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4.1 INTEGRATION OF PROBABILISTIC WEATHER INFORMATION WITH AIR TRAFFIC MANAGEMENT DECISION SUPPORT TOOLS: A CONCEPTUAL VISION FOR THE FUTURE

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1. INTRODUCTION

Convective storms exert a disruptive influence on aviation—both in the terminal area and en-route air traffic flow—causing flight delays and cancellations (e.g., Krozel et al. 2003; Krozel and Murphy 2007). Strategic flight planning requires weather forecasts several hours into the future, which draws heavily 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 6 – 12 hours, but also information about storm structure, intensity, and organization, and the associated forecast uncertainty.

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, incomplete understanding of weather processes across a wide range of scales, and caveats in NWP models. The use of probabilistic weather forecasts is an emerging area of research that attempts to characterize and quantify this inherent prediction uncertainty often based on ensemble modeling (e.g., Hamill et al. 2000; Roebber et al. 2004; Lewis 2005). An ensemble forecast—i.e., a collection of typically 10 – 50 weather forecasts with a common valid time—may be obtained in different ways based on a time-lagged, multi-model, and/or multi-initial conditions approach (e.g., Arribas et al. 2005; Stensrud and Weiss 2002; Lu et al. 2007; Lawrence and Hansen 2007). The hope of ensemble modeling is that the spread achieved among the various ensemble forecast members may, on average, bracket the true weather outcome. How to achieve well-calibrated ensemble forecasts with reliability and resolution, however, is an area of active research (e.g., Jolliffe and Stephenson 2003; Hamill et al. 2004; Gneiting et al. 2007).

Many weather services around the world are employing ensemble-based forecasting techniques for large-scale, coarse-resolution, medium- (2 – 10 days) and long-range weather and climate prediction purposes. Such an approach, however, hasn't transcended yet into operational mesoscale, high-resolution, short-range (0 – 2 days) and storm-scale ensemble weather forecasting. There are many challenges, including much higher demands on computing capabilities and an increasing need to understand boundary-layer, cloud, and precipitation processes at smaller scales with increasing model resolution (e.g., Roebber et al. 2004). For example, a NWP model run at 10 km (or coarser) resolution may employ parameterized convection schemes, while high-resolution models with grid sizes of a few kilometers require explicit physics packages to fully describe the dynamic and microphysical processes (e.g., Weisman et al. 1997). For many practical reasons, there has been a trade-off between high-resolution (e.g., providing details about storm structure and organization) and ensemble modeling (providing information about prediction uncertainty). Thus far, high-resolution mesoscale and storm-scale ensemble forecasting have been attempted only on limited-area, regional domains and primarily in a research or real-time demonstration mode (e.g., Grimit and Mass 2002; Xue et al. 2003; Liu et al. 2006; Jones et al. 2007; Stensrud and Yussouf 2007). Yet aviation users may significantly benefit from the wealth of information that such short-range (0 – 2 days), high-resolution (<10 km grid size) ensemble weather prediction models will be able to provide.

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Optimization of air traffic management (ATM), especially under future scenarios of anticipated much increased demand, requires automated decision support tools that integrate probabilistic weather information to estimate airspace capacity and provide guidance for managing air traffic flows (e.g., Prete and Mitchell 2004; Schleicher et al. 2004; Hunter et al. 2005; Krozel et al. 2006a; Spencer et al. 2006; JPDO 2007; Souders et al. 2007).

This paper presents a novel approach of how high-resolution ensemble weather forecasts in the not-too-distant future may get analyzed from an aviation point of view and packaged for integration with automated ATM decision support tools (see Steiner et al. 2007 for details). This new approach draws upon recent experience gained with probabilistic convective scenario forecasts (e.g., Davidson et al. 2004, 2006). The focus of the study is on convective storms primarily because of their disruptive influence on air traffic flows. However, the concepts discussed here may be applicable to other en-route weather hazards, such as turbulence and icing, as well.

2. AVIATION WEATHER FORECASTING

2.1 A novel approach

This section introduces a new concept of how probabilistic weather forecast information may be generated and interfaced with automated ATM decision support tools. The novel aspect concerns the way weather data gets processed to yield aviation-relevant information. Figure 1 sketches the weather data processing steps at a high level.

In the future, weather forecast systems will provide ensemble-based, high-resolution and explicit microphysics, probabilistic forecasts, where each ensemble member may be regarded as a “deterministic realization” of the potential weather outcome. The expectation is that the breadth of potential weather outcomes exhibited by the ensemble members, on average, brackets the true weather outcome. However, this is not necessarily the case and constitutes a topic of active research.

An ensemble forecast may typically include somewhere between 10 and 50 members. Rather than creating an ensemble mean and spread (e.g., standard deviation), as is often done, the following processing steps are applied to each ensemble forecast member. First, a grid network is overlaid on the forecast—for simplicity a Cartesian grid is shown in Figure 1, but any other grid, such as airspace structures (e.g., Air Route Traffic Control Centers or sectors), may be used instead as well. Second, within each grid box the patterns of weather hazards (e.g., convective storms, areas of turbulence or icing) are analyzed in terms of their location, intensity, organization and spatial extent, orientation, and temporal persistence (e.g., movement, growth, or decay). From an aviation perspective, it is crucial to obtain information on how much of a region may be impacted by hazardous weather, its spatial organization, and whether there may be gaps in between hazardous areas that are large enough for aircraft to pass safely through. This analysis of the hazardous weather pattern may yield information on the permeability or porosity of the spatial organization, for example, characterized by the physical spacing between storm cells or the bottleneck from an aviation standpoint (i.e., the use of MinCuts determined according to Mitchell et al. 2006). Third, compositing this kind of information across all ensemble forecast members yields a probability distribution function (pdf) for each grid box, and thus a forecast of gridded pdf’s, as shown in Figure 1. Figure 2 shows how this new approach differs from a more common practice of generating ensemble means (that tends to smear out storm intensity and organizational details), and how the advocated new approach may be beneficial to aviation users.

If multiple parameters are computed as part of the weather hazard pattern analysis (e.g., fractional area coverage, number of storms and sizes, gaps in between storms, MinCuts, echo tops, etc.), a forecast of gridded pdf‘s will result for each one of them. We anticipate that a handful of carefully selected parameters may yield enough information to satisfy aviation needs—for instance, to estimate maximum airspace capacity—although the choice of these parameters remains a research issue.

Note that we haven’t specified any forecast lead time so far. It is anticipated that for very short-term outlooks (less than 1 – 2 hours) the various ensemble forecast members will be rather similar, which may result in well-defined, narrow pdf’s. On the other hand, long lead times will produce forecasts with substantial uncertainty and thus likely wide pdf’s. A detailed assessment of this and also what constitutes a meaningful and useful pdf from an ATM perspective is the subject of further study.

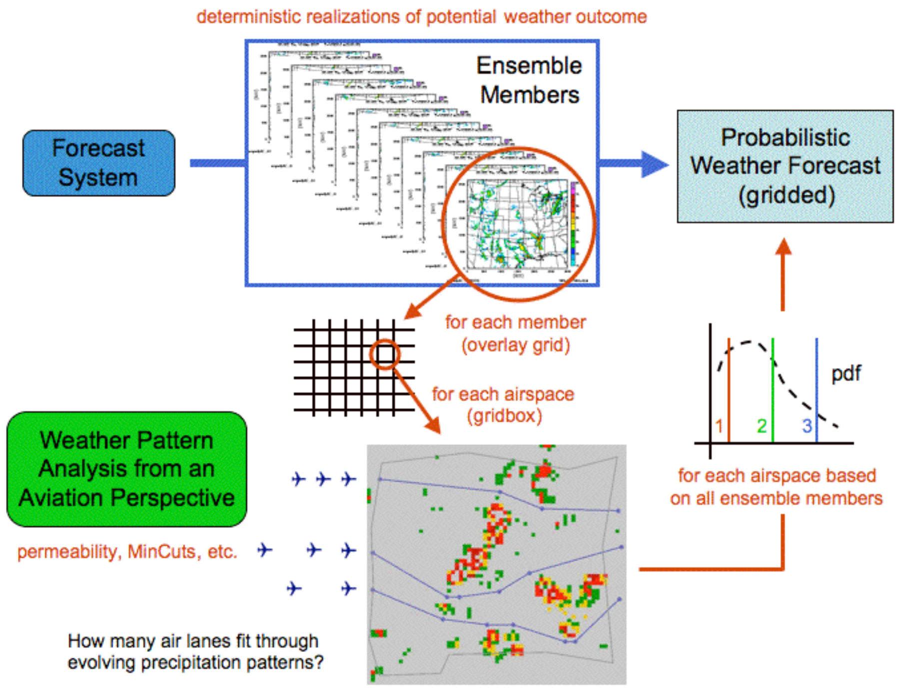

Figure 1. Novel processing of weather information tailored to aviation needs.

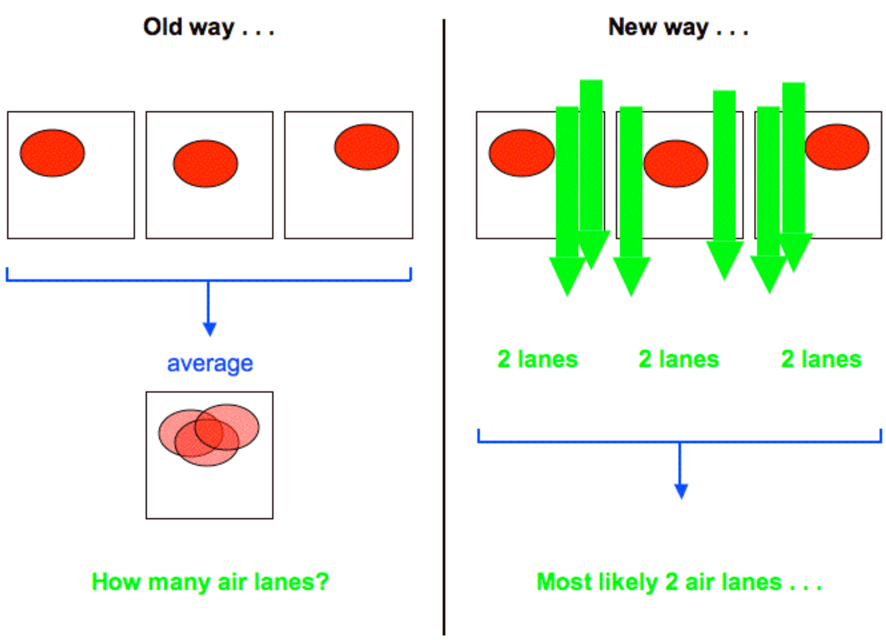

Figure 2. Contrast between the "old" (i.e., ensemble mean) and "new" ways (advocated in this paper) of using ensemble weather forecasts for aviation purposes.

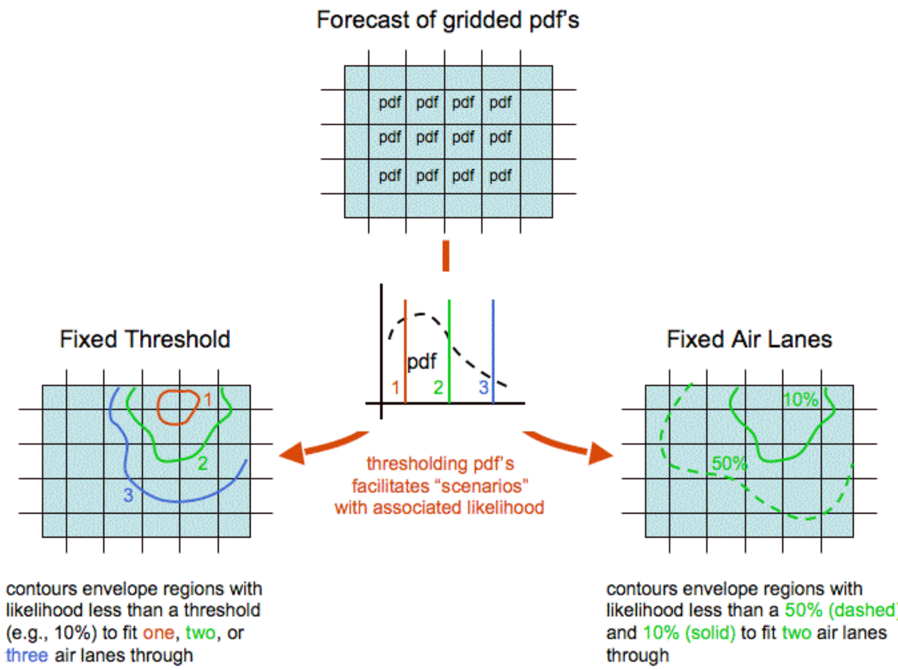

Figure 3. Visualization of weather impact on air traffic flow. Regions of reduced potential capacity can be highlighted with contours, where the applied threshold assigns a likelihood to a particular contour.

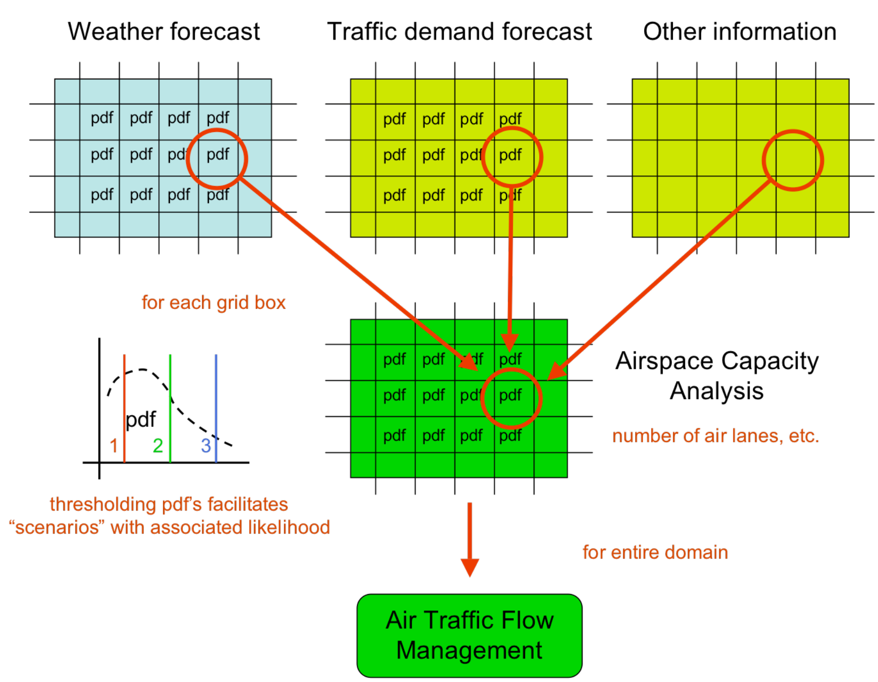

Figure 4. Integration of probabilistic information on weather and air traffic demand, plus other relevant information, such as airspace structure, equipage or pilot behavior, into an airspace capacity analysis used for ATM decision making.

2.2 Utility of probabilistic forecasts

The working hypothesis is that the forecasts of gridded pdf's, discussed above, will provide a comprehensive weather information basis for an airspace capacity analysis. For example, as shown in Figure 3, a pdf representing a given domain in space reveals the likelihood that one, two, three or more air lanes may fit through that domain, which could be interpreted in terms of scenarios with associated likelihood. Moreover, this information can be visualized across a larger region to provide a human with a broader spatial context that shows where weather may potentially impact air traffic flow and to what extent. Shown here are two options: Figure 3 highlights areas with reduced capacity, where (1) chances to fit one, two, or three air lanes through the hazardous weather may be less than a selected threshold (e.g., 10% in bottom left panel) or (2) chances to fit two air lanes through the hazardous weather may be less than several selected thresholds (e.g., 50% and 10% in bottom right panel). Note that we have used air lanes (according to Mitchell et al. 2006) here simply as an example, but any other weather-related parameter could be displayed in a similar fashion as well.

2.3 Integration with air traffic management

For each domain (i.e., grid box, sector, center, or flow constraint area), the estimation of an expected (probabilistic) airspace capacity—or multiple scenarios thereof with associated likelihood—will be based upon pairing the above discussed probabilistic (pdf) weather information with an anticipated (forecasted) air traffic demand and its uncertainty (another pdf), existing airspace structures and other relevant information (e.g., type of aircraft, pilot behavior, airline regulations), as sketched in Figure 4. It is recognized that the estimation of air traffic demand in advance is burdened with significant uncertainty (e.g., Wanke et al. 2003; Cobb et al. 2004; Jardin 2004, 2005; DeLaura and Evans 2006; DeLaura et al. 2008) similar to weather forecasting. ATM decisions will ultimately be based upon analysis of the capacity in space (i.e., across many domains) as a function of time. Space-time analyses are at the root of these analysis techniques.

Figure 4 is a generic depiction of how probabilistic weather and air traffic demand information is combined to estimate airspace capacity, or a reduction thereof given impacting weather hazards. Nothing has been said about how exactly the capacity will be estimated; all that has been laid out so far (e.g., Figure 1) is how the weather information may get packaged into a probabilistic form (i.e., pdf's) tailored according to aviation needs. Therefore, the presented concept could be combined with a variety of airspace capacity estimation approaches, such as explored by Martin et al. (2006), Mitchell et al. (2006), Krozel et al. (2007), or Ramamoorthy et al. (2006). For example, Martin et al. (2006) explore a statistical model relating weather characteristics to en-route airspace blockage, while Mitchell et al. (2006) study idealized computations of the geometric flow capacity in a region experiencing either deterministic or stochastic weather constraints to obtain probability distributions of the throughput capacity of an airspace given a probabilistic weather forecast. Ramamoorthy et al. (2006) discuss a real-time experimental software tool that can be used both as an evaluation and a development platform for traffic flow management strategies.

Once the airspace capacity is assessed, decisions can be made about how to manage the air traffic flow and, especially, how to manage airspace congestion. Ramamoorthy et al. (2006) promote an advanced tool for exploring various traffic flow management strategies, while Wanke et al. (2005) and Zobell et al. (2006) discuss a novel approach to probabilistic airspace congestion management. Bilimoria et al. (2000) and Menon et al. (2005) elaborate on NASA's Future ATM Concepts Evaluation Tool (FACET), a simulation environment for the development and evaluation of advanced ATM concepts. Krozel et al. (2006b) are exploring new traffic flow management strategies from a theoretical perspective, based on analyzing the geometry of hazardous weather constraints and how flows must pass around such constraints.

2.4 Issues warranting further research

There are a number of issues related to the weather information, ATM, and the integration and verification thereof that require further in-depth evaluation. The elaborations below aren't meant to be fully comprehensive (and they certainly are not), but to provide a flavor of the kinds of research that may be needed to fortify the presented concept and identify its opportunities and limitations. The order of the issues listed doesn't necessarily reflect upon their importance, rather they are grouped thematically.

(a) Weather:

- How does the spatial organization of weather hazards depend on storm type and storm environment? How persistent are these features? This may provide information that could be useful to enhance predictive skills.
- How well do NWP models reproduce the spatial organization of storms (e.g., see Bateman et al. 2008; Phillips et al. 2008)? What are the tradeoffs between higher model resolution and number of ensemble members?
- What is an effective way to generate ensemble members that bracket a potential weather outcome while at the same time providing reliable and sharp forecasts, and how many ensemble members may be needed? Note, that this and the issue above are major ongoing research foci of the atmospheric modeling community.
- How should the weather patterns be analyzed to be most valuable from an aviation perspective? What convective (or other hazardous) weather parameters are useful in predicting sector capacity reductions (e.g., see DeLaura et al. 2008)? What is the appropriate scale (i.e., resolution) for the overlaid "weather analysis" grid network?
- To what extent can predictions be made about the type of storm organization within a domain even in the absence of skill in forecasting the correct location? What is the useful prediction horizon for those parameters? To what extent does this depend on spatial (i.e., box size) and temporal (i.e., outlook time) scales?
- What makes a weather pdf useful for ATM? How do weather pdf's depend on storm type and storm environment? What are the space and time correlations among pdf's in different grid boxes?

(b) Air traffic management:

- How does uncertainty in weather forecasts measure up against uncertainty in air traffic demand and pilot behavior? It seems that one can do little about weather uncertainty (besides properly accounting for it), but maybe there is hope to somewhat influence air traffic demand uncertainty? Can individual pilot behavior be recorded and accounted for in the future ATM system?
- There are many ways to deal with uncertainty. However, how do we make sure that situational combinations—both from a weather and aviation perspective—yielding extreme flight delays and/or cancellations are grasped properly?
- What role does weather really play in the ATM of the national and international airspace? In other words, how much improvement could be achieved if ATM would have access to the perfect forecasts today, or in the future?
- How many different types of weather products are required to satisfy the weather information needs for terminal and en-route ATM? What are the differences and common needs for forecasting terminal versus en-route weather constraints? If multiple products have to be tailored to specific aviation needs, they should nonetheless be consistent with each other—i.e., a consensus is needed among various weather forecast products.
- How should weather information be integrated into a future, largely automated ATM decision making process, yet enable a human (e.g., airline dispatcher or air traffic controller) oversight and interaction with the system?

(c) Diagnostic, calibration, and verification:

- What is the baseline air traffic pattern to measure weather impacts against? What is the baseline for assessing improved performance of one integrated weather/ATM approach over another?
- What diagnostics should be computed in real time—both on the weather and air traffic flow side—to provide useful feedback on prediction performance? Preferably they should be intuitive and simple.

3. SUMMARY

Air traffic delays and cancellations, to a very large extent, are caused by weather hazards impacting terminal and en-route airspace. With air traffic demands expected to substantially increase in the future, weather-related impacts will remain a primary concern for aviation. Significant efforts have been and continue to be devoted, therefore, to integrate weather information with ATM decision support tools. This paper presents a novel approach of how weather forecasts in the not-too-distant future may get analyzed from an aviation perspective and packaged for integration with automated ATM decision support tools. The focus here has been on convective storms primarily because they are the leading disruptive influence on air traffic flows. However, the concepts developed here may be applicable to other en-route weather hazards, such as turbulence and icing, as well. Moreover, strategic flight planning requires weather outlooks several hours ahead, which draws heavily upon NWP models that (hopefully) are able to forecast weather patterns with great detail (i.e., need for short-range, high-resolution and explicit microphysics models) and provide forecast uncertainty (i.e., make use of ensemble techniques).

Probabilistic ensemble weather forecasts so far haven't really found their way into aviation applications. Besides model resolution, physical process understanding and parameterization, how to create calibrated and sharp ensemble systems, and computational issues, part of the problem has been the way the information gets packaged and communicated. For example, weather information relevant for ATM users, such as storm organization and intensity, is getting too blurred in ensemble-mean forecasts. Thus, a different approach of processing ensemble-based weather forecasts is called for. This paper provides a new way of characterizing weather patterns, not only specifically from an aviation user perspective, but also by analyzing every ensemble member forecast individually before compiling that information into an aviation-tailored probabilistic forecast that can be integrated with automated ATM decision support tools.

This study does not provide a final, turn-key solution. Rather, it lays out a new conceptual approach for how probabilistic weather information may be created and integrated with automated ATM decision support tools. This new concept needs to be further developed and evaluated. Therefore, the paper lays out a roadmap providing a direction for new aviation weather research and development activities.

Moreover, the advocated approach of making use of ensemble weather forecasts to generate probabilistic weather forecast tailored for aviation needs, is fitting nicely with complementary efforts going on at Metron Aviation (Krozel et al. 2007), MIT Lincoln Laboratory (DeLaura et al. 2008), and MITRE's CAASD (Zobell et al. 2006).

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