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The Certainty of Uncertainty: Understanding and Exploiting Probability-Based Aviation Weather Products

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THE CERTAINTY OF UNCERTAINTY: UNDERSTANDING AND EXPLOITING PROBABILITY-BASED AVIATION WEATHER PRODUCTS

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Introduction

Probability-based weather forecasts (*i.e.*, forecasts that quantify uncertainty) have been available for certain weather elements for over 40 years; for example, the probability of precipitation forecast. More recently, probability forecasts designed specifically for aviation have become widely available on the internet through two National Weather Service (NWS) forecast centers, the Aviation Weather Center (AWC) and the Environmental Modeling Center (EMC). Although these probability-based products are generally not recognized by the Federal Aviation Administration (FAA) for operational use, their potential is beginning to be recognized by the aviation community. For example, the Joint Program Development Office (JPDO) Next Generation Air Transportation System (NEXTGEN) Air Traffic Management (ATM)-Weather Integration Plan cites probabilistic forecasts as playing a key role in future air traffic management decision support tools by the year 2023 (JPDO, 2010). Specifically, the JPDO identified the integration of weather uncertainty information (*i.e.*, probabilities and confidence information) into decision-support tools as the highest of four levels of weather integration into the air traffic management system.

The American Meteorological Society in a policy statement (AMS, 2008) also recognized that probability forecasts offer benefits over categorical (yes/no) forecasts. They specifically stated that the "dissemination and effective communication of uncertainty information will lead to substantial economic and social benefits" (AMS, 2008). They attribute the reason for the benefit to the ability of the end user to improve decision making by explicitly accounting for uncertainty (AMS, 2008).

In addition to the AMS, the NWS has also made similar observations regarding the benefits of exploiting probability-based forecasts. The NWS additionally highlighted the importance of end-user understanding of probability-based information. They noted uncertainty information is currently not widely used or even fully understood by the general public despite the potential for improved decision making for a wide range of operations (NRC, 2006).

To address this deficiency, the NWS commissioned a committee in 2005 to investigate and provide recommendations as to how they could more effectively estimate and communicate uncertainty in weather and climate forecasts (NRC, 2006). A key finding in the report was a need for enhanced, enterprise-wide, educational initiatives to improve communication and use of uncertainty information. They indicated that these education initiatives should focus on three critical areas: (a) undergraduate and graduate information, (b) recurring forecaster training, and (c) user outreach and education (NRC, 2006).

To support the NWS initiatives described above, the goal of this paper is to provide a non-technical primer for current or future aviation professionals on probability-based weather forecast information currently available to the aviation community. The information provided herein is appropriate for use in a graduate or undergraduate setting as well as user outreach and education. The paper provides aviation educators a starting point for classroom discussions on the use of weather uncertainty information in aviation operations. The topics covered in this paper include three techniques currently used to determine forecast uncertainty, current aviation weather products that employ these techniques, and the potential benefits of exploiting uncertainty information in aeronautical decision making, aviation operations, and NEXTGEN.

Subjective and Objective Methods for Quantifying Uncertainty in Aviation Weather Products

Background.

The chaotic nature of the atmosphere combined with limits on our ability to observe the true state of the atmosphere at any given time guarantees that all weather forecasts will have some degree of uncertainty. Historically weather forecast uncertainty information has been most commonly expressed in terms of probability of occurrence, and these probabilities have traditionally fallen into two basic categories, subjective and objective.

Subjective probabilities simply provide the forecaster's degree of belief that a given event will occur (De Elia & Laprise, 2005). A commonly observed example of a subjective probability forecast is the local TV weather forecaster's rain forecast expressed as a percentage. While subjective probabilities provide a measure of forecaster confidence in their prediction of the weather event, the probabilities themselves are somewhat arbitrary. That is, the probabilities are highly dependent on each individual forecaster's training, skill, risk adversity, and experience with forecasting a particular event.

An aviation example of a weather forecast that includes subjective uncertainty information is the Collaborative Convective Forecast Product (CCFP). The CCFP provides short-term forecasts regarding the areal coverage of convective activity over the conterminous United States and Canada along with a subjective measure of the forecasters' confidence in the forecast. The forecasters' confidence is expressed in a simple binary format as either high confidence (50-100% probability) or low confidence (25-49% probability) that the product will meet the minimum areal coverage requirements. The product, available on the Aviation Weather Center's (AWC) Aviation Digital Display System (ADDS), was designed specifically for strategic air traffic management use rather than local terminal traffic management or individual flight briefing purposes (FAA, 2010). While the product is issued by AWC, it is created as a collaborative effort primarily between the AWC, the Meteorological Services of Canada (MSC), and the Air Route Traffic Control Center (ARTCC) Center Weather Support Units (CWSU). To create the product, the AWC issues a preliminary version of the CCFP then hosts an on-line chat to receive inputs from other agencies. The AWC then considers all inputs, makes any modification based on the input, then issues the final CCFP. The AWC has final authority over all US locations, while the MSC has final authority for Canadian areas (AWC, 2010). An example of the CCFP is shown in Figure 1. Areal coverage of convective activity is depicted using differing levels of hashing while confidence is displayed using two different colors, blue for high confidence and gray for low confidence. The product also includes information on storm movement and echo tops. A full product description can be found on the AWC website.

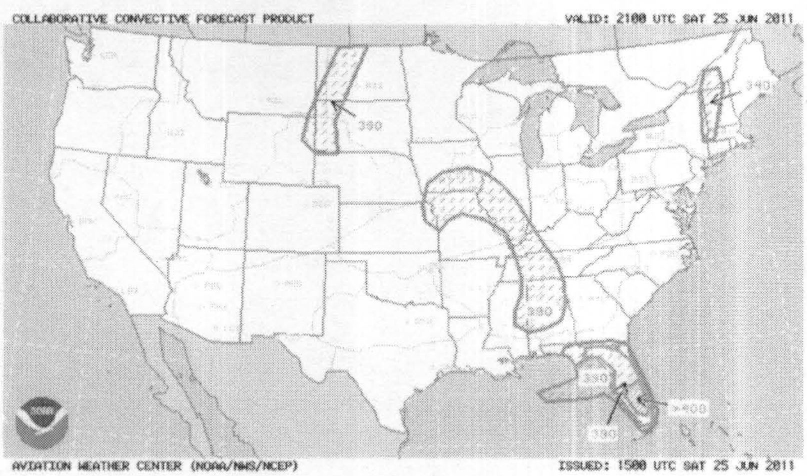

Figure 1. Sample Collaborative Convective Forecast Product (CCFP) valid at 21Z on Jun 25, 2011. Shading color (grey vs. blue) provides a subjective measure of high versus low confidence in the convection fore

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In contrast to subjective methods for assessing aviation weather forecast uncertainty, objective methods attempt to provide a more repeatable process that removes forecaster skill and/or bias from the uncertainty of the forecasted event. Advances in numerical weather prediction, computer processing speeds, and statistical techniques have allowed meteorologists to quantify the degree of uncertainty in weather forecasts using a variety of objective methods. Objective methods rely solely on the observational data and numerical weather prediction models; thus, they are repeatable. That is, when given the same data, an objective method will produce the same probabilities every time because the data is independent of the individual forecaster's input.

Although a variety of methods exist for producing objective, probability-based forecasts and diagnostics, this paper will explore three techniques used to produce aviation-specific products currently available on NWS websites. These techniques include: (a) ensemble modeling, (b) Model Output Statistics (MOS), and (c) fuzzy logic techniques. The products created by these methods include the Short-Range Ensemble Forecast (SREF) aviation product suite available from the NWS EMC, the Localized Aviation MOS Program (LAMP) product available on the NWS home website, and the Current Icing Potential (CIP) product available on the AWC ADDS. All three methods use different approaches, but the end goal is the same–they all attempt to create objective probabilities of occurrence for a variety of weather criteria. These methods as well as some of their strengths and weaknesses are discussed below.

Ensemble Techniques and the SREF Model Aviation Product Suite.

Traditional numerical weather prediction (NWP) forecast products are "deterministic" in nature. That is, the initial state of the atmosphere determines the future state of the atmosphere, and for any given time in the future, there is only one possible outcome. As mentioned earlier, the atmosphere is inherently chaotic; therefore, small errors in our observations of the initial state of the atmosphere can grow rapidly leading to significant forecast error. The sources of errors in our observations are numerous. First, it is physically impossible to observe the entire atmosphere at any one time. There exist significant gaps in data collection, especially over less-populated regions and the oceans. In addition, operational costs of launching weather balloons with radiosondes make it unfeasible to observe the upper-levels at high spatial and temporal resolution. In the U.S. these observations are limited to only two per day at each observing site and have an average horizontal spacing of approximately 315km in the United States (FMH-3, 2006). Secondly, all observing systems contain some degree of instrument error; even *in situ* observations from automated surface observing stations (ASOSs) contain error. Because of these errors, our observation networks only provide an approximation or "best guess" of the true state of the atmosphere.

In addition to observing errors, once the observations are collected, this irregularly spaced data must then be interpolated to a uniform grid to simplify and expedite calculations within the numerical models. This interpolation process also introduces error.

The gridded "best guess" of the true state of the atmosphere is then used as the initial input to the computer model (*i.e.*, the model initialization). This initialization is then used to solve a complex set of equations governing atmospheric motion to produce estimates of the future state of the atmosphere. It should be mentioned that the term "numerical model" simply refers to the set of equations and numerical method used to create the forecast. Numerical models can differ in resolution, fundamental equations, numerical techniques, approximations (or parameterizations), etc.

Since we traditionally have only a single initial data field or "best guess," the model calculations can only provide a single possible outcome for any given future time. However, because our best guess of the true state of the atmosphere inherently contains some degree of error, any forecasts stemming from this initial state will also contain error. The error growth can be very rapid because the equations governing the atmospheric flow are highly non-linear; meaning, small changes in the initial conditions can have disproportionately large effects on output.

The classic example of a non-linear process often used in the classroom is the "straw that broke the camel's back." Assume you have a camel and you load single bale of hay to the camel's back causing it to sag one inch. Likewise, a second bale of hay causes the camel's back to sag two inches, and so on. This is a linear relationship. Now, after several bales of hay have been loaded, a single piece of straw is loaded causing the camel's back to collapse. This is a non-linear response. The breaking of the camel's back (*i.e.*, the complete the collapse) was disproportionate to the added amount of weight. Likewise, in the atmosphere, small differences in model initial data, under certain conditions, can lead to significantly different forecast results.

This same effect will also occur if identical initial conditions are used in slightly different numerical models. An example of this is when two models approximate small-scale processes, such as convective motions, slightly differently. Because of differences, the two models could produce different, but equally likely, forecast results despite having identical initial conditions.

The results from deterministic model forecasts therefore depend both on our ability to accurately represent the initial state of the atmosphere as well as our ability to mathematically describe the physical processes governing atmospheric motion. (Note that the former error would exist even if a "perfect" NWP model existed.) Ensemble techniques seek to quantify the uncertainty in the model forecast by examining model results from a large number of models using a wide range of initial conditions rather than simply using one model with one set of initial conditions.

The ensemble technique is relatively simple in concept. They quantify uncertainty by solving one or more deterministic NWP models (typically between 15 and 50) using several different but equally likely initial states of the atmosphere, where each individual model solution is referred to as a "member" of the ensemble. The models may be all the same, all different, or a combination. The variations in both models and initial conditions are designed to help capture the range of possible future states of the atmosphere. Since running 15-50 numerical models is far more computationally expensive than running a single deterministic model, each ensemble member is typically run at a slightly lower resolution than the operational versions of the individual deterministic models to minimize the total number of computations required.

When using ensemble techniques, the initial states of the atmosphere are chosen using a variety of techniques, most typically by introducing small perturbations to a "control" initial data field. The perturbations, however, are not purely random, but rather are chosen to excite fast growing errors, to capture the widest range of possible outcomes (Toth & Kalnay, 1997). The end result of the ensemble process is multiple, equally likely forecasts from which probabilities can easily be determined. The simplest probabilities are determined by directly comparing the number of ensemble members that forecasted a specific event to the total number of ensemble members. For example, if only five of twenty ensemble members predict icing at a specific location and flight level, the probability of icing at that location and flight level would be 25%.

The Short Range Ensemble Forecast (SREF) Aviation Product Suite provides probabilistic forecasts of several aviation parameters (*e.g.,* icing, turbulence, instrument meteorological conditions, thunderstorms) for various thresholds (*e.g.,* light, moderate, severe), for multiple flight levels. At the present time, the SREF aviation product suite is considered experimental and not for operational use; however, the product information is readily available on the NWS EMC website for examination. The SREF uses three different models (although there are 2-4 slight variations of each model) and multiple different initial conditions to create 21 ensemble members (Zhou et al., 2009). These members are then used to create a suite of 14 aviation-specific forecasts out to 87 hours. The SREF aviation pages are available for CONUS, Alaska and Hawaii. Figure 2 shows an example of a 24-hour forecast for icing at 15,000ft MSL over CONUS. As mentioned earlier the probabilities are simply created by evaluating the number of members that forecast "yes" for icing at any given model grid point and dividing by the total number of model members. This is a purely binary membership; that is, the grid point either meets the criteria or it doesn't, there is no evaluation of *how closely* a grid point meets the criteria.

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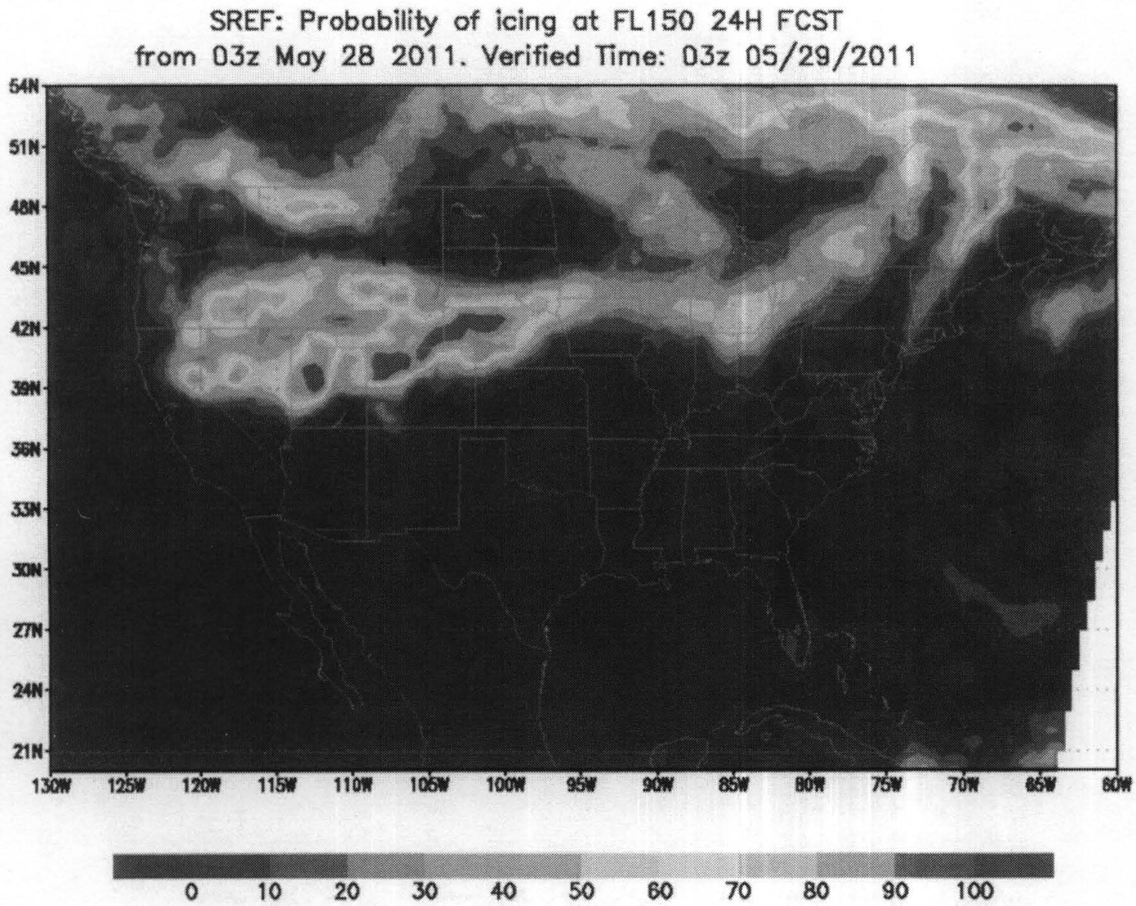

Figure 2. Sample Short-Range Ensemble Forecast (SREF) Aviation Suite probability of icing forecast for 15,000ft MSL at 03Z on May 29, 2011.

To understand fully the quality of the ensemble forecast for operational decision making, the user of the information must be familiar not only with ensemble techniques in general, but the specific algorithms used to forecast the hazard of interest as well. For example, the SREF aviation suite uses a very simple icing algorithm that examines only the relative humidity and the air temperature. The relative humidity helps identify the potential for clouds, while the temperature helps determines if the cloud droplets will be super-cooled. Specifically, if the relative humidity at a grid point exceeds 70%, while the temperature at the same grid point lies between 0°C and -10°C, the grid point is set to "yes" for icing (Zhou et al., 2004). The assumption, based on observations, is clouds will likely be present when the relatively humidity is greater than 70%, and the clouds will likely contain super-cooled water if the temperature is between 0°C and -10°C. It should be noted that a grid point with a temperature of -10.1°C and a relative humidity of 75% will be identified as a "no" for icing, despite being only one tenth of a degree outside the "yes" range for icing. As we'll see in later sections, "fuzzy logic" techniques attempt to account for how closely a grid point meets a threshold rather than a simple binary or "yes/no" evaluation.

Model Output Statistics (MOS) and the Localized Aviation MOS Product (LAMP).

The second method of producing objective, probability-based forecasts is MOS. MOS products, in general, were developed to identify and exploit statistical relationships between numerical model forecasts for individual locations and the weather that actually occurred at the locations. The motivation for the technique is that while model forecasts for locations may not always be 100% accurate, there are likely correlations between the model forecast and the observed weather at the same location. If these correlations are quantified over long periods of observations, statistical relationships can be developed to improve the model forecasts at individual sites as well as produce probabilities.

As mentioned previously, NWP models perform their computations at uniformly spaced grid points. The distance between individual grid points typically ranges between 12-40km or greater for most operational models. As a result, the forecast for a particular airport may be based on model grid points that are located 6-20km away. Figure 3 provides an example of a model grid. The dots represent evenly spaced grid points where model calculations are performed, and the x-marks represent individual forecast locations, such as cities or airports. Forecast information for the x-marks must be interpolated from the nearest model grid points. No matter how accurate the model forecast at each grid point, the forecast at a specific location will always contain a certain degree of spatial error (except in the rare instance where the grid point and location are identical). This error is especially significant if the location in question and nearest the grid points are over significantly different terrain. In addition, and as mentioned previously, the model equations and approximations themselves are not perfect.

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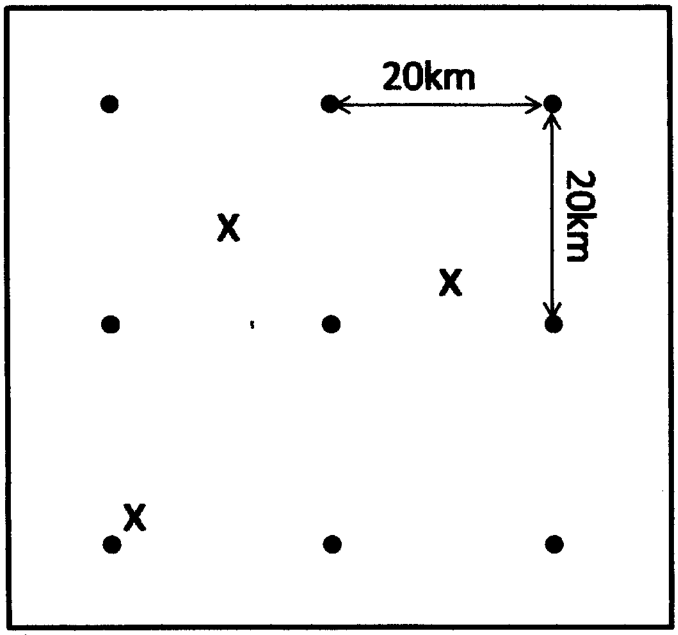

Figure 3. Representative example of model grid points (black dots) using a 20km grid spacing. The x-marks represent locations of interest such as such as cities or airports. The model data is only calculated at the grid points and must therefore be interpolated to the x-marks.

These errors and errors like these (*e.g.*, poor initial representation of the data) can be addressed as follows. Even though these errors may produce inaccurate results at a location, if the model consistently produces similar errors for similar situations, having *a priori* knowledge of these errors may be used to improve the forecast as well as produce objective probabilities. For a simple example, assume a numerical model routinely under-predicts precipitation at a location. However, after examining several years of forecast data from a specific NWP model, forecasters observe that when the model predicts a relative humidity of 70% for the location, precipitation is observed in 90% of the time. Using this information, a simple algorithm may be constructed using the model-derived relative humidity forecast to not only improve the precipitation forecast but provide a probability of precipitation forecast for the observations site as well. That is, whenever the model forecasts a relative humidity of 70% relative humidity for that specific location, the probability of precipitation for that location is 90%, assuming the statistics used in the algorithm were from a sufficiently large data sample to be considered representative.

In the previous example there was only a single predictor (relative humidity) for the "predictand" (precipitation). In reality there may be many predictors that contribute to the probability of occurrence of precipitation. Again using the previous example, the forecasters may also notice that it only rains 60% of the time when the relative humidity is 70% and the winds are from the north. A new algorithm could be developed that makes use of both predictors. The goal of MOS data is to find and quantify these correlations to create statistical relationships (*i.e.*, regression equations) relating the model forecast for a location to the likelihood of observed weather conditions. Once the statistical relationships are known, they can be applied to the deterministic forecasts to either improve forecast accuracy or create probabilities of a variety of events (e.g., precipitation, thunderstorms).

In reality, the MOS algorithms are much more complicated than the simple examples just presented. They, in fact, typically involve many different possible predictors for a specific forecast variable (the "predictand") and they are often stratified by season. It must also be noted that the statistical algorithms are dependent on both the specific location and the model used in the forecast. Each location of interest, usually a single observing location but can also be expanded to represent a small region, requires a separate and distinct statistical algorithm relating model output to the observed weather. Once established, the statistical relationships remain valid until the model is updated (or the climatology of the location changes significantly). Any changes to the model require the development of updated statistical relationships, which require several seasons of data to create. For this reason, the version of the deterministic model used for MOS guidance is not always the most recent version of the numerical model used for traditional deterministic model output.

So far we have only discussed the use of model data as predictors; however, predictors are not limited to model data alone. The most current observation at a location often correlates very strongly with the predictand. For example, if it's currently raining at a location, the statistics may show there is a higher probability rain will still be occurring one hour later. Since the output from deterministic models is often not available for several hours after the model calculations start, the current observations provide updated information. This updated information has been found to have strong predictive value in MOS guidance (Ghirardelli, 2005). For this reason, observations are also used as predictors in the MOS process.

In 1997, the NWS began running the Localized Aviation MOS Program (LAMP) locally at NWS forecast offices to provide hourly MOS data containing aviation-specific forecast parameters (e.g., ceiling, visibility, wind gusts) out to 20 hours (Ghirardelli, 2005). The program was "redeveloped" in 2005, and rather than being run locally at each NWS forecast office, the new LAMP product was designed to run at the NWS Environmental Modeling Center (EMC) and disseminated via the internet. This new LAMP became operational in July 2006 and is available on the NWS website, providing hourly MOS guidance out to 25 hours.

LAMP data is unique in that it uses MOS output from another model as a predictor in addition to pure model output. So in a sense, LAMP is the "MOS of a MOS." LAMP uses the NWS's Global Forecast System (GFS) model MOS as a starting point. The GFS is a global-scale model, meaning it covers the entire globe, and the MOS data from this model (GFS-MOS) data is currently issued four times daily at 00Z, 06Z, 12Z, and 18Z. Because of the computational requirements for running a global-scale model, the data is typically not available until approximately four hours after the model calculations start. In addition, the forecast output from each GFS-MOS model is only provided in 3-hr increments. For aviation flight planning; however, hourly forecast updates (rather than 6-hour updates) with output in 1-hour increments (rather than 3-hour increments) are more beneficial to operations. The current version of the LAMP model is run each hour, updating the GFS-MOS with the most current observations, to provide a 25hr forecast in 1-hr increments. Since the LAMP model relies heavily on the GFS-MOS as a predictor, it is referred to as the "GFS-LAMP" on the NWS website. In addition to the GFS-MOS data and current observations, the GFS-LAMP also uses three simple deterministic models (a sea-level pressure model, an advection model, and a moisture model) as additional predictors.

The end-product of the GFS-LAMP is a suite of textual and graphical web products providing a 25-hour forecast in 1-hr increments of key aviation parameters, including wind speed/direction, ceiling, visibility, precipitation, and thunderstorms. However, LAMP does not provide any information regarding traditional en route hazards such as icing, turbulence, and mountain obscurations. The entire suite of LAMP products is updated every hour. It should be noted that although LAMP was completed and fully operational in 2009, it has not been approved by the FAA as a primary or supplementary aviation weather product for operations.

Traditionally, MOS data has been displayed as a text product providing location-specific forecasts of a variety of weather parameters. This is true for the GFS-LAMP. Figure 4 shows a typical text-based GFS-LAMP product for Topeka, KS issued for 14UTC on 28 May 2011. The leftmost column provides the weather parameter in question, including temperature, dew point temperature, wind direction and speed, etc. While probabilities could be provided for all values using the statistical algorithms, the text product provides only the most likely value for most parameters. Probabilities are only used in this product for the hourly probability of precipitation (PPO), the 6-hour probability of precipitation (PO6), and the 2-hour

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probability of thunderstorms (TP2). A detailed description of all parameters can be found on the NWS website.

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KTOP   TOPEKA       ASOS      GFS LAMP GUIDANCE    5/28/2011   1400 UTC
UTC  15 16 17 18 19 20 21 22 23 00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15
TMP  61 62 63 64 64 65 66 66 66 66 66 65 64 64 64 64 64 64 64 64 64 65 68 71 73
DPT  58 58 58 58 59 59 60 60 61 61 61 61 61 61 61 61 61 61 61 61 61 62 63 64 65
WDR  04 05 05 05 05 05 05 05 05 06 07 06 07 07 08 08 07 07 07 08 09 11 14 15 16
WSP  08 09 09 09 09 09 09 09 09 08 06 05 04 04 04 04 05 05 05 05 05 06 08 10 13
WGS  NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG NG 19
PPO   2  3  4  6  5  2  0  1  1  1  2  2  3  5  8 11 13 15 17 18 18 17 13  9  5
PCO   N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N
P06                             6                 4                 40
TP2         0  0  0  0  0  0     0     2     5     8    19    19    17     9
TC2         N  N  N  N  N  N     N     N     N     N     N     Y     Y     N
POZ   1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
POS   2  1  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
TYP   R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R  R
CLD  OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV OV
CIG   5  5  6  6  6  6  5  5  5  5  5  5  5  4  4  2  2  2  2  2  3  3  3  3  3
CCG   5  5  5  5  5  5  4  4  5  5  5  5  5  5  5  5  4  3  3  3  3  3  3  3  4
VIS   5  5  5  5  5  6  7  7  7  6  5  5  5  5  5  4  3  3  3  4  4  4  4  5  5
CVS   3  4  4  4  4  4  5  4  5  4  5  5  5  4  5  5  5  4  5  5  5  5  5  5  5
OBV  BR BR BR BR HZ HZ HZ  N HZ HZ HZ BR BR BR BR BR BR BR BR BR BR BR BR BR BR
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Figure 4. **Sample GFS-LAMP Text Product for Topeka, KS issued at 14Z on May 28, 2011.**

Although text products are the more traditional means for viewing MOS data, graphical displays are now available for GFS-LAMP on the NWS website. An example of the graphical versions of thunderstorm probability is shown in Figure 5. Figure 5 shows the probability of thunderstorms for the 2-hour period ending at 4a.m. EDT (08UTC). Note the probability for Topeka, KS is 19% based on the text product, which aligns well with the shading on the graphical product.

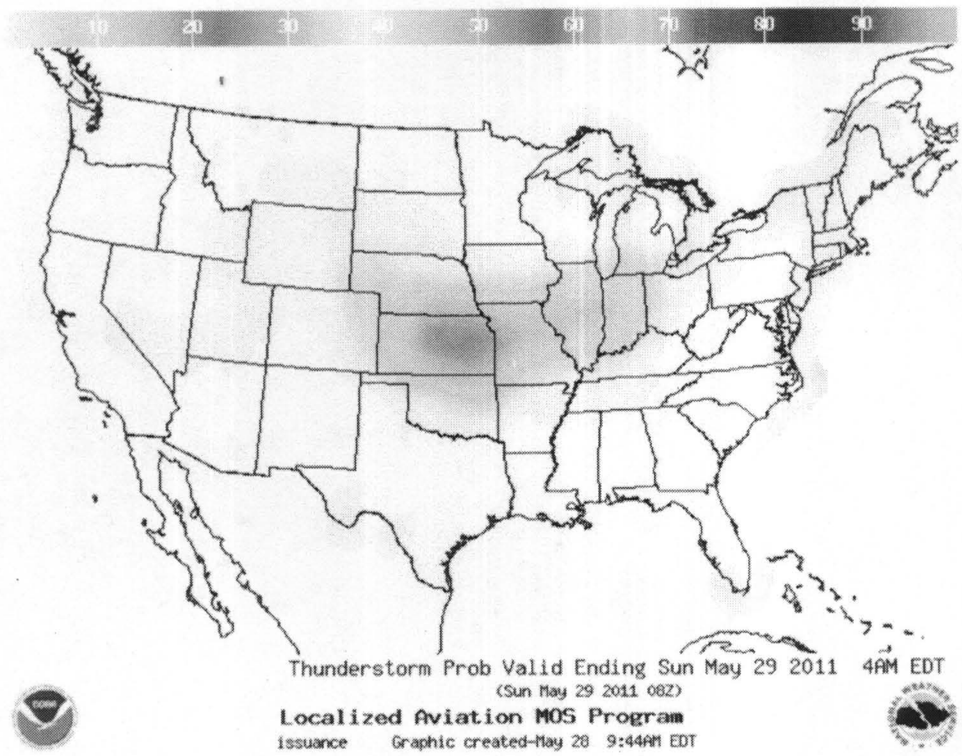

Figure 5. Sample GFS-LAMP Graphical Thunderstorm Probability Forecast for May 29, 2011.

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The MOS guidance probabilities differ from the ensemble probabilities in that MOS data compares a single model's forecast to the actual observations or climatology at individual sites. Ensemble models on the other hand examine the results of multiple model forecasts, with no knowledge of how the model performs at individual locations. MOS data therefore attempts to bring the inherent forecast uncertainty more in line with the observed climatology of the site; whereas ensemble forecasts attempt to provide detailed information regarding the forecast uncertainty or predictability of a particular weather event (Zhu et al., 2002). A key advantage to the ensemble method is that if the models change, there is no need to establish new statistical algorithms that relate the new model performance to observations.

Fuzzy Logic Techniques and Current Icing Potential (CIP) Product.

A third technique for developing probabilistic information involves "fuzzy logic." Fuzzy logic techniques provide uncertainty information by examining relationships between the predictor and the predictand in a different way. Fuzzy logic recognizes that not all relationships are binary, (*i.e.*, simple "yes/no" relationships), and that significant gray areas can exist. As we discussed earlier, the SREF icing algorithm assumes icing is only observed between the temperatures of 0°C to -10°C when the relative humidity greater than 70%. Using a binary logic system would imply there is zero potential for icing when the relative humidity is 70% but the temperature is -10.1°C. While the potential for icing at a grid point is 100% if the relative humidity is the same, but the temperature is a mere 0.1°C warmer. In reality this is not the case. In our example, observational studies indicate a greater frequency of occurrence of icing events for the temperature range 0 to -10C. However it also remains relatively high until -20°C is reached (Schultz and Politovich, 1992). So rather than using distinct thresholds, fuzzy logic algorithms instead examine how closely, or the degree to which, a threshold is met.

An example of the application of this technique is the creation of a fuzzy-logic tool to study the problem of aircraft structural icing developed by Bernstein et al (2005). This product evolved from a research model to the operational Current Icing Potential (CIP) currently available on the AWC ADDS website as an FAA recognized supplemental product (*i.e.*, it is authorized for enhanced situational awareness use only and is only to be used in conjunction with one or more FAA-designated primary products).

Since the CIP is designed to provide the potential for structural icing, the CIP process first begins with identifying current 3D locations of visible moisture (*i.e.*, clouds and precipitation) using current surface, radar, and satellite information. Once the areas of visible moisture are identified, fuzzy logic membership functions are applied to determine the potential for icing within the areas of visible moisture. The fuzzy membership functions were designed to identify the potential for icing based on a four parameters (temperature, cloud-top temperature, vertical velocity, and relative humidity). Bernstein et al. (2005) derived these functions by comparing several years of pilot reports of icing to numerical model data of temperatures, relative humidity and vertical velocities as well as satellite observations of cloud-top temperature. The functions, referred to as "maps," provide a measure of the frequency of observed icing events for each of the four parameters.

For example, Bernstein et al. (2005) evaluated over 19,000 pilot reports (PIREPS) of icing and noted icing was observed most frequently when the temperature was -7C. The frequency of occurrence dropped off sharply for warmer temperatures and more gradually for colder temperatures. The resulting temperature map (T_{map}) based on this data effectively creates a fuzzy membership function relating the potential for icing to the model forecasted temperature. Figure 6a shows the T_{map} functions used in the model for both convective and non-convective scenarios as well the observed data curve from which the maps were derived. Note that Bernstein et al. (2005) adjusted the T_{map} function to improve CIP performance, so it does not identically match the frequency of occurrence based solely on a comparison of pilot reports to the model data. The T_{map} shows a 100% potential for icing when the temperature is between approximately -4°C to -7°C, drops gradually to 0% by -25°C (or -30°C if clouds are determined to be convective) and rapidly drops rapidly to 0% by 0°C. By providing a relationship between the temperature and the *potential* for icing, the need for simple binary "yes/no" thresholds is eliminated. The potential for icing doesn't jump instantaneously from 100% to 0% as the temperature changes from -7°C to -8°C. Instead, the potential for icing gradually decreases as the temperature drops below -7°C. As mentioned earlier, however, temperature alone is not the only parameter that can affect icing. Bernstein et al. (2005) also identified cloud-top temperature, relative humidity, model vertical velocity, and proximity to known PIREPS as key indicators.

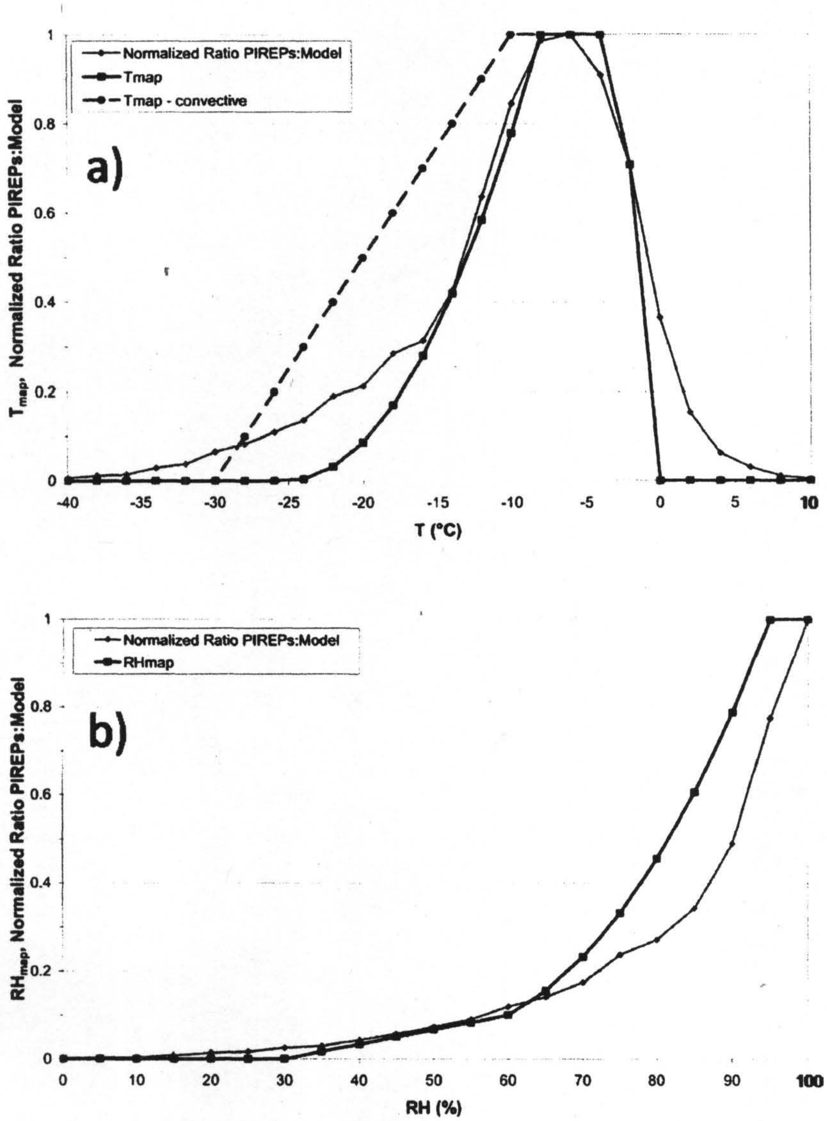

Figure 6a and b. T_{map} (a) and RH_{map} (b) lines used in the CIP algorithm and the observed frequency occurrence lines (normalized by the number of PIREPS available). Note that T_{map} varies depending on whether or not the observed weather scenario is convective or non-convective. (From Bernstein, et al (2005)

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Relative humidity is particularly important to icing determination because the observing systems only detect cloud tops (via satellite) and cloud bases (via surface observations). In some instances, the cloud top could potentially result from a high cloud while the observed cloud base could result from a completely different low cloud. Relative humidity is therefore needed to help detect the potential for cloud layers between the observed cloud base and observed cloud top. As with temperature, Bernstein et al. (2005) created a fuzzy relative humidity membership function (RH_{map}) relating the potential for icing to the relative humidity. Again these were based on over 19,000 PIREPS. The potential for icing is 100% when the relative humidity is greater than 95% and then gradually decreases to 0% at a relative humidity of 30% (Fig. 6b). Again the RH_{map} was adjusted slightly from the observed frequency of occurrence to produce improved model performance.

Cloud-top temperatures are also important because they indicate the possibility of ice crystals near the top of the cloud. Ice crystals, when falling through a region of super-cooled water droplets cause the water droplets to freeze. Once the droplets freeze, the cloud is considered to be "glaciated" and no longer poses a structural-icing threat. Using as a similar technique as discussed for temperature, Bernstein et al. (2005) observed the potential for icing to be 100% for cloud-top temperatures warmer than -12°C and then smoothly drop to 20% for cloud-top temperatures less than -50C.

Once the fuzzy membership functions or "maps" for each parameter are known, the CIP process uses the potential for icing from each of the membership functions to determine the initial probability for icing. This is most typically calculated by multiplying all icing potentials; that is, the initial probability of icing determined from the potential for icing based on temperature times the potential for icing determined from the cloud-top temperature times the potential for icing determined from the relative humidity. For example, if the potential for icing due to temperature is 0.90, the potential for icing due to cloud top temperature is 0.80, and the potential for icing due to relative humidity is 0.85, the initial probability for icing would be 61% (0.9 x 0.8 x 0.85 x 100%). Note that this specific algorithm for determining the initial probability for icing is not identical for all icing events; but rather, it varies slightly depending on the actual weather scenario, e.g., multiple cloud layers vs. single cloud layers (Bernstien et al., 2005).

Once the initial icing probability is determined, the CIP process determines the final icing probability by adjusting the initial value up or down based on the proximity to known PIREPS of icing, as well as numerical model predicted values of vertical motion and super-cooled liquid water (Bernstein et al., 2005). For example, the initial probability of icing is increased near locations where PIREPS confirm the presence of icing conditions as well as within regions where the model predicts super-cooled water and upward vertical motion. On the other hand, the initial icing probability is decreased if the model predicts downward vertical motion within region. It should be noted that the absence of PIREPs or even negative icing PIREPs do not decrease the probability of icing since the absence of a report doesn't negate the existence of icing and negative icing PIREPS are sometimes indicative of embedded ice-free pockets within a larger icing region (Bernstein et al., 2005).

Figure 7 shows an example of the CIP valid at 14UTC on 28 May 2011, depicting the probability of icing at 15,000ft MSL. Also depicted on the chart are icing symbols denoting locations of observed icing used in the preparation of the chart. It should be noted that the CIP is only an icing analysis tool; that is, it does not provide a forecast for the probability of icing. However, the ADDS website does offer a Forecast Icing Potential (FIP) product which also uses fuzzy logic techniques based solely on model predicted data.

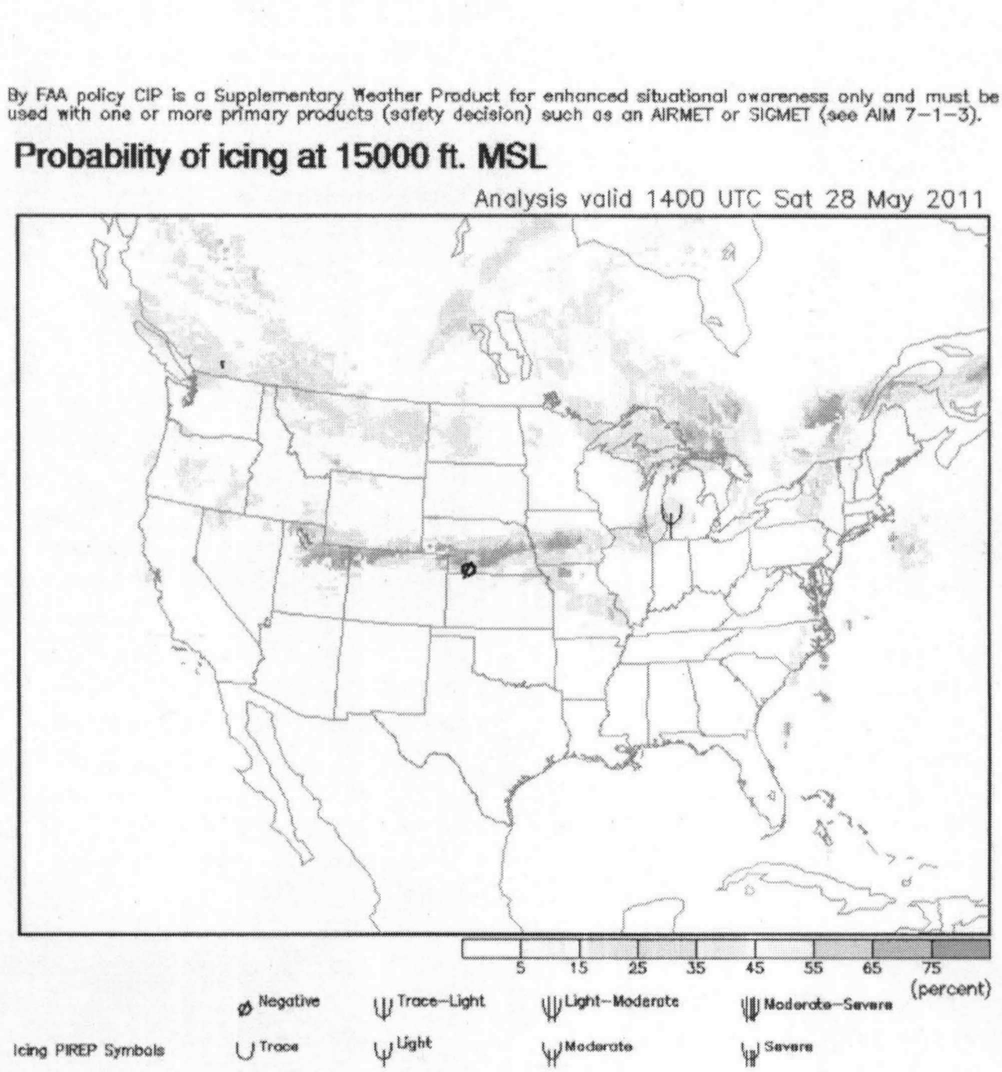

Figure 7. Sample CIP probability of icing at 15,000ft MSL for 14Z on May 28, 2011.

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Exploiting the Benefits of Uncertainty Information

The incorporation of probability-based weather products has the potential to improve decision making by enabling the user to explicitly quantify the degree of uncertainty in the forecast. Knowing and properly applying the uncertainty information to the users' operational decision process can both improve operational risk management as well as potentially add economic value to other decision processes. This section first discusses the the incorporation of probability-based weather products in the risk assessment process then discusses how probability-based products can be used to improve the ecbnomic value of decisions. The section finishes with a discussion of the anticipated use of probability-based products in NEXTGEN.

The use of purely deterministic weather information provides incomplete information regarding the weather scenario because the end-user has no information regarding how likely the event is to occur. Therefore, the user must base any operational decisions on their own beliefs of the accuracy of the forecast. This may be affected by past experience with a particular weather provider or perhaps their personal understanding of the local climatology. Unfortunately, neither of these may be pertinent to the predictability of the specific weather scenario in question.

When the uncertainty in the forecast is provided, however, the user has a more complete understanding of the inherent risk in any operational decisions they make using the forecast information. Having *a priori* knowledge of forecast uncertainty therefore has the potential to enhance the risk-mitigation process for many aspects of aviation operations, including both flight planning and air traffic management, leading to improved aeronautical decision making (ADM).

For example, one of the key elements of ADM, as defined in the FAA's Pilot Handbook of Aeronautical Knowledge (FAA, 2008), is assessing risk. To properly assess the risk associated with a forecast weather event, the operator must not only understand the consequences of conducting operations during the forecasted weather event but also the likelihood of the event occurring (Fig. 8). The likelihood of a weather event occurring, however, can only be known if some measure of forecast uncertainty is provided, such as a probability-based forecast.

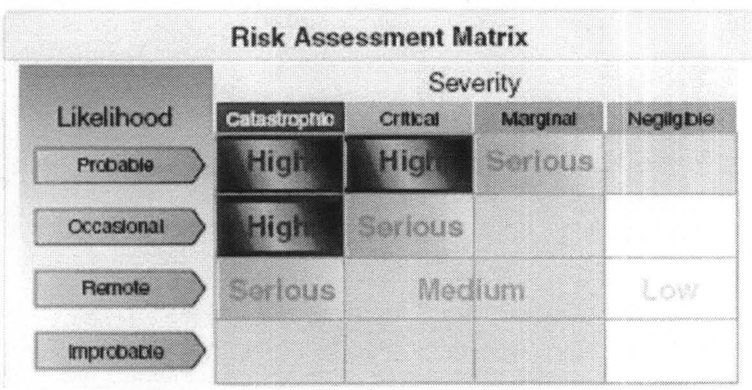

Figure 8. Risk Assessment Matrix for use in Aeronautical Decision Making. From the Pilot Handbook of Aeronautical Knowledge (FAA, 2008).

By combining the consequences of flying in a given weather event with the probability of occurrence of that same event, the severity of risk can readily be determined. The consequences can even be tailored to the specific skill-level of the pilot. For example, a visual flight rule (VFR) student solo pilot would most likely assess the consequences of inadvertently flying into instrument meteorological conditions (IMC) as catastrophic. On the other hand, a 1,500-hour instrument-rated pilot would likely assess the consequences of inadvertently flying into IMC weather as negligible. Therefore, using Fig. 8, the student pilot's risk would be serious to high if the likelihood of IMC weather was judged to be any category other than improbable. However, the instrument rated pilot's risk would be at most medium, even if the likelihood of IMC were near 100%. It should be noted that to properly use such a chart, vague terms such as "remote" or "occasional" would need to be quantified and tailored for operational use. This would then be consistent with the quantification of forecast probability.

Not only can using uncertainty information potentially improve risk management, but research has shown the incorporation of weather forecast uncertainty information into the decision process can result in potentially significant operating-cost savings (Zhu et al., 2002; Keith, 2003; Keith & Leyton, 2007). These benefits are most commonly achieved through use of cost-loss models.

Simple cost-loss models examine the cost of taking action compared to the potential loss if protective measures are not taken. An extremely simple example of a cost-loss model is a flight training school that could suffer significant damage if aircraft were not relocated prior to the onset of a 50 knot wind event. If the potential loss due to damage (L) were, for example, $2 million and the cost of evacuating the aircraft a safe distance (C) were, for example, $200,000, the cost-loss ratio (C/L) would be approximately 0.10 (neglecting any unprotectable losses that could occur even if all planes were safely evacuated). The flight school would therefore be wise to evacuate the aircraft anytime the probability of occurrence of 50 knot winds exceeded 10%. If the school took action for probabilities less than 10%, over time the cost of evacuation would exceed the loss due to aircraft damage. Likewise, taking action only when the probability of a 50 knot wind event exceeds a higher threshold, for example 25%, would likely result in damage costs that greatly exceed protective costs. Of course, this assumes the probabilities from the forecasts are reliable. That is, when a probability of 40% is predicted, the event occurs 40% of the time.

Research shows economic value is added when probability-based forecasts are used. Economic value is positive when the probability forecast provides better results (*i.e.,* less expense) than if the user relied solely on the climatological probability of occurrence for their decision to take protective action or not. Zhu et al. (2002) demonstrated that the use of forecast probabilities greatly extended the potential range of cost-loss ratios where economic value was increased. Thus probability forecasts add greater value for a greater number of potential users, from those with high cost-loss ratios (*i.e.*, the cost of protection is nearly equal to the potential for loss) to those with small cost-loss ratio (*i.e.*, the cost of protective action is much less than the potential for loss).

Keith (2003) and Keith and Leyton (2007) demonstrated the potential economic value of combining probability forecasts with cost-loss models to determine when it was cost-effective for aircraft to carry extra fuel for diversions potentially necessitated by low clouds and/or ceilings. Carrying extra fuel provides the pilot more options for landing, such as longer holding-patterns to wait for weather to improve or being able to attempt a landing with sufficient fuel to return to cruise altitude and proceed to an alternate airport if the landing attempt unsuccessful. However, carrying extra fuel unnecessarily adds extra carriage weight and therefore adds expense due to increased fuel burn. Similar to Zhu et al. (2002), Keith (2003) and Keith and Leyton (2007) established critical thresholds based on detailed cost-loss analyses. Probability forecasts were then applied to determine if the economic value of the decision process was greater than the economic value of a decision process that relied solely on deterministic (yes/no) terminal aerodrome forecasts (TAFs).

In Keith (2003), forecast probabilities were generated simply by asking TAF forecasters to provide a *subjective* degree of confidence in their forecast of ceiling and visibility. These subjective probabilities were then applied to a cost-loss model to determine the need to carry extra fuel. In this first study, Keith (2003) only examined one specific flight profile. The economic value of the decision process using probability-based forecasts was then compared to the economic value of the same decision

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process using purely deterministic forecasts. In Keith and Leyton (2007), a similar but more robust study was conducted. The new study had two significant changes. First, the new study examined a much wider range of aircraft flight profiles provided by American Airlines. Second, the study used objective probability forecasts rather than subjective probabilities. The objective forecast probabilities were derived statistically (similar to MOS) but using only surrounding observations as predictors (Leyton and Fritsch, 2003). Both studies demonstrated significant cost-savings potential when probability forecasts combined with cost-loss models were incorporated into the decision-making process. Specifically, Keith and Leyton (2007) demonstrated a potential 2.5% cost reduction in American Airline's annual $4 billion fuel expense.

The potential benefits of determining and exploiting uncertainty information in aviation weather forecasts has also been recognized by the JPDO responsible for the NEXTGEN air traffic management system. Probabilistic weather data is planned for use in several air traffic management decision support tools that will compare the probability of an event occurring against the operational risk tolerance to produce decision-quality output (JPDO, 2010).

For example, weather forecast uncertainty information is planned to be used in conjunction with air traffic congestion models to improve strategic traffic flow management. Air traffic congestion models use historical air traffic data to determine the probability of increased air traffic congestion caused by the occurrence of weather events (e.g., convection, turbulence, icing) at specific locations (both horizontal and vertical) at specific times. However, rather than basing the probability of congestion on a simple binary "yes/no" forecast of a constraining weather event occurring, ensemble weather models would be used to provide the likelihood of the event occurring (JPDO, 2010). That is, the probability information from the congestion models would be used in conjunction with the probability of occurrence of the weather events themselves to provide a more accurate description of the potential for air traffic capacity reductions in any given region. When the probability of air traffic congestion at a location due to a weather event exceeds a tolerable threshold, the air navigation service provider can take appropriate actions to manage the anticipated congestion (JPDO, 2010).

In addition to en route congestion, forecast weather uncertainty information for terminal weather is also planned for use in assessing ground delays and airport capacity, since forecasts of ceiling and visibility, surface winds, precipitation, winter weather, and convective activity can all have a significant impact on the available airport capacity at any individual airport. An example of such a use is forecasting the fog burn-off time at the San Francisco International Airport (SFO). Fog has a significant impact on airport capacity at SFO when the early morning fog doesn't burn off but rather it persists well into the late morning rush of air traffic arrivals. To help minimize impacts, research is being accomplished to incorporate weather uncertainty information into the SFO ground delay program (GDP) algorithms. The goal is to use probability forecasts of fog burn-off times in conjunction with GDP algorithms to help determine optimal aircraft arrival times in an effort to minimize delays and manage risks, such as excessive airborne holding, diversions, and controller workload (JPDO, 2010).

While these are only two examples of several methods identified in the JPDO NEXTGEN Weather and Air Traffic Management Integration Plan for integrating weather forecast uncertainty information into decision support tools, they do help highlight the important role uncertainty information is expected to play in the future of air traffic management operations.

Summary and Conclusions

Uncertainty in weather forecasts is an unavoidable aspect of the prediction process, but having *a priori* knowledge of the degree of uncertainty provides the decision-maker a more complete picture of the expected environmental conditions and potential impact to their operations. Research to combine forecast uncertainty information with operational decision-support tools (such as cost-loss models) has demonstrated significant potential cost savings for various aspects of aviation operations. In addition, the JPDO NEXTGEN leadership has placed significant emphasis on the use of uncertainty information in future air traffic congestion mitigation and airport capacity planning.

There are a variety of methods for objectively determining forecast uncertainty in aviation weather products. Three such methods were discussed in this paper, ensemble modeling, model output statistics, and "fuzzy" logic algorithms. These methods are currently used to produce, respectively, the SREF aviation product suite, the LAMP, and the CIP, which are currently available from NWS websites. It should be emphasized, however, that the only product discussed in this article currently recognized by the FAA is the CIP icing product, and this product is only recognized as a supplemental product for enhanced situational awareness.

Because of the potential benefits of uncertainty information and the extensive planned use in NEXGEN, instructors in aviation, especially at the graduate level, have a responsibility to open discussions with students regarding the exploitation of uncertainty information in aviation operations. While this paper provides a basic primer on three currently used methods for determining objective uncertainty information, it is by no means exhaustive. Many others techniques are being developed or currently used in the research environment.

Before using any uncertainty information the user should be knowledgeable of the strengths and limitations of the product. Questions to ask include, how is the uncertainty assessed, is it objectively determined or subjectively determined? Is the uncertainty information well-calibrated such that when a 40% probability of occurrence is given, the event occurs 40% of the time? What algorithms are used to determine if the hazard exists? If the probabilities are based on climatology, how long of a historical record was used? If the record is too short, the product may be incapable of predicting extreme events. These are just a few of a long list of potential questions that could be discussed in an academic setting.

Although the use of objective uncertainty information provides the potential for improved decision-making, the information has little use unless combined with a decision support tool. To exploit uncertainty information to the fullest requires the user to thoroughly analyze their operations and tolerable risks to develop appropriate decision-support tools. This is not always straightforward and often requires the use of extremely complex decision models. Extensive research for the NEXTGEN effort is currently being conducting in this area. Again, discussions in this area are also well-suited for the academic as well as operational environment.

On a final note, this article was not intended to make an expert out of the reader, but rather to increase awareness of the projected increased use of uncertainty information in weather information as well as provide a sample of methods used to assess uncertainty information. The goal is to provide a basic overview of the issue as well as help stimulate discussion both in the classroom and in operations regarding the use of weather forecast uncertainty information in aviation operations.✈

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