# THE IMPACT OF EMBEDDED IoT SENSOR OBSERVATIONS ON ROAD WEATHER FORECASTS

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## ABSTRACT

Efficient winter road maintenance is achieved through access to timely and accurate information on current and future road conditions. Traditionally, this information is obtained from Road Weather Information System (RWIS) stations and observation-driven road weather forecasts from a road weather model (RWM). Newly developed IoT embedded sensors can be deployed as “gap-filling” devices to achieve enhanced observation coverage, therefore helping increase situational awareness and obtain more accurate forecasts over a greater number of locations across a road network. Knowing precisely how observations from such devices contribute at improving the accuracy of forecasts throughout a network is a key piece of information needed for a more effective deployment of observational assets that best supports the decision-making process in winter weather road maintenance.

A quantitative assessment of the impact of observations from a new IoT sensor on road weather forecasts is presented. The embedded IoT sensor provides in-situ measurements of road surface temperature and sub-surface temperatures at different depths, along with information on surface state (dry or not) and amount of residual treatment material on the road surface. A series of data-denial forecast experiments are conducted with a road weather forecast system, in which a selected observation is withheld, and the resulting forecasts are compared to a twin experiment where all observations are used. A comparison of forecast errors provides a quantitative assessment of the impact of the selected observation. We discuss the role of IoT observations in the reduction of forecast errors in parameters of importance to winter road maintenance operations; and compare with the estimated impact of professional-grade observations from RWIS stations. This extra insight into the forecast enhancing effect of in-fill observations lays the foundations for designing optimized hybrid network topologies, consisting of RWIS and IoT devices.

## 1. INTRODUCTION

Forecasts of weather-influenced road conditions are a key source of information used by road authorities and organizations in their decision-making process for the efficient deployment of winter road management resources. These forecasts are produced by systems based on a numerical energy balance model and incorporate weather information from numerical weather prediction (NWP) models and dedicated observations from Road Weather Information System (RWIS) stations. The accuracy of forecasts depends on how well the characteristics of a road segment (under pavement material type, road tilt angles, traffic density etc.) are represented, as well as on the quality of the NWP input and the sets of observations used to define the model’s initial state. However, RWIS stations are typically deployed at a limited number of strategic locations along a road network, covering only a small portion of the overall road segments that require maintenance. Despite this fact, forecasts at RWIS locations often serve as anchor information points on future road conditions due to the more reliable predictions generated with the more comprehensive set of observations.

In this work, we investigate whether simpler IoT sensors, more easily deployed over multiple locations, can help provide more accurate forecasts covering a larger number of segments in a road network. More specifically, the impact of observations from a newly developed IoT sensor is evaluated using a series of specifically designed forecast experiments. This impact is contrasted with the total impact provided by the more comprehensive observations from RWIS stations. The gained insights are expected to drive future deployments of observational assets that enhance road forecasting capabilities across various road networks.

## 2. ROAD WEATHER MODEL AND FORECASTS

Forecasts of road conditions are produced using a modified version of METRo [2], referred here as the road weather model (RWM). The RWM is based on a numerical representation of the energy balance of a road surface to predict the evolution of key road state conditions such as pavement temperature and amount of water, snow and/or ice found on the road.

The RWM uses information on atmospheric conditions during its initialization and forecast phases from a numerical weather prediction (NWP) system. Predicted values of temperature, humidity, wind and precipitation (intensity and type), as well as cloudiness conditions and related downwelling radiation fluxes reaching the road surface, are all used as input by the RWM. The RWM initial state is further refined using available local observations. More or less comprehensive sets of observations are available depending on the type of stations/sensors deployed at any particular location. Table 1 lists the observations typically available at RWIS locations, and at locations where embedded IoT devices might be installed. The main differences between an RWIS and the *GroundCast* IoT device [4] are the absence of atmospheric observations and the coarser information on road state conditions from the IoT device. The latter only provides binary “dry”/“not dry” information, whereas detailed information on layer thicknesses for water, snow or ice present on the road can be obtained from an RWIS.

Table 1 ─ Observations available from RWIS and embedded *GroundCast* IoT devices. A checkmark indicates availability, while an x indicates non-availability.

| Observed parameter | RWIS | *GroundCast* IoT |
|---|---|---|
| 2-m air temperature | ✓ | x |
| 2-m dewpoint temperature | ✓ | x |
| 10-m wind speed | ✓ | x |
| Road surface temperature | ✓ | ✓ |
| Sub-surface temperature | ✓ | ✓ |
| Road state conditions<br>(water, snow, ice layers & derived grip) | ✓ | ✓* |

*Device does not differentiate between water, snow and ice, only reports whether conditions are dry or not dry.

The availability or not of this information has significant implications for how RWM forecasts are initialized. With RWIS data available, the RWM initial values for water/snow/ice layer thicknesses are simply taken from the latest observations available. When not available, as in the case of the IoT sensor, other information and assumptions are needed to provide the RWM with realistic values of layer thicknesses at the initial time, when “not dry” is reported by the IoT sensor. Here we use estimates of layer thicknesses obtained from recent prior RWM forecasts. As these estimates are subject to forecast errors, we apply simple corrections depending on the latest observed ambient conditions. First, the total thickness of water, snow and ice is taken from the prior forecast:

$$Total = \ water\ layer\ thickness + \ snow\ layer\ thickness + ice\ layer\ thickness$$

and the fraction of the total for each phase ($F_{water}$, $F_{snow}$ $F_{ice}$) are derived from:

$$\begin{gathered} water\ layer\ thickness = F_{water} Total \\ snow\ layer\ thickness = \ F_{snow}\, Total \\ ice\ layer\ thickness = F_{ice}\, Total \end{gathered}$$

The total thickness is checked to see if a minimum threshold is reached, as prior forecasts may present dry conditions. The following rules are applied:

If *total thickness* < $M_t$: *total thickness* = $M_t$
If *total thickness* ≥ $M_t$: *total thickness* is kept as is.

We use a value $M_t$ = 0.1 mm, which appears to provide an appropriate correction for errors in the prior forecasts used as input.

Second, partitioning among water, snow and ice is adjusted based on road surface temperature (RST) as follows:

If RST ≥ 1.0°C, the total layer is taken as water ($F_{water} = 1, F_{snow} = 0, F_{ice} = 0$).
If -1°C < RST < 1.0°C: all three phases can co-exist, and the fractions from the prior forecast are kept as is but applied to the possibly modified total thickness.
If RST < -1.0°C: no water is allowed, so the fraction of water is distributed equally to the snow and ice layers ($F_{snow} = F_{snow} + 0.5F_{water}, F_{ice} = F_{ice} + 0.5F_{water}, F_{water} = 0$).

Finally, the modified layer thicknesses used as initial conditions by the RWM are obtained using the modified $Total$ and fractions $F_{water}\,, F_{snow}, F_{ice}$ using the relations previously shown.

From Table 1, we note that another parameter of interest is *grip*, which is a quantitative index of how slippery a road surface is. This parameter, ranging from 0 to 0.82 (lower values indicate less grip, more slippery conditions), is derived from observations of water, snow and ice layers and is therefore only available at RWIS locations. Estimates of grip are also provided by the RWM, and a comparison of the predicted values and those derived from RWIS observations constitutes a key part of our analysis (see section 4).

## 3. DATA AND OBSERVATION SYSTEM EXPERIMENTS

### 3.1. Data

This study relies on observations obtained from nine RWIS stations located in Fort Collins Colorado, USA (Fig. 1), during the 2021-2022 winter season. The observations are used to initialize RWM forecasts in a reference set of forecasts and are also used for verifying the accuracy of all forecasts generated in this study. The results for road state conditions are taken from four stations equipped with sensors providing more detailed observations of road conditions (see Fig. 1).

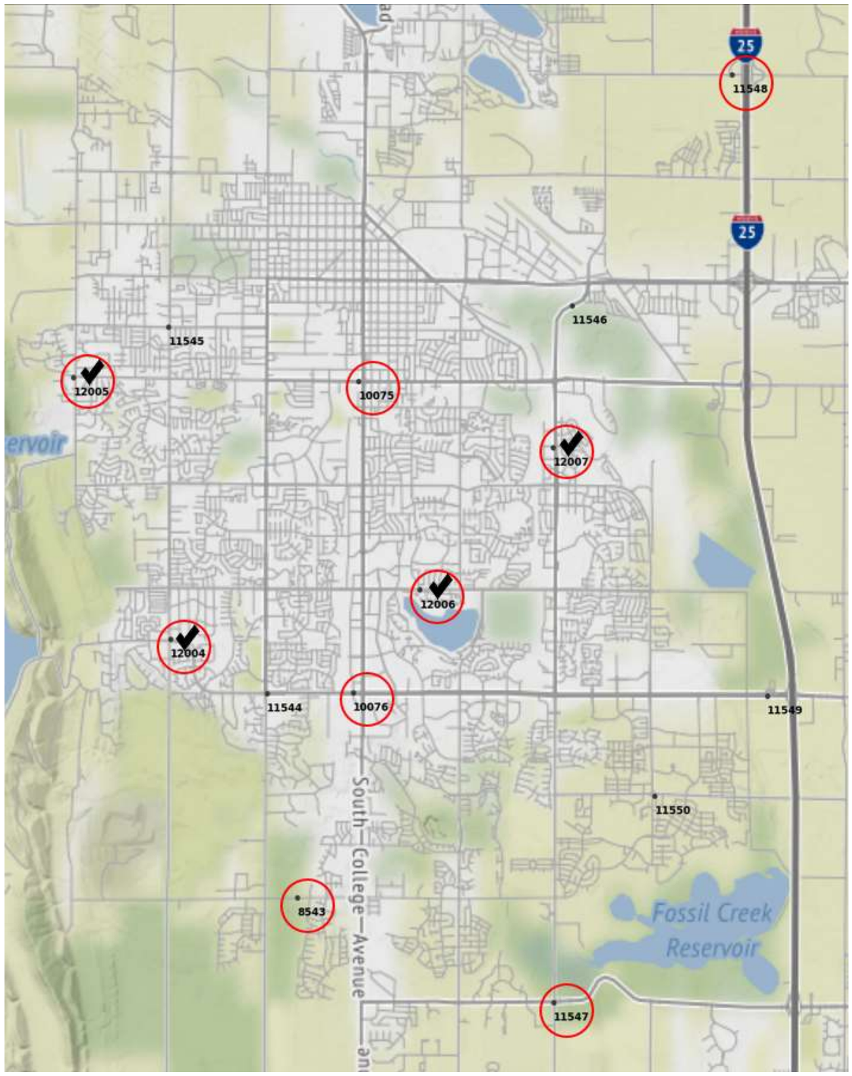


Figure 1 ─ Locations of RWIS in Fort Collins, Colorado, from which road surface temperature observations (red circles) and road state observations (check marks) are used in this study.

The RWIS data is also used to emulate IoT sensor observations, as long time series of data from this newly developed sensor are not yet available at numerous locations. The emulation considers actual sensor characteristics. The temperature sensors on the IoT device provide observations with similar accuracies as from the RWIS sensors. Therefore the emulated IoT temperature observations are taken as the RWIS observations themselves. One simplification applied here is the use of subsurface temperature observations at a single depth (30 cm) to constrain forecasts, instead of the two measurement depths (6 and 30 cm) available from the IoT sensor. The most significant difference resides in the observation of road state, from detailed later thicknesses from the RWIS to the coarser “dry” or ”not dry” classification from the IoT sensor. Here, the detection threshold of the IoT sensor for “not-dry” conditions is used to coarse-grain the RWIS observations of road state into the IoT binary “dry”/”not dry” categories. This way, an emulated IoT dataset is generated from the

RWIS data and used as input in a separate set of RWM forecasts to be compared to the original forecasts generated with actual RWIS data. We note that the impact of having observations of chemical amounts on the road (treatment) from the IoT sensor is not evaluated here. We leave this for future work.

The approach using emulated observations provides important advantages. For one, it allows for the evaluation of forecast accuracy using professional-grade RWIS observations, for forecasts produced at the same locations and with identical input for all other parameters to the RWM.

In this study, the NWP input to the RWM is taken from the High Resolution Rapid Refresh (HRRR) [3] forecasts updated hourly and interpolated to the locations of the RWIS. HRRR forecasts extend to 18 hours. But with a realistic latency of about 2 hours for HRRR data availability, this leaves forecast horizons up to 16 hours for the RWM in a real-time operational context.

### 3.2. Observation System Experiments

The impact observations have on forecast accuracy are evaluated from Observation System Experiments (OSE). OSEs are common practice in weather prediction to assess the impact of specific observations or sets of observations on the quality of weather forecasts [1]. These experiments consist of running different sets for forecasts over extended periods of time, with one set using all observations, while another is run while withholding the observations we want to assess. The data denial approach is the most direct way to evaluate the contribution of a set of observations to the quality of forecasts generated by a forecast system.

The OSEs in this study consists of three series of forecasts generated with different sets of input observations. These are:

1. A baseline set of forecasts generated without the use of any observations ("no obs.").
2. Forecasts generated using the complete set of RWIS observations.
3. Forecasts generated using the emulated IoT subset of observations.

Set 1 corresponds to forecasts generated for road segments away from the influence from any nearby sensor. Set 2, with forecasts generated at the RWIS locations, represent the best available road forecasts as they include the most complete set of detailed observations. The level of accuracy from set 3 forecasts (with IoT observations) can then be contextualized with respect to sets 1 and 2. Note that all sets use the exact same NWP input.

Our analysis consists of comparing the change in forecast errors between sets 2 and 1 and between sets 3 and 1. This change in forecast errors with respect to the "no obs." baseline represent the total impact of observations used in each set. A comparison of RWIS to IoT observation impacts should provide insights into how the deployment of IoT devices can contribute at improving forecasts across a road network. The impact of observations is evaluated here on the basis of two key parameters in winter road maintenance: road surface temperature (RST) and grip. Errors in both parameters are computed by subtracting values from the RWM output for various forecast horizons and the corresponding observations at the nine RWIS stations in Fort Collins. Errors are summarized by calculating the bias (mean error), Mean Absolute Error (MAE) and Root-Mean Square Error (RMSE). RMSE is used in addition to MAE as it is more sensitive statistic to large errors.

Forecasts from the three experiments are generated for the nine stations for the period of 2021-12-15 to 2022-02-28. The first 15 days are discarded from the analysis to leave enough time for the RWM to adjust its subsurface temperatures. New forecasts are initiated every 10 minutes with new observations (10-minute cycling) for sets 2 and 3. The same frequency is used for the “no obs.” forecasts despite not using observations. Instead, pseudo-observations are used by recycling values from the most recent previous RWM forecast.

## 4. RESULTS

### 4.1. Road surface temperature

Arguably among the most important variables in road weather is surface (pavement) temperature. Pavement temperature determines whether any condensate on the road surface melts or freezes, greatly impacting slipperiness conditions. The role of observations in reducing forecast errors in RST for all forecasts over the evaluation period, as a function of forecast horizon, is illustrated in Figure 2.

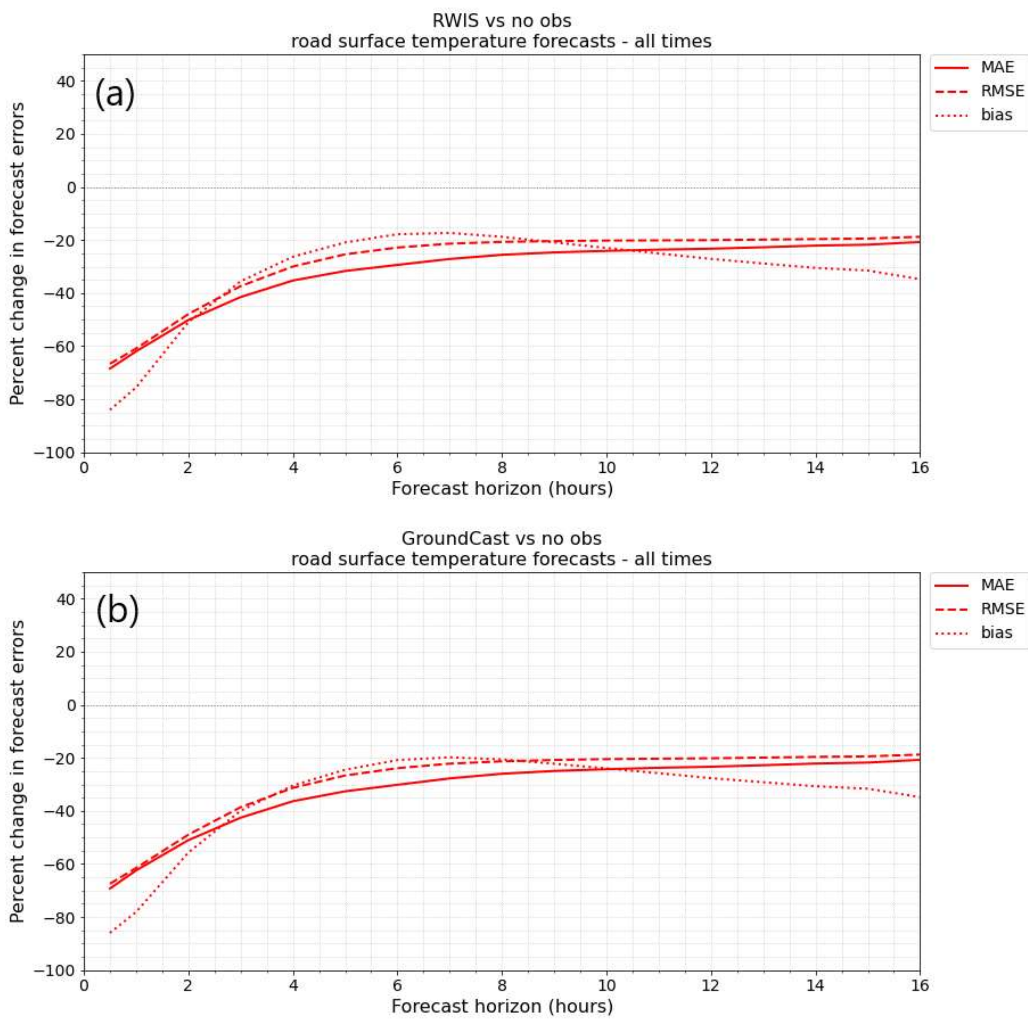


Figure 2 – Change in forecast errors statistics (bias, MAE and RMSE) for road surface temperature when using (a) the complete set of RWIS observations, (b) the subset of observations available from the *GroundCast* embedded IoT sensor. Negative values indicate reductions in errors over the reference (“no obs.”) forecasts.

The reductions in bias, MAE and RMSE obtained when RWM forecasts are produced with the use of RWIS observations are shown in Figure 2a. Reductions are expressed as percentages over errors in the baseline forecasts generated without the use of observations.

The results show that the complete set of RWIS observations contribute at reducing RST forecast errors by more than 80% for bias, and between 65 to 70% for MAE and RMSE, for forecasts of 30 minutes. This impact is gradually reduced along forecast horizons, reaching levels around 30% reductions for forecasts of 4 to 6 hours and beyond.

Figure 2b shows the results obtained for forecasts generated only using the subset of IoT sensor observations (forecasts from set 3). Nearly identical reductions in forecast errors are obtained, indicating an absence of loss of performance in RST forecasts when the embedded IoT sensor is used instead of an RWIS. Here the critical element is the availability of RST observations from the IoT sensor.

As results from Figure 2 include all conditions encountered during the evaluation period, we also show results obtained focused on conditions in the critical temperature range of -1 to +1$^{o}$C (i.e. near freezing conditions) (see Figure 3). The improvements in RST forecasts with IoT observations (and RWIS observations, not shown) are maintained in this critical range of temperatures, of greater importance for winter road maintenance decision making.

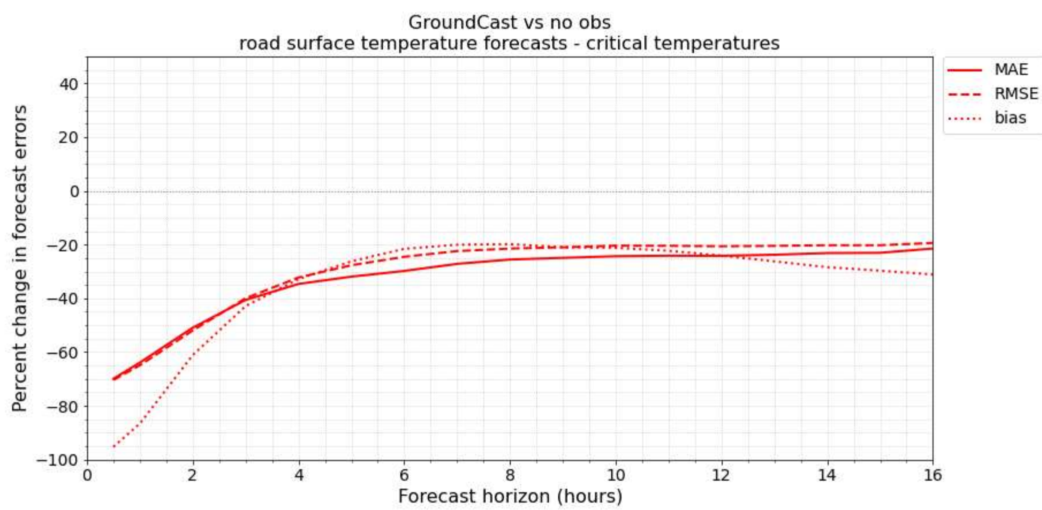


Figure 3 ─ Change in forecast errors statistics (bias, MAE and RMSE) for road surface temperature for forecasts produced using the subset of observations available from the *GroundCast* embedded IoT sensor, for conditions when observed road surface temperatures are in the critical -1 to +1$^{o}$C range. Negative values indicate reductions in errors over the reference (“no obs.”) forecasts.

## 4.2. Grip

Grip is an interesting parameter to consider as it integrates information on water, snow and ice layers present on the road into a single easy to interpret index. This index indicates the level of slipperiness of the roadway. Grip is derived from detailed observations of amounts of water, snow and ice on the road, obtained from state-of-the-art optical sensors. Values of this index from observations and predicted by the RWM are used as important sources of information on current and predicted road conditions by winter maintenance decision makers.

As grip values are available from both RWIS observations and RWM forecasts, errors in this parameter can directly be evaluated. Two distinct ranges in grip reductions are considered in our analysis:

$0.4 \leq grip < 0.6$ : "impactful" reductions
$grip < 0.4$ : "very impactful" reductions

Forecast errors are compiled when observed grip conditions are in either in the "impactful" of "very impactful" ranges, and summary statistics are reported in Figure 4. Shown are the percent error reductions over the baseline forecasts produced without the input of observations. We see that observations, either from RWIS or from the IoT sensor, bring significant benefits to grip forecasts as reductions in errors are obtained for all available forecast horizons. The magnitude of reductions vary by how severely grip is reduced or by which set of observations are used to constrain forecasts.

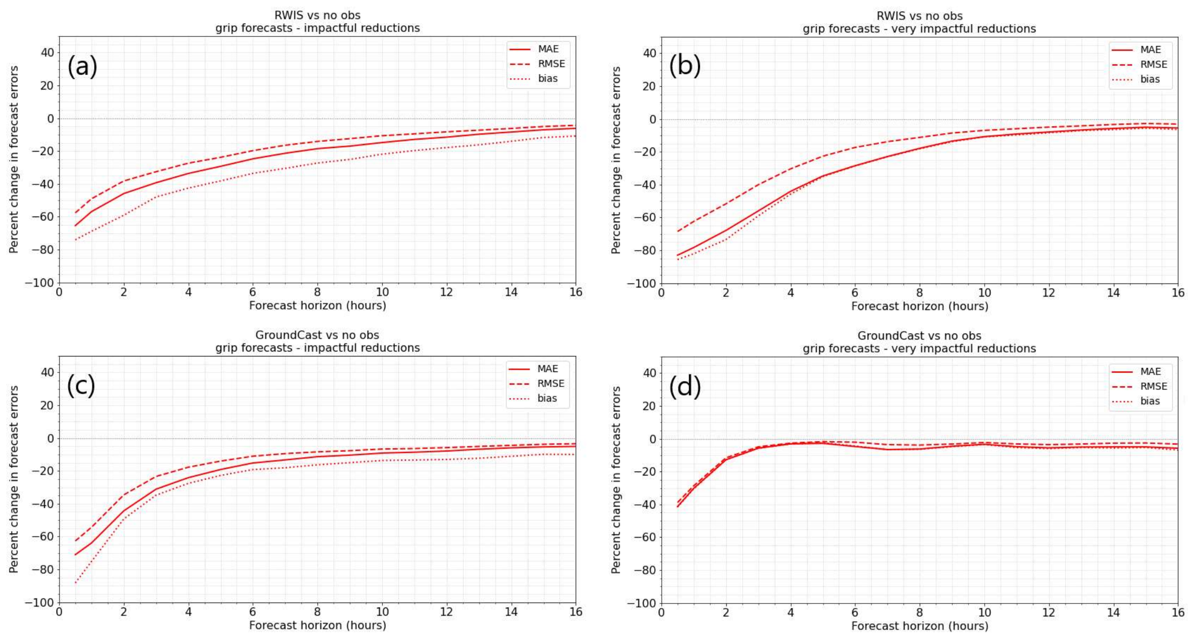


Figure 4 ─ Change in forecast errors statistics (bias, MAE and RMSE) for grip, (a) and (b) for forecasts produced using the full set of RWIS observations, and (c) and (d) using the subset of observations available from the *GroundCast* embedded IoT sensor, for "impactful" grip reductions (a) and (c), and "very impactful" reductions (b) and (d). Negative values indicate reductions in errors over the reference ("no obs.") forecasts.

For "impactful" reductions, using the more detailed RWIS observations of layer thicknesses (Figure 4a) leads to reductions in forecast errors by 55 to 65% over the "no observation" baseline (for RMSE and MAE) for 30-minute forecasts Bias is reduced by about 75%. Improvement in forecast due to observations gradually decrease over forecast horizons, reaching levels of about 10% at the longest horizon considered (16 hours). Reductions in forecasts errors for grip conditions in the "very impactful" range (Figure 4b) are larger, in the 70 to 85% range for RMSE, MAE and bias at 30 minutes, also gradually decreasing during forecasts.

The use of less-detailed road condition observations from IoT sensors (“dry”/”not dry” classification instead of detailed layer thicknesses) in the initialization of forecasts also leads to reductions in forecast errors of grip (Figure 4c and d). Maximum reductions are in the 60 to 70% range for “impactful” grip reductions for MAE and RMSE, and near 90% for bias (Figure 4c), and about 40% for “very impactful” grip reductions (Figure 4d) for 30-minute forecasts. It is also noticed that improvement in forecasts using the IoT observations are less persistent along forecast horizons. The observation impact drops more rapidly along horizons for IoT observations compared to the impact of RWIS observations. Reductions remain greater than 10% over the first 6 to 8 hours and 2 hours for IoT sensor data for “impactful” and very impactful” conditions respectively. This is compared to 9 to 12 hours when the RWIS layer thickness observations are used to initialize the RWM.

## 5. CONCLUSION

This study presents a first evaluation of the impact of observations from a newly available IoT sensor on road weather forecasts. Results demonstrate the positive impact of these observations on forecasts of road surface temperature and grip conditions. The reductions in forecast errors from the input of IoT observations are in fact similar to those obtained from RWIS observations for road temperature forecasts. Their impact is somewhat reduced for forecasts of road conditions (grip) compared to using the more detailed RWIS road state observations, but their use still leads to more accurate forecasts.

We note that this is a first look into the role of novel observations on improving road forecasts. A rather simple implementation has been tested and promising results have been obtained. The results suggest that further improvements in road state forecasts using IoT observations are within reach, mostly by refining the initialization of the RWM water, snow and ice layer thicknesses through use of additional sources of information on the presence and phase of precipitation, when the IoT sensor reports “not dry”.

The positive results also provide motivation for further studies aiming at better defining the role IoT sensors in designing efficient observation networks that best support winter road maintenance activities.

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