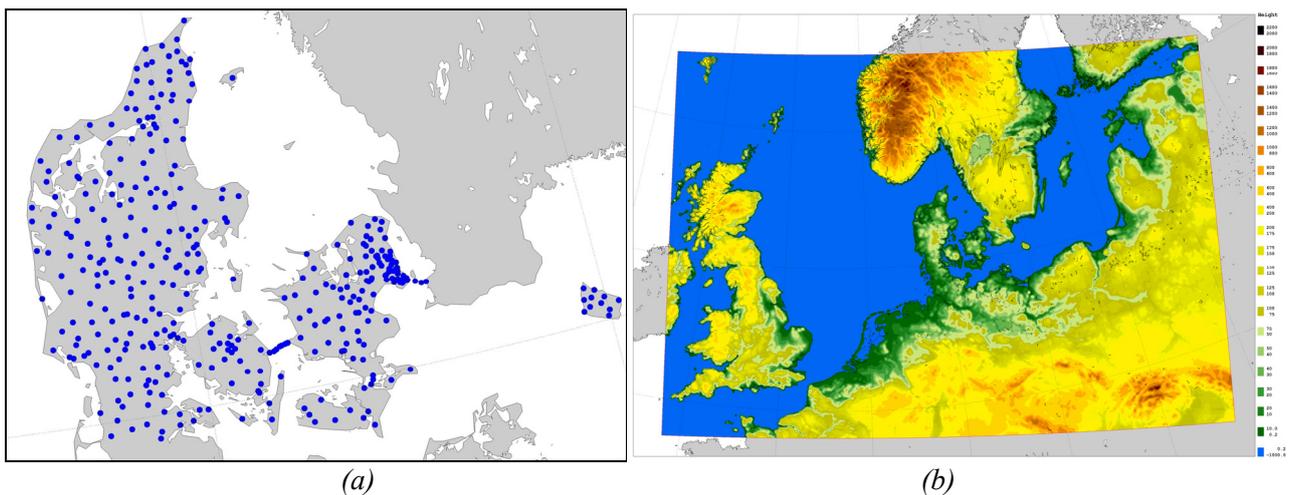
The **specific objectives** are the following: 1) Perform statistical evaluation of the  $T_s$  bias on a monthly and hourly basis for each road station of the Danish road network; 2) Develop and test approach and module for correction of originally forecasted  $T_s$  taking into account available observational data and forecasts of meteorological parameters; and 3) Verify developed approach for the recent road weather seasons.

## 2. Methodology

### 2.1. Operational road weather modeling

#### 2.1.1. Road network and observations

The Danish road network is equipped with more than 500 sensors (measuring the road surface temperature) placed at about 400 road stations (Figure 2.1.1a). Some stations have two or more sensors placed in asphalt surface of driving lanes. For Denmark, if roughly estimated, there is 1 road station per about 10 km of the driving lane. The surrounding environmental conditions around stations could be different. For example, these stations can be placed in airports or on bridges, in urban/sub-urban/rural locations, or surrounded by forest, fields, water, and individual trees (see *Mahura et al., 2009, 2010*). At each of these stations there are continuous measurements of meteorological parameters such as road surface, air and dew point temperatures, relative humidity, wind speed and direction, etc. Among these parameters, the road surface temperature is the key parameter for decision-making. It is required to be predicted with the highest possible accuracy. It is especially important during the winter period when near zero temperatures are associated with slippery conditions on the roads.



**Figure 2.1.1:** (a) Spatial distribution of road stations within the Danish road network; and (b) Geographical boundaries and terrain for the NWP HIRLAM modeling domain (with Denmark in the center of the domain) used to provide forecasts for the RCM.

#### 2.1.2. Numerical weather prediction model

The High Resolution Limited Area Model (HIRLAM) is used as the Numerical Weather Prediction (NWP) model and interface to the Road Conditions Model (RCM). Because this model is a limited area model, the boundary conditions are applied from an outer model (which is running on a larger size domain). HIRLAM includes data-assimilation for free atmosphere and surface, as well as cloud observations into the model. The data-assimilation uses observations from surface stations, weather balloons, satellites and airplanes. Outcome of data-assimilation is used to initialize the NWP model. Digital filter is used to filter noise from unbalances in initial conditions. Description of the model (dynamics, physics, etc.) including basic system of equations, parameterizations, solution methods, etc. is given at the HIRLAM official website (<http://hirlam.org>; *Uden et al., 2002*)

Figure 2.1.1b shows the chosen NWP model domain with an area chosen in such a way that Denmark is placed in the centre of the domain. The boundaries and size (650 x 460 grid points along

longitude/latitude in rotated system of coordinates) of domain were chosen to ensure that it will reflect weather conditions likely to influence Danish area during the forecasted period. The horizontal resolution is approximately 0.03 degree with 40 vertical levels, and time step of 120 seconds. The model is running with data-assimilation accounting the latest observations. There are 24 runs daily with a forecast length up to 1 day.

### 2.1.3. Road conditions model

The Road Conditions Model (RCM) is a so-called energy balance model developed at DMI (*Sass 1992, 1997*). It is a local model, which, in principle, means that the forecast for each horizontal point does not depend on other surrounding points. All advection parts of atmospheric processes are done in the NWP model. Indirectly these processes are incorporated by obtaining the atmospheric state from the NWP model at each time step. The energy balance model in RCM is different than in NWP. The RCM has 15 layers in the road and solves the heat equations for these layers, and it is optimised for road (asphalt) surfaces. The RCM model is called every time step from the NWP model with the first call after 1 hour. Daily the RCM model is running 24 times making forecast 24 hour ahead. It is run as a module inside the NWP model. Contrary to the NWP model, which is defined on a grid, the RCM model makes forecasts for points (i.e. road stations and from 2008 – for road stretches), and the NWP input is interpolated to these points.

At first steps, an analysis of the initial conditions is done. Observations of road surface, 2 m air and dew temperatures from road stations are used to run the RCM. The equations of heat conduction for the road points are solved using the forecast from the last model run as initial conditions. Then run the RCM 3 hour ahead with observed  $T_s$  as boundary condition. This provides an analysis of the temperature profile of all road layers. After initial steps, a forecast of the road surface temperature, 2 m temperature and dew point temperature, accumulated water (rain water, dew) and ice (snow, rime, frozen water) on the road are calculated for each time step. For these forecasts, the processes of heating/cooling, turbulent fluxes from/to, evaporation-melting-freezing-sublimation of water/ice from the road surface are taken into account.

## 2.2. Approaches to correction of $T_s$ forecast

### 2.2.1. Bias correction: statistical mean, median, and mode

For road weather modeling it is important to predict temperature conditions leading to salting activities organized by the road authorities. At the same time, the RWM system should be capable to predict common typical meteorological situations as well as relatively rare events, such as heavy rain/snow conditions. In general, evaluation of such system forecasting performance is done through analysis of the mean error or bias, *BIAS* (thereafter, **bias**) and the mean absolute error, *MAE* (thereafter, **mae**) for the road surface temperature ( $T_s$ ).

The MAE and BIAS are estimated using the following equations:

$$BIAS = \frac{1}{N} \sum_{i=1, N} (T_{s_{f_i}} - T_{s_{o_i}}),$$
$$MAE = \frac{1}{N} \sum_{i=1, N} |T_{s_{f_i}} - T_{s_{o_i}}|,$$

where:  $N$  is the number of pairs (observed and forecasted value of temperature at the road station) or total number of observations/forecasts,  $i$  denotes the  $i^{\text{th}}$  observation/forecast,  $T_{s_f}$  and  $T_{s_o}$  are the forecasted and observed values for temperatures, respectively.



For bias, the positive difference sign shows over prediction (i.e. the forecasted value is higher compared with observed), and the negative – under prediction (i.e. the forecasted value is lower compared with observed) of temperatures compared with observed value.

The bias was used as a starting point in development of statistical approach for possible correction of the original road surface temperature forecasts. We have observations for  $T_s$  at road stations as well as forecasts at the same locations. The “perfect” forecast (when the bias is approaching close to 0) is almost impossible to reach. It would be very rare event, and analysis shows that in general it could be up to a few percent from a total number of forecasts. Mostly there is always a deviation of the forecast from the observation. This difference could have both positive and negative signs, and it could be small or large by an absolute value. For a specific location (station) there is a probability that due to specific local conditions (terrain, surroundings, etc.) a positive or negative sign of deviation could be dominating. The magnitude of such deviation could be also of specific value as well. From statistical point of view, knowing such peculiarities and/or parameters (sign and magnitude/value) could lead to improvement of the original forecast. If a relatively large dataset (the longer time-series of observations/forecasts is the better) is used than it is also possible to estimate statistical parameters in existing distribution. These basic parameters are the mean, median and mode of the distribution. Many meteorological parameters, including the road surface temperature, are characterized by variability on a diurnal cycle and on a month-to-month basis. Hence, the  $T_s$  bias estimation can be done also on hourly and monthly scales. Moreover, when the forecasts and observations are performed for a long period of time than the statistical parameters can be evaluated on yearly or multi-year scales. It leads to possibility to consider two approaches to calculate statistical mean, median and mode: one is based on the one (last/previous) year data, and the other is based on the multi-year data. Let’s call these the previous year method (PYM) and the multi-year method (MYM) for calculation of selected statistical parameters.

Annually the road weather season is extended from October till April inclusive. Hence, calculation of statistical parameters for each road station within the road network, for each month of the road season, and for each hour on a diurnal cycle is required. Such calculations are done for each forecast length (1-5 hours) as well. Note, although RCM forecasts are provided at every 30 minute interval, but hourly statistics could be sufficient. I.e. improvement at intermediate times between hours (fx. 00:30, 01:30, etc.) could be done through interpolation of statistical parameters between standard hours.

Because there is always probability that one type (positive vs. negative) of the bias could be dominating for a station at specific hour and at specific month, the number of such cases (or percentage of occurrence) is also important to estimate for each forecast length. Hence, at first, it was decided to divide biases into two intervals – with assigned negative and positive values only. Then into three intervals: 1)  $< -0.1^\circ\text{C}$  - negative  $T_s$  bias; 2)  $> +0.1^\circ\text{C}$  - positive bias or  $T_s$  bias; and 3)  $-0.1^\circ\text{C} < T_s$  bias  $< +0.1^\circ\text{C}$  - “zero” bias. The last “zero” interval assumes that the model generated almost “perfect” forecast, which in principle is not needed to be corrected.

As a first approximation, for each station it is assumed that the correction to original  $T_s$  forecast is equal to one of the values (mean, median, mode) of the  $T_s$  biases. This value is taken based on one of the dominating biases for the station.

$$T_{s_{new}} = \begin{cases} T_{s_{orig}} + T_{s_{bias}} & : \text{negative} \\ T_{s_{orig}} - T_{s_{bias}} & : \text{positive} \\ T_{s_{orig}} \pm 0 & : \text{"zero"} \end{cases} \quad T_{s_{bias}} = \begin{cases} T_{s_{bias}}(\text{mean}) \\ T_{s_{bias}}(\text{median}) \\ T_{s_{bias}}(\text{mode}) \end{cases}$$

Note, that the “zero” interval has the lowest probability to be identified as the dominating bias due

to extremely low probability of maes below 0.5°C (it is very rare case when evaluation for stations might show such number). At the same time it allows to remove small values (within a range of  $\pm 0.1^\circ\text{C}$ ) from consideration in two other intervals. This leads to obtaining distributions for each of intervals to be more isolated or clustered (having clearly recognized individual pattern/signature) as well as it increases slightly the calculated values of statistical parameters.

In order to decide if it is necessary to make a correction of  $T_s$  forecast at all, it is important to evaluate existing relationships between  $T_s$  and its bias and other meteorological parameters. In operational runs, the three calculated values – mean, median, and mode – for correction should be justified to decide which one of these is the most suitable to choose. That could be based on evaluation of other meteorological parameters. In particular, because observations are not available yet, it could be based on forecasted parameters. For that existing correlations between parameters and  $T_s$  should be evaluated, and corresponding to three  $T_s$  bias intervals the mean, median, and mode values for forecasted meteorological parameters need to be calculated as well.

### 2.2.2. Correlation factor

In principle, when physics and dynamics of the modelling system are well described (e.g. solved through a system of equations or parameterised where it is possible) and as many as possible processes are accurately resolved than the correlations would be stronger or, at least, will have fair value. In operational practice, since at the moment of the  $T_s$  forecasts there are no  $T_s$  observations available yet, the other forecasted meteorological parameters could be used to identify relationship with forecasted  $T_s$ . Among such parameters, for example, the cloud cover, wind speed and wind direction, air temperature and dew point temperature can be used (let's call these as  $Y$ 's parameters). Hence, the statistical relationship between mentioned parameters and  $T_s$  as well as its bias can be estimated.

Assuming that the linear relationships are dominating among listed meteorological parameters, the Pearson correlation coefficients  $r$  (as dependencies between datasets of pairs of variables) can be calculated:

$$r = \frac{\sum_{i=1}^N (Ts_i - \overline{Ts})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^N (Ts_i - \overline{Ts})^2} \sqrt{\sum_{i=1}^N (Y_i - \overline{Y})^2}}$$

The range of  $r$  is between  $\pm 1$  inclusive. The sign of the correlation coefficient determines whether the correlation is positive or negative:  $r = -1$  (perfect negative correlation),  $r = 0$  (there is no linear correlation between meteorological parameters), and  $r = +1$  (perfect positive correlation).

As a correlation coefficient value gets closer to  $\pm 1$ , it is getting stronger (note, for example, that a sign just show the direction of correlation). The magnitude of the correlation coefficient determines the strength of the correlation. Let's assume that:  $0 < |r| < 0.3$  (weak),  $0.3 < |r| < 0.7$  (moderate), and  $|r| > 0.7$  (strong) correlations.

### 2.2.3. Hierarchy in importance of forecasted meteorological parameters

It is known that at some degree different meteorological parameters (as well as their derivatives) and their combinations could define/describe specific meteorological conditions, which are always varying in time (on a diurnal cycle, month-to-month and inter-annual) and space (geographical location/ area/ region).

Evaluation of correlations between parameters would be the initial step to proceed. Once a set of

representative meteorological parameters, influencing selected parameter/s of concern or process/es under evaluation, is defined, a hierarchy of parameters' importance could be defined as levels of importance. Evaluation of forecasted meteorological parameters (considering their mean, median, and mode values) and correlation coefficients between these parameters is important step required. In our study, because the focus is on the road surface temperature, and hence, the distribution in percentage of negative and positive  $T_s$  biases would be of the first importance in hierarchy (e.g. Level 1).

### Top Level - Level 1:

**Dominating bias** is defined based on percentage of occurrences of specific sign ( $- / \pm 0.1 / +$ ) of the  $T_s$  bias. It is considered among three intervals (see Ch. 2.2.1). For example, if the most frequent bias is positive, than the correction (which is represented by the mean, median, and mode values of  $T_s$  bias) to  $T_s$  should be by subtracted from originally forecasted  $T_s$ . When the negative bias is the most frequent than correction should be added to originally forecasted  $T_s$ . Note that it is just a first level of decision to make. The further analysis in hierarchy includes evaluation of other parameters (or levels) of importance.

### High Level - Level 2:

**Cloud cover** is the parameter of the 2<sup>nd</sup> importance, and it is defined on a scale from 0 (cloud free) to 1 (overcast). Its mean, median, and mode values are calculated for three  $T_s$  bias intervals as well. If the dominating bias interval is "positive" than the value of the forecasted cloud cover is compared with the statistically calculated corresponding mean, median and mode values assigned to the positive  $T_s$  bias interval. Once the forecasted cloud cover is validated with its statistical value, it means that both parameters of the 1<sup>st</sup> and 2<sup>nd</sup> levels show strong support of the sign of correction and a type (mean, median, and mode) of correction to be applied. If these are not validates, the parameter of the 3<sup>rd</sup> level of importance is considered.

### Medium Level - Level 3:

**Wind speed** is the parameter of the next importance, and it is defined on a scale from 0 m/s (calm) to maximally possible wind conditions. Similarly, as for all other meteorological parameters of importance the mean, median, and mode values are calculated for the same three  $T_s$  bias intervals. For the same dominating  $T_s$  bias interval the value of the forecasted wind speed is compared with their statistically calculated mean, median and mode values for the  $T_s$  bias interval. Similarly, the forecasted wind speed is validated with its statistical value. Depending on outcome the next meteorological parameters are considered step-by-step in a hierarchy of importance.

### Lower Levels - Levels 4-6:

Wind direction and **Temperature differences** ( $T_s - T_a$  and  $T_s - T_d$ ) are parameters of the lower importance levels. Wind direction is defined on a scale from 0 to 360 degrees. Temperature differences are defined on a temperature scale ( $^{\circ}\text{C}$ ) from negative to positive numbers.

The percentage contributions of different parameters/levels of importance into the total are shown in Table 2.2.1 (see column 2). The contribution of the dominating bias should be, at least, 50% in order to start to be accounted. Although note that it might be even higher if a statistical bias with a specific sign is more frequent. The one of the three values (average, median, or mode) is considered to be valid (and hence further used for correction) if the forecasted value is within a 10% of variability of statistical value. For example, for the wind speed: if the statistical mode value is 3 m/s, than the forecasted wind speed should be within 2.7-3.3 m/s interval. In a rare case if there is an overlap between two or even three statistically calculated parameters and the forecasted parameters than the mode value of  $T_s$  bias is selected.

Several examples explaining application of the hierarchy approach are shown in Table 2.2.1 for the

negative  $T_s$  bias. Note, a similar way of hierarchy analysis is used for the positive  $T_s$  bias as well. For example, for the 2<sup>nd</sup> case, the forecasted cloud cover is closer to the median value of the statistically calculated cloud cover than to the average value. Similarly, it is valid for the wind speed and differences between  $T_s$  and air/dew temperatures. Hence, 4 of 6 parameters showed that the statistical median value of the negative  $T_s$  bias should be used to correct original  $T_s$  forecast. Analogously, for the 1<sup>st</sup> case – 3 of 6 parameters ( $T_s$  bias itself, cloud cover and wind direction) showed that the statistical average value of the negative  $T_s$  bias should be used for correction; and for the 3<sup>rd</sup> case – 4 of 6 parameters (cloud cover, wind speed and direction, and  $T_s-T_a$ ) showed that the statistical mode value should be used for correction. In opposite, for the 4<sup>th</sup> case, only 1 parameter (i.e. cloud cover) showed a link with the negative bias, and hence, the most probable decision that the positive  $T_s$  bias should be considered for correction.

**Table 2.2.1:** Application of the hierarchy approach for correction of original  $T_s$  forecast /on examples of the negative  $T_s$  bias/ as a function of the level of importance vs.  $T_s$  bias statistics (avg, med, mod).

Level of importance	Contribution	Negative $T_s$ bias											
		Case 1			Case 2			Case 3			Case 4		
1: $T_{sbias}$	% calc	avg	med	mod	avg	med	mod	avg	med	mod	avg	med	mod
2: CC	20	avg	med	mod	avg	med	mod	avg	med	mod	avg	med	mod
3: WU	10	avg	med	mod	avg	med	mod	avg	med	mod	avg	med	mod
4: WD	10	avg	med	mod	avg	med	mod	avg	med	mod	avg	med	mod
5: $T_s-T_a$	5	avg	med	mod	avg	med	mod	avg	med	mod	avg	med	mod
6: $T_s-T_d$	5	avg	med	mod	avg	med	mod	avg	med	mod	avg	med	mod
<b>Decision</b>		avg			med					mod	move to $T_s$ pos bias		

If there is no strong support (e.g. except only the 1<sup>st</sup> level is validated) to choose the sign/direction of correction, the correction to  $T_s$  should be considered for the other sign of the  $T_s$  bias or it should assumed to be zero.

### 2.3. Implementation of $T_s$ correction procedure

The procedure for the statistical correction of the  $T_s$  forecasts is based on using information from so-called look-up tables (saved as ascii-files). These tables include statistically calculated (based on multi-year datasets) the average, median and mode values (with corresponding number and percentage of cases used in statistics). Statistics is calculated for: 1) positive/zero/negative  $T_s$  biases intervals, and 2) cloud cover, wind speed and direction, and differences between  $T_s$  and air/dew temperatures for three  $T_s$  bias intervals. For each road station there are separate files for each of parameters. And each file contains calculated statistics on a diurnal cycle (00-23 UTCs) for each month (from Oct till Apr). Structurally, these calculations are done for each forecast length (1-5 hours). Several visualized examples of such look-up tables are shown in Ch. 3.4.

The statistical correction procedure is run every hour, e.g. once the RCM 5 hour forecast run is completed and the forecasted data became available. At first, the forecasts of mentioned above meteorological parameters are extracted. At second, for each road station the dominating  $T_s$  bias is estimated, and then the hierarchy of importance approach is used for comparison of currently

forecasted meteorological parameters with statistically calculated (e.g. average, median, and mode). Following outcome of evaluation the decision is made about selection of exact value of correction to  $T_s$  (e.g. average, median, or mode value) or a change to another sign of correction.

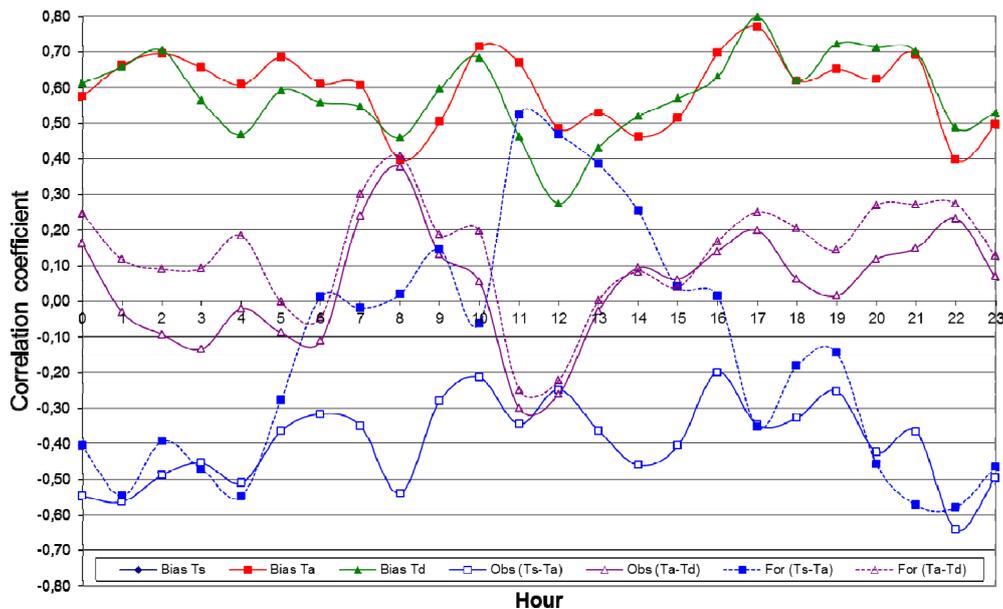
Before the next road weather season start, the statistics for each – forecast length, road station, month and hour – is completely re-calculated for all parameters by adding extra data from the last season. In principle, if the model continues to run than after a few (3-5) years the statistics will became closer to climatologically averaged situation.

The code is written in FORTRAN. The CPU time required for each run of procedure is relatively fast, but the more stations will be included the more time will be needed for recalculation of statistics. Further, an option for daily recalculation of statistics (not only once per season) could be also considered, which might allow adapting to new variations in  $T_s$  biases. It is especially might became important when the on-going (i.e. current for operational runs) month became more deviated from a climatologically averaged previous multi-year period.

### 3. Results and Discussions

#### 3.1. $T_s$ correlations with meteorological parameters

The correlations ( $r$ ) between forecasted  $T_s$  and mentioned parameters are variable with a time, and hence, both hourly and monthly variability of correlations would be of importance. Let's us consider the following selected meteorological parameters. The cloud cover or cloudiness ( $CC$ ) is a dimensionless parameter ranging from 0 (cloud free) to 1 (overcast). The wind speed ( $WU$ ) varies from 0 to maximum (in m/s) and wind direction ( $WD$ ) changes from 0 to 360 degrees. In addition to observed and forecasted air and dew point temperatures (in deg C), the differences between  $T_s$  and the two latter could be used:  $T_s - T_a$  and  $T_s - T_d$ .



**Figure 3.1.1:** Variability of correlation coefficients on a diurnal cycle between  $T_s$  bias and  $T_a$  &  $T_d$  biases, differences for observations ( $T_s - T_a$  &  $T_s - T_d$ ) and forecasts ( $T_s - T_s - T_a$  &  $T_s - T_d$ ) /calculated based on observed and modeled data from road weather seasons 2011-2012/.

As expected the correlation between temperatures  $T_s$  and  $T_a$  and  $T_d$  is the strongest (on average  $r = +0.9$ ) compared with other meteorological parameters. It is decreasing when biases and differences between these observed and forecasted values are considered (see Figure 3.1.1). As seen in Figure 3.1.1, on a diurnal cycle there is strong variability between biases of  $T_s$  vs.  $T_a$  and  $T_d$ . On average it is about  $+0.6$ . The  $T_s$  bias is always negatively correlated with observed ( $T_s - T_a$ ), and on average it has fair correlation of about  $-0.4$ . It is the highest during night times (up to  $-0.6$ ) and the lowest (up to  $-0.2$ ) during daytime. The  $T_s$  bias with forecasted ( $T_s - T_a$ ) has negative correlation during nighttime and late evening hours (up to  $-0.6$ ). It changes sign to positive from morning hours till 16 pm, reaching a highest values (up to  $+0.5$ ) at noon hours. The correlation of  $T_s$  bias with the forecasted ( $T_a - T_d$ ) and observed ( $T_a - T_d$ ) differences have shown a very similar pattern. In particular, it is mostly negligible (within a range of  $\pm 0.2$ ) during late evening and night hours. At morning hours  $r$  became fair reaching up to  $+0.4$ , and then it is decreasing fast reaching negative ( $-0.3$ ) correlation at noon.

Hour	Correlation coefficients between <b>negative</b> $T_s$ bias &			Correlation coefficients between <b>positive</b> $T_s$ bias &			% of occurrence $T_s$ biases in 3 intervals		
	CC	WU	WD	CC	WU	WD	Neg	Zero	Pos
1	0,091	-0,161	0,343	0,098	0,062	0,089	16,67	6,67	<b>76,67</b>
2	0,380	0,600	0,182	0,021	0,288	0,220	19,35	12,90	<b>67,74</b>
3	0,161	0,704	0,231	0,206	0,263	0,107	13,79	6,90	<b>79,31</b>
4	0,050	0,969	0,607	0,308	0,313	0,002	12,90	12,90	<b>74,19</b>
5	0,174	-0,140	-0,281	-0,071	0,168	0,050	29,03	6,45	<b>64,52</b>
6	-0,619	0,080	0,046	0,072	-0,371	0,172	29,03	3,23	<b>67,74</b>
7	0,324	0,495	-0,369	-0,034	0,425	0,007	<b>35,48</b>	16,13	48,39
8	0,515	0,470	-0,150	0,013	0,377	0,013	<b>38,71</b>	16,13	45,16
9	0,606	0,467	-0,362	0,305	-0,146	-0,365	<b>45,16</b>	16,13	38,71
10	0,558	0,589	-0,420	0,514	-0,647	0,038	<b>41,94</b>	22,58	35,48
11	0,608	0,130	0,220	0,429	-0,212	0,008	32,26	3,23	<b>64,52</b>
12	0,598	0,416	0,369	0,336	-0,190	-0,079	19,35	16,13	<b>64,52</b>
13	0,632	0,442	0,039	0,298	-0,370	0,101	16,13	22,58	<b>61,29</b>
14	0,401	0,469	0,105	-0,007	0,063	0,257	29,03	0,00	<b>70,97</b>
15	-0,353	-0,912	0,693	0,158	-0,222	0,075	20,69	6,90	<b>72,41</b>
16	0,295	0,431	0,541	0,167	-0,108	-0,226	32,26	9,68	<b>58,06</b>
17	0,326	-0,040	-0,058	0,024	-0,317	0,006	25,81	12,90	<b>61,29</b>
18	0,148	0,356	0,072	0,113	-0,273	0,151	29,03	9,68	<b>61,29</b>
19	-0,021	0,403	-0,207	-0,034	0,207	-0,056	23,33	10,00	<b>66,67</b>
20	-0,035	0,338	-0,375	-0,012	0,404	0,005	23,33	16,67	<b>60,00</b>
21	0,817	0,284	-0,340	0,222	0,220	0,103	26,67	20,00	<b>53,33</b>
22	-0,027	0,422	0,711	-0,055	-0,087	0,336	22,58	9,68	<b>67,74</b>
23	-0,954	-0,444	1,000	0,323	-0,018	0,283	10,00	20,00	<b>70,00</b>
							<b>25,85</b>	<b>12,08</b>	<b>62,07</b>

**Table 3.1.1:** Correlation coefficients between  $T_s$  bias (negative and positive) vs. cloud cover (CC), wind speed (WU) and wind direction (WD) on a diurnal cycle, and percentage of occurrence of negative, "zero", and positive values of  $T_s$  biases at the road station 6002  
/calculated based on observed and modeled data from road weather seasons 2011-2012/.

An example of correlations with other meteorological parameters such as CC, WU, and WD is shown and discussed for the road station N-6002 in Table 3.1.1. The  $|r|$  values higher than  $\pm 0.4$  are marked:  $r > 0$  – light red color, and  $r < 0$  – light blue color. The values of  $|r|$  higher than  $\pm 0.3$  are also included. The percentage of occurrence  $T_s$  bias values higher than 50% is also marked (as seen on example of positive  $T_s$  bias – light orange color).

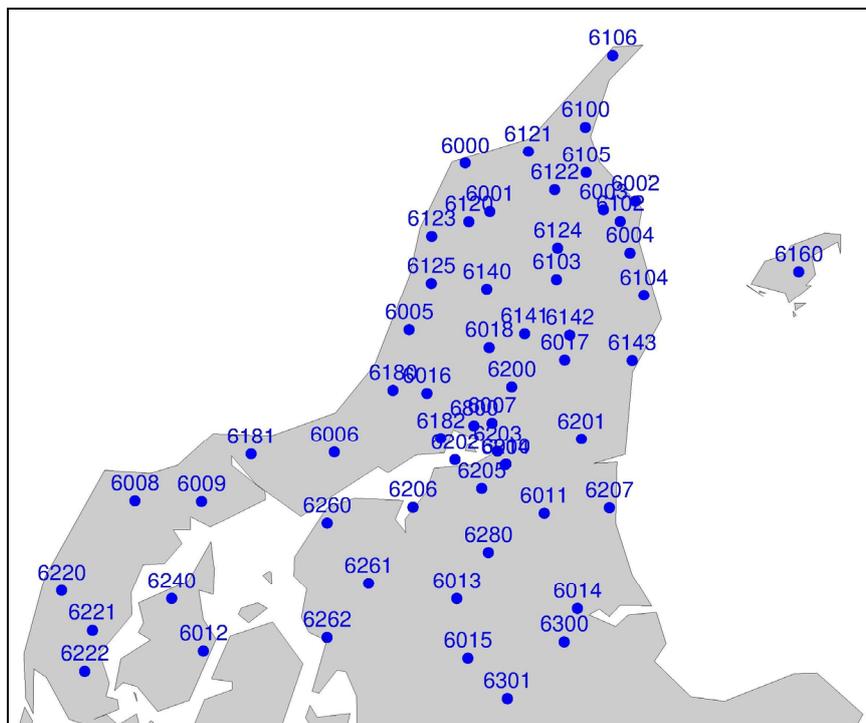
As seen in Tables, on a diurnal cycle, in about 62% of the cases the positive  $T_s$  bias is observed as

dominating; in about 26% - the negative bias, and in about 12% - the bias is within  $\pm 0.1^\circ\text{C}$  interval. The positive bias dominates on a diurnal cycle (reaching almost 80% at 03 hours), except on interval from 07 to 10 hours. During this time the negative bias is the most frequent or comparable (i.e. above 35% of the cases). On average, in about 12% of the cases the  $T_s$  bias is very small and hence, the correction of the  $T_s$  forecast is not needed. During the day it varied from 3 to 23%.

As seen in Table 3.1.1, on a diurnal cycle the cloud cover is mostly (almost 75% of the time) positively correlated with the negative  $T_s$  bias, and this correlation became fair and stronger in about 35% of the time. Similarly, it is also mostly positively correlated with  $WU$ ;  $r$  became fair and stronger even in about 57% of the time. The correlation with the wind direction is not so well pronounced: in about 40 (vs. 60%) of the time the  $WD$  is negatively (vs. positively) correlated with negative  $T_s$  bias. As seen,  $r$  (both positive and negative values) is fair and stronger for a half of the time during the day for the cloudiness and wind speed, but it is less frequent (about 25%) for the wind direction. On example of the selected road station, such analysis of correlations between the negative  $T_s$  bias and selected meteorological parameters (such as  $CC$ ,  $WU$ , and  $WD$ ) showed existence of significant correlations. For positive  $T_s$  bias the lower values of the correlation coefficients are more frequent compared with the negative  $T_s$  bias. Except only about 10% of the time on a diurnal cycle, the correlation was fair with the cloud cover and wind speed. As expected, for the “zero”  $T_s$  bias interval (not shown), for about 55, 70 and 60% of the time, the  $T_s$  bias was mostly well correlated with  $CC$ ,  $WU$ , and  $WD$ , respectively.

### 3.2. $T_s$ bias climatology factor

A list of road stations (in total 59, see Figure 3.2.1), situated in the Region N6 of the North Jutland Peninsula, was considered in analysis for  $T_s$  bias climatology (which was based on multi-year period of 2008-2010). Note that in this analysis only the RCM model forecasts with the forecast length of 5 hours ahead were evaluated, but similar approach could be also used for other forecast lengths.



**Figure 3.2.1:** Geographical position of 59 road stations in the region N6 (Nordjylland; Jutland Peninsula, Denmark).



Variability of  $T_s$  bias on a diurnal cycle is shown for winter vs. spring months in Figure 3.2.2. As seen in Figure 3.2.2a, on average, for winter month (December) the negative bias mostly dominated during daytime hours, and it was positive for the rest of the day. During spring month (March), the situation is more complex. Although during late evening and night-time hours the bias is similar to December, but it is highly variable during daytime hours (Figure 3.2.2b). On average, it is between  $\pm 2.5^\circ$ . Note (not shown) that the patterns of variability in October, November, and January are similar to those in December; and the patterns of variability in January and April are similar to those in March.

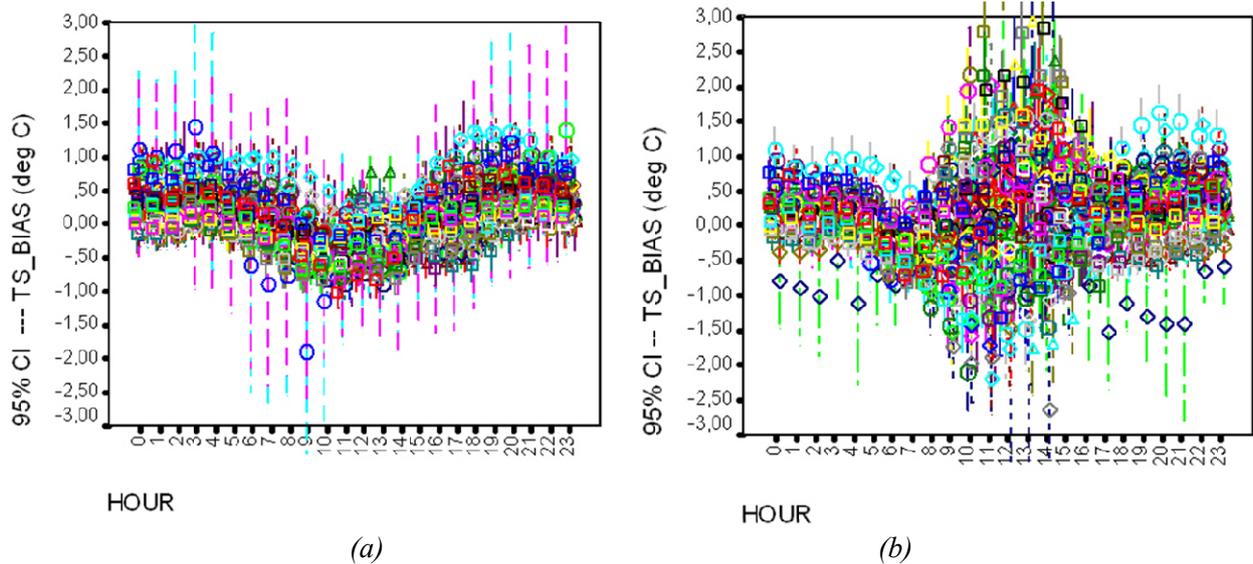


Figure 3.2.2: Multi-year climatology of the road surface temperature ( $T_s$ ) bias on a diurnal cycle for (a) December and (b) March months/ based on analysis for 59 road stations in region N6/.

Table 3.2.1: Diurnal cycle (00-23) variability of the  $T_s$  bias for December (12) and March (3) for selected road stations in region N6 based on a multi-year (9999) approach to calculate statistics /blue – negative bias less than  $-0.25^\circ\text{C}$ ; orange – positive bias more than  $+0.25^\circ\text{C}$ /

RST	YY	MM	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	AVG
6000	9999	12	0.62	0.93	0.38	0.52	0.45	0.39	0.28	0.17	-0.05	-0.47	-0.61	-1.02	-0.75	-0.83	-0.51	0.05	0.49	0.86	0.79	0.44	0.74	0.64	0.58	0.52	0.19
6001	9999	12	0.25	0.28	0.31	0.51	0.39	0.23	0.10	-0.09	-0.33	-0.69	-0.73	-0.63	-0.29	-0.41	-0.35	-0.03	0.09	0.24	0.22	0.25	0.30	0.27	0.31	0.28	0.02
6002	9999	12	0.82	0.68	0.67	0.84	0.86	0.74	0.61	0.43	0.37	0.02	-0.23	-0.18	-0.21	-0.24	-0.21	0.11	0.39	0.53	0.83	1.03	1.02	0.85	0.84	0.85	0.48
6003	9999	12	0.01	-0.05	-0.03	0.17	0.12	0.02	-0.03	-0.21	-0.23	-0.63	-0.74	-0.86	-0.67	-0.69	-0.46	-0.08	0.20	0.05	0.14	0.28	0.19	0.21	0.12	0.10	-0.13
6004	9999	12	0.17	0.30	0.27	0.51	0.45	0.31	0.10	-0.12	-0.22	-0.48	-0.29	-0.09	0.07	0.22	0.24	0.25	0.28	0.12	0.16	0.03	0.22	0.35	0.13	0.23	0.13
6005	9999	12	0.08	-0.05	0.04	0.09	0.05	-0.09	-0.08	-0.20	-0.33	-0.38	-0.33	-0.20	0.03	0.10	0.15	0.08	-0.07	-0.04	0.03	0.11	0.21	0.31	0.25	0.15	0.00
6006	9999	12	0.04	0.00	0.14	0.17	0.06	-0.08	-0.14	-0.19	-0.52	-0.44	-0.24	-0.13	-0.19	-0.19	-0.14	-0.08	-0.14	-0.12	0.12	0.16	0.18	0.17	0.14	0.16	-0.05
6007	9999	12	0.14	0.06	0.17	0.31	0.26	0.07	-0.24	-0.52	-0.63	-0.77	-0.82	-0.72	-0.68	-0.77	-0.80	-0.51	-0.37	-0.42	-0.14	0.18	0.34	0.48	0.31	0.22	-0.21
6008	9999	12	0.54	0.41	0.39	0.39	0.19	0.16	0.14	0.04	-0.02	-0.14	-0.15	-0.28	-0.07	0.06	0.13	0.22	0.23	0.53	0.56	0.67	0.60	0.61	0.63	0.47	0.27
6009	9999	12	0.10	0.04	0.09	0.03	-0.08	-0.03	-0.18	-0.27	-0.46	-0.46	-0.68	-0.80	-0.63	-0.66	-0.61	-0.38	-0.22	-0.07	0.07	0.19	0.18	0.24	0.24	0.12	-0.18
6010	9999	12	0.13	0.01	0.01	0.08	0.09	-0.14	-0.40	-0.46	-0.66	-0.74	-0.83	-0.81	-0.63	-0.58	-0.53	-0.32	-0.37	-0.37	-0.30	0.13	0.08	0.24	0.19	0.16	-0.26
6011	9999	12	0.42	0.36	0.29	0.58	0.57	0.38	0.20	0.03	-0.13	-0.38	-0.28	-0.23	0.04	0.11	0.12	0.27	0.22	0.13	0.36	0.53	0.59	0.67	0.57	0.45	0.24
6012	9999	12	0.48	0.53	0.51	0.53	0.20	0.10	-0.13	-0.24	-0.25	-0.40	-0.24	-0.36	-0.37	-0.39	-0.35	-0.51	-0.66	-0.26	-0.03	0.11	0.21	0.56	0.52	0.38	0.00
6013	9999	12	-0.14	-0.15	-0.06	0.07	-0.01	-0.13	-0.21	-0.29	-0.49	-0.64	-0.54	-0.18	0.33	0.39	-0.10	-0.21	-0.49	-0.63	-0.60	-0.39	-0.16	0.19	0.25	0.09	-0.17
6014	9999	12	-0.09	0.03	0.04	0.14	0.11	-0.06	-0.09	-0.25	-0.39	-0.41	-0.42	-0.59	-0.47	-0.27	-0.34	-0.31	-0.15	-0.06	0.02	0.09	0.02	0.07	-0.01	-0.02	-0.14
6015	9999	12	0.30	0.31	0.35	0.44	0.37	0.15	0.11	0.03	-0.13	-0.10	-0.38	-0.55	-0.23	-0.39	-0.51	-0.29	0.05	0.23	0.27	0.53	0.51	0.68	0.57	0.29	0.11
6000	9999	3	0.33	0.73	0.17	0.32	0.24	0.09	-0.24	-0.70	-0.67	-0.72	-0.69	-0.10	0.35	0.41	1.93	1.41	0.39	0.19	0.33	0.02	0.32	0.39	0.69	0.59	0.24
6001	9999	3	0.41	0.37	0.24	0.25	0.14	0.02	-0.29	-0.23	-0.29	-0.46	-0.75	-0.79	-0.90	-0.59	-0.72	-0.43	-0.24	-0.06	0.29	0.30	0.46	0.61	0.61	0.55	-0.06
6002	9999	3	0.77	0.72	0.60	0.69	0.67	0.54	0.16	0.04	0.42	0.45	0.25	-0.08	-1.31	-0.79	-0.88	-0.66	-0.11	-0.25	0.30	0.55	0.64	0.83	0.66	0.91	0.21
6003	9999	3	0.40	0.35	0.21	0.28	0.19	0.14	-0.24	-0.29	0.13	0.22	0.22	-0.13	-0.94	0.47	-0.03	0.86	1.01	0.76	0.68	0.54	0.42	0.51	0.11	0.43	0.26
6004	9999	3	0.06	0.28	-0.01	0.03	0.09	-0.01	-0.36	-0.54	-0.84	-1.06	-1.35	-0.89	-0.88	-0.57	-0.35	-0.21	-0.04	0.10	0.52	0.43	0.47	0.46	0.34	0.26	-0.17
6005	9999	3	-0.01	0.11	0.05	0.05	-0.11	-0.16	-0.36	-0.20	-0.16	0.31	1.45	1.46	1.48	1.58	1.22	0.72	0.49	0.17	0.17	0.06	-0.07	0.15	0.06	0.05	0.36
6006	9999	3	-0.07	-0.12	-0.24	-0.11	-0.25	-0.40	-0.45	-0.32	0.01	0.29	0.91	1.17	1.36	1.09	0.43	0.12	-0.23	-0.58	-0.63	-0.50	-0.37	-0.15	-0.14	0.10	0.04
6007	9999	3	-0.02	-0.02	-0.07	0.09	0.02	-0.16	-0.61	-0.82	0.24	0.79	1.41	0.78	1.86	2.76	2.15	2.14	1.17	0.52	0.04	-0.17	-0.29	-0.37	-0.26	-0.09	0.47
6008	9999	3	0.36	0.25	0.16	0.22	0.06	0.00	-0.13	-0.11	-0.05	0.91	0.21	0.36	0.03	-0.17	0.09	0.15	0.37	0.00	0.12	0.24	0.26	0.32	0.43	0.52	0.19
6009	9999	3	0.26	0.14	0.07	0.05	-0.03	-0.15	-0.30	-0.37	-0.32	-0.01	1.12	2.15	-0.12	-0.43	-0.94	-0.25	-0.49	-0.85	-0.18	-0.04	0.21	0.10	0.37	0.49	0.02
6010	9999	3	-0.10	-0.04	-0.06	0.10	0.00	-0.20	-0.71	-0.61	-0.62	-0.24	1.05	2.79	3.97	4.18	3.42	2.06	1.03	0.26	-0.09	-0.31	-0.37	-0.30	-0.23	-0.07	0.62
6011	9999	3	-0.06	-0.02	-0.02	0.23	0.24	0.18	-0.31	-0.05	0.40	0.01	0.20	0.52	0.98	1.07	1.09	0.66	0.65	0.41	0.40	0.34	0.25	0.29	0.07	0.01	0.31
6012	9999	3	0.24	0.16	0.06	0.11	-0.03	-0.23	-0.45	-0.13	0.30	0.34	0.58	0.79	1.11	0.59	-0.17	-0.43	-0.46	-0.52	-0.53	-0.33	-0.03	0.13	0.25	0.31	0.07
6013	9999	3	-0.18	-0.20	-0.20	-0.07	-0.15	-0.24	-0.44	-0.51	0.31	0.74	1.28	1.44	1.59	1.49	1.00	0.57	0.27	-0.20	-0.46	-0.46	-0.58	-0.39	-0.43	-0.18	0.17
6014	9999	3	-0.03	-0.07	0.07	0.25	0.12	0.05	-0.27	-0.52	-0.01	0.09	1.08	1.64	1.00	0.81	0.51	0.16	-0.21	-0.47	-0.17	-0.05	-0.19	0.10	0.09	0.07	0.17
6015	9999	3	0.27	0.22	0.23	0.33	0.25	0.18	-0.13	-0.32	0.15	0.22	0.54	1.95	2.15	2.08	2.86	1.78	1.44	0.74	0.66	0.45	0.17	0.35	0.10	0.32	0.71

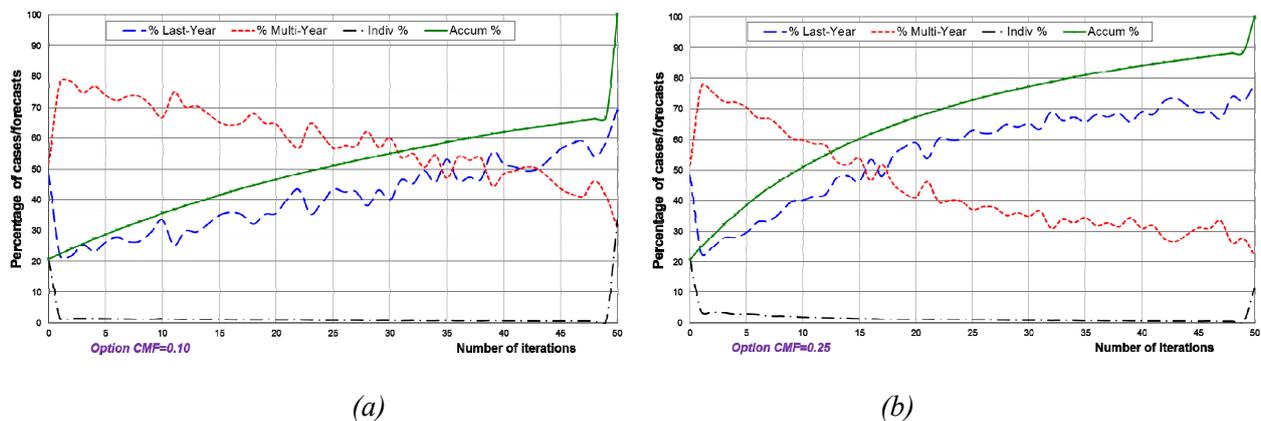
The  $T_s$  biases were calculated taking into account division into multiple intervals of positive and negative biases, but mostly focusing on occurrences of biases having absolute value of larger than  $\pm 0.25^\circ\text{C}$ . At start, the look-up tables were constructed (as shown in Table 3.2.1 as an example).

These include information on averaged values of  $T_s$  bias for each hour of the day, for each road station, and for each month.

Also two variants of such tables were created: the first was based on the last year statistics for biases, and the second was based on the previous multi-year statistics. Structurally, for each road station the “Look-Up” tables (individual files for each month of the road weather season: Oct-Nov-Dec-Jan-Feb-Mar-Apr) have two sets of values of the mean  $T_s$  bias for each hour on a diurnal cycle based on a last year and on a multi-year statistical evaluation. Hence, for example, to correct  $T_s$  forecast in Mar 2010: 1) based on the last year approach - the averaged  $T_s$  biases from the previous Mar 2009 are used; and 2) based on the previous multi-years approach – the averaged  $T_s$  biases from the previous Marches of 2009, 2008, 2007, etc. are used (note, the longer will be the time-series the more closer to climatologically averaged value will be the bias).

In order to estimate computational resource required for correction of  $T_s$  forecast, a test on a number of iterations required to improve the original forecast was performed. A small increment (starting from  $0.05^\circ\text{C}$  and proportional to statistical value of the  $T_s$  bias) for iterations was selected for a step-by-step simultaneous improvement of the both bias and mae. The increment varied from 0.05 with a step of 0.05, and the computational multiplication factor ( $CMF$ ) varied as 0.1 and 0.25 (results are shown in Figure 3.2.3ab), and 0.5 (results are not shown).

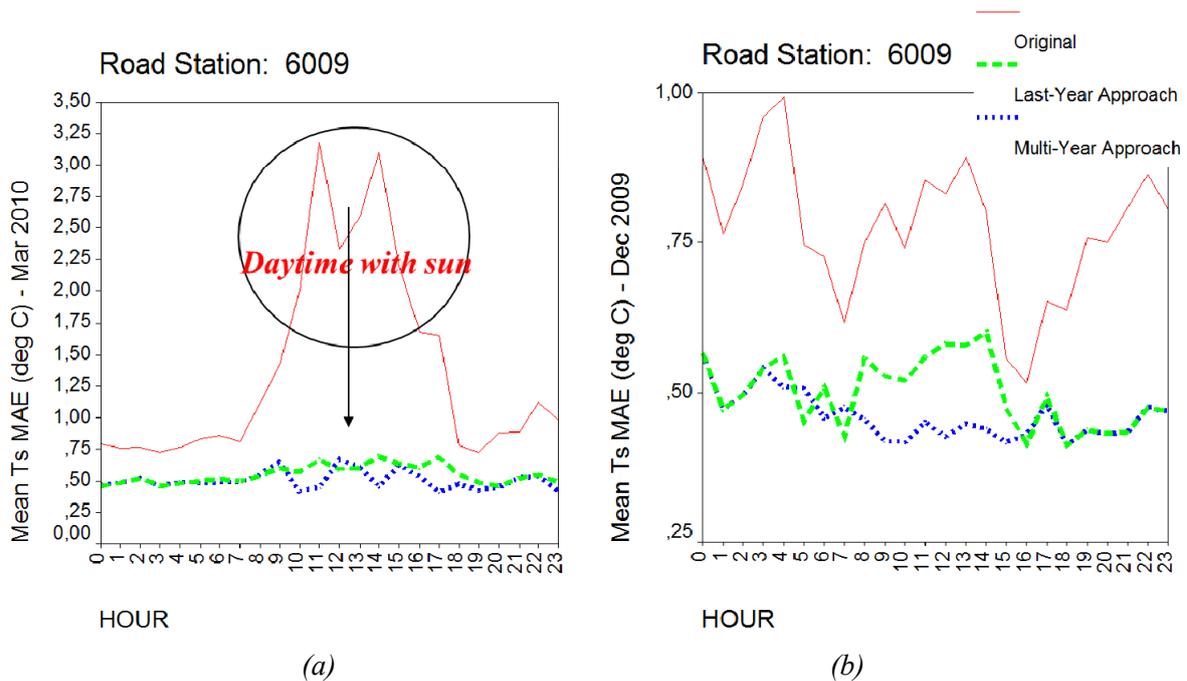
Figure 3.2.3a shows distribution of resources (e.g. number of iterations) required to reach improvement of the bias (down to  $\pm 0.25^\circ\text{C}$ ) and improvement of mae (down to  $0.5^\circ\text{C}$ ) with the  $CMF$  factor equal to 0.1. As seen, about 21% of forecasts were initially of a good quality (within  $\pm 0.25^\circ\text{C}$  interval for the bias), simply – there is no need to correct such  $T_s$  forecasts. In about 46% of the cases, the number of iterations is less than 50, and for the rest of the cases (33%) the number of iterations will be more than 50. Note, that the larger number (more than 50) of iterations is required mostly for the daytime forecasts.



**Figure 3.2.3:** Percentage of cases/forecasts as function of distribution of number of iterations required to reach the outlined  $T_s$  bias and mae with the computational multiplication factors ( $CMF$ ) – (a) 0.1 and (b) 0.25 – for the last and multi-year approaches.

/Blue line – method based on  $T_s$  bias statistics from the last year of RWSeason;  
 Red line – method based on  $T_s$  bias statistics from multiple years of RWSeasons;  
 Green line – accumulated number (in %) of  $T_s$  forecasts as a function of # iterations;  
 Black line – individual number (in %) of  $T_s$  forecasts as a function of # iterations/

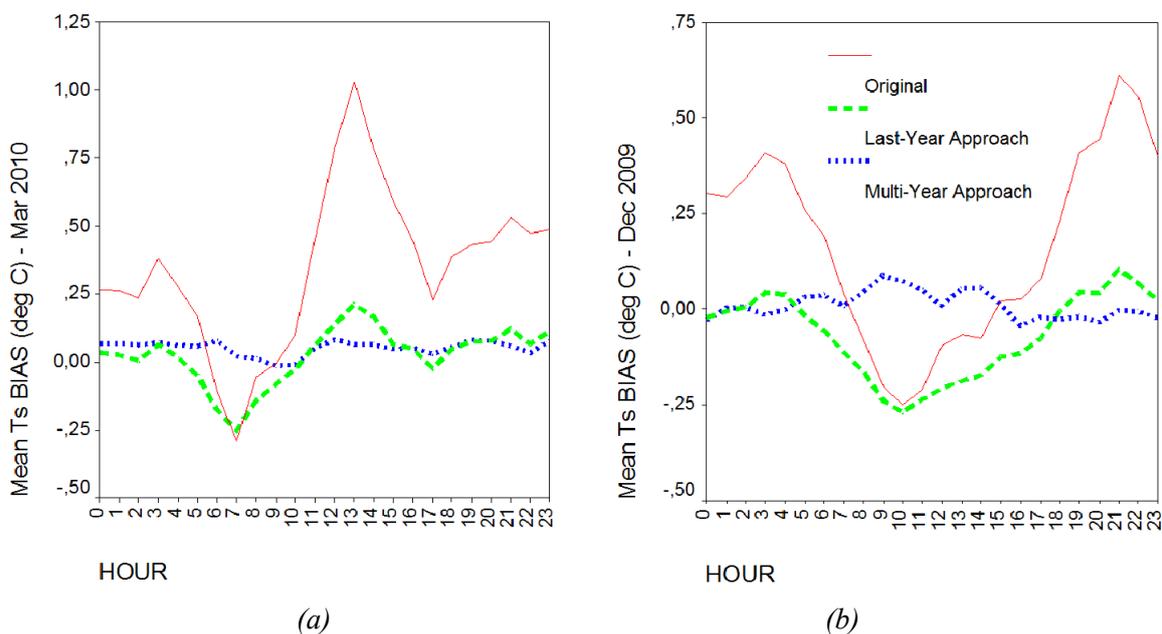
As seen in Figure 3.2.3b, a distribution/picture has changed for corrected forecasts when both interval for  $T_s$  bias (within  $\pm 0.50^\circ\text{C}$ ) and limit for mae ( $0.75^\circ\text{C}$ ) were increased with increased  $CMF$  factor up to 0.25. With a number of iteration up to 50 it is possible to correct up to 88% of forecasts in total. These also include 21% of good quality forecast. Although note that this correction will lead to larger values of  $T_s$  bias. Hence, the corrected forecasts will be of lower quality compared with  $CMF=0.1$ .

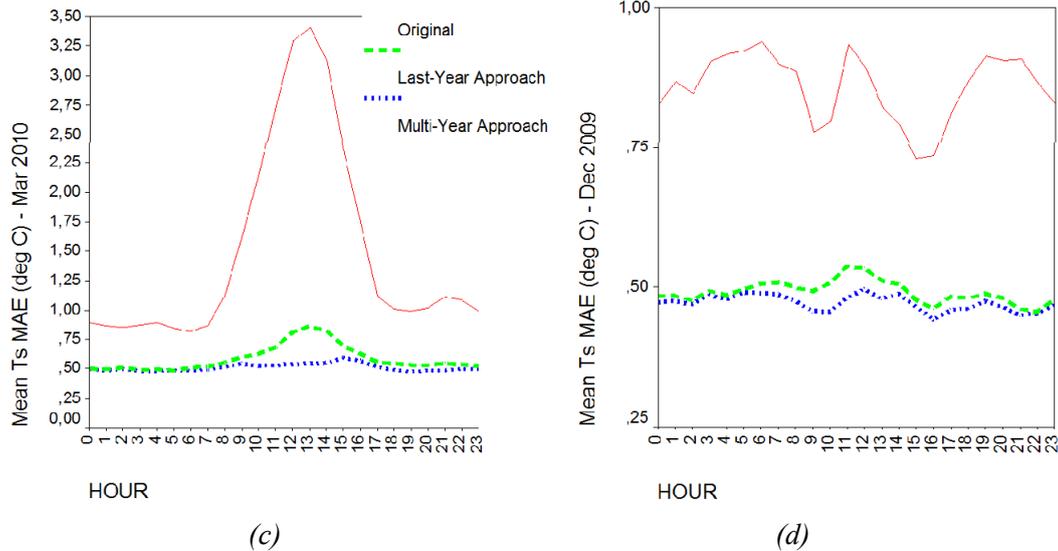


**Figure 3.2.4:** Road station N-6009: Average/mean  $T_s$  mae for original and corrected (based on the last & multi-year approaches for  $T_s$  bias) forecasts on a diurnal cycle for months of (a) Mar 2010 and (b) Dec 2009.

As seen in Figure 3.2.4a, on example of the road station N-6009, there is a possibility of improvement of original  $T_s$  forecasts having largest maes (during daytime) on a diurnal cycle. Although note, that it will require a large number of iterations (and hence, it will be too expensive computationally for operational use). Although both methods showed possibilities for improvement, but the multi-year approach provides slightly better results, especially during winter months and during daytime hours (see for December in Figure 3.2.4b).

As seen in Figure 3.2.5a, for Mar 2010 mostly the original positive  $T_s$  bias had dominated on a diurnal cycle being negative at morning hours, and reaching more than  $+1^\circ\text{C}$  at 13 pm. After correction the bias became closer to  $+0.1^\circ\text{C}$  for both approaches, although it had a larger variability (especially during morning vs. around noon hours) for the last-year approach.





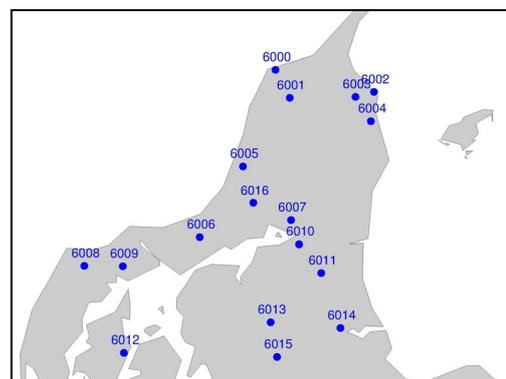
**Figure 3.2.5:** Average/mean  $T_s$  (ab) bias and (cd) mae for original and corrected (based on the last & multi-year approaches for bias) forecasts on a diurnal cycle for (a) Mar 2010 and (b) Dec 2009 /averaged over 59 stations in region N6/.

For Dec 2010 (Figure 3.2.5b), on average both methods also showed improvement in  $T_s$  bias and especially during evening-night hours, but this improvement was better for the multi-year approach. For the other, the negative bias up to  $-0.25^{\circ}\text{C}$  continued to dominate during morning-noon hours.

As seen in Figure 3.2.5c, for Mar 2010 the original mae, averaged over the entire diurnal cycle, has improved from  $1.5^{\circ}\text{C}$  to  $0.6^{\circ}\text{C}$  and  $0.5^{\circ}\text{C}$  based on multi- and last-year approaches, respectively. This improvement was the largest at daytime hours, but at the same time it required the largest number of iterations as well. At these hours mae was reduced down to  $0.8^{\circ}\text{C}$  for the last-year approach. Similarly, for Dec 2010 the mae has changed from  $0.9^{\circ}\text{C}$  to about  $0.5^{\circ}\text{C}$  for both methods (Figure 3.2.5d).

### 3.3. Corrections to $T_s$ for stations in NordJylland: Jan 2011

To study applicability of  $T_s$  statistical correction based on two methods, the month of January 2011 was selected and analyzed in more details. A list of selected 17 road stations of the region N6 in the northern part of the Jutland Peninsula is shown in Figure 3.3.1. Forecasts and observations of  $T_s$  from Januarys of 2008, 2009, and 2010 were used to calculate mean values of  $T_s$  biases on a diurnal cycle by averaging over the last year 2010 (for PYM method) and over 2008-2010 period (for MYM method). The newly calculated biases for January 2011 (as shown in Table 3.3.1) were obtained by applying two different methods to statistically correct the original  $T_s$  forecast.



**Figure 3.3.1:** Geographical positions of selected road stations (N6000-6016) in the NordJylland region N6 of the Danish road stations network.

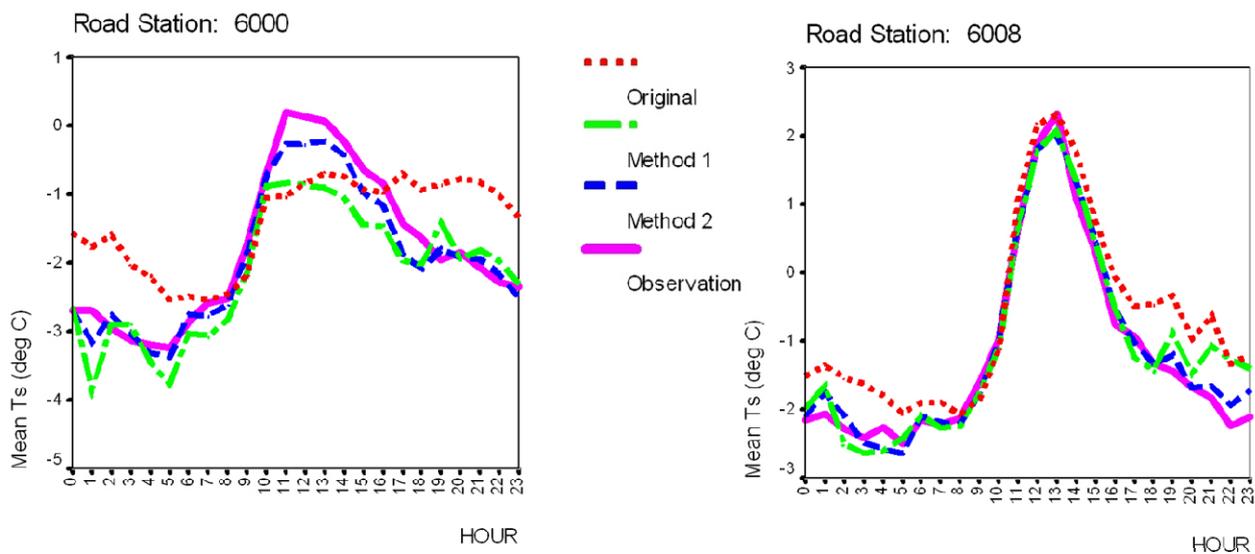


As seen, on examples of two stations (N-6000 and N-6008), the improvement of bias could be substantial, although averaged over the day, it might be about 0.5°C. For some stations (N-6008) it is comparable between the methods, for others (N-6000) - it could be better for one of the methods applied. The improvement – for mae – is larger for both methods during evening-night hours compared with daytime. It is also larger by an absolute value for the MYM compared with PYM method. Averaged over the day, the mae is better improved for the MYM method. For example, for the road stations N-6000 and 6008 it improved by 0.28 vs. 0.15°C and 0.20 vs. 0.14°C, respectively.

**Table 3.3.1:** Diurnal cycle (00-23) of the average  $T_s$  bias and mae for original forecast, corrected forecasts applying the previous/last year (PYM) and multi-year (MYM) methods, and corresponding changes (“-“ improved & “+” dis-proved forecast) for road stations N-6000 and 6008 for January 2011.

BIAS	Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	ALL
	Station																									
Original	6000	1,14	0,92	1,37	1,10	0,99	0,70	0,37	0,06	0,07	-0,43	-0,36	-1,21	-0,98	-0,77	-0,51	-0,29	-0,12	0,74	0,70	1,10	1,08	1,24	1,28	1,02	0,38
PYM		0,06	-1,16	0,07	0,21	-0,23	-0,53	-0,69	-0,95	-0,60	-0,32	-0,11	-0,92	-1,01	-1,10	-1,01	-1,12	-0,96	-0,53	-0,38	0,53	-0,09	0,25	0,32	0,06	-0,43
MYM		0,02	-0,46	0,20	0,09	-0,12	-0,13	-0,12	-0,38	-0,21	0,16	0,12	-0,04	-0,14	0,00	-0,02	-0,36	-0,44	-0,43	-0,45	0,16	-0,07	0,11	0,13	-0,15	-0,11
change PYM		-1,08	-2,08	-1,30	-0,89	-1,22	-1,23	-1,06	-1,01	-0,67	0,11	0,25	0,30	-0,03	-0,33	-0,50	-0,83	-0,84	-1,27	-1,08	-0,57	-1,17	-0,99	-0,96	-0,96	-0,81
change MYM		-1,12	-1,39	-1,17	-1,02	-1,11	-0,83	-0,49	-0,44	-0,28	0,59	0,48	1,18	0,84	0,77	0,49	-0,07	-0,32	-1,17	-1,15	-0,94	-1,15	-1,12	-1,16	-1,17	-0,48
Original	6008	0,64	0,71	0,74	0,79	0,48	0,44	0,26	0,32	0,05	-0,25	-0,14	0,44	0,27	-0,02	0,71	0,47	0,71	0,46	0,85	1,10	0,70	1,19	0,90	0,90	0,53
PYM		0,17	0,42	-0,24	-0,21	-0,34	0,07	-0,11	-0,44	-0,28	-0,08	-0,09	-0,06	-0,18	-0,32	0,19	-0,03	-0,07	-0,29	-0,10	0,55	0,20	0,74	0,96	0,71	0,05
MYM		0,05	0,32	0,18	-0,07	-0,30	-0,15	-0,13	-0,28	-0,20	-0,08	0,12	-0,08	-0,15	-0,40	0,16	0,03	-0,05	-0,08	-0,01	0,24	-0,02	0,16	0,30	0,38	0,00
change PYM		-0,47	-0,29	-0,98	-1,00	-0,82	-0,37	-0,37	-0,76	-0,33	0,17	0,06	-0,50	-0,45	-0,30	-0,52	-0,50	-0,77	-0,75	-0,96	-0,55	-0,50	-0,45	0,05	-0,20	-0,48
change MYM		-0,59	-0,39	-0,56	-0,86	-0,76	-0,59	-0,39	-0,60	-0,25	0,17	0,26	-0,52	-0,42	-0,37	-0,56	-0,44	-0,76	-0,54	-0,86	-0,86	-0,72	-1,03	-0,60	-0,52	-0,53
MAE	Hour																									
	Station																									
Original	6000	1,25	0,98	1,47	1,14	1,10	1,05	1,05	0,97	0,99	0,79	0,67	1,52	1,27	1,31	1,07	0,87	0,73	1,03	1,05	1,38	1,34	1,29	1,33	1,11	1,12
PYM		0,72	1,23	0,84	0,62	0,57	0,95	1,16	1,23	1,12	0,77	0,72	1,35	1,29	1,50	1,32	1,30	1,06	0,74	0,90	1,06	0,76	0,59	0,77	0,54	0,97
MYM		0,72	0,76	0,85	0,61	0,56	0,81	0,94	0,98	1,01	0,81	0,82	1,15	0,99	1,14	1,05	0,88	0,76	0,70	0,92	0,95	0,76	0,55	0,75	0,56	0,84
change PYM		-0,53	0,25	-0,64	-0,52	-0,53	-0,10	0,12	0,26	0,13	-0,02	0,05	-0,17	0,02	0,19	0,25	0,43	0,34	-0,29	-0,15	-0,33	-0,59	-0,70	-0,56	-0,57	-0,15
change MYM		-0,53	-0,22	-0,62	-0,53	-0,55	-0,24	-0,11	0,01	0,03	0,02	0,15	-0,37	-0,27	-0,17	-0,03	0,01	0,03	-0,33	-0,14	-0,43	-0,59	-0,74	-0,57	-0,55	-0,28
Original	6008	0,99	1,12	1,35	1,15	1,26	1,28	1,29	1,11	1,09	0,99	1,04	1,49	0,94	0,74	1,03	0,82	1,10	1,04	1,17	1,41	1,00	1,26	0,94	0,97	1,11
PYM		0,72	0,93	0,97	0,92	1,17	1,23	1,20	1,03	1,03	1,08	1,04	1,40	0,83	0,83	0,90	0,77	0,93	0,97	0,69	1,04	0,79	0,92	0,98	0,82	0,97
MYM		0,70	0,88	1,02	0,88	1,16	1,25	1,20	1,03	1,03	1,08	1,10	1,40	0,83	0,85	0,89	0,76	0,93	0,93	0,71	0,85	0,73	0,55	0,54	0,61	0,91
change PYM		-0,26	-0,19	-0,38	-0,23	-0,09	-0,05	-0,09	-0,08	-0,06	0,08	0,01	-0,09	-0,11	0,09	-0,14	-0,06	-0,17	-0,08	-0,48	-0,37	-0,21	-0,35	0,04	-0,15	-0,14
change MYM		-0,29	-0,24	-0,34	-0,27	-0,10	-0,03	-0,09	-0,09	-0,06	0,08	0,06	-0,09	-0,11	0,11	-0,14	-0,06	-0,17	-0,12	-0,46	-0,56	-0,27	-0,71	-0,39	-0,36	-0,20

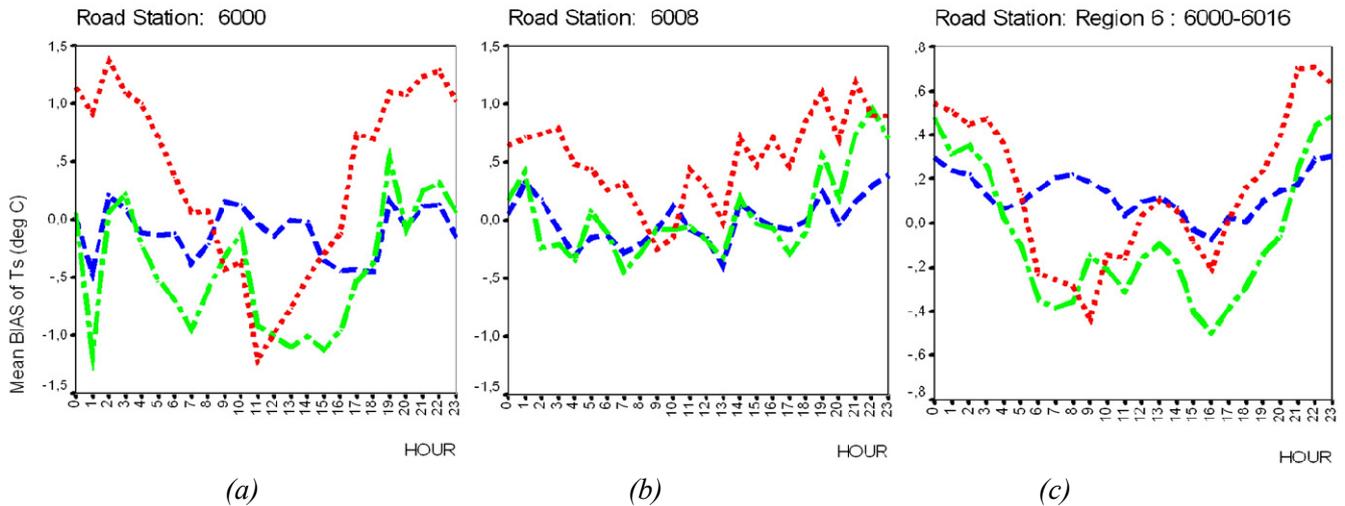
Averaged over 17 stations, the mae improved by about 0.1°C (e.g. from 0.9 to 0.8°C) as well as bias from 0.2 to 0.1°C. Although the bias improvement based on the PYM method is better or comparable with MYM method, the improvement of mae has a higher importance for overall procedure of verification, and hence, the MYM method is more suitable for application in statistical correction of operational  $T_s$  forecasts.



**Figure 3.3.2:** Diurnal cycle of the mean  $T_s$  road surface temperature for observation, original forecast, corrected forecasts (applying the previous/last year (PYM =method 1) and multi-year (MYM=method 2) methods) for road stations N-6000 and 6008 for January 2011.

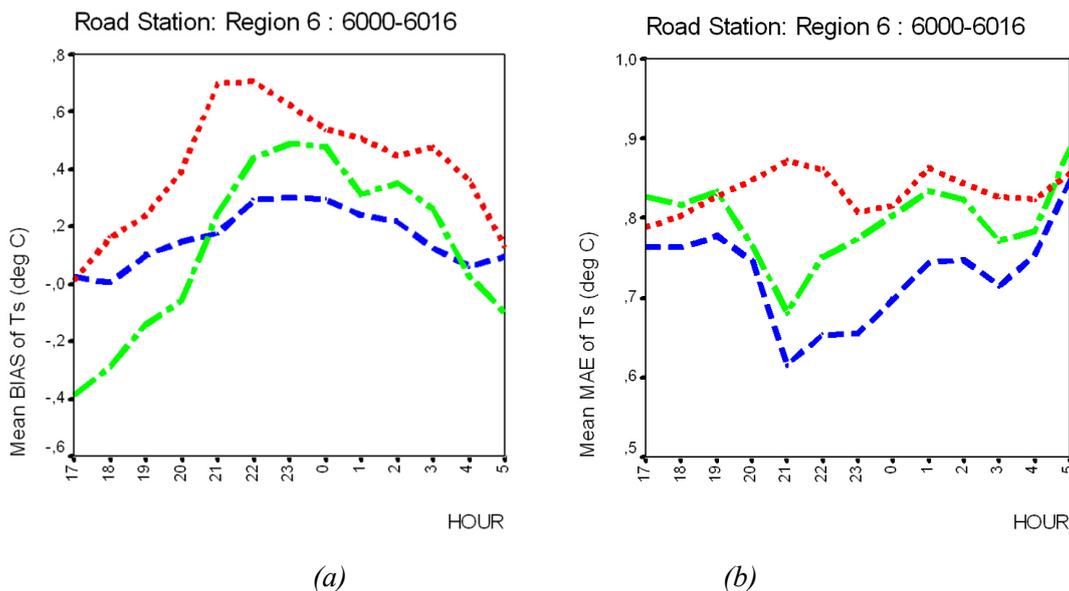
For these two road stations, as seen in Figure 3.3.2, the diurnal cycle of the  $T_s$  temperature is better

represented after the statistical correction is applied. The corrected forecasts became closer to observations, especially during night and evening time hours by about 0.5-1°C. Similarly, mean bias variability is shown in Figure 3.3.2ab for the same stations as well as averaged over all stations (Figure 3.3.2c). Note that both methods show potential for the bias improvement.



**Figure 3.3.2:** Diurnal cycle of the average/mean bias of the  $T_s$  road surface temperature for original forecast and corrected forecasts (applying the previous/last year and multi-year approaches) for road stations (a) N-6000, (b) N-6008 and (c) group of 17 stations /6000-6016/ for January 2011 /see legend in Figure 3.3.1/.

Taking into account that the time period from 17 pm till 5 am is important for taking the preventive salting measures the corresponding results are shown in Figure 3.3.3. Averaging over all selected stations in the region showed that after correction applied the bias and mae had improved. This improvement was larger when the multi-year method was applied compared with only previous last year method.



**Figure 3.3.3:** Evening-night time variability of the road surface temperature  $T_s$  (a) bias and (b) mae based on initial forecast and corrected forecasts by the multi- and previous year methods /averaged over selected stations in region 6/ /see legend in Figure 3.3.1/.

For bias both methods allowed mostly to improve the original forecast by reducing an absolute value of bias (Figure 3.3.3a). The bias substantially (up to 0.5°C) reduced, especially during mid-night hours. At early evening (as well as at early morning) hours the previous year method showed changes in a sign of the bias from positive to negative, and it also showed dis-provement of the bias.



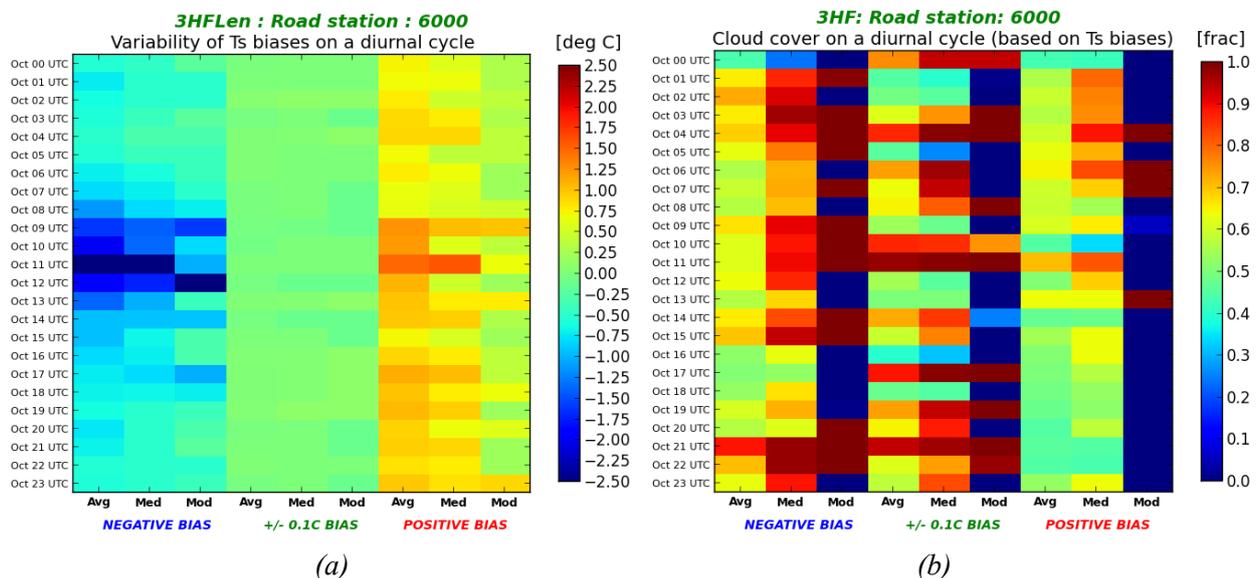
On average, the mae improved by 0.05°C (Figure 3.3.3b). The largest improvements have occurred during 21-01 UTCs changing from original 0.8°C to about 0.7°C (the best mae is 0.62°C at 21 UTC). At early evening (17-19 pm) and late night (4-5 am) hours these changes are relatively small. The mae's improvements are larger when the multi-year method was applied. For the previous year method there is even a slight dis-provement of mae at the beginning and at the end of the shown period. It should be noted that although in general both bias and mae of  $T_s$  are improved by both methods, but the hit-rate (e.g. when  $T_{s/obs} \leq 0$  &  $T_{s/for} \leq 0$  and when  $T_{s/obs} > 0$  &  $T_{s/for} > 0$ ) remains almost unchanged (e.g. 0.09%).

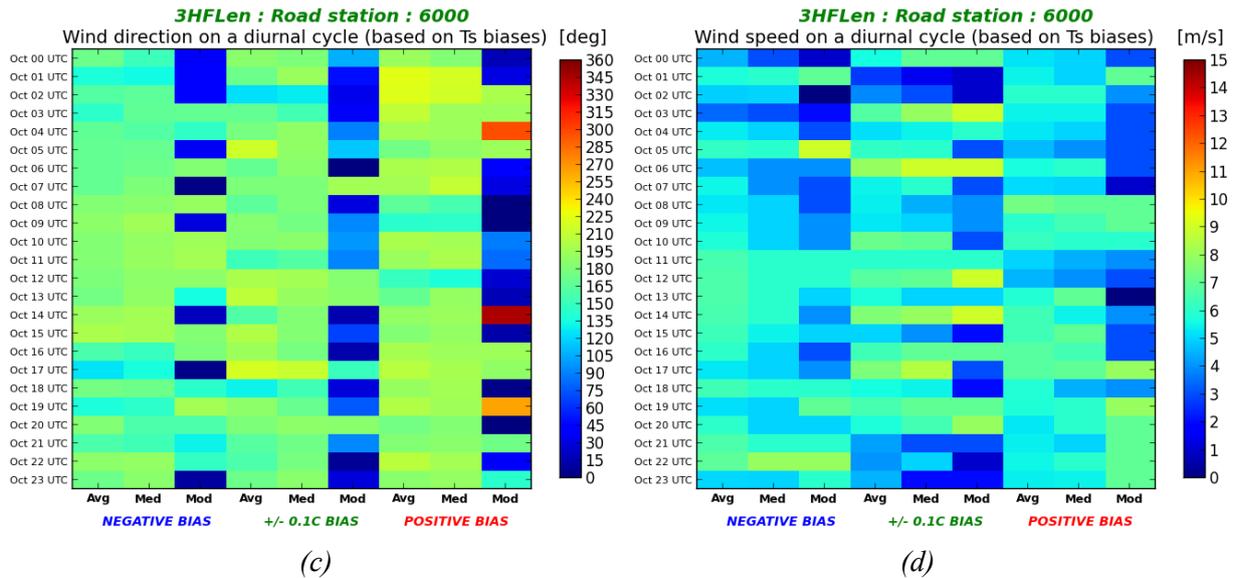
This analysis had shown that the multi-year method is more suitable (e.g. it shows larger improvements) for statistical correction of the originally forecasted road surface temperature compared with the previous/last year method. Hence, for statistical correction of  $T_s$  forecasts a statistical evaluation of  $T_s$  biases for different temperature intervals and corresponding to these biases forecasted meteorological parameters (see Ch. 3.1) such cloud cover, wind speed and direction, air and dew point temperatures is required. Moreover, it should be done for different forecast lengths (1-5 h), different hours (00-23 h) on a diurnal cycle and different months (Oct-Apr) of the road season.

### 3.4. Variability of $T_s$ biases: negative, "zero", and positive

Analysis for Oct 2008 – Feb 2012 showed that for 395 road stations, on average, the negative bias was observed for about 46% of the time vs. 54% – for positive bias. When more than 75% of the cases from total cases showed the same sign of  $T_s$  bias for the station, than overall dominating was assigned. For 55 stations such bias was dominantly negative, and for 94 stations - as dominantly positive. For the rest of the stations the situation is variable with a range of 50±25% for positive/negative biases.

The available observations for  $T_s$  at road stations were used to obtain statistics on bias variability for forecasted  $T_s$  on hourly (from 00 till 23 h) and monthly (from October till April) scales for each road station. Three intervals for  $T_s$  bias were considered: 1) negative, when bias is less than -0.1°C; 2) "zero bias", when bias is within ±0.1°C interval; and 3) positive, when bias is more than +0.1°C. Simply, in a case of the negative bias - the model underpredicted  $T_s$ ; in a case of the positive bias – the model overpredicted  $T_s$ . In these later cases, the correction of the original  $T_s$  forecast will be needed. Note that the "zero bias" interval was selected to identify and show that there are cases when the model, in principle, performed well, and due to such small changes (within an accuracy of the temperature measurements) in bias there is no real need to correct the original  $T_s$  forecast.

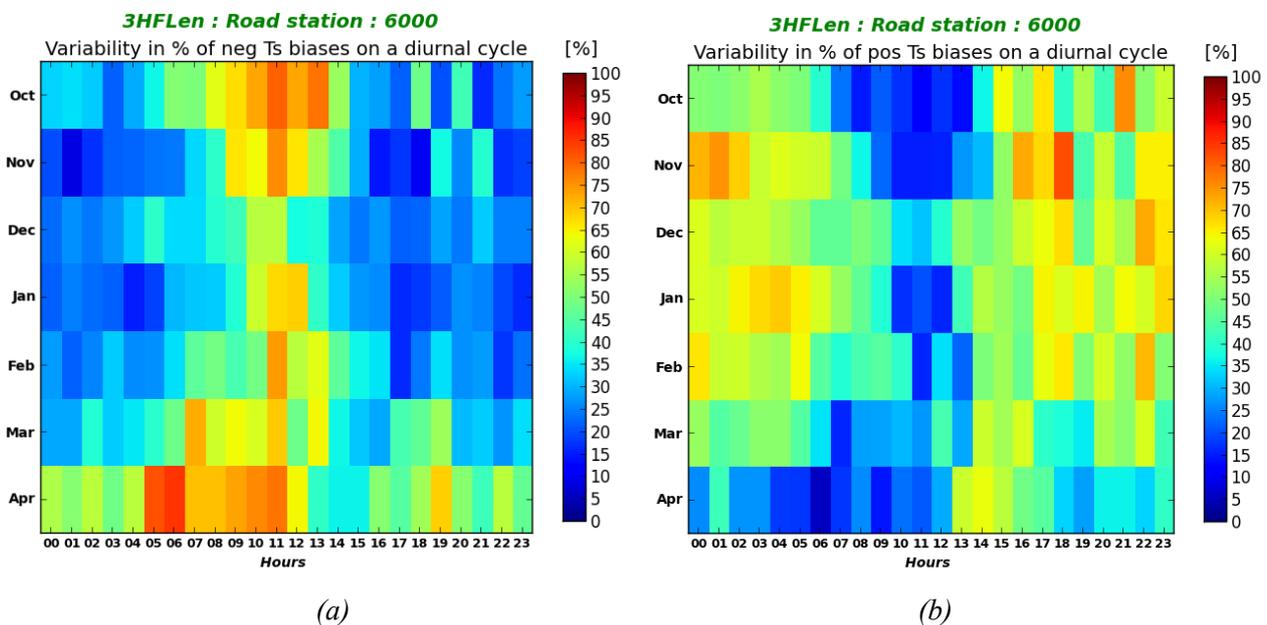


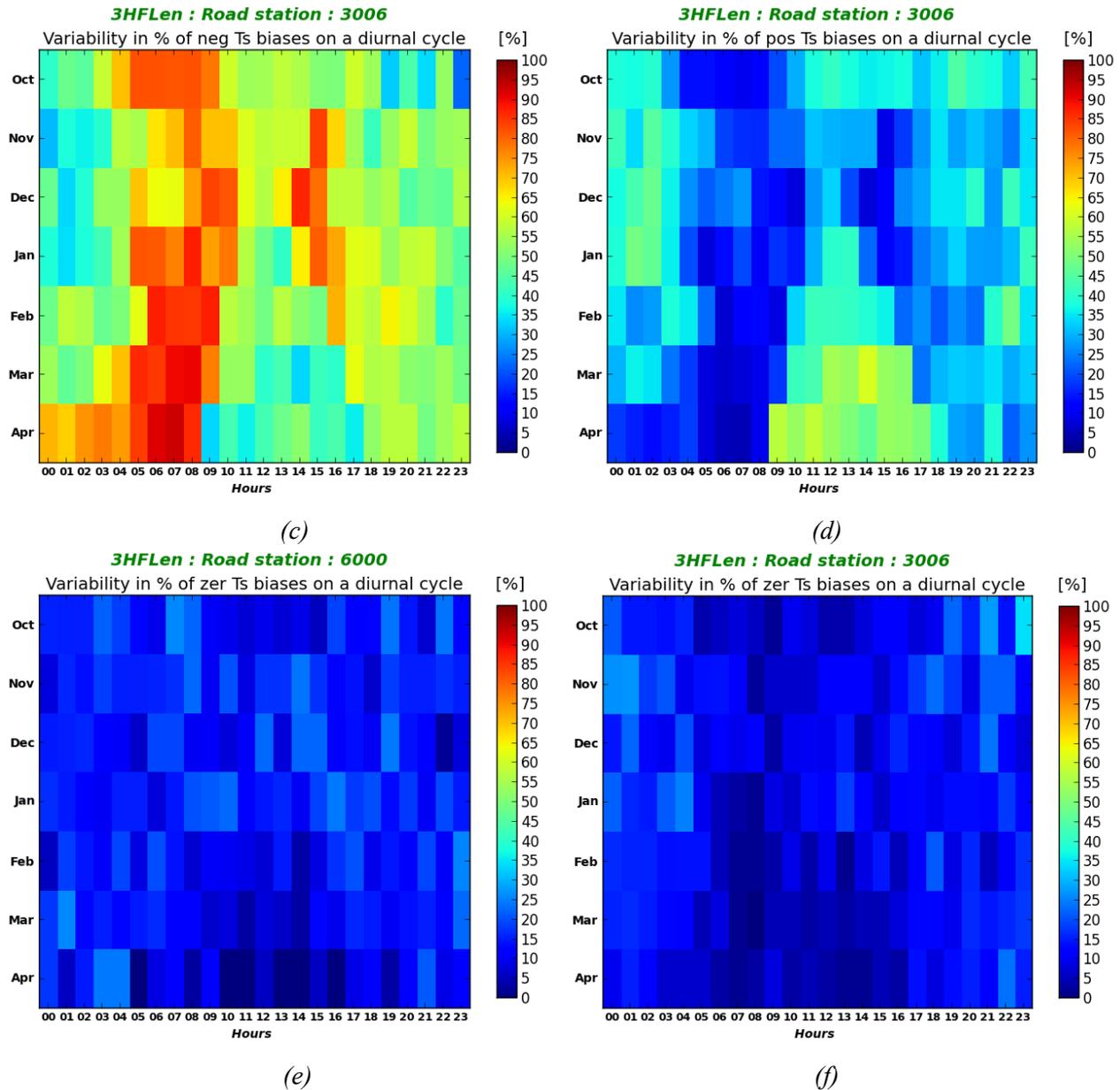


**Figure 3.4.1:** October variability of the (a) biases of the road surface temperature ( $T_s$ ) 3 hour forecasts, (b) cloud cover, (c) wind direction and (d) wind speed based on  $T_s$  bias intervals (negative;  $\pm 0.1^\circ\text{C}$ ; positive) on a diurnal cycle (00-23 hours) for the road station N-6000.

For each of the three selected  $T_s$  bias intervals ( $- / \pm 0.1^\circ\text{C} / +$ ), a list of basic statistical parameters was calculated. It includes the mean, median, and mode values for  $T_s$  bias, as well as corresponding number and percentage of the cases assigned to each of three intervals. Generally speaking, the mean/average is the arithmetic average of a dataset (within a selected  $T_s$  bias interval); the median is the value separating the higher half of a set of values; and the mode is the most frequent value appearing in a dataset. All these were composed into “look-up” tables (ascii-files) for each station for each forecast length to be read by the  $T_s$  statistical correction procedure. Moreover, for each of these  $T_s$  bias intervals the statistics (also mean, median, and mode values) was calculated for selected forecasted meteorological parameters – cloud cover wind speed and direction, differences in  $T_s$  and air/dew point temperatures – used in the hierarchical approach (see Ch. 2.2.3 for details).

For example, for the road station N-6000 for October for 3 hour forecast length, the Figure 3.4.1 shows variability on a diurnal cycle for: three  $T_s$  bias intervals (Figure 3.4.1a), cloud cover (Figure 3.4.1b), wind direction (Figure 3.4.1c), and wind speed (Figure 3.4.1d).





**Figure 3.4.2:** Monthly (Oct-Apr) variability in percentage of the (ac) negative, (bd) positive and (ef)  $\pm 0.1^\circ\text{C}$  biases of the road surface temperature ( $T_s$ ) 3 hour forecasts on a diurnal cycle (00-23 hours) for the road stations (abe) N-6000 and (cdf) N-3006.

As seen in Figure 3.4.1a, the larger (by an absolute value; up to  $2.5^\circ\text{C}$ ) average both negative and positive  $T_s$  biases are more often occurred near noon hours. The median values are similar or very close to the average values, although the mode values (more frequent values of biases) are generally smaller than the two latter. For the cloud cover (Figure 3.4.1b), on average, the higher values of cloud cover are characteristics for  $T_s$  negative biases interval and the lower values - for the positive biases. But the mode of cloud cover is most frequent and closer to low ones for positive bias, compared with two other intervals. The wind direction and speed have more complex structure (Fig 3.4.1cd), but the eastern directions of wind were more frequent (mode value) for all  $T_s$  biases. The lower wind speeds are more characteristic for night-time compared daytime hours.

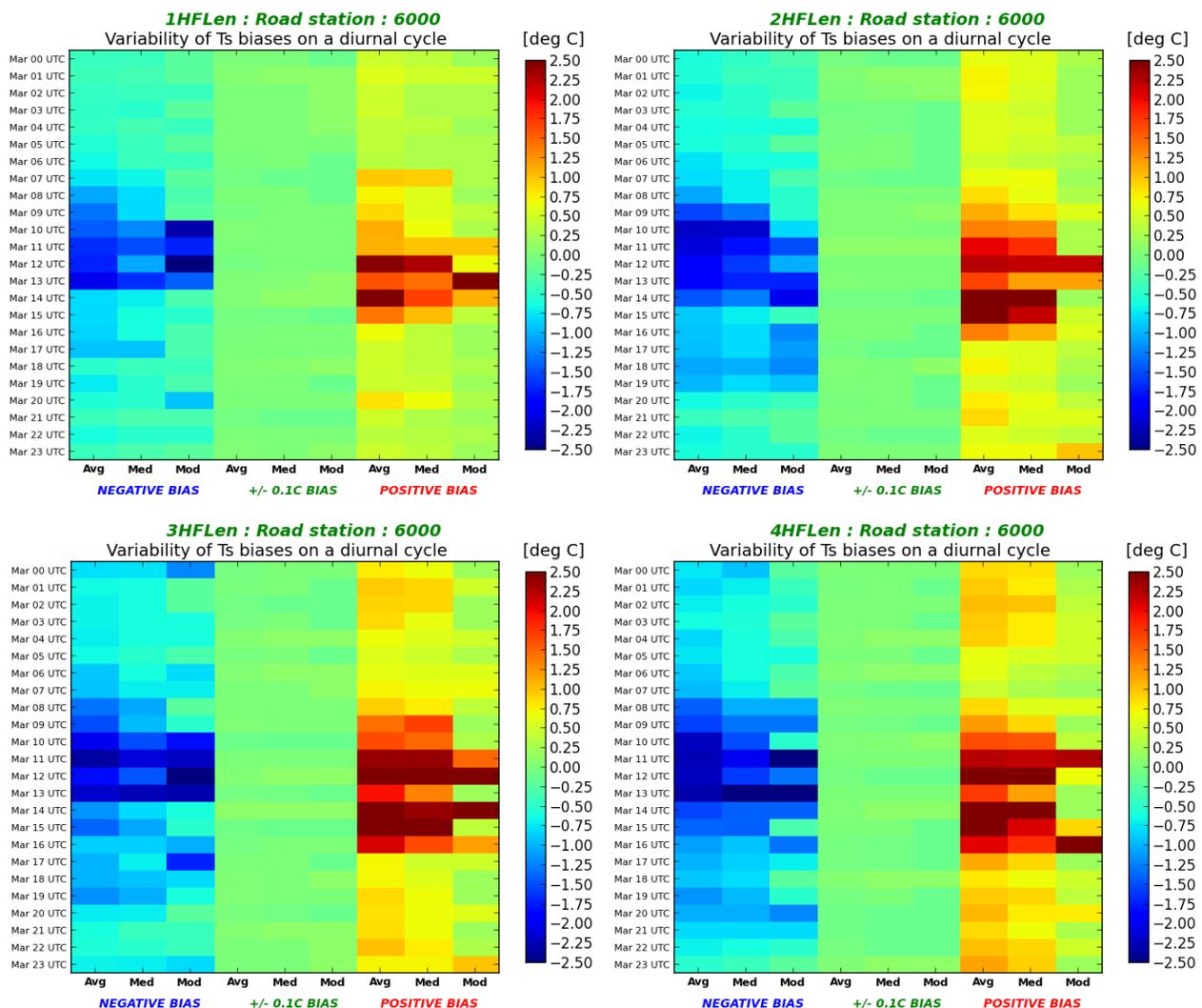
As seen in Figure 3.4.2ab, an opposite mirror reflection of the  $T_s$  negative (Figure 3.4.2a) vs. positive (Figure 3.4.2b) biases is observed. There are periods on a diurnal cycle when the negative  $T_s$  bias is dominating. The duration of these periods varies throughout the road season. It is the



longest at the beginning (Oct) and at the end (Apr) of the season. It is decreasing from the start (Oct-Nov) till Dec-Jan, and then it is again increasing (Feb-Apr). The same tendency (but for the lowest percentage of *T<sub>s</sub>* bias occurrence) is observed for the positive bias. The positive bias is more frequent in other hours on a diurnal cycle (Figure 3.4.2b), and moreover, it mostly dominates for the road station N-6000, and especially during winter months.

Another situation with the dominating bias – as mostly the negative – is shown for the road station N-3006 (Figure 3.4.2cd). As seen, the periods with dominating negative bias are substantially longer on a diurnal cycle (Figure 3.4.2c). The highest occurrence of these biases is observed at morning hours during all months and partially at 15-16 pm during Nov-Jan. At the same time the probability of positive biases is the lowest during the same hours (Figure 3.4.2d). It increases in daytime during Mar-Apr. Note that for the “zero bias” (Figure 3.4.2ef) there are no clearly defined patterns, although it is slightly lower around morning-noon hours.

The changes in variability of three *T<sub>s</sub>* biases intervals are shown in Figure 3.4.3 for different forecast lengths ranging from 1 till 5 hours forecast length. As seen, in general there are similar patterns on a diurnal cycle for both negative and positive biases at all forecast lengths. E.g. the biases became larger by an absolute value starting from the morning hours. The further is the road season, the longer is the period of time when larger values of the bias are observed. It could expand even into the afternoon hours as well. Although during evening-night hours the bias variability is roughly within  $\pm 1^{\circ}\text{C}$ , during sun-light hours it might increase up to  $\pm 2.5^{\circ}\text{C}$  or larger. For the “zero bias” such variability is negligible.



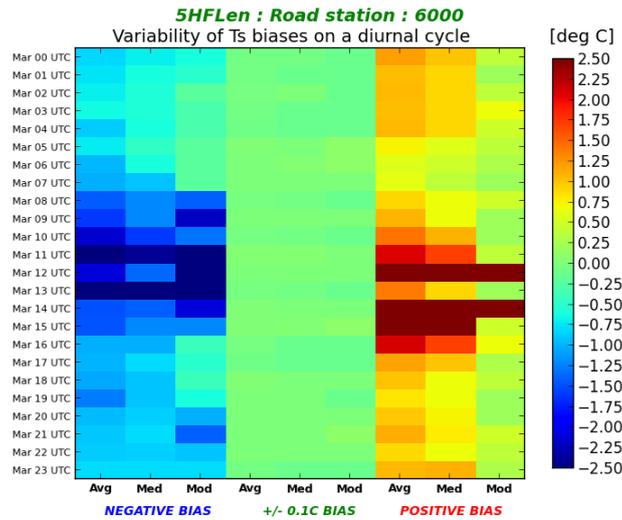
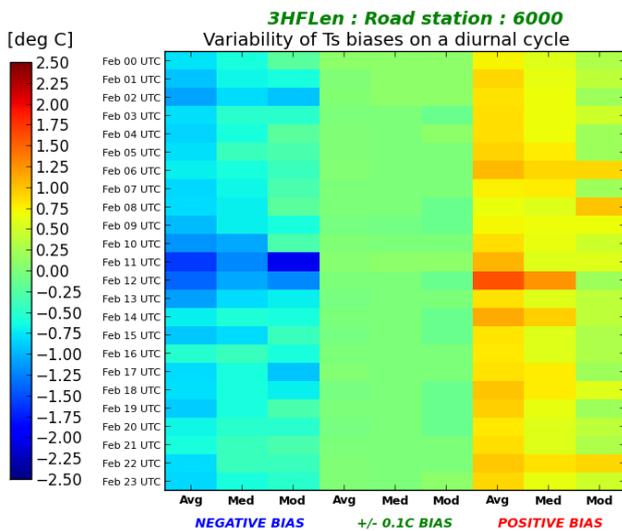
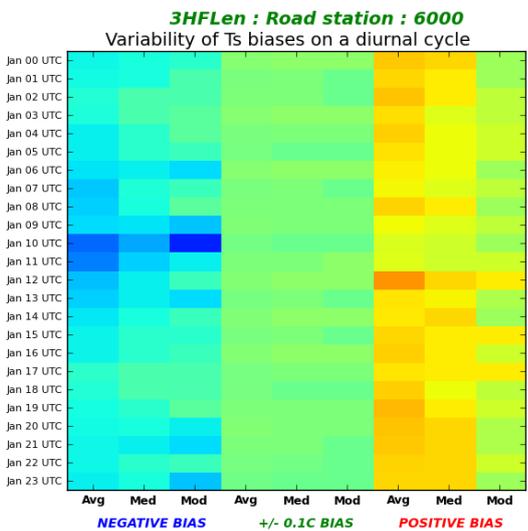
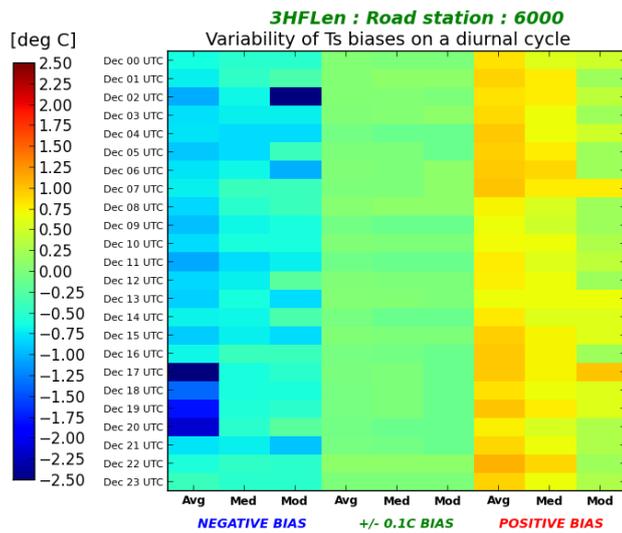
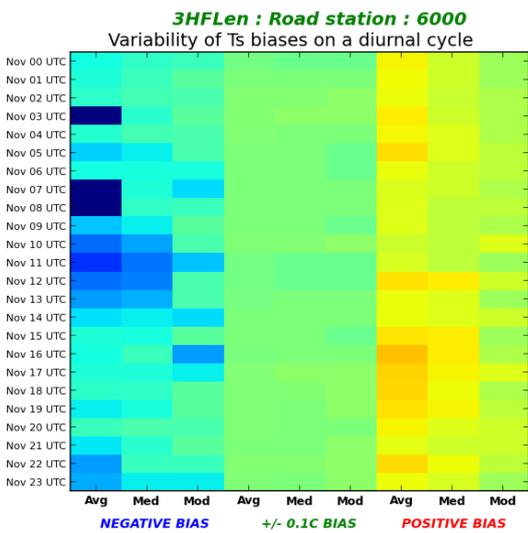
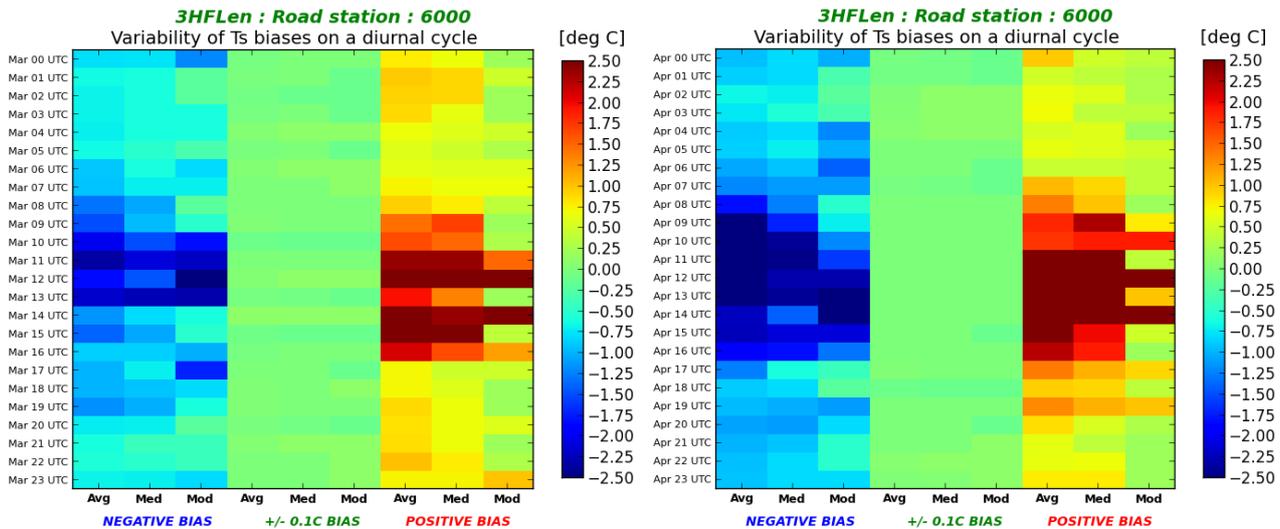


Figure 3.4.3: March variability of the road surface temperature (Ts) biases (negative;  $\pm 0.1^{\circ}\text{C}$ ; positive) on a diurnal cycle (00-23 hours) vs. different forecast lengths (1,2,3,4,5 hours) for the road station N-6000.





**Figure 3.4.4:** Monthly (Nov, Dec, Jan, Feb, Mar, Apr) variability of the road surface temperature ( $T_s$ ) biases (negative;  $\pm 0.1^\circ\text{C}$ ; positive) on a diurnal cycle (00-23 hours) for the forecast length of 3 hours for the road station N-6000.

The changes in variability of three  $T_s$  biases intervals are shown in Figure 3.4.4 for different months of the road season (note, for Oct it is shown in Figure 3.4.1a). Example is shown for 3h forecast length. Note that in general similar patterns (station dependent) are also observed for other forecast lengths. As seen, in general there are similar patterns on a diurnal cycle for both negative and positive biases. But these are more pronounced on a diurnal cycle at the beginning (Oct-Nov) and at the end of the road season (Mar-Apr). Biases are larger by an absolute value for these months compared with others. Similarly to Figure 3.4.3 analysis, in these months the highest biases are observed starting the morning hours and could increase up to  $\pm 2.5^\circ\text{C}$  or larger during daytime.

### 3.5. Road stations with largest maes: Oct 2008 – Feb 2012

The road stations having the largest maes are stations of the most concern, because the improvement at these stations can change the overall picture of verification scores. The data from Oct 2008 till Feb 2012 (inclusive) were analysed by calculating averaged monthly values for maes for each of the road stations. Then, month-to-month variability in number of road stations satisfying different mae limitations (see Figure 3.5.1) and frequencies (in our case, the number of months) of the maes larger than  $1^\circ\text{C}$  were estimated (see Figure 3.5.2).

Month-to-month variability in number of stations with different maes (consider: more than  $1^\circ\text{C}$  - as “problematic” stations, and less than  $0.5^\circ\text{C}$  – as “good” stations) is shown in Figure 3.5.1. As seen, during the studied period there are months when the number of problematic stations is large compared with other months. For example, there are 210 (in Nov 2011), 104 (in Feb 2012), and 82 (Oct 2010) stations which can be attributed to such group of stations.

The largest number of stations with maes less than  $0.5^\circ\text{C}$  is more frequently observed in October and April (e.g. at the beginning and at the end of the road season). For example, there are 184 (Apr 2009), 148 (Apr 2010), and 142 (Oct 2011) such stations. In general, the smallest number of such stations is more frequently observed during months of Dec-Jan-Feb.

From totally analysed 9365 cases (e.g. all cases available taking into account missing data for some stations and new stations installed for operational use within the studied period), only 7.9% (or 736) were associated with mae higher than  $1^\circ\text{C}$ , and 11.3% (or 1055) showed mae less than  $0.5^\circ\text{C}$ , and 48.4% - for mae less than  $0.7^\circ\text{C}$  (inclusive that latter one).

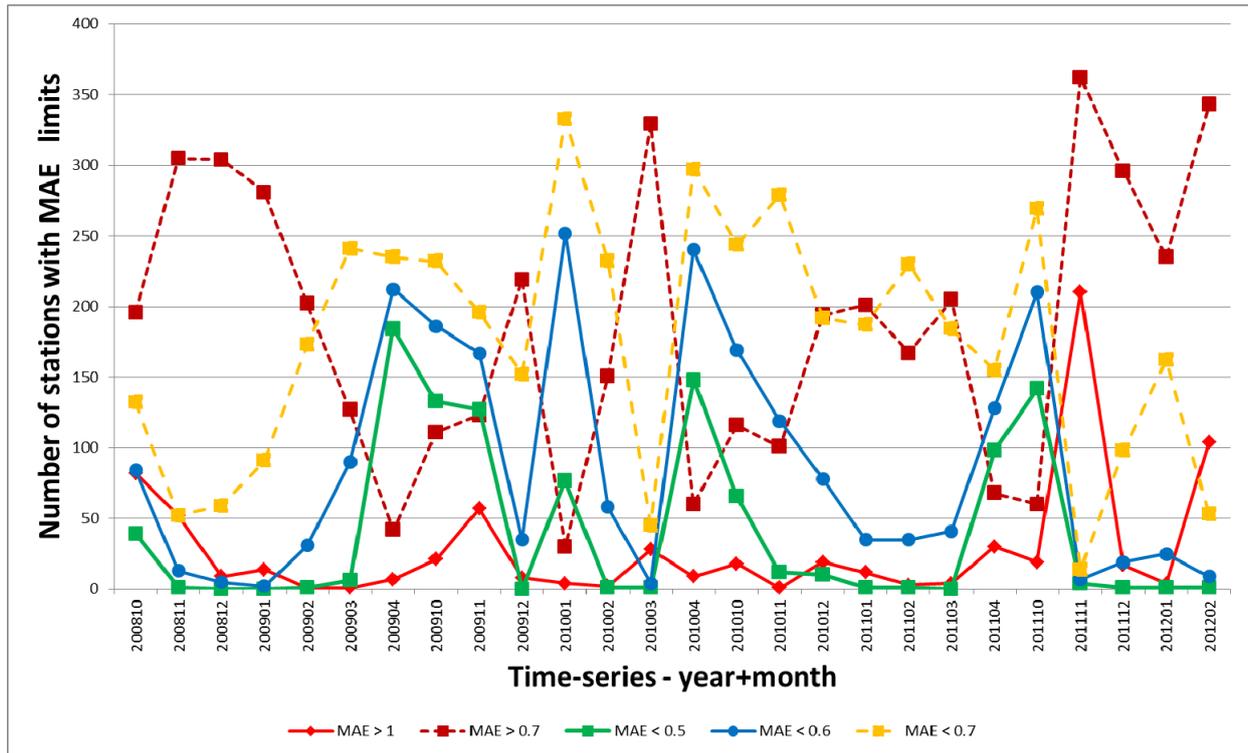


Figure 3.5.1: Month-to-month (from Oct 2008 till Feb 2012) variability in number of road stations satisfying different mae limitations.

Among all road stations, there are stations where the mae higher than 1°C is observed more frequently compared with others (see Figure 3.5.2a). Let's call these as the "worst" stations. As seen, majority of such stations is situated on the Jutland Peninsula compared with Zealand Island (only 6 stations). Figure 3.5.2b shows frequency of occurrence of mae ≥ 1°C (focus only on stations which had it, at least, 5 times during the period studied) for such stations on a month-year scale.

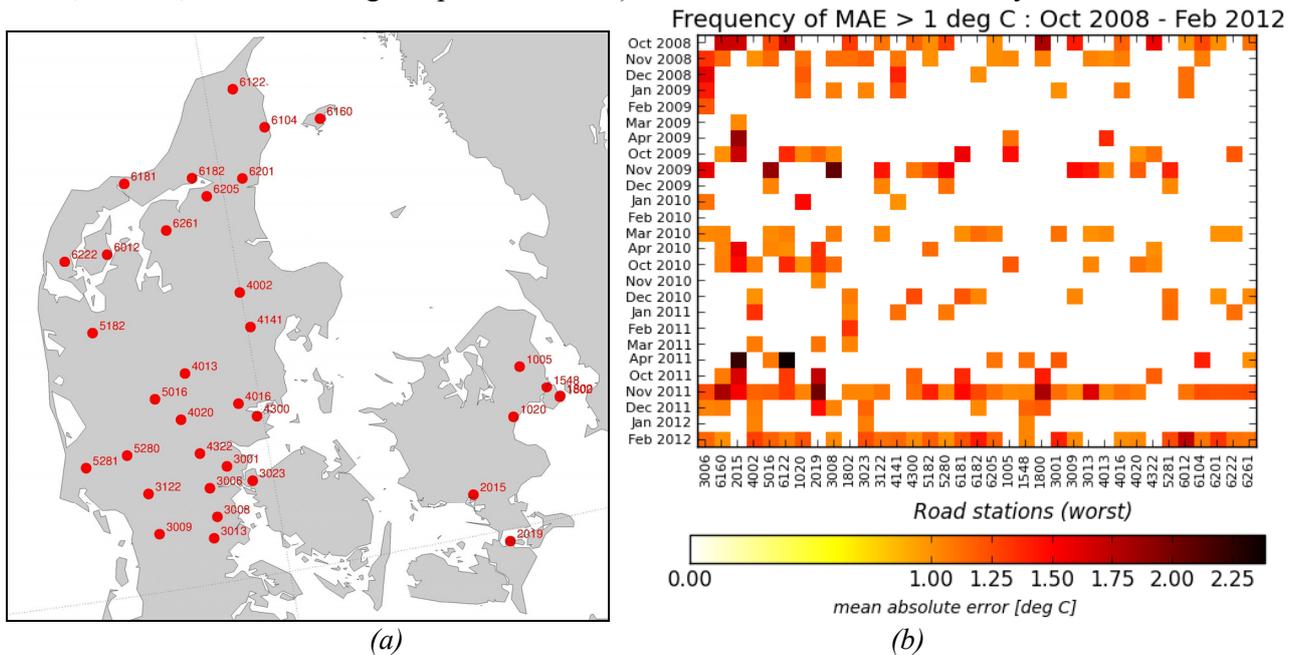


Figure 3.5.2: (a) Geographical distribution of road stations, and (b) Month-to-month (from Oct 2008 till Feb 2012) variability of the monthly MAEs ≥ 1°C - for the road stations having the largest frequencies (e.g. ≥ 5 times);

The most frequently (10 times) it was identified for road stations N-3006 and 6160. These two stations are located in the surrounding environment of forest vs. open fields. Four other stations – N-2015, 2015, 4002, and 6122 – showed frequency of 9 times. All these are placed on bridges, as well as two extra stations (N-1020 and 2019; frequency - 8 times) also located on bridges, but with surroundings of forest. Among all stations, months of Nov 2011 and Feb 2012 showed the largest number of stations having  $mae \geq 1^\circ\text{C}$ .

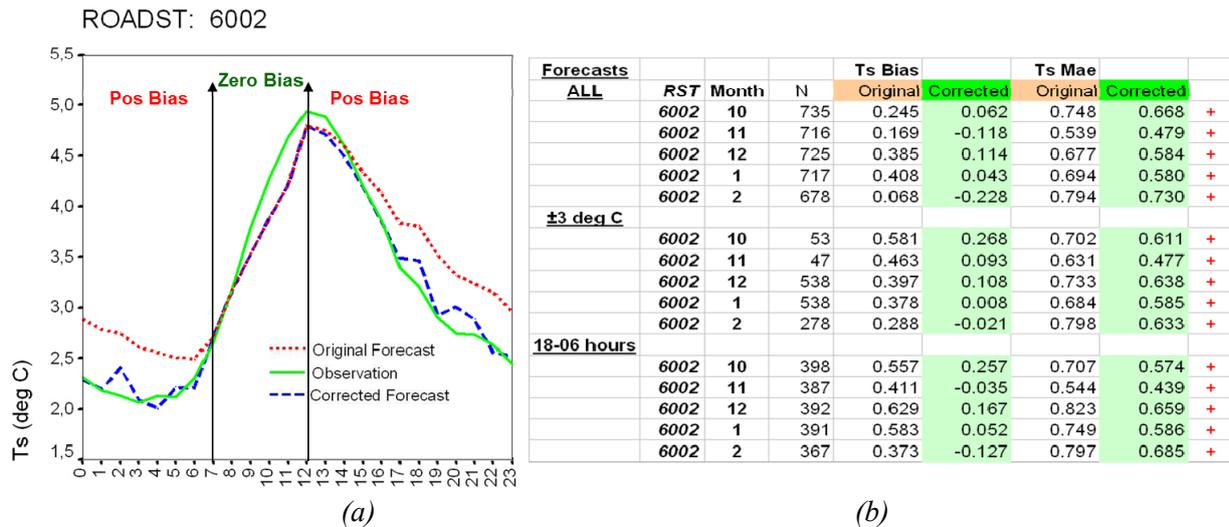
### 3.6. Correction and verification in road network: Oct 2011 – Feb 2012

Results of verification for the  $T_s$  bias and mae covering first 5 months (Oct-Feb) of the road weather season 2011-2012 are summarized in Table 3.6.1. In analysis, the data for the period of time from 18 till 06 hours included in total 1.31 mln of pairs  $T_s$  forecasts vs. observations. On average, for every month it was about 54%. For  $T_s$  temperature within a range of  $\pm 3^\circ\text{C}$ , the data (435 thousands) varied from month to month with the largest percentage (58%) of such data in January 2012 (for other months: Oct – 8%; Nov – 10%; Dec - 56%; and Feb – 34%). The verification of the  $T_s$  correction was performed for three groups of data: 1) all data, 2) only data for the period of time from 18 till 06 hours, and 3) only  $\pm 3^\circ\text{C}$  interval for  $T_s$  observations.

Although overall (averaged over stations) the correction to  $T_s$  showed improvement in both bias and mae, but this improvement was not observed for all stations. In particular, several examples are shown in Figures 3.6.1-3.6.2a (stations showed improvement in  $T_s$  forecast) and Figure 3.6.2b (station showed dis-provement of forecast). For example (Figure 3.6.1), for the road station N-6002 the correction showed improvement for all three groups of data analyzed. When overall sign of the bias had changed to an opposite, but an absolute value of the bias became closer to 0, than the improvement is visible. In a case when the bias became slightly larger (although still within acceptable limits of  $\pm 0.25^\circ\text{C}$ ) than the original, but the mae value had improved, than the improvement should be considered as acceptable. The mae's contribution into the overall score of the forecast has higher value/importance than compared with bias.

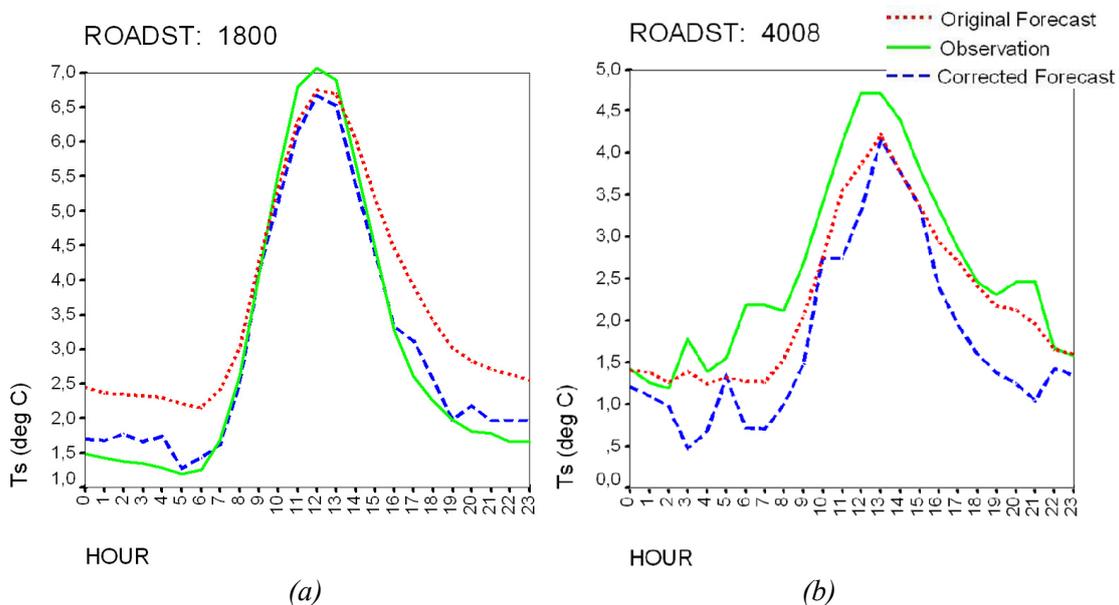
**Table 3.6.1:** Results of verification of  $T_s$  bias and mae for 3 groups of data (including all data, period from 18 till 06 hours, and  $\pm 3^\circ\text{C}$  interval for  $T_s$ ) for Oct 2011 – Feb 2012.

Forecast Dataset Month	Original			Corrected		
	All data	18-06 h	$\pm 3^\circ\text{C}$	All data	18-06 h	$\pm 3^\circ\text{C}$
<i>Mean Error or Bias (<math>^\circ\text{C}</math>)</i>						
Oct 2011	-0,075	0,119	0,336	-0,150	-0,016	0,184
Nov 2011	-0,047	0,135	0,453	-0,186	0,054	0,348
Dec 2011	-0,052	0,218	0,069	-0,208	0,069	-0,011
Jan 2012	-0,040	0,147	0,028	-0,119	0,052	-0,089
Feb 2012	-0,114	0,074	0,006	-0,124	-0,008	-0,068
<b>RWSeason</b>	<b>-0,065</b>	<b>0,138</b>	<b>0,075</b>	<b>-0,156</b>	<b>0,030</b>	<b>-0,021</b>
<i>Mean Absolute Error (<math>^\circ\text{C}</math>)</i>						
Oct 2011	0,927	0,644	0,692	0,815	0,540	0,566
Nov 2011	0,623	0,552	0,800	0,516	0,444	0,667
Dec 2011	0,663	0,657	0,705	0,576	0,558	0,614
Jan 2012	0,711	0,666	0,717	0,604	0,563	0,620
Feb 2012	0,896	0,743	0,858	0,766	0,640	0,746
<b>RWSeason</b>	<b>0,762</b>	<b>0,652</b>	<b>0,746</b>	<b>0,643</b>	<b>0,542</b>	<b>0,645</b>



**Figure 3.6.1:** Road station N-6002: (a) Variability of  $T_s$  (observed, originally forecasted, and corrected) on a diurnal cycle; and (b) Results of verification for  $T_s$  bias and mae for 3 groups of data (including all data, period from 18 till 06 hours, and  $\pm 3^\circ\text{C}$  interval for  $T_s$ ) for Oct 2011 – Feb 2012.

As shown in Figure 3.6.2a, for the road station N-1800 the largest improvement was observed between 07-16 hours. It was lower smaller (improved only by  $0.25^\circ\text{C}$ ) during evening-night times. The difference between forecast and observations still remained more than  $1^\circ\text{C}$ , and hence, further options for improvement might be needed. As seen in Figure 3.6.2b, although improvement is seen at selected hours (fx. 13-16 pm), but correction applied makes worse for other hours on a diurnal cycle. Hence, at simplest, the correction procedure could be switched-off for a list of such stations, or other approaches/methods need to be elaborated. In addition, following a hierarchy approach some of such stations will be excluded (or zero correction value will be assigned).



**Figure 3.6.2:** Variability of  $T_s$  (observed, originally forecasted, and corrected) on a diurnal cycle for road stations (a) N-1800 – correction improves and (b) N-4008 – correction does not improve forecast.

Note, that in Oct 2012, a new NWP+RCM model setup was implemented for the NWP model used in the road weather modelling system. This led to substantial changes in statistical parameters calculated as look-up tables (based on multi-year method) for each station and used for  $T_s$  corrections. The recalculated statistical parameters (% of occurrence, average, median, and mode values)

showed large additional changes for both groups of positive and negative biases (see Appendix A and Table 3.6.2). For December, on average, the negative bias became more frequent by almost 14%, at the same time reducing occurrence of the positive bias by almost the same value. The average negative bias became larger by 0.22°C, the median of  $T_s$  bias - by 0.17°C, and the mode of  $T_s$  bias - by 0.28°C. Considering extremes (max and min values), the changes are even larger. Among stations, the largest change (by 2.7°C) was for average negative  $T_s$  bias, and about 1.3°C for the median value of the positive  $T_s$  bias.

**Table 3.6.2:** Changes (on average, maximum and minimum values among all road stations) for  $T_s$  negative and positive biases intervals in statistics (occurrence of sign of  $T_s$  bias, its average, median and mode values) occurred due to differences in the NWP+RCM model setup /inter-comparison is between Decembers 2012 vs. 2010+2011/.

<u>Negative <math>T_s</math> bias</u>					<u>Positive <math>T_s</math> bias</u>			
<u>%</u>	<u>Avg</u>	<u>Med</u>	<u>Mod</u>		<u>%</u>	<u>Avg</u>	<u>Med</u>	<u>Mod</u>
<b>13,52</b>	-0,22	-0,17	-0,28	<b><u>AVG</u></b>	<b>-14,02</b>	-0,17	-0,68	-0,06
	0,48	0,19	0,29	<b><u>MAX</u></b>		0,65	-0,47	0,20
	-2,66	-1,12	-2,30	<b><u>MIN</u></b>		-0,67	-1,31	-0,35

## 4. Conclusions

Based on analysis of meteorological observations and forecasts from the RWM system the method for statistical correction of the road surface temperature ( $T_s$ ) forecasts was elaborated and tested. Modelling, statistical analysis and verification were done for different periods within Oct 2008 - Dec 2012.

The developed approach is based on using of forecasted and observed meteorological parameters – road surface, air and dew point temperatures, wind speed and direction, cloud cover. For the road temperature, the statistics of  $T_s$  bias variability (within three intervals: negative bias,  $\pm 0.1^\circ\text{C}$ , and positive bias) is calculated considering average, median and mode values. For these intervals the other mentioned forecasted parameters are calculated in a similar manner. The so-called look up tables, containing statistics for each month and each hour on a diurnal cycle, are provided for each road station. The statistics was calculated and tested based on last/previous year and multi-year datasets. Verification for selected stations in region N6 (Nordjylland) showed better performance with the multi-year calculation of statistics. Before the road weather season 2012-2013 for the correction of  $T_s$  forecasts the statistical correction procedure was implemented (during summer 2012). The focus was on the first 5 hours forecast lengths.

The further elaboration of the statistical correction approach will include tuning of the hierarchy of levels for each station in order to get the best (i.e. the lowest values) maes; improving procedure for decision-making when the correction should be applied or assumed 0; implementing a self-learning/adaptation process for  $T_s$  corrections based, at least, on a daily recalculation of  $T_s$  bias related monthly statistics; and considering possibility to integrate detalisation of shadowing effects (which are contributing the largest changes in  $T_s$  bias) on examples of selected stations.

Although research will be continued on further development and improvement of methodology for statistical correction of the road surface temperature forecasts, but other studies relevant to road modelling will be also outlined and planned. In particular, there is an urgent need for improvement of the short-range forecasting of winter precipitation. In addition, attempts to build a quality control



system for thermal mapping measurements/data are needed as well. Moreover, modelling and analysis of slippery road conditions for on a new type of asphalt (as a test mode) is planned.

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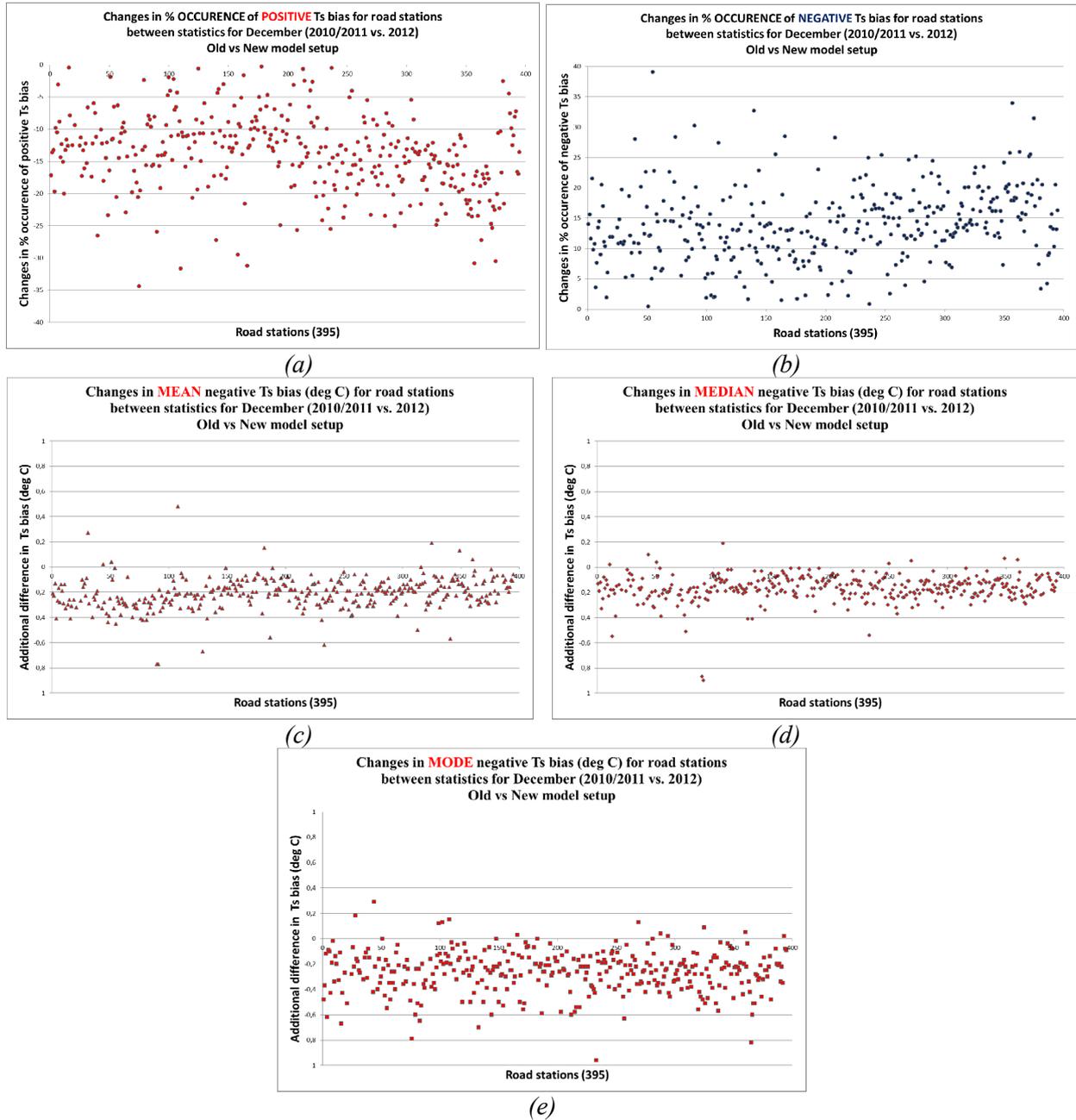
Thanks to DMI's Computer Department for advice and assistance.

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## Appendix A

# Revised biases' statistics due to changes in model set-up: Dec 2010/2011/2012



**Figure A:** (ab) Changes in % occurrence of (a) positive and (b) negative Ts biases; and (cde) Additional changes in negative Ts biases for (a) mean, (b) mode, and (c) median /for road stations between statistics for December (2010/2011 vs. 2012) for the old vs. new (since Oct 2012) model setup/.



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