J1.5 AN INFERRED ICING CLIMATOLOGY – PART I: ESTIMATION FROM PILOT REPORTS AND SURFACE CONDITIONS

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1. INTRODUCTION

The estimation of a climatology of in-flight icing conditions has been a goal of the icing research community for a number of years. Much effort has been expended to develop forecasts of icing conditions aloft, but little is known about the distribution of icing over the continental United States. However, development of a climatology of icing conditions is not straightforward, due to the limited observations of this phenomenon. Widespread observations of icing are only available in the form of pilot reports (PIREPs) from aircraft. Unfortunately, these observations are sporadic and non-systematic, and cannot be used directly to provide a coherent or meaningful measure of the frequency of icing conditions in many locations (Brown and Young, 2000).

A statistical approach is taken in the development of a model for the icing climatology, using observations available in the regions of large cities. Icing reports are expected to be nearly systematic in those regions, because the air traffic is relatively frequent and is consistent from day to day. Surface climatological variables have been found to be related to the icing observations in these locations, and these variables are used to develop a statistical model of icing frequency. The resulting model is applied to airport locations serving smaller populations, using their local surface climatological observations to provide estimates of the true frequencies of icing conditions. The frequency estimates from the model provide a more coherent and consistent climatology of icing than obtained from the PIREPs alone. Methods to quantify the uncertainty in the estimates are also investigated and applied.

2. METHOD

Due to the non-systematic and spatially irregular nature of PIREPs, a direct observational climatology of icing is ill advised. A well-documented problem with PIREPs is their very limited null information. That is, conditions of "no icing" are very rarely reported. However, a lack of positive icing reports does not necessarily indicate the absence of icing. Figure 1 shows the relationship between population and the proportion of days with an icing PIREP for the regions around 131 US cities in January 1993-2000. A strong positive relationship is exhibited. Most notably, small cities never exhibit a high proportion of icing days. Excepting a particularly peculiar meteorological phenomenon, population clearly has an effect on reporting. PIREPs are concentrated around large airports and common flight paths, where air traffic is the highest. Also, aircraft are more likely to encounter icing on landing or takeoff than while cruising, as they move through the lower portions of the atmosphere. As the reporting of icing conditions is much more reliable in high traffic areas, this research focused on developing statistical models linking icing with surface observations in these regions. These models are then applied to areas with less air traffic but where surface observations are readily available. The focus was on developing a climatology for comparison to other estimates of icing and providing a basis for new forecasting techniques.

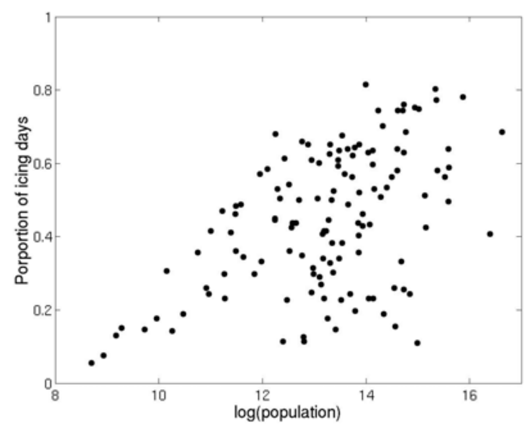

Fig. 1 – Plot of log transformed population vs. proportion of days with at least one icing PIREP, January 1993-2000, for the regions around 131 U.S. cities.

2.1 "Cities based" approach

PIREPs from 1993-2000 were included in this analysis. This research adopted a "cities based" approach essentially using only those PIREPs within 100 km of a large city (population greater than one million). For each city and day in the study period, a binary response was generated indicating the presence or absence of an icing PIREP. For the purposes of this study, several icing PIREPs within 100 km of a given city on a given day were treated the same as a single icing PIREP. In this manner, daily dichotomous data were generated for all the cities in the study region and

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period. The proportion of icing days in a time period (e.g. a month) was calculated from these data.

The implicit assumption in this technique is that if icing existed above a large city, then at least one PIREP would be recorded. On days where no icing PIREPs were recorded, there was assumed to be no icing present. These binary responses were generated for 38 metropolitan areas with populations over one million from the eastern half of the continental United States. The dearth of large cities in much of the western US prohibited reliable statistical analysis in this area. Figure 2 shows the region and cities used in the analysis.

Fig. 2 – Region of the CONUS considered in the analysis. Cities with populations over one million are indicated.

2.2 Surface observations

A 30-year (1961-1990) climatology of selected surface variables was produced using data from the National Climatic Data Center. Bernstein et al (1997) demonstrated how surface conditions can give an indication of the potential presence of supercooled liquid water aloft. Roughly 25 weather parameters were derived from the 30-year history, all of which are possible indicators of icing. In keeping consistent with the measurement of icing as a proportion of days with at least one icing PIREP, these variables were also computed as proportions with the exception of temperature. Variables such as the proportion of days with liquid precipitation, the proportion of days with at least 12 hours overcast, and the proportion of days with a cold frontal passage were used.

2.3 Statistical model

While reliable estimates for the proportion of icing days could be generated for the large cities, a modeling approach must be taken for regions with smaller populations and thus less frequent air traffic. Using linear regression, a model was fit to the large city data and then applied to the smaller cities. Standard regression diagnostics were employed in examining the fit. A maximum of two predictors was used in the models to prevent over-fitting of the data and poor prediction.

3. RESULTS

Individual models were fit for the months of November through March, when conditions are most favorable for icing in the CONUS. While the predictors selected for the model varied slightly from month to month, they concentrated on a few meteorological criteria. Most prevalent was temperature, followed by cloud cover and precipitation. Table 1 shows the predictors selected for each time period and the model's r^2 (proportion of variability explained). Figure 3 shows the contours of icing frequency (the proportion of days with at least one icing PIREP) based on the model fit and observations for the five-month period November through March. Figure 4 shows contours for November, January and March individually.

Period	Predictors	Model r^2
Nov.-Mar.	Temperature Drizzle	0.92
Nov.-Mar.	Temperature Cold Frontal Passage	0.90
Dec.	Overcast Temperature	0.90
Jan.	Overcast Temperature	0.92
Feb.	Temperature Overcast	0.86
Mar.	Temperature Rain	0.88

Tab. 1 – Predictors used in each model and the corresponding r^2.

Immediately apparent from Figure 3 is a tendency for icing frequency to increase from the south to the north. While this pattern is true in the continental US, it likely would change if data were available from Canada (Bernstein and McDonough, 2002). Temperatures there soon become too cold in the winter months for supercooled liquid water to exist. The Great Lakes region of the Midwest seems to encounter icing most frequently: Figure 4 shows a maximum in that region for each of the months. A seasonal change in the icing frequency can be discerned in the three plots, with the January contours showing the furthest progression of icing conditions to the south.

3.1 Measures of uncertainty

While informative, contour plots give little indication of the uncertainty in the data or model. In order to quantify the variability in the estimates of icing frequency, two approaches were considered. For the locations with over one million inhabitants and therefore reliable data, an assumption of first-order

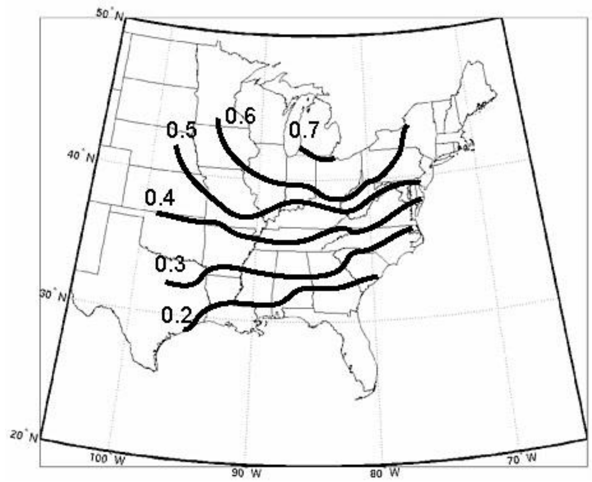

Fig. 3 – Contour plot of the November – March icing frequencies.

Markov dependence was used to estimate the sampling variance. For the smaller cities, standard errors were derived from the regression model itself under normality conditions.

First-order Markov dependence supposes that the state of a process is independent of past states if the state immediately previous is known. Let J_t represent the occurrence or nonoccurrence of an icing PIREP. Specifically,

$$J_t = \begin{cases} 1, & \text{if an icing PIREP occurs at time } t \\ 0, & \text{otherwise} \end{cases}$$

The Markov assumption can now be expressed as the following conditional probability

$$\Pr\{J_t = j \mid J_1 = i_1, \ldots, J_{t-1} = i_{t-1}\} =$$
$$\Pr\{J_t = j \mid J_{t-1} = i_{t-1}\}.$$

In the icing scenario, the presence of icing on day *t* is independent of icing on days previous to day *t-1*, if we know whether or not there was icing on day *t-1*. This assumption restricts persistence to a single day. The measure of one step dependence was calculated as the autocorrelation coefficient for the binary "icing days" variable at each location. The November – March time period was used to estimate the autocorrelation. The equation

$$\text{var}(\hat{p}) \approx \left[\frac{\hat{p}(1-\hat{p})}{n}\right]\left[\frac{1+\hat{\rho}}{1-\hat{\rho}}\right]$$

used by Katz (1983) estimates the variance of the sample proportion $\hat{p}$, where $\hat{\rho}$ is the sample autocorrelation. This formula is the familiar variance of the sample proportion inflated to account for dependence between the observations.

Figure 5 shows contours of the standard errors of the estimates for the November – March time period. These errors represent the uncertainty present in the observational sample of icing. Predictably, more

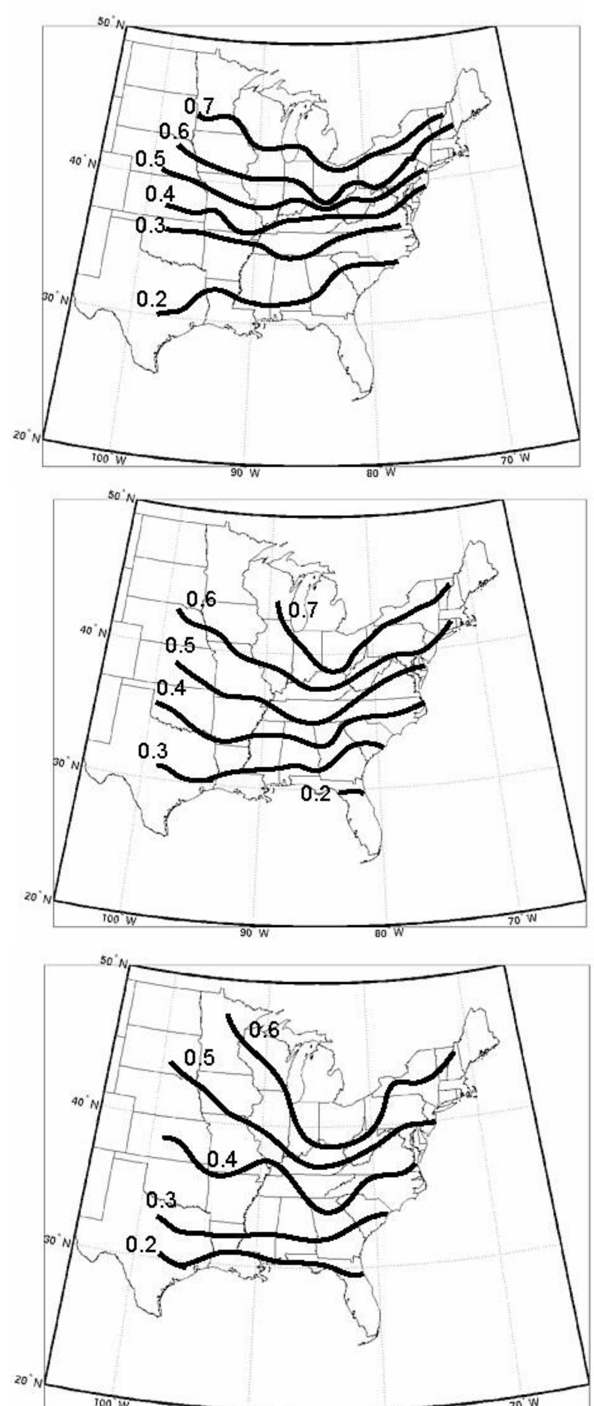

Fig. 4 –Contour plots of the November, January, and March icing frequencies.

uncertainty is present in the northern regions where the proportion of icing days is closer to 0.5.As a modeling approach was used in this study, it is also important to examine the uncertainty in the model chosen. Figure 6 shows the contours for the standard error of a mean response. This plot essentially demonstrates the

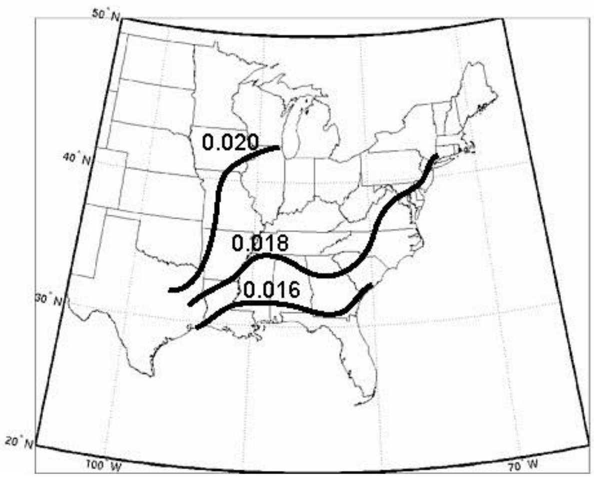

Fig. 5 – Standard error contours for proportion of observed icing days under first-order Markov dependence.

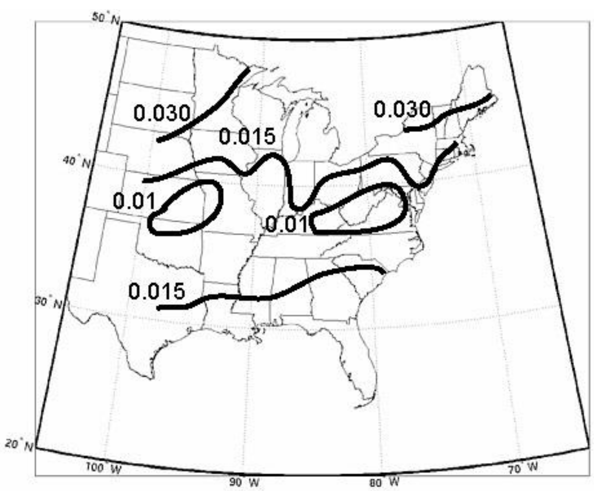

Fig. 6 – Standard error contours for predicted proportion of icing days from the model fit.

uncertainty in the predictions from the model assuming that the model is correct. The minimum values occur in the middle of the region, one in eastern Kansas and another in Virginia. The error then increases to the north and south of these areas. Regression fits are most robust near the mean values of the predictors used. As temperature is a very significant component of icing and included in the model, this minimum in the central part of the region is not surprising. While the increase southward from the minimum areas is fairly gradual, to the north the change is quite drastic. Note that the contours in Figures 5 and 6 are dissimilar because they represent different aspects of the variability. Figure 5 shows the variability associated with the seven-year sample of icing days that was collected, while Figure 6 shows the expected error for the model predictions, without explicitly considering sampling error in the observations.

4. CONCLUSIONS

This statistical technique produced an estimate of icing frequency consistent with other analyses (Bernstein and McDonough, 2002, Fowler et al, 2002). Environmental conditions are much more conducive to the formation of supercooled liquid water in the northern portions of the eastern US than the southern. Most striking in this climatology was the local maximum in the Great Lakes region. In examining the contour plots of the error surfaces, there was less certainty in the icing frequency estimates in the northern half of the country. The higher rate of icing occurrence and the more extreme climatic conditions led to increased variability in the north as compared to the southern region.

While this method produced a reasonable climatology of icing, its usefulness is clearly limited by the absence of systematic and spatially unbiased observations as well as the dependence on surface observations alone. The incorporation of atmospheric data could enhance this analysis. However until automated observations of icing are available, all observation-based analyses will face significant limitations.

5. REFERENCES

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6. ACKNOWLEDGEMENTS

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