9.13 Current Icing Potential (CIP) Algorithm with TAMDAR Data - A Verification Analysis

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1. INTRODUCTION

This research was started to determine if incorporation of TAMDAR (Tropospheric Airborne Meteorological Data Reporting) icing data, collected during the Great Lakes Fleet Experiment (GLFE) (please see Daniels et al 2002 for more information on GLFE), into the Current Icing Potential (CIP) algorithm would improve the accuracy using standard verification methods. CIP combines model output (20-km RUC interpolated to 5 km) with weather observations (METARs, GOES imagery, NEXRAD mosaic, and lightning) to determine an initial potential field. CIP then uses pilot reports (PIREPs), along with model forecasts of supercooled liquid water and vertical velocity, to boost this potential. In this study TAMDAR icing reports, both positive and negative, are being added to the voice PIREP database. The CIP icing potential fields are then re-run with these updated PIREP data sets. The accuracy of the CIP output, with and without the additional TAMDAR data, will be evaluated using standard verification methods for a period from January 6 to April 4, 2005. In addition, this study will include case studies of significant icing or non-icing events to illustrate the potential for improvement.

2. DATA

2.1 High resolution CIP (HRCIP)

The Current Icing Potential (CIP; Bernstein et al. 2005) gives an hourly, three dimensional diagnosis of the potential for icing and supercooled large drops (SLD) over the continental United States and southern Canada. It uses decision trees and fuzzy logic to combine RUC model data with information from satellite, radar, surface observations, voice pilot reports (PIREPs), and lightning sensors in order to calculate these potentials, which are presented on a scale from 0 (no icing or SLD) to 1 (icing or SLD very likely). The operational version of CIP is run on a grid with 20-km horizontal resolution. Recently, an experimental version of CIP was created with 5-km horizontal grid spacing. This high-resolution CIP (HRCIP) is run on a subset of the CIP grid over the Ohio Valley (see Fig. 1) and uses the same input data and equations as CIP.

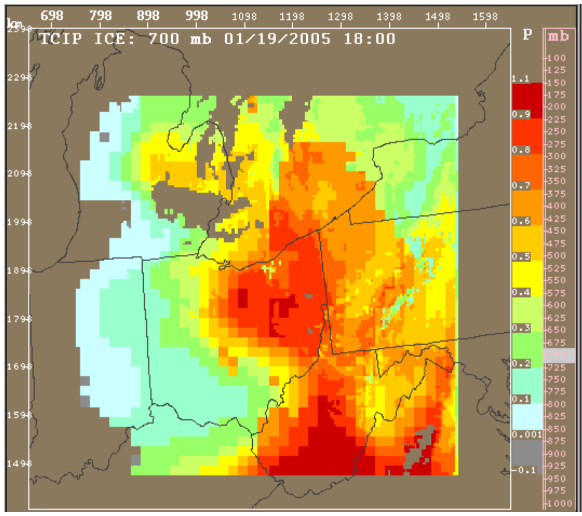

Figure 1. *Icing potential at 700 mb at 1800 UTC on 19 January 2005 over the HRCIP domain.*

2.2 Pilot reports (PIREPs)

PIREPs of positive icing are used as a boosting factor in the icing potential calculation. A positive icing PIREP nearby in space and time to a point at which icing is expected gives added confidence to the initial icing potential. A $PIREP_{map}$ value between 0 and 1 is calculated, which is based on the horizontal (out to 150 km) and vertical (up to 300 m) distance between a grid point and the positive icing PIREP. The closer in space this PIREP is to a grid point the closer to 1 $PIREP_{map}$ will be. The age of PIREP is not used except to determine if the PIREP occurred less than an hour before the CIP runtime. Time is also important to the amount of influence a PIREP has and may become a contributor in future versions of CIP. The reported icing intensity of the PIREP is also not

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considered. All positive icing PIREPs are treated the same in this version. Once $PIREP_{map}$ has been calculated it is used to boost the initial icing potential along with model forecasts of supercooled liquid water (SLW) and vertical velocity (VV), which have also been mapped to a 0 to 1 scale to reflect their interest. In the final icing potential calculation $PIREP_{map}$ can boost the initial icing potential by 0.35 times $PIREP_{map}$ of the difference between 1 and the initial icing potential value, with SLW and VV accounting for a possible boost of 0.4 and 0.25, respectively. Consider the following situation. The initial icing potential is 0.4. There is a positive PIREP 40 km away and 100 m above the grid point. This results in a $PIREP_{map}$ value of 0.5. SLW and VV give no additional information so their map values are 0. In this scenario the final icing potential would be 0.4 + [(1.0 – 0.4) * 0.35 * 0.5]. This results in a final icing potential of 0.505.

The use of negative PIREPs by the HRCIP algorithm is not a current feature and is being implemented for this exercise. For voice PIREPs, there are relatively few "null" icing reports, so the CIP developers decided not to use such sparse information. Conversely, TAMDAR "no icing" reports outnumber the "yes icing" reports by 10:1 from our initial data inspection. Thus, incorporation of these to suppress icing potential could have a noticeable effect on CIP. The methods that are used to implement this process in HRCIP as well as the results from the comparison of these data will be included in an amendment to this paper before the AMS conference in January.

PIREPs, which are an indicator of presence or absence of icing, are also used as the ground truth observations to verify icing potential. Since the HRCIP uses information from the *previous* hour's PIREPs to increase the potential for icing, the verification uses only PIREPs that are within the hour *past* the HRCIP valid time.

2.3 TAMDAR Data

As part of the GLFE, 64 turboprop Saab 340 aircraft (Figure 2) were outfitted with the TAMDAR sensor (Figure 3). The TAMDAR sensor measures winds, temperature, humidity, air speed, turbulence, and icing. The data from these sensors are downlinked via satellite to a ground-based processing center. These data are available to users within one minute of actual measurement. For this study the data from the icing sensor are being used.

The TAMDAR icing sensor contains two independent infrared emitter/detector pairs mounted in a leading edge recess of the probe to detect ice accretion. The accretion of at least 0.5 millimeters of ice on the leading edge surface will block the beams and result in a positive detection. When ice is detected, internal heaters mounted within the probe melt the ice and the measurement cycle repeats. The heaters are powered for at least one minute and the de-icing cycle occurs each time ice is detected. The icing data is given as a yes (icing) or a no (no icing) report.

Figure 2. *A Saab 340 aircraft operated by Mesaba Airlines.*

Figure 3. *Tamdar Sensor*

For this study the TAMDAR data were converted to a PIREP format that the HRCIP algorithm would recognize. This format includes such variables as date, time, latitude, longitude, and altitude as well as whether or not there was icing.

3. METHODS

3.1 High Resolution CIP

For this comparison three versions of the HRCIP are being run. The first version is HRCIP with only voice PIREPs, while the second version also includes positive TAMDAR icing data. The third version will add negative TAMDAR icing data. All of these HRCIP versions are run for the same time period (January 6 to April 4, 2005) and with the same initial data. This will allow two comparisons: introduction of TAMDAR data using the current PIREP boosting technique (see Sec. 2.2) and ingesting of negative icing data so as to take full advantage of the TAMDAR information.

3.2 Verification Technique

The verification in this study was completed by comparing the icing potential fields to PIREPs of positive and negative icing from the surface to 30,000 feet. Once this initial comparison was complete then the three versions of HRCIP were compared to one another.

The forecast verification methods this evaluation of HRCIP utilizes are based on standard techniques that are described in greater detail in Brown et al. (1997). Icing potential produced by HRCIP are converted into a set of yes/no values by using a variety of thresholds. If the HRCIP potential value is greater than or equal to the threshold value then it is counted as a "yes" diagnosis. If it is less then the threshold then it is counted as a "no" forecast. This is done for each grid point in the domain. These icing potentials are then matched to PIREPs, using a nearest neighbor approach, which are also using yes/no values. These matches are counted and then put into a two-by-two contingency table (Table 1).

There are three primary verification statistics that are used in the evaluation. These are probability of detection of YES observations (PODy), probability of detection of NO observations (PODn), and True Skill Statistic (TSS) which is also known as the Hanssen-Kuiper's discrimination statistic (e.g., Wilks 1995). PODy and PODn are estimates of the proportions of yes and no observations that are correctly diagnosed. Using both PODy and PODn we can measure the ability of the HRCIP diagnosis to correctly categorize icing observations. The TSS is a combination of PODy and PODn that give an overall measure of discrimination capability. Table 2 provides definitions and descriptions of these three verification statistics.

Table 1. Contingency table for YES/NO forecasts. Elements in cells are counts of forecast-observation pairs.

Forecast	*Observation*		*Total*
	YES	***NO***	
YES	YY	YN	YY+YN
NO	NY	NN	NY+NN
Total	YY+NY	YN+NN	YY+YN+ NN+NY

Table 2. Verification Statistics used for the evaluation of HRCIP.

Statistic	*Definition*	*Description*
PODy	YY/(YY+NY)	Probability of detection of YES observations
PODn	NN/(NN+YN)	Probability of detection of NO observations
TSS	PODy+PODn-1	True Skill Statistic

The relationship between PODy and 1-PODn for different thresholds is the basis for the verification approach known as "Signal Detection Theory" (SDT). This relationship can be represented for a given algorithm with the curve joining the 1-PODn and PODy points for different thresholds. The resulting curve is known as the "Relative Operating Characteristic" (ROC) curve in SDT. When PODy is plotted on the y-axis, the closer a given curve comes to the upper left corner, the better the diagnosis. The area under the curve (AUC) is a measure of overall forecast skill and provides another measure that can be compared among products. This measure is not dependent on the threshold used. A forecast with zero skill would have an ROC area of 0.5. (Chapman et al. 2006)

4. RESULTS

Results are not yet available but will be presented at the conference.

5. ACKNOWLEDGEMENTS

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