Translation of Ensemble Weather Forecasts into Probabilistic Air Traffic Capacity Impact

Matthias Steiner, Richard Bateman, Daniel Megenhardt, Yubao Liu, Mei Xu, Matthew Pocernich, and Jimmy Krozel

Today's trend in probabilistic weather forecasting is toward utilizing ensemble prediction systems. In the Next Generation Air Transportation System (NextGen), ensemble-based weather forecasting will be a common practice. Therefore, this paper explores a novel approach of using high-resolution, ensemble-based numerical weather prediction model data for weather-related, probabilistic aviation impact forecasting. The concept represents a paradigm shift from "creating ensembles of weather information" (e.g., maps of predicted weather hazard intensity) to "developing ensembles of aviation-relevant information" (maps of potential throughput as measured by the available flow capacity ratio), which entails a translation of weather forecasts into predictions of reduced airspace capacity. The proof-of-concept is exemplified by focusing on convective storms; however, in principal, the approach may be applicable to other aviation hazards, like turbulence, icing, or ceiling and visibility. The concept is most pertinent to strategic en route traffic flow management, but it also applies to terminal area applications. A probabilistic approach is appropriate for strategic planning horizons, for which deterministic weather forecasts are significantly less accurate and an ensemble of forecasts may provide guidance about the weather (and impact) uncertainty.

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INTRODUCTION

Convective storms exert a disruptive influence on aviation—both in the terminal area and en route—causing flight delays and cancellations [Krozel et al., 2003; Krozel and Murphy, 2007]. The Aviation Capacity Enhancement Plan [Federal Aviation Administration (FAA), 2003] lists weather as the leading cause (65% – 70%) of delays greater than 15 min, followed by terminal volume (12% – 22% of delays). Strategic flight planning for the airlines and traffic flow management (TFM) planning for air traffic management (ATM) require weather forecasts several hours into the future, which are based upon numerical weather prediction (NWP). Aviation users need forecasts that provide not only details about the likely weather outcome, with lead times of up to 8 h for transcontinental flights and up to 18 h for some intercontinental routes, but also information about storm structure, intensity and organization, and the associated forecast uncertainty for risk and cost-benefit assessments.

Increasing ATM efficiency, especially under scenarios of increased demand, requires automated decision support tools (DSTs) that make use of probabilistic weather information to estimate airspace capacity and provide guidance for managing air traffic flows [Nilim et al., 2002; Prete and Mitchell, 2004; Schleicher et al., 2004; Hunter et al., 2005; Krozel et al., 2006; Spencer et al., 2006; d'Aspremont et al., 2006; Joint Planning and Development Office (JPDO), 2007; Souders et al., 2007; Grabbe et al., 2008]. In order to be most effective, weather forecasts need to be fully integrated in the TFM decision-making process—i.e., translated into aviation impact forecasts. This is one of the key goals for both the Next Generation Air Transportation System (NextGen) [JPDO, 2007] and the Single European Sky ATM Research (SESAR).

Today's trend in probabilistic weather forecasting is toward utilizing ensemble prediction systems. In the NextGen era, ensemble-based weather forecasting is expected to be common practice. Therefore, this paper explores how high-resolution ensemble weather forecasts may be utilized to better estimate weather impact on ATM. It also discusses potential ways of integrating ensemble-based forecasts with automated ATM DSTs. The approach, as introduced by Steiner et al. [2007; 2008], draws upon recent experience gained with probabilistic convective scenario forecasts [Davidson et al., 2004, 2006]. The current focus is on convective storms, primarily, because of their significant impact on traffic flows [FAA, 2003]. However, in principal, the concept is applicable to other en route weather hazards, such as turbulence, icing, or ceiling and visibility. Moreover, the same approach could be tailored, for example, to predict major wind shifts on runways, the timing of precipitation, rain-snow transitions, or ceiling and visibility in the terminal area.

The paper provides a brief introduction to NWP with a particular focus on ensemble forecasting. Following that, a new way of making effective use of ensemble weather forecast information is advocated that realizes a translation into probabilistic aviation capacity impact prediction. Furthermore, a proof-of-concept demonstration is provided that exemplifies how this approach can work. Application of this concept is aimed at NextGen, but potential uses in today's air transportation system are discussed as well.

NUMERICAL WEATHER PREDICTION USING ENSEMBLES

Weather forecasting is inherently uncertain for a variety of reasons, including the chaotic nature of the atmosphere, our inability to grasp present conditions well enough with limited observations, and incomplete understanding of weather processes across a wide range of scales [e.g., chapters 1 and 6 in Wilks, 2006]. Moreover, NWP models are based on nonlinear mathematical equations for the physics and dynamics of the atmosphere that cannot be exactly solved. Probabilistic weather forecasts attempt to characterize and quantify this inherent prediction uncertainty, often based on ensemble modeling [Hamill et al., 2000; Hacker et al., 2003; Roebber et al., 2004; Lewis, 2005]. Ensemble forecasting is a prediction technique that aims to generate a representative sample of the possible future states of the atmosphere. An ensemble forecast—i.e., a collection of typically 10 to 50 weather forecasts with a common valid time—may be obtained in different ways based on time-lagged, multi-model, and/or multi-initial conditions approaches [Arribas et al., 2005; Stensrud and Weiss, 2002; Lu et al., 2007; Lawrence and Hansen, 2007; Pappenberger et al., 2008].[2] In a perfect ensemble forecasting system, the spread among the ensemble members provides a measure of sensitivity of the forecast to variations in model physics and initial conditions. Due to imperfections in ensemble modeling, however, a forecast with little spread among the ensemble members can still be significantly wrong and the small spread should not be falsely perceived as forecast accuracy, because a systematic bias in either the model physics or initial/boundary conditions may drive all ensemble members in a wrong direction. Ensemble-based NWP modeling has not matured yet; thus, achieving well-calibrated ensemble weather forecasts with significant reliability and resolution constitutes an area of active research [e.g., Jolliffe and Stephenson, 2003; Hamill et al., 2004; Gneiting et al., 2007].

[2]Another possibility for creating an ensemble forecast is to apply several diagnostics on a single NWP forecast, such as done with the Graphical Turbulence Guidance (GTG) product discussed by Sharman et al. [2006].

Many weather services around the world are employing ensemble forecast techniques for large-scale, coarse-resolution (30 km or larger grid spacing), medium- (2 – 10 days), and long-range weather and climate prediction purposes. Such an approach, so far, has not transitioned into operational, high-resolution (10 km or less grid spacing), short-range (0 – 2 days) meso- and storm-scale ensemble weather forecasting, which is essential for aviation applications. There are many challenges for mesoscale ensemble forecasting, including high demands on computing capabilities and an increasing need to understand atmospheric boundary-layer, cloud, and precipitation processes at smaller scales with increasing model resolution [e.g., Mass et al., 2002; Roebber et al., 2004]. For example, a NWP model run at 10 km (or coarser) resolution may employ heuristic convection schemes, while high-resolution models with grid sizes of only a few kilometers require explicit physics schemes to fully describe the convective processes [e.g., Molinary and Dudek, 1992; Weisman et al., 1997]. For many practical reasons, there exists a trade-off between higher resolution (i.e., providing details about storm structure and organization) and ensemble modeling (providing information about prediction uncertainty). Thus far, high-resolution ensemble forecasting has been attempted only on limited-area, regional domains and primarily in a research or real-time demonstration mode [Grimit and Mass, 2002; Liu et al., 2007; Jones et al., 2007; Stensrud and Yussouf, 2007]. Aviation users are expected to benefit significantly from the wealth of information that short-range (0 – 2 days), high-resolution (<10 km grid size) ensemble weather prediction models may be able to provide, as discussed in this paper.

A NEW APPROACH TO AVIATION WEATHER FORECASTING

Concept

Ensemble-based weather forecasting involves handling a substantial amount of data. It is not surprising, therefore, that weather forecast providers aim to reduce that wealth of information by creating summary products, such as an ensemble mean, standard deviation, or likelihood of exceeding a user-relevant threshold. For certain user applications, this may be appropriate. However, aviation users require detailed information about the spatial organization and structure of storms that tends to get lost by averaging (Figure 1a). Therefore, a different approach is required to satisfy aviation user needs.

Ensemble means of properties that are continuously distributed in the atmosphere, such as temperature and wind, can sometimes

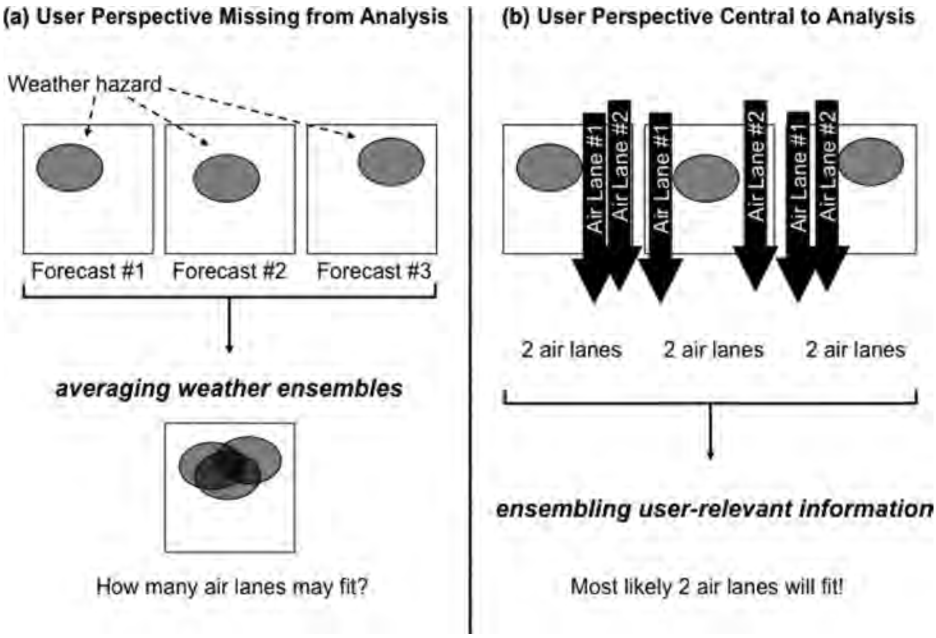

Figure 1. Contrasting concepts of aviation users dealing with ensemble weather forecasts.

resemble plausible instantaneous states of the atmosphere. However, the same is not true of atmospheric properties that are discontinuous and transitory, such as clouds and precipitation. Averaging over many occurrences of discrete weather features, whose durations are relatively short and/or have limited geographical extent, will generally result in a smooth and formless field. For example, when averaged over a large enough sample of ensemble members, episodes of sporadic, local, intense rainfall across a region will appear in the ensemble mean as widespread light rain, as will be shown later.

In NextGen and SESAR, weather forecast systems will provide ensemble-based, high-resolution forecasts, where each ensemble member may be regarded as a "deterministic scenario" of a potential weather outcome. Rather than summarizing the wealth of information provided by the ensemble forecasts into a probabilistic weather depiction, we advocate extracting aviation-relevant characteristics from each ensemble member and subsequently ensemble user-relevant information instead. These two approaches are contrasted in Figure 1 by means of finding how many air lanes may fit through an airspace given forecasted weather constraints. Figure 1b illustrates that getting two air lanes through the domain is highly likely; however, a user confronted with the ensemble mean, as shown in Figure 1a, struggles to arrive at the same conclusion. Thus, weather and impact forecasts for aviation stakeholders' strategic planning should include analysis of the individual ensemble members rather than an ensemble mean.

Translating Weather into Aviation Impact

Hazardous weather causes a reduction of the available airspace capacity. The maximum amount of traffic flow through a weather-impacted airspace is dictated by the flow bottlenecks between weather constraints (Figure 2), which may be estimated based on the *max-flow min-cut theorem* [Ford and Fulkerson, 1956; Mitchell et al., 2006; Krozel et al., 2007]. For a given situation, the computed MinCut value depends on the spatial scale of the domain of interest, which is why a normalization of the MinCut is applied by dividing it with the corresponding MinCut value under no weather obstruction (Figure 2). The resulting *available flow capacity ratio* [Song et al., 2007, 2008] represents a non-dimensional measure ranging between zero (i.e., unusable airspace without any capacity) and unity (fully usable airspace without weather constraints). Note that today's airspace is burdened by the need for pilots to conform to jet routes while avoiding weather hazards [Martin et al., 2006; Martin, 2007] and constraints imposed by controller workload, which can seriously limit capacity [e.g., Histon et al., 2002]. Depending on the degree of automation in NextGen and SESAR, jet route conformance and controller workload constraints may become less of an issue. For simplicity, we neither consider jet route conformance nor workload constraints in the present analyses.

Extracting aviation-relevant information from each ensemble forecast member, as sketched in Figure 1b, facilitates a translation

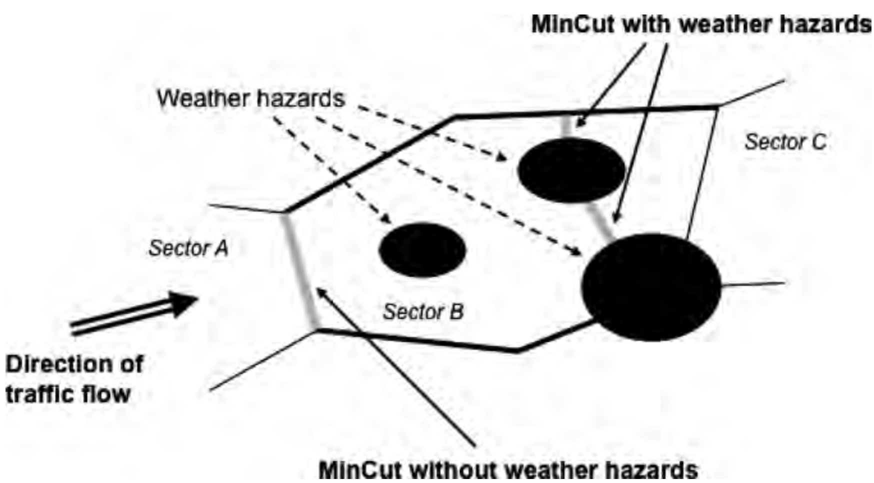

Figure 2. Translation of weather into ATM capacity impact based on utilizing MinCut theory.

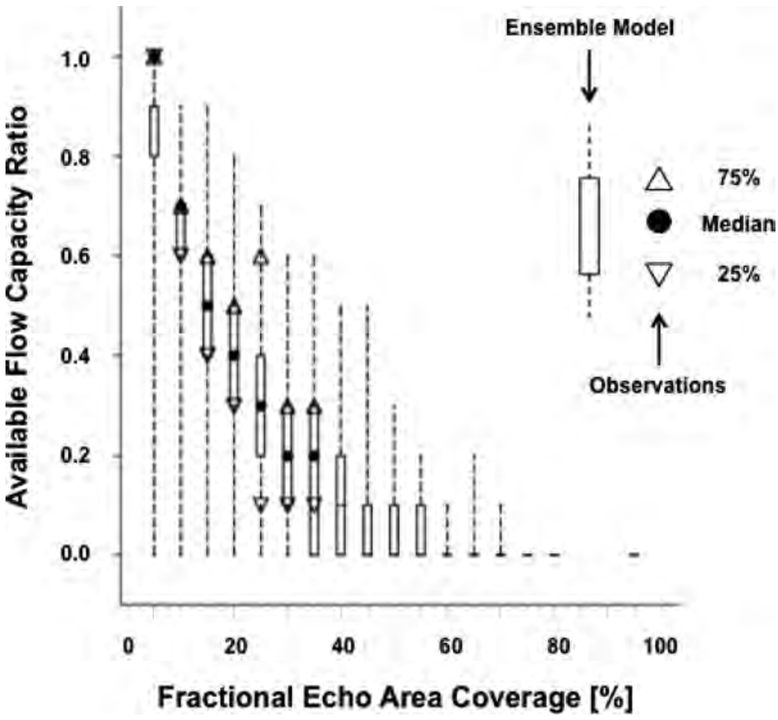

Figure 3. Dependence of airspace capacity (available flow capacity ratio) on weather hazards (fractional echo area coverage).

of weather forecast data into aviation impact information. We used air lanes for making our point in Figure 1; however, the subsequent analyses will be based on the available flow capacity ratio, utilizing a Required Navigation Performance (RNP)[3] of 4 (i.e., air lanes are 8 nmi wide). For a given airspace, the available flow capacity ratio depends on the spatial extent and organization of the weather hazards present and the traffic flow direction. Increasing areas of aviation weather hazards yield a rapidly decreasing airspace capacity. Figure 3 illustrates the available flow capacity ratio in East – West (E-W) direction as a function of the fraction of airspace covered by storms, which was computed as the size of storm area exhibiting at least 2 mm of precipitation accumulation during the past hour. This inverse relationship between weather and capacity is visualized based on analyses of NWP forecasts from 24 – 29 June 2007 (shown as boxplots, comprising lead times of 0, 3, 6, and 9 h) using the ensemble model introduced in the next section and corresponding observations (median shown as bold dot and quartiles as

[3]Traffic density may be increased for RNP-equipped aircraft that can safely operate routes with less separation (i.e., with higher precision) than otherwise required.

triangles).[4] Results are depicted for a 200 $\times$ 200 km gridbox scale of analysis, but a similar behavior was found for other analysis scales (e.g., 400 $\times$ 400 km and 100 $\times$ 100 km gridboxes) as well. The relatively wide scatter about this inverse relationship between weather and capacity is caused by the natural variability of how storms are organized. For example, a North – South (N-S) oriented line storm of a given size yields a much smaller available capacity ratio in E-W flight direction than a similar-sized storm that is oriented parallel to the flight path. Overall, the model predicted relationship between available flow capacity ratio and fractional echo area coverage agrees pretty well with the observed one for the analysis scales investigated.

ANALYSIS OF 24 – 29 JUNE 2007 ENSEMBLE FORECAST DATA

Weather and Aviation Impact on 27 June 2007

Next, our concept is demonstrated using an example. The 27 June 2007 date exemplifies a day when weather caused major delays across much of the United States (US) east of the Mississippi River, as shown in Figure 4. The New York area was particularly affected, with Newark, New Jersey (EWR) experiencing average delays of 4 – 5 h, but long delays were common to all major airports in the southeast (e.g., Atlanta, Georgia – ATL), mid-Atlantic (Washington, District of Columbia – DCA), northeast (Boston, Massachusetts – BOS), and midwest (Chicago, Illinois – ORD).[5] This large, weather-related aviation impact was caused by an outbreak of convective storms across much of the eastern US that affected en route traffic as well as arrival and departure routes of major airports.

Ensemble Model

This study uses a state-of-the-art ensemble model developed by the National Center for Atmospheric Research (NCAR). The so-called Real-Time Four-Dimensional Data Assimilation (RT-FDDA) and forecasting system [Liu et al., 2006, 2008] is a multi-nested, mesoscale ensemble modeling system with continuous data assimilation and rapid forecast cycles [Liu et al., 2007]. For the present study, we used an ensemble of 28 members that was created based on utilizing both the Pennsylvania State University/NCAR Mesoscale Model

[4]The observations were remapped from 4 km to 10 km to match the spatial resolution of the model output data (thus avoiding introduction of uncertainty due to resolution discrepancies) independent of the scale of analysis.
[5]Information retrieved from the FAA Operations Network (OPSNET) database.

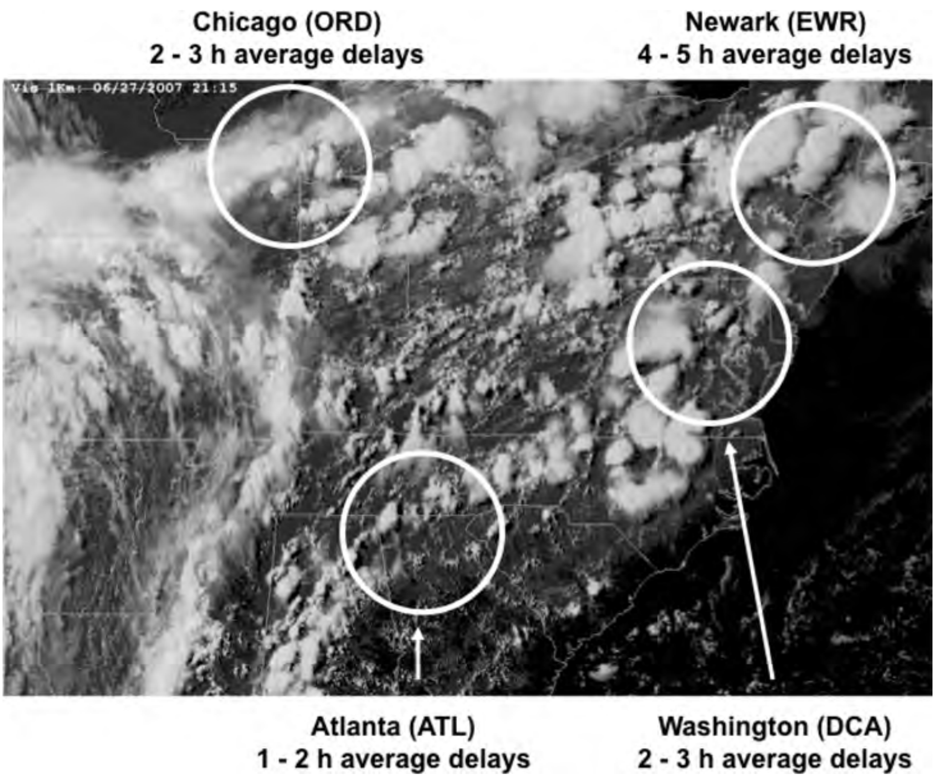

Figure 4. Visible channel (VIS) satellite observation of cloud coverage on 27 June 2007 at 2115 UTC with aviation delays at major hubs.

Version 5 (MM5) [Grell et al., 1995] and the Weather Research and Forecasting (WRF) [Skamarock et al., 2007] modeling systems, combined with a mixture of land surface, boundary layer and microphysics packages, multiple perturbation schemes, and different initializations. Steiner et al. [2009] provide further details about the particular ensemble member configuration. The analyses build upon forecasts with a 24-h outlook that were initiated every 6 h, beginning at 18 UTC on 24 June 2007. The last run relevant for this study was started at 06 UTC on 28 June 2007. The results discussed here are based on the 10-km resolution domain that covers most of the US east of the Mississippi River.

The domain covered by the 10-km ensemble model runs is shown in Figure 5a together with the radar-observed and rain gauge-adjusted hourly precipitation accumulation (i.e., Stage IV precipitation) ending at 21 UTC on 27 June 2007 (approximately the same time as in Figure 4). Figures 5b and 5c depict spatial maps of the grid-based ensemble mean and standard deviation, respectively, for a 9-h forecast of hourly precipitation accumulation valid at the same time as the observation shown in Figure 5a. A map of the number of ensemble members exceeding a 2-mm hourly precipitation accumulation

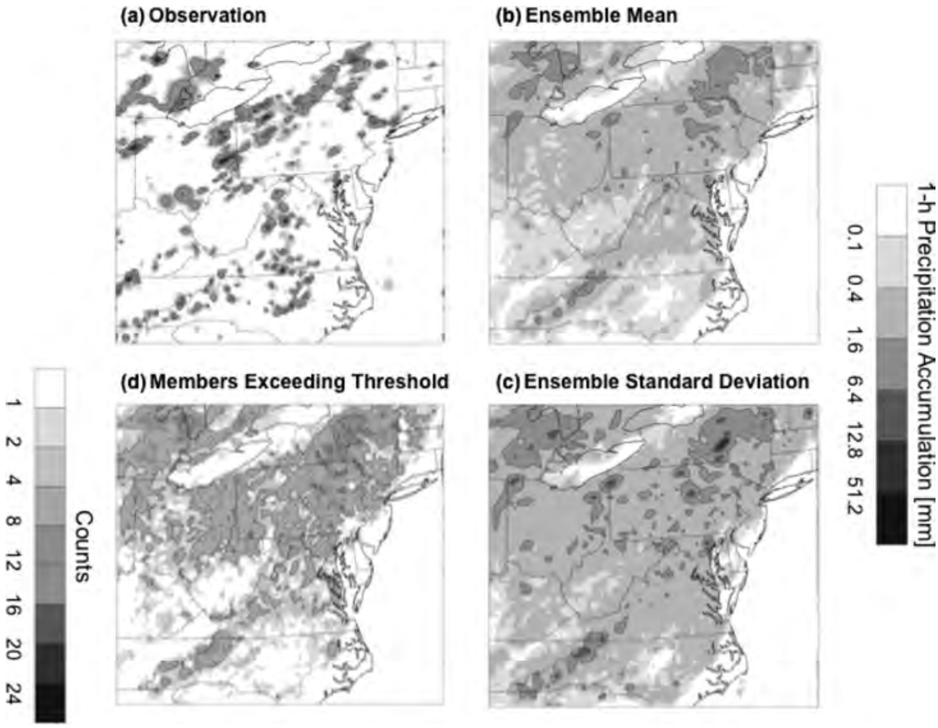

Figure 5. Observed storms and 9-h ensemble forecast information valid for 21 UTC on 27 June 2007.

threshold in each gridbox is provided in Figure 5d. These summary plots of the 9-h ensemble model forecast (Figures 5b, 5c, and 5d) indicate widespread storm activity over the eastern US; however, storm organization details are clearly lost in the averaging process, which reinforces the point made with Figure 1.

The individual 28 members of that same 9-h ensemble precipitation forecast are presented in Figure 6. They represent various combinations of forecast models, initialization, and perturbation techniques aimed at creating a representative sample of the future weather outcome [see Steiner et al., 2009]. The 15 MM5-based forecasts (labeled "-M-") are shown on the left, 7 of which were initialized using the Global Forecast System (GFS) and 8 using the North American Model (NAM). The 13 WRF-based members (labeled "-W-") are shown on the right, with 10 members based on a GFS and 3 based on a NAM initialization, respectively. Figure 6 highlights a wide variety of possible weather outcomes, ranging from a few isolated intense storms (e.g., members GFS-M-CBM1 and NAM-M-CBM1) to widespread weak-to-moderate intensity precipitation (member GFS-W-CBMJ), and much in between these two predictions. It would be difficult to pick one ensemble member as the most likely forecast, but the ensemble of forecasts exhibits enough spread to embrace the

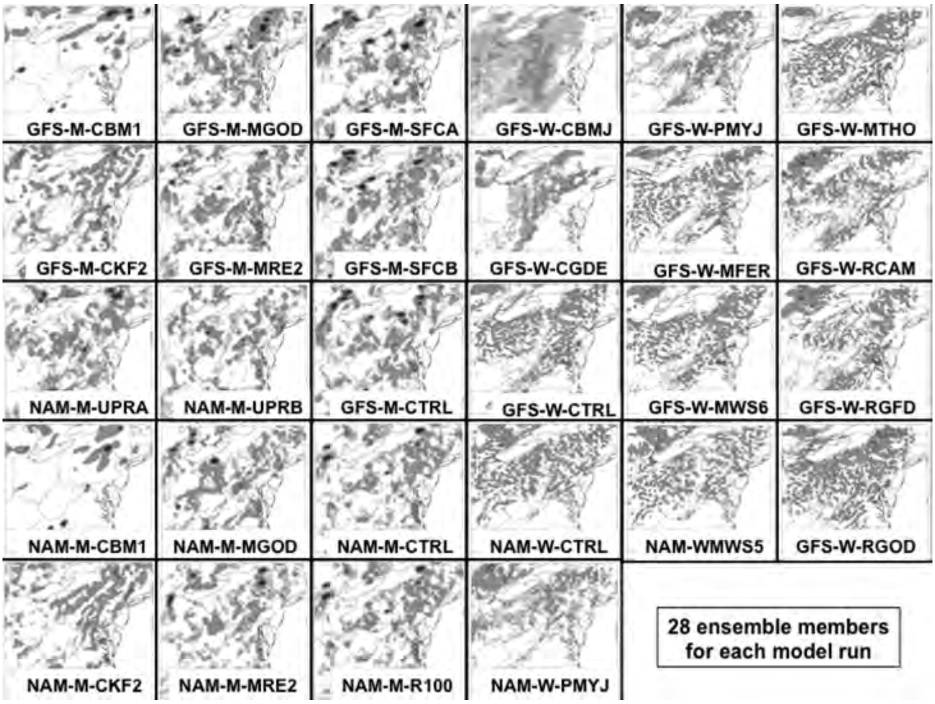

Figure 6. Individual ensemble members of the 9-h storm prediction (hourly precipitation accumulation) valid for 21 UTC on 27 June 2007.

actual weather outcome at forecast valid time, which is what one would like to achieve.

Probabilistic Forecasts using New Concept

The prediction accuracy for a specific location decreases rapidly with increasing forecast lead time, somewhat depending on the type of convective storm system encountered [Golding, 1998; Wilson et al., 1998; Carbone et al., 2002; Germann et al., 2006]. High-resolution NWP models are getting better at predicting the type of storms, although they may not be able to predict exactly where the storms will occur [Roberts and Lean, 2008; Weisman et al. 2008]. That is where the ensemble modeling approach, utilizing a variety of initial and boundary conditions, and model physics to characterize observational and model uncertainty, may help define a representative sample of potential weather scenarios that hopefully includes the actual weather outcome. For ATM purposes, especially for strategic en route planning, it is important to have a good understanding of the type, size and organization of future weather outcomes over some domain (e.g., a sector) even if exact location information may not be available—although the latter matters for terminal areas. The ensemble approach provides a measure of forecast uncertainty.

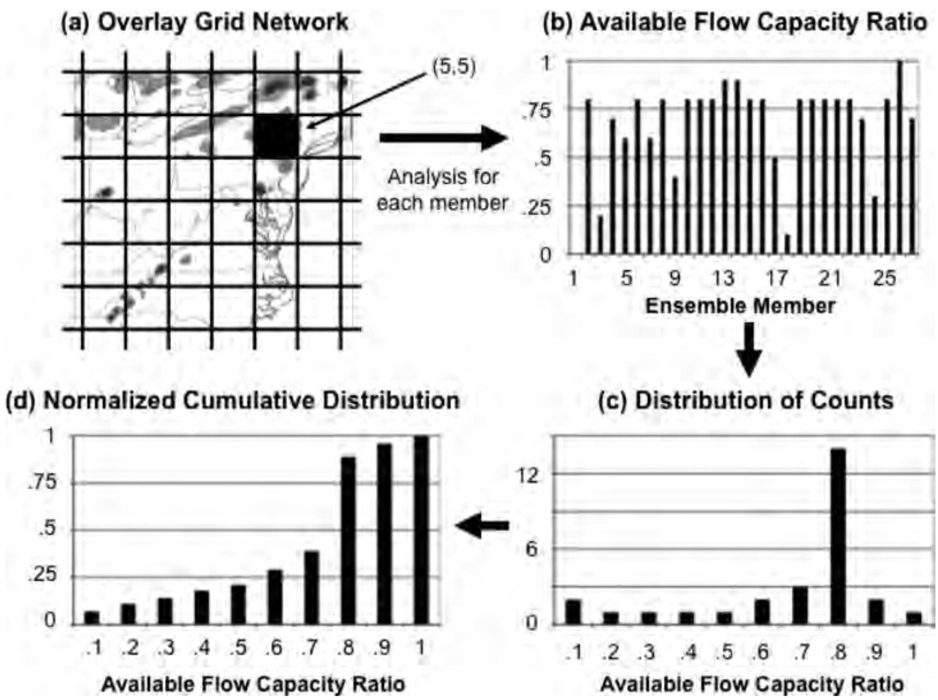

Figure 7. Analysis steps for creating aviation-relevant probabilistic information.

By relaxing the location specificity requirement and focusing instead on what is happening within a larger domain, better predictive accuracy may be achieved [Ebert and McBride, 2000; Zepeda-Arce et al., 2000; Roberts and Lean, 2008]. The subsequent analyses, therefore, were carried out by overlaying a grid network (Figure 7a) on each ensemble forecast member (and similarly the observation) and then computing the fractional echo area coverage and available flow capacity ratio values for each gridbox. The grid was fixed for each analysis. We explored different spatial analysis scales by utilizing gridboxes of 50 km, 100 km, 200 km, and 400 km sidelength. For simplicity, we used a Cartesian grid, but any size or shape (e.g., sector) could be used.

The values of the available flow capacity ratio in E-W direction computed for the 200-km gridbox (identification x = 5, y = 5) based on each of the 28 individual ensemble member 9-h forecasts (see Figure 6) are highlighted in Figure 7b. Capacity ratios cover the full range from zero to unity, but mostly concentrate around 0.7 – 0.8 (Figure 7c).[6] The corresponding available flow capacity ratio for gridbox (5,5) based on the actual weather observation at forecast valid time is 0.3, while the ensemble mean-based value is 0.6. In this

[6]The resolution of the available flow capacity ratio depends on the analysis scale (i.e., gridbox size), the RNP (air lane width), the weather hazard pattern (spatial organization), and the grid-resolution of observation and NWP model output. For smaller analysis domains, the capacity ratios may come in finite values only.

situation, the ensemble spread embraced the true outcome, but this might not always be the case. For a properly calibrated ensemble forecast system, Figure 7c (rearranged information from Figure 7b) would reflect true probabilities. However, a proper calibration of such a forecast system will require large amounts of data collected over long time periods [Gneiting et al., 2007; Jones et al., 2007; Stensrud and Yussouf, 2007]. Therefore, Figure 7c simply shows counts in each bin for this proof-of-concept demonstration. Adding up the number of ensemble members that exceed a certain value of available flow capacity ratio and dividing them by the total number of ensemble members yields a normalized cumulative distribution, as shown in Figure 7d.

The analysis of ensemble forecast data, as discussed above, produces a cumulative distribution of the predicted available flow capacity ratio (like in Figure 7d) for each gridbox and outlook time. In NextGen and SESAR, such information may be easily communicated between computers; however, visualization of this wealth of probabilistic information for human oversight and evaluation could be overwhelming. For illustration purposes, Figure 8a reveals the probabilistic landscape (i.e., chance) of losing 30% of the available flow capacity in E-W direction (i.e., available flow capacity ratio ≤ 0.7) based on the 9-h ensemble forecast that was translated into an aviation impact. According to this 9-h prediction, a traffic flow manager would have to expect significant weather-related delays for much of the eastern US.

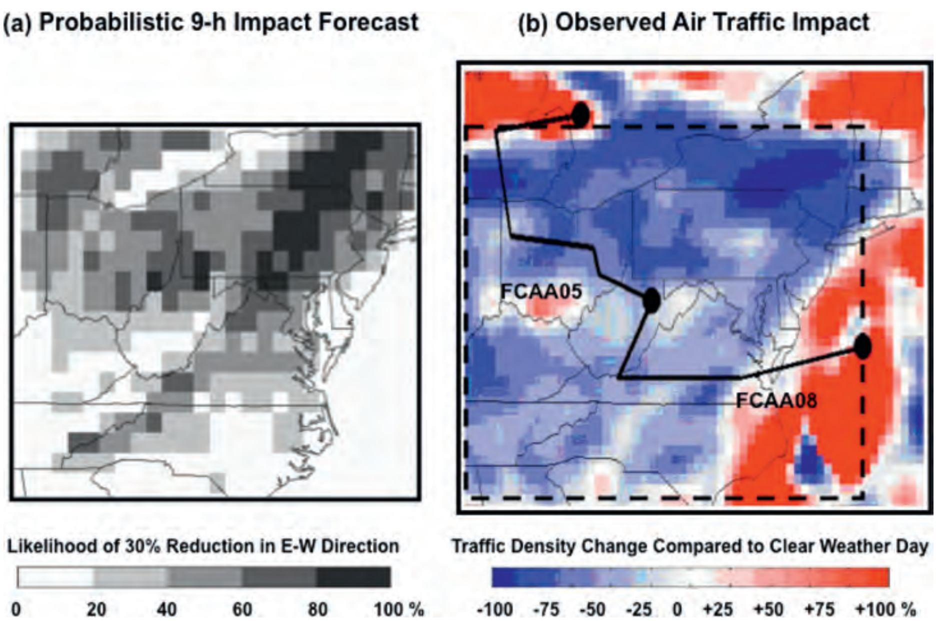

Figure 8. Predicted probabilistic available flow capacity ratio (left) based on weather hazards expected to be present at 21 UTC on 27 June 2007 versus observed air traffic impact (right).

This is, in fact, what unfolded on 27 June 2007. Figure 8b shows the actual traffic impact at forecast valid time, which was obtained by comparing the traffic density in the broader northeastern airspace relative to the traffic density that occurred at that time of day on a clear weather day (we selected a clear weather day that occurred on the same day of the week—so that the scheduled traffic would be very similar—exactly three weeks prior to the weather impacted day being analyzed). Clearly, traffic demand was reduced by convective weather constraints; however, TFM planners anticipated this problem and created two Airspace Flow Programs (AFPs) [Brennan, 2007] that limited the flow rate into the northeast of the US. The Flow Constrained Areas (FCAs) named FCAA05 and FCAA08 (see line segments on Figure 8b) were used to regulate the traffic flow rate into the northeast. Figure 9 visualizes this reduction of traffic flow rate compared with a clear weather day. The number of aircraft crossing over FCAA05 in E-W direction was reduced by 27% – 42% between 19 and 23 UTC; the reduction of traffic across FCAA08 was

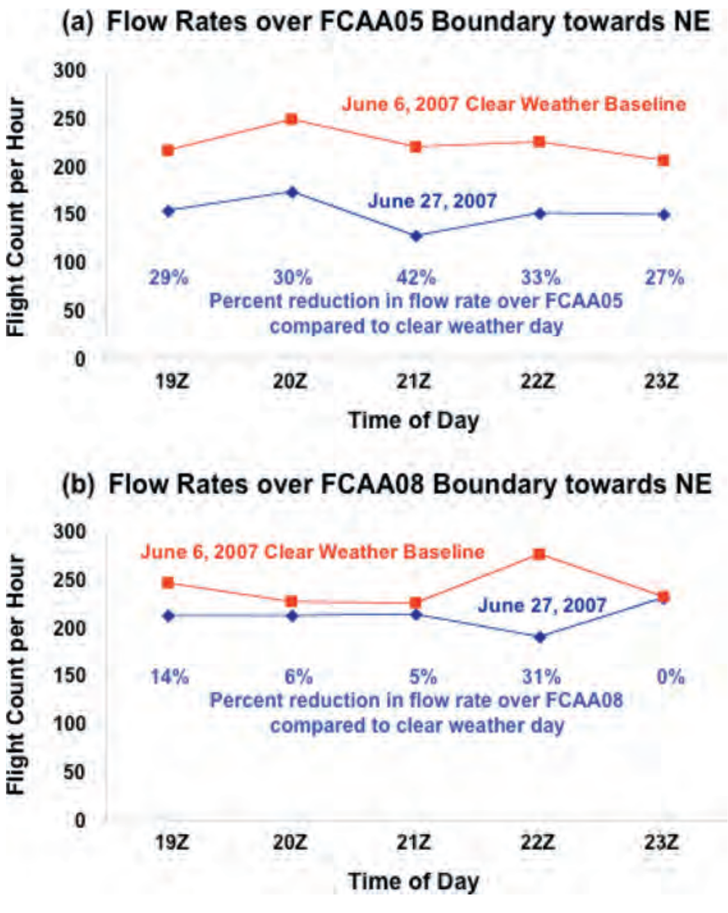

Figure 9. Comparison of traffic flow rates over FCAA05 and FCAA08 on a clear weather day versus weather impacted day.

somewhat less (0% – 31%). The maximum air traffic reduction occurred between 21 and 22 UTC on 27 June 2007. This forced some traffic north into Canadian airspace and east over the Atlantic Ocean (Figure 8b), where the AFP was not in effect and also where there were no hazardous weather constraints at the time.

Note that instead of thresholding the cumulative distributions of available flow capacity ratio at 0.7, as applied to obtain the depiction in Figure 8a, any other user-relevant threshold might be utilized. Moreover, the probabilistic landscape of a threshold exceedance could be contoured (rather than shown in grayscale) to enable visualization of likely capacity losses based on multiple critical thresholds (utilizing different colors and line styles); for example, based on levels of expected air traffic demand.

Examination of Forecast Performance

An objective assessment of performance of the ensemble forecast system requires long-term comparisons of predictions and observations [Gneiting et al., 2007; Jones et al., 2007; Stensrud and Yussouf, 2007]. The amount of data collected and processed as part of this proof-of-concept analysis provides only limited insight to the overall ensemble forecast system performance. However, our analyses revealed some noteworthy results.

Table 1 provides a list of the six time periods analyzed. These periods comprise several days when aviation was highly impacted by convective weather. Ensemble forecasts were generated for all six time periods, similarly to the 24 – 29 June 2007 discussed in detail in this paper. Combining the data of all six periods, Figure 10 shows a *reliability diagram* [Jolliffe and Stephenson, 2003; Wilks, 2006] that reflects the skill of the ensemble forecast system to predict an available flow capacity ratio less than 0.7 (i.e., a 30% capacity reduction due to weather impact). Separate reliability curves are shown for analysis scales of 50 $\times$ 50 km, 100 $\times$ 100 km, 200 $\times$ 200 km, and 400 $\times$ 400 km domains. Figure 10 demonstrates that the observed frequency of a 30% capacity reduction increases with increasing prediction probability, as one would hope for. However, for a well-calibrated probabilistic forecast system, one expects the reliability curves to follow the diagonal (i.e., 1:1 line), which is clearly not the

Table 1. High Weather Impact Periods for Aviation.

24 June – 29 June 2007
8 July – 12 July 2008
29 July – 2 August 2008
2 August – 6 August 2008
12 August – 16 August 2008
24 August – 28 August 2008

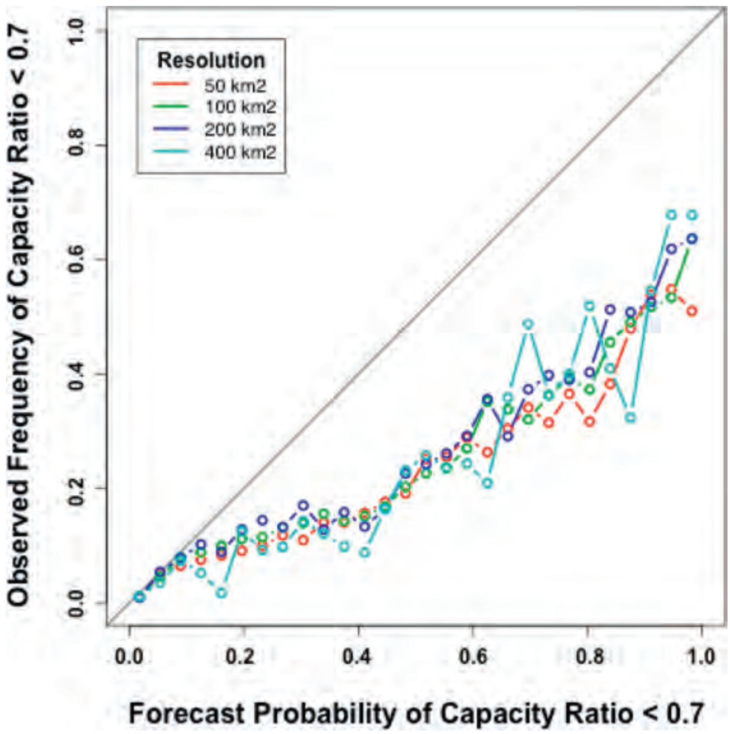

Figure 10. Reliability diagram for ensemble predictions of available flow capacity ratio in E-W direction.

case for our ensemble model in its present state. A proper calibration is definitely needed, but this will require a substantial amount of long-term data collection that is not currently available.

As is, the ensemble forecast system overpredicts the likelihood of a capacity reduction by about a factor of two—that is, an 80% probability of losing at least one third of the capacity due to convective weather is observed only about 40% of the time. On the positive side, the reliability curves behave rather similarly across different spatial analysis scales, as shown in Figure 10. A comparable behavior was found as a function of forecast lead time (i.e., 0 – 9 h outlooks) and various capacity reduction thresholds (not shown). Moreover, the ensemble spread tends to increase with increasing deviation of the ensemble median from the truth. For accurate ensemble median forecasts, the spread among the ensemble members is small, but it increases with increasing discrepancy between the observed value and the median forecast. The ensemble forecast system performance, however, depends on the type of weather encountered—there was a fair amount of variability among the six time periods individually. This dependence of ensemble model performance on the magnitude and type of weather outbreak requires additional detailed analyses to facilitate a proper creation of ensemble membership and calibration of the overall forecast system.

DISCUSSION

Applicability in today's National Airspace System versus NextGen

In today's National Airspace System (NAS), there is no established and accepted indicator of airspace capacity and thus no automated tool to predict it. While the Enhanced Traffic Management System (ETMS) provides a congestion alerting function, which uses the peak one-minute aircraft count as a sector congestion alerting criterion—the Monitor Alert Parameter (MAP)—the MAP is not meant to be a measure of airspace capacity and estimates of capacity based on ETMS are not accurate enough for the long term 2-h, 4-h, and 6-h predictions needed for TFM decision making [Krozel et al., 2002]. The MAP is a threshold which, when exceeded by predicted demand, alerts traffic managers to examine the sector for potential congestion. However, the actual capacity of a sector is dependent on the geometry of hazardous weather constraints and complexity of the traffic flows within the airspace (which relates to controller workload) [Athenes et al., 2002; Histon and Hansman, 2008]. Given the uncertainty in weather forecasts today for 2-h, 4-h, and 6-h predictions, strategic TFM decision making is largely pursued based on a single weather forecast [e.g., Huberdeau and Gentry, 2004]. However, in setting up FCAs, for instance the 27 June 2007 example given above, there is no DST that assists the controller in estimating the impact that weather will have on the FCA throughput. So the FCA throughput is determined largely based on controller experience in setting such rates, consulting with the current convective weather forecast. As an alternative, a probabilistic capacity impact map, such as shown in Figure 8a, can provide useful information about the expected capacity reduction crossing over the FCA boundary in a given region of the NAS. And furthermore, basing such results on an ensemble of forecasts allows the DST to suggest the best and worst case expected FCA throughput given the uncertainty of the 2-h, 4-h, or 6-h forecast.

While today the FCA is located on sector boundaries and the probabilistic ATM impact over such a FCA can be evaluated, in NextGen, this will likely be reversed. The ATM impact will be determined first given the expected set of filed flight plans and weather forecasts, and then the FCA will be generated by analyzing ATM impact maps. So for instance, in Figure 8a, maps of 30%, 40%, and 50% likelihood of capacity reduction exceeding a given value can be used to determine the most appropriate FCA boundary given the expected ATM impact. In this way, the FCA boundary will be as large or small as it needs to be to contain the traffic flow problem.

Applicability to other Aviation Hazards

In this paper, we have demonstrated a proof-of-concept on how to utilize ensemble weather forecast data to obtain a probabilistic aviation impact prediction. We used hourly precipitation accumulation as a proxy for convective summer storms, but any other weather parameter or aviation hazard could have been used instead (e.g., vertical integrated liquid, echo top, or a combination of both). For example, we explored generation of turbulence diagnostic fields as a function of flight level based on the present ensemble model output (not discussed here), and we are confident that also icing or ceiling and visibility diagnostics could be obtained. Moreover, the advocated concept of extracting aviation-relevant information from the ensemble NWP data is applicable to other fields, such as the Weather Avoidance Field (WAF) developed by DeLaura et al. [2008].

The current study was primarily focused on the en route TFM problem and how weather hazards may reduce the available airspace capacity. Our analyses built upon idealized computations of the geometric flow capacity [via Mitchell et al., 2006 and Krozel et al., 2007] in a region experiencing deterministic weather constraints to obtain probability distributions of the throughput capacity of an airspace given an ensemble weather forecast. However, there is no apparent reason that would prevent utilization of other approaches to estimate airspace capacity, such as proposed by Martin et al. [2006], Ramamoorthy et al. [2006], or Song et al. [2008], based on ensembles.

In principle, the presented concept may also be tailored for probabilistic forecasting of terminal area weather aspects, like ceiling and visibility, major changes in wind shifts on runways, onset of precipitation, or transitions from rain to snow. The critical thing is to define an aviation-relevant "event" in such a way that it can be computed based on both observations and ensemble NWP model output.

Future Research Issues

A variety of issues await further evaluation. Among them, the optimal composition of ensemble NWP model membership remains a top priority. For example, how can ensemble members be effectively generated such that they provide a representative sample of the actual weather (and thus ATM) outcome, while at the same time providing reliable and sharp forecasts? Moreover, what are the potential benefits of mixing several coarser spatial model resolution ensemble members with one or more high-resolution members? How many ensemble members are really needed to achieve a desired outcome for aviation applications? Should all ensemble members have equal weight, or would some model configurations be preferred depending on the type of synoptic situation? How capable are today's NWP models in reproducing the spatial organization of storms? Clearly, the above questions cannot be addressed in isolation, but have to be combined with a proper assessment and calibration of the predicted probabilistic information. Thus, finding answers to such questions represents a major ongoing research focus of the atmospheric modeling, verification, and ATM communities.

Additional research relates to the many ways of dealing with uncertainty. How do we make sure that situational combinations—both from a weather and aviation perspective—yielding high-cost events, such as extreme flight delays and/or cancellations, are modeled properly? What is the baseline air traffic pattern to measure weather impacts against? What is the baseline for assessing improved performance of one integration approach over another? What diagnostics should be computed in real time—both on the weather and aviation side—to provide useful feedback on prediction performance? Preferably they should be intuitive and simple.

Some time should be spent dwelling on the human role in a future, largely automated ATM decision-making process to enable oversight and interaction with the system, for example, by an airline dispatcher or air traffic manager. This includes addressing aspects of the visualization of probabilistic forecast information. Moreover, extensive real-time demonstrations and appropriate training are needed to build the user trust in and acceptance of new approaches of predicting weather-related aviation impacts. Workload issues of air traffic controllers need to be evaluated in light of probabilistic forecasting of weather and aviation impacts as well.

The foregoing elaborations are not comprehensive but provide a flavor of the kinds of research that is needed to fortify the presented concept and identify its opportunities and limitations.

CONCLUSIONS

In the future, air traffic management will largely rely on automated decision support tools that integrate probabilistic weather information. Toward developing that capability, this paper presents a novel concept of using ensemble-based numerical weather prediction model data for weather-related, probabilistic aviation impact forecasting. The approach combines the use of ensemble model data to create probabilistic information and extraction of aviation-relevant characteristics from ensemble weather forecast data. The second aspect, in particular, reflects a paradigm shift from “ensembles of weather information” to “ensembles of aviation-relevant information”, which entails a translation of weather forecasts into aviation impact predictions. Creating probabilistic forecasts that provide a representative sample of the potential aviation impact will enable air traffic managers to reason about expected best and worst case outcomes, and be ready for both.

This paper demonstrates a proof-of-concept, using convective storms as an example, but the approach is, in principal, applicable to other aviation weather hazards, such as turbulence, icing, or ceiling and visibility. Probabilistic, weather-related aviation impact forecasts will be used by air traffic controllers, traffic flow managers, and airline dispatchers to make strategic decisions on en route traffic flow and individual flights. However, it may also be possible to tailor the presented concept for terminal area applications, such as predicting ceiling and visibility, major wind shifts on runways, the onset of precipitation, or a transition from rain to snow at aviation-critical locations.

The performance accuracy of probabilistic aviation impact predictions was assessed as a function of forecast lead time, spatial scale, and severity of the impacting weather event. The ensemble forecast system utilized in this study was found to overpredict the likelihood of exceeding a given capacity reduction by about a factor of two compared with the observed frequency, more or less independent of spatial scale, forecast lead time, and capacity reduction threshold evaluated. A proper calibration of ensemble prediction systems, however, requires a long-term data collection that is not currently available.

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LIST OF ACRONYMS AND SYMBOLS

AFP	Airspace Flow Program
AIAA	American Institute of Aeronautics and Astronautics

ATEC	Army Test and Evaluation Command
ATL	Hartsfield-Jackson Atlanta international airport
ATM	Air Traffic Management
BOS	Boston, Massachusetts Logan international airport
DCA	Ronald Reagan Washington national airport
DST	Decision Support Tool
EWR	Newark Liberty international airport
ETH	Swiss Federal Institute of Technology ("Eidgenössische Technische Hochschule" in German), Zurich, Switzerland
ETMS	Enhanced Traffic Management System
FAA	Federal Aviation Administration
FCA	Flow Constrained Area
GFS	Global Forecast System
GTG	Graphical Turbulence Guidance (product)
JPDO	Joint Planning and Development Office
MAP	Monitor Alert Parameter
MM5	Pennsylvania State University/NCAR Mesoscale Model Version 5
NAM	North American Model
NAS	National Airspace System
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NextGen	Next Generation Air Transportation System
NSF	National Science Foundation
NWP	Numerical Weather Prediction
NWS	National Weather Service
ORD	Chicago O'Hare international airport
OPSNET	FAA's Operations Network
RNP	Required Navigation Performance
RT-FDDA	Real-Time Four-Dimensional Data Assimilation (and forecasting system)
SESAR	Single European Sky ATM Research
TFM	Traffic Flow Management
US	United States (of America)
UTC	Universal Time Coordinated
VIS	Visible (satellite observing channel)
WAF	Weather Avoidance Field
WRF	Weather Research and Forecasting (model)

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