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COMPARING RAWINSONDE AND MODEL SOUNDINGS TO IMPROVE AIRCRAFT ICING FORECASTS

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1. Introduction

Meteorologists at the National Center for Atmospheric Research (NCAR) have developed algorithms for the diagnosis and prognosis of aircraft icing over the CONUS and Alaska. Numerical models provide data for all of the products and their accuracy is very important to the correct representation of icing conditions. The Current and Forecast Icing Potential (CIP and FIP, respectively) algorithms (Bernstein et al., 2004; McDonough et al., 2004) use the NCEP Rapid Update Cycle (RUC) model. Similar products are also created over Alaska (CIP-AK and FIP-AK) and use the Alaska ETA as an input.

One way to verify the model accuracy is to compare the forecasts with NWS rawinsonde observations. These observations allow verification throughout the depth of the atmosphere and at points across the model domain. Among other fields, the icing products use temperature (T) and relative humidity (RH) forecasts to create a vertical profile of the atmosphere that can be compared to observed profiles from balloon-borne soundings.

It is known that the RUC produces more accurate forecasts with the introduction of the 20 km grid (Benjamin et al., 2003; Schwartz and Benjamin, 2002). Benjamin et al. show that the average temperature and relative humidity errors vary from 0.9 to 1.6 °C and 15 to 19%, respectively. Temperature was most accurate in the mid levels while relative humidity performed best near the surface and at the tropopause for all forecast lengths. In order to improve the icing algorithms we must determine the situations in which the model performs well and adjust our use of them accordingly. For example, the algorithms assume that the models have problems forecasting moisture. This is taken into account by using fuzzy logic member ship functions that allow for the possibility of icing at relative humidities well below saturation (Bernstein et al., 2004; McDonough et al., 2004). If it can be shown that the model performance in predicting moisture is better than expected then the algorithms may be changed to make that function less charitable.

For the comparisons it was assumed that the rawinsonde observations are the “truth”. However, instrument errors and biases have been documented. Rawinsonde observation errors are generally accepted to be 0.5 °C for temperature and about 8% for relative humidity (Benjamin et al., 2003). Wang et al. (2002) found biases in the relative humidity measurements of certain rawinsondes due to a variety of factors such as contamination and temperature dependence.

The methodology used for the comparisons will be described in section 2. Verification results for the RUC and Alaska-ETA models will be discussed in section 3. The potential impact of the model error on icing products will be presented in section 4.

2. Methodology

Rawinsondes are launched each day at 0 and 12 UTC from stations across the CONUS and Alaska (Fig. 1). For this study comparisons are made between the profiles of T and RH from these soundings and coincident forecast profiles from the shortest-term forecast available from each model. This means that 3-hour forecasts from the 9Z run of the RUC and 6-hour forecasts from the 6Z run of the Alaska ETA were used to compare to the 12Z rawinsonde observations. The current icing products (CIP and CIP-AK) use these runs for the diagnosis of icing while the forecast icing products (FIP and FIP-AK) use them plus longer-term forecasts to create prognosis. Although FIP and FIP-AK also make forecasts out to 12 hours, only the 3-hour forecasts will be verified in this study, as they are the most commonly used products for the icing diagnoses. It is expected that the 3-hour forecast will provide the most accurate forecast with some degradation in the longer-range (Benjamin et al., 2003).

For each case the nearest model grid point to the sounding location was chosen and a vertical profile was extracted from the model. The rawinsonde observations were interpolated to the model surfaces to allow for a direct comparison. This interpolation was only done if there was a

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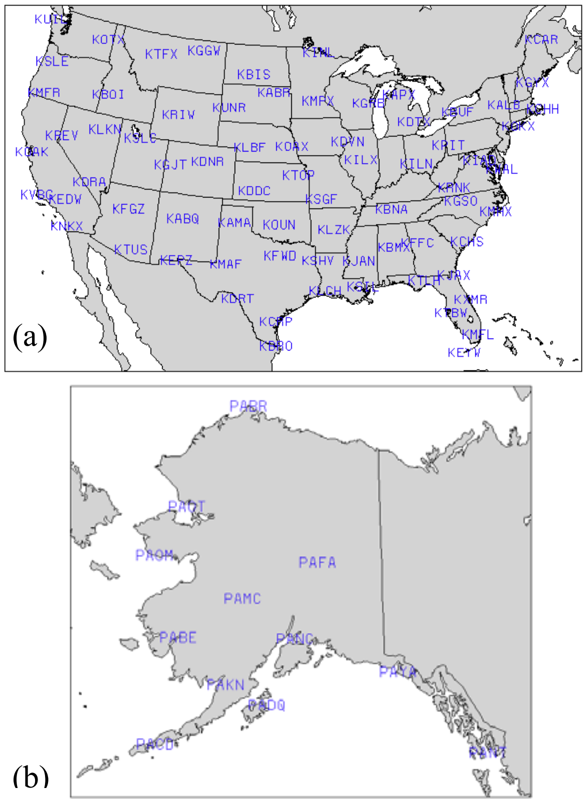

Figure 1. (a) CONUS and (b) Alaska rawinsonde sites.

sounding observation within 1000 ft. (305 m) of the model surface.

Distributions of model vs. observations were created to get an idea of the overall accuracy and bias. Average absolute differences and biases were also calculated for each station to identify possible geographic biases. These were calculated by taking the difference between the model and observation and calculating the average, taking into account the sign of the difference (bias) or not (absolute difference). For icing products we are most interested in model performance in conditions where icing might be expected (e.g. temperatures between 0 and –10 °C and RH > 80%). The data were further divided into ten-degree temperature bins to gauge the model performance in these areas.

3. Model Comparisons

a) RUC

This comparison used CONUS soundings and 40 km (degraded 20 km) RUC output from a four-month period between 9/15/2002 and 1/15/2003.

Figure 2 shows the temperature bias for all of the stations throughout the depth of the atmosphere. Temperature is quite accurate, with the bias being less than half a degree too warm in almost every case. There was no obvious geographical tendency in the temperature bias field. However, examining the absolute average difference (Fig. 3) shows that, while the overall averages are less than 1.4 °C, the model seems to perform better in the Southeast, Southern Plains, and Ohio Valley.

As expected, relative humidity has higher average biases and differences because it is a more difficult field to predict. The model showed a dry bias across the CONUS (Fig. 4) with smaller biases in the Gulf and Atlantic Coast regions. Overall, it was only 3.5% too dry on the average. The Pacific Coast, Rocky Mountain, northern High Plains, and Great Lakes regions actually have the strongest dry biases. Figure 5 shows the average absolute difference for the RH field. The west has the highest values, especially along the Pacific Coast, while the Central and Southern Plains appear to be the most accurate for moisture prediction. An examination of the distribution of

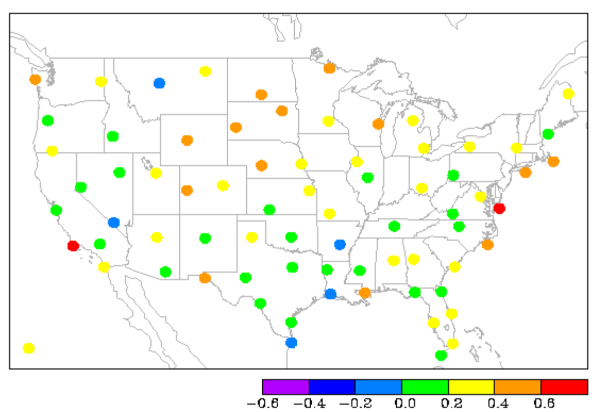

Figure 2. Average temperature bias in degrees C. Positive values represent average model temperatures warmer than the observed and vice versa. The dot in the lower left corner represents the overall average for all stations.

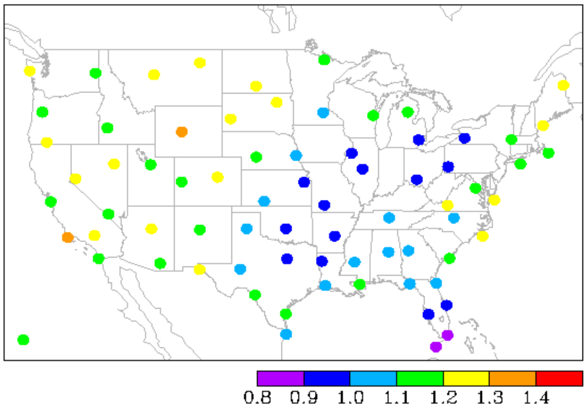

Figure 3. Average absolute temperature difference in degrees C. The dot in the lower left corner represents the overall average for all stations.

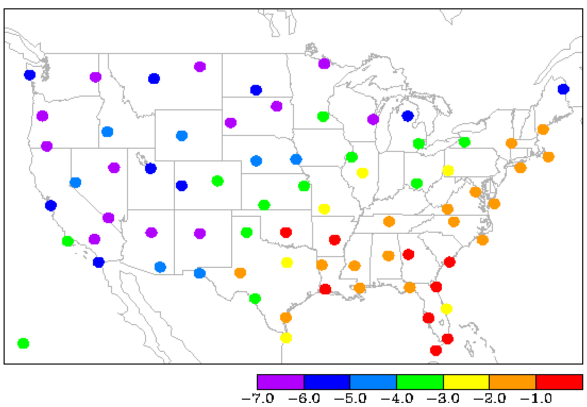

Figure 4. Average RH difference (bias) in percent. Negative values represent average model RH values drier than observed. The dot in the lower left corner represents the overall average for all stations.

the model vs. observed RH (Fig. 6) shows that there is a large spread of values across the domain. At high RH values there does not appear to be a very large bias, which is encouraging. The dry bias is especially evident at low RH values. This may have more to do with the quality of observations at low RH and cold temperatures rather than the model itself.

It appears that the strong dry bias at low RH values may be skewing the overall results. Since a dry bias in areas of very dry air will not harm the algorithm's performance all model relative humidities less than 30% were removed from further analysis. The 30% threshold was chosen as the lower bound because that is where the CIP

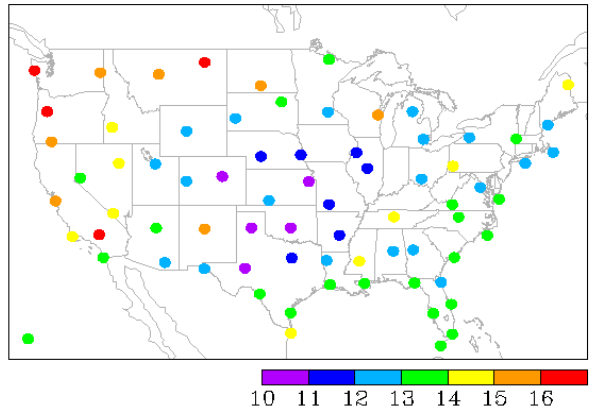

Figure 5. Average absolute RH difference in percent. The dot in the lower left corner represents the overall average for all stations.

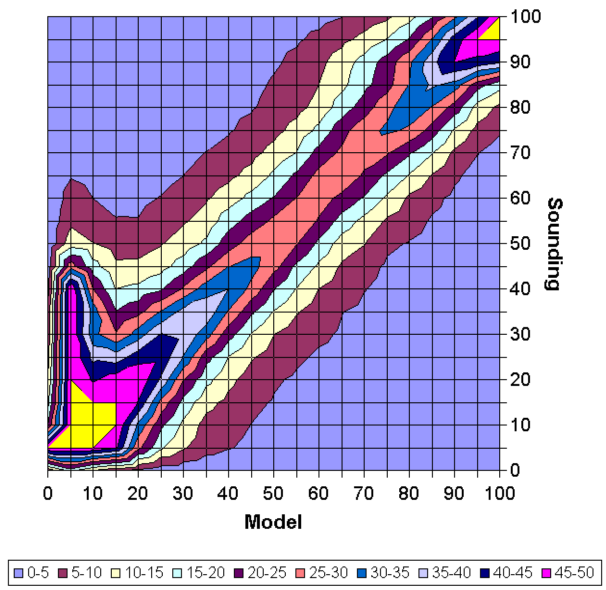

Figure 6. Distribution of model vs. observed RH values for the RUC. The colors and their associated ranges represent the number of matching points for a certain RH value (in hundreds).

and FIP relative humidity maps begin to show non-zero interest in the relative humidity values (Bernstein et al., 2004). Leaving out these values had a dramatic effect on the bias (Fig. 7). The overall average bias went from 3.5% too dry to 1.6% too moist, and the majority of stations are now showing a moist bias. Examining individual stations also shows a remarkable reversal. For example, KTFX (Great Falls, MT) went from a 5% dry bias to a 5.4% moist bias.

An analysis was done on the accuracy of the RH predictions in 10 °C bins in the 20 to –60 °C range. Figure 8 shows the average RH bias for the 0 to –10 °C bin, where temperatures are ideal for icing to occur. The model is fairly accurate in this temperature range with less of a dry bias (0.6%) in this range than for all temperatures (3.5%). One feature that sticks out is the change from a dry bias in the Rocky Mountains and Plains to a moist bias in the Southeast and along much of the Pacific Coast. An examination of the average absolute difference (Fig. 9) shows the model to be the most inaccurate in these high bias areas.

RH performance degrades with decreasing temperature (not shown). The large spread and dry bias at low RH values shown in Figure 6 appears to come mostly from these cold temperature bins.

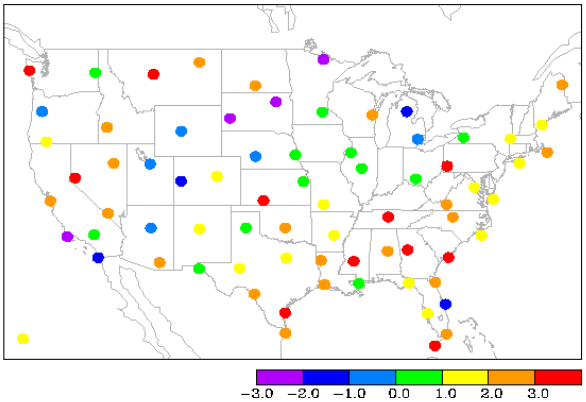

Figure 7. As in Fig. 4 but for all relative humidities ≥ 30%.

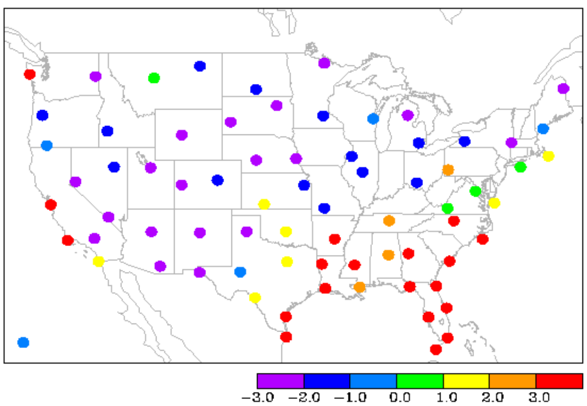

Figure 8. As in Fig. 4 but for temperatures between 0 and –10 °C.

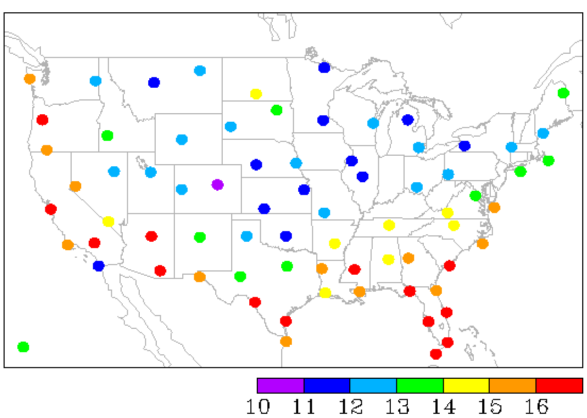

Figure 9. As in Fig. 5 but for temperatures between 0 and –10 °C.

b) Alaska ETA

Alaskan soundings and 45 km (degraded 11.25 km) Alaska ETA output were compared for a five-month period between 7/10/2002 and 12/17/2002. The earlier time frame was chosen because the icing season begins earlier in Alaska with a maximum in the fall before tapering off somewhat in the winter due to the extremely cold temperatures.

Like the RUC, the AK ETA was very accurate

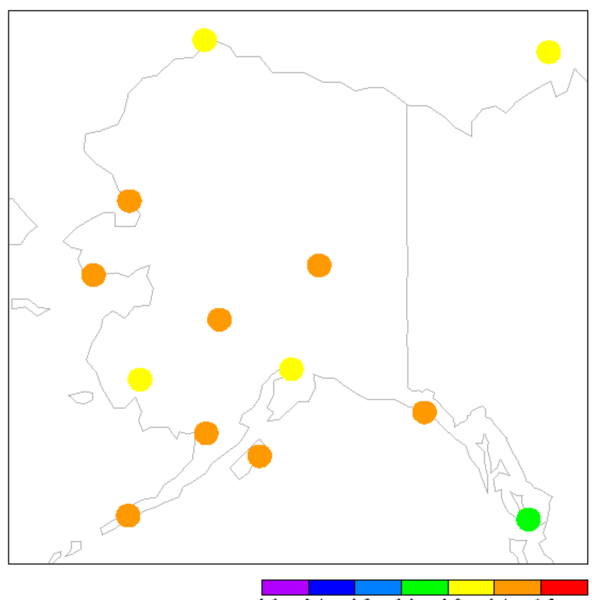

Figure 10. Average temperature bias in degrees C. Positive values represent average model temperatures warmer than the observed and vice versa. The dot in the upper right corner represents the overall average for all stations.

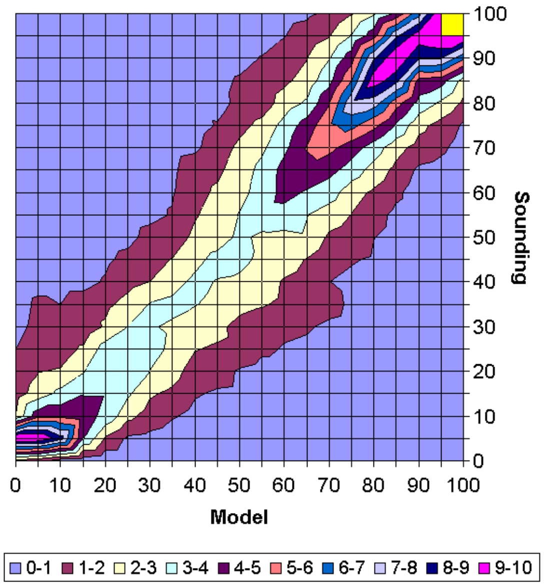

Figure 11. Distribution of model vs. observed RH values for the AK ETA. The colors and their associated ranges represent the number of matching points for a certain RH value (in hundreds).

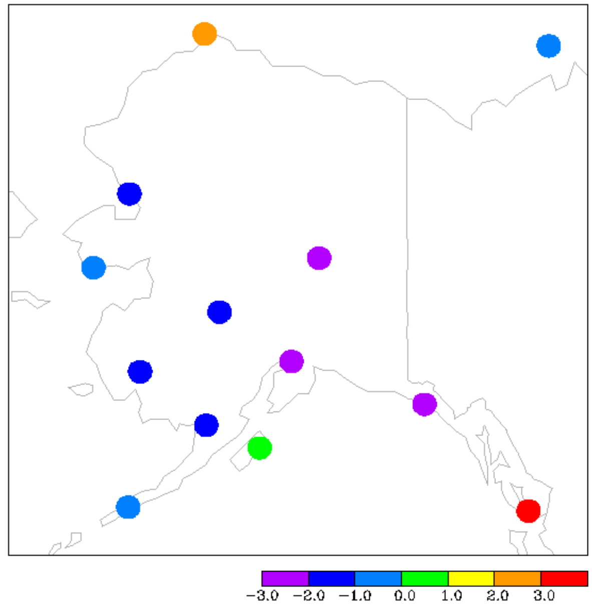

Figure 12. Average RH difference (bias) in percent. Negative values represent average model RH values drier than observed. The dot in the upper right corner represents the overall average for all stations.

in its temperature forecasts. Figure 10 shows the average bias for the temperature fields of the model and observations for the twelve Alaska stations combined. As in the RUC, there was a slight warm bias to the model, but it was less than half a degree in every case but one.

Again, the relative humidity field shows more variability than the temperature. Figure 11 shows the relative humidity distribution for all stations. There appears to be a dry bias of approximately 5% in the model at high RH values (>75%), with little to no bias either way between 30% and 60%. However, the spread between the measured and model values can be quite large. In some cases the model is predicting low relative humidity values where the sounding is reporting near saturation and vice versa. Examining the overall bias (Fig. 12) shows the model to be slightly dry (0.5%) on the average with an overall accuracy (Fig. 13) in line with the RUC. Figure 11 did not show a strong dry bias at low RH values and this is the main reason for the small overall dry bias. However, it is still of value to the algorithms to identify any bias in RH values ≥ 30%. Figure 14 shows the relative humidity biases for this situation. Once again, there is a moist bias, but it appears that it may be skewed somewhat by the high values at PABR (Barrow, northernmost

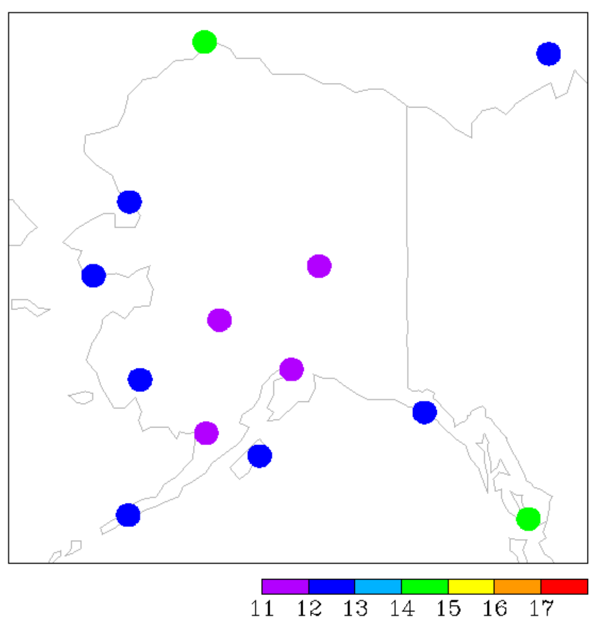

Figure 13. Average absolute RH difference in percent. The dot in the upper right corner represents the overall average for all stations.

station) and PANT (Annette Island, far southeastern station). These stations will be further discussed later. However, all of the stations have less of a dry bias in this RH range.

The data were once again divided into 10°C bins from -60°C to 20°C. The model is quite accurate when the temperature is above -10°C. There is still a large amount of spread in the values for these warmer temperatures, but the bias is not as evident. There is a slight moist bias for temperatures between 0 and –10 °C (Fig. 15). At colder temperatures (e.g. –20 to –30 °C, Fig. 16) the spread between the predicted and observed RH becomes even larger. Notice that the model does not predict RH values above 85% at these temperatures (–20 to –30 °C) even though there are soundings that are nearly saturated with respect to water. The Alaska ETA microphysics package currently assumes that clouds glaciate at temperatures colder than –10 °C so that saturation with respect to water is impossible below this threshold (Brad Ferrier, NCEP, personal communication). This upper bound on the relative humidity with respect to water decreases with decreasing temperature. In the –50 to –60 degree bin the largest RH value predicted by the model is 65%.

Comparison of a particular sounding side-by-side helps to better illustrate how well the model represents the actual conditions. Figures 17 and 18 show model and rawinsonde plots of temperature and relative humidity from PANC at 12Z on 12/17/2002. The temperature profile shows a rather strong inversion about 2000 m above the surface. The model reproduces it, but shows it to be weaker. However, the model has the temperature and height of the inversion top almost exactly right. The temperatures remain within two degrees up to around 10000 m, where they begin to diverge somewhat above the

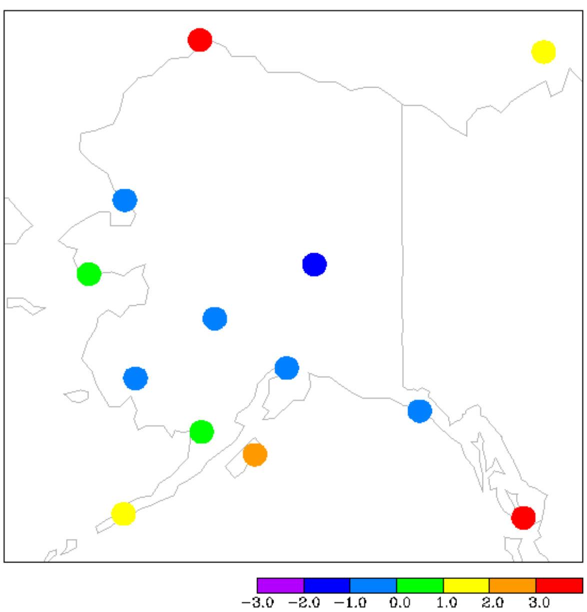

Figure 14. As in Fig. 12 but for all relative humidities ≥ 30%.

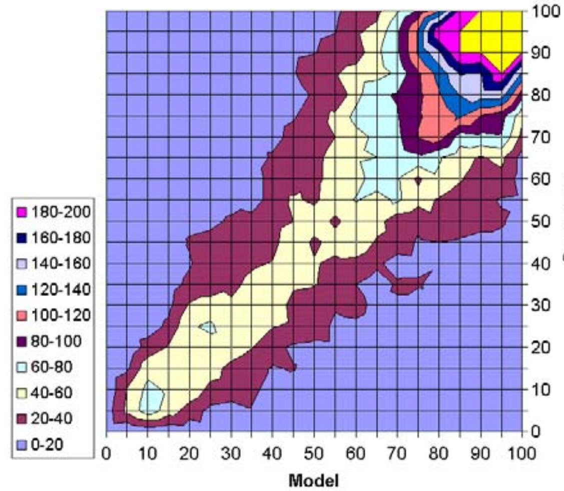

Figure 15. Distribution of model vs. observed RH values for the AK ETA for temperatures between 0 and –10 °C. The colors and their associated ranges represent the number of matching points for a certain RH value.

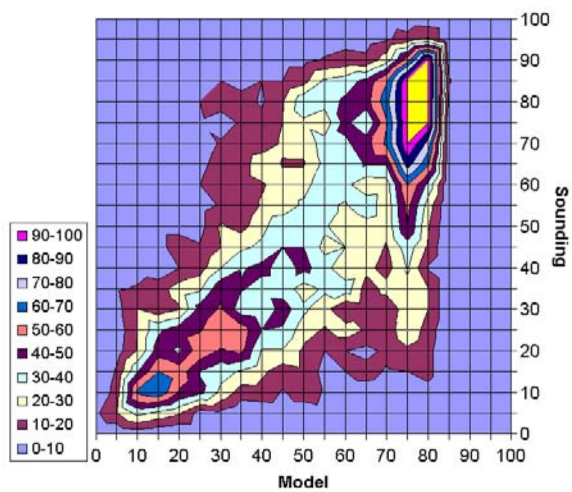

Figure 16. As in Fig. 15 but for temperatures between –20 and –30°C.

tropopause. The height of the tropopause is also predicted very well. The relative humidity fields for this sounding are also similar with the same trends, though the sounding suggests the presence of some low level clouds that the model doesn't quite capture. Between 3000 and 9000 m the RH fields are within about 5% of each other. Above the tropopause the fields diverge very quickly, as the model has essentially no moisture. The largest differences in both fields are above the tropopause, an area of no interest to the icing algorithms.

One interesting feature of the soundings revealed during this study was the lack of saturated or near saturated conditions at several sites (Table 1). Barrow (PABR) and Annette Island (PANT) had such a low number of saturated

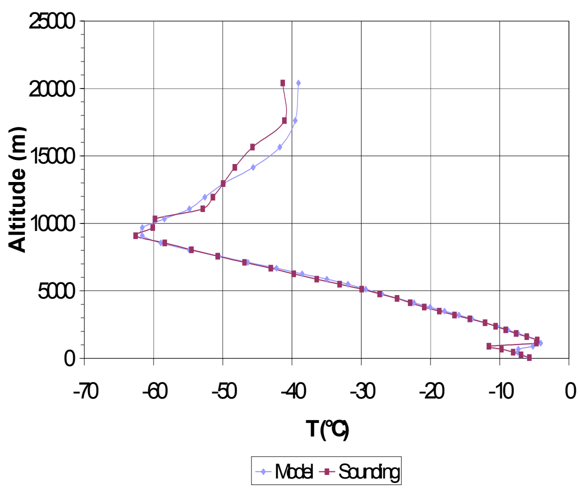

Figure 17. Temperature soundings from PANC on 20021217 at 12Z.

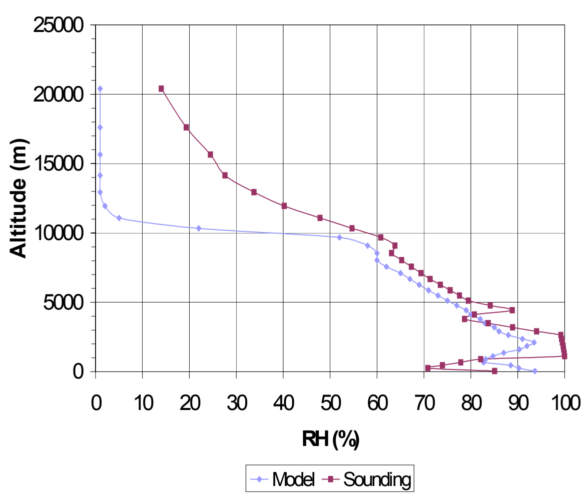

Figure 18. Relative humidity soundings from PANC on 20021217 at 12Z.

Station	Saturated	Nearly Saturated
PABR	50	548
PAOT	466	1403
PANT	101	311
PAYA	997	2488
PANC	427	1390
PAOM	477	1507

Table 1. Number of observations with RH = 100% (saturated) and RH ≥ 95% (nearly saturated) in the rawinsonde dataset for selected stations. Anchorage (PANC) and Nome (PAOM) are included as extra comparison points.

conditions when compared to other stations that it bears further analysis. This is especially true of PANT, which is located fairly close to and in much the same environment as Yakutat (PAYA). Both stations are situated along the coast in the southeast part of the state. However, PAYA has almost ten times the number of saturated conditions as PANT. It is not clear why Barrow had such few saturated conditions during the period of interest, but may have simply been due to a lack of liquid clouds. At Kotzebue (PAOT, the site nearest to Barrow) there were almost ten times the number of saturated conditions as in Barrow. Because full saturation of an air parcel may not be measured properly it was determined that examining the number of observations of 95% or greater would help answer any questions about data quality. When these near saturation conditions are taken into account the number of observations increases by about a factor of 3 for all stations except PABR, which increases by a factor of 11. At Barrow near saturation occurs in a much higher percent of the total than at other stations. Including the nearly saturated observations does very little to close the gap in the number of observations between PANT and PAYA. This may help explain why these two stations (PABR and PANT) have the greatest moist bias (Figs. 12 and 14). The model is predicting saturated or near saturated conditions far more often than they are being observed.

There may be a consistent instrument or analysis error at these sites that could be resulting in a dry bias in the observations (Wang et al, 2002). It is also possible that the rawinsondes being launched at PABR and PANT are manufactured by Sippican (formerly VIZ). The hygristors used in these rawinsondes have a dry bias in areas of high RH, with observations greater than 95% very rare (Wade and Schwartz, 1993).

4. Summary and Effects on Icing Products

Temperature is well represented by both models with more spread and bias associated with the relative humidity field. The differences in RH were smaller at warmer temperatures (i.e. lower altitudes) where icing is most common and grew larger with decreasing temperature. Part of this can be attributed to model physics and part may be due to instrument inaccuracies. Both models showed a slight warm and dry bias when considering all stations and altitudes. However, there were some areas where these biases were reversed.

Of concern to the algorithm developers is the correct identification of the presence of clouds and multiple cloud layers in model RH profiles. Because multiple cloud layers can vastly change the icing conditions, the identification of these situations is imperative. These results can be used to help improve the cloud layer detection in the icing products by comparing observations of multiple cloud layers from the rawinsondes to the corresponding model sounding to improve the layer detection schemes.

The icing algorithms are all fuzzy logic based systems that implicitly take model errors into account by using a set of membership functions for calculating icing potential (Bernstein et al., 2004; McDonough et al., 2004). This study shows that the approach is well founded, but that model outputs are somewhat more accurate than previously thought, allowing the RH membership function to be more restrictive. If geographic biases continue to be observed they may play a role in how the model data are interpreted in different parts of the country as the algorithms continue to evolve.

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