Using Stochastic, Dynamic Weather-Impact Models in Strategic Traffic Flow Management

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1. Introduction

Traffic flow management (TFM), i.e. the balancing of demand with capacity in a transportation network through prescient action, is a key need in the United States National Airspace System (NAS). While TFM capabilities have been extensively developed for the NAS over many years, the increasing cost of air transportation as well as the ever-growing congestion of the NAS requires new approaches for managing traffic. As the NAS operates near its tolerance, it is critically important that automated decision-support tools be developed that coordinate TFM capabilities at increasingly larger spatial scales and provide plans over longer time horizons. A key goal of the Next Generation Air Traffic System (NextGen) project is the development of such *strategic* decision-support tools that enable coordinated controls to be identified that effectively manage congestion at a NAS-wide scale and 2-24 hour time horizon.

A wide research effort is underway in the air transportation community, to develop strategic traffic flow management capabilities. As this research progresses, several key challenges in strategic TFM are coming to the forefront. One key challenge, which is the motivation for the work presented here, is the critical role of uncertainties – specifically, uncertainties in weather evolution and its impact on air transportation – in decision-making at the strategic time horizon. For instance, stakeholders in the NAS must often develop a plan to respond to a potential weather event (e.g., a developing winter storm in the Northeastern United States) for a long look-ahead time (e.g., a full day). At this time horizon, there is a significant uncertainty in forecasting weather evolution and its impact on the NAS. As such, there often is not a single plan that can manage the disruptions from all possible weather outcomes to the satisfaction of the stakeholders. The development of decision-making tools that can account for and react to these uncertainties efficiently and equitably is a difficult challenge.

Flow Contingency Management (FCM) is a proposed operational concept for a decision support tool for strategic TFM that can address core challenges including the need for action in the face of significant uncertainty. The core principle of FCM is that it generates and manages multiple sets of control action plans, or *contingencies*, at the resolution of aggregated traffic flows in the NAS, in order to span the range of likely outcomes. For FCM to define such plans it is critical that tools and capabilities be developed that 1) can rapidly identify probabilistic trajectories or futures or *scenarios* of weather and its impact on traffic flows, 2) permit computation of weather-impact statistics, and 3) can readily be interfaced with dynamic traffic models to permit efficient design of contingency plans. We believe that these modeling needs currently are not fully addressed in either the weather forecasting or the air transportation community, and that collaborative effort between transportation engineers and weather forecasters is needed to achieve the required weather-impact modeling capabilities. The purpose of this

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article is to introduce one approach to weather-impact scenario generation for the NAS that leverages existing weather-forecasting capabilities and yet can provide the necessary information for FCM. Through this development, we also intend to convey more broadly that weather and weather-impact forecasting capabilities for the National Airspace System (NAS) are badly needed and challenging to develop, and as such aim to foster discourse between weather forecasters and air transportation engineers on suitable methodologies.

Given the need for probabilistic scenarios of weather impact in FCM, ensemble-forecasting and probabilistic-forecasting tools are of significant interest to us, and we have considered their use in scenario-generation for FCM. For several reasons, these forecast products do not directly yield solutions for FCM:

1) The forecasts describe weather phenomena, while we require models for the NAS-related parameters (e.g., regional capacities, airport acceptance rates, etc), many of which are discrete-valued quantities. Thus, the probabilistic forecasts require translation to weather-impact forecasts.
2) The ensemble and probabilistic forecasts often do not provide trajectories of weather (or weather impact) evolution at the temporal and spatial resolution necessary for providing the TFM decision support capabilities desired as current propagations of weather display complex uncertain spatial and temporal correlations (rather than only initial-condition uncertainties). As such, FCM requires tools and information that can provide a much larger family of scenarios with realistic temporal and spatial correlations than are directly evident from ensemble or probabilistic forecasts.
3) We require tools that permit scenario-generation and statistical analysis at low computational cost, and can be integrated or interfaced with traffic flow models. To produce the information required for FCM, an abstraction of the physics of weather dynamics is permissible, if it enables fast estimation of the variability of weather impact.

While ensemble and probabilistic forecasts do not directly address our needs in FCM, it is critical that we leverage these forecasting capabilities to inform weather-impact scenario generation. The approach for scenario-generation that is suggested here makes use of ensemble and probabilistic forecast capabilities to construct the scenario generator which generates FCM-relevant scenarios that match and interpolate the probabilistic weather forecast.

In pursuit of the FCM goals stated above, we have introduced a new concept for dynamic weather-impact modeling in our earlier work (Roy, 2010). This methodology aims to fulfill the FCM concept requirements of providing weather-impact rather than weather information, tracking dynamics at the proper resolution, and achieving low-computation analysis. Our approach to weather-impact simulation is based on a stochastic, dynamic network model known as the influence model. At its essence, the simulator aims to capture the propagation of weather-impact among airspace regions using simple probabilistic selection and adaptation rules. This abstract description appears to permit realistic scenario-generation and statistical analysis with little computational effort, while capturing the rich temporal and spatial propagations/correlations that are observed in real weather. This simulator is able to generate multiple simulated weather impact outcomes for each set of initial conditions, and allows simple analysis of weather-impact statistics at critical airspace locations. While the simulator thus shows promise as a tool for FCM, in our previous work we did not attempt to construct the simulator to match real weather-forecast outcomes. Thus, a key need in further development and evaluation of the simulator is to parameterize the model to match a particular period's weather forecasts so that the model generates weather futures that are likely for that particular forecast period. In this paper, we envision and then illustrate the use of ensemble-forecast and probabilistic-forecast data for this parameterization, and thus clearly link ensemble or probabilistic forecasting with weather-impact modeling. Our initial results are promising, but also bring forth many new questions at the interface of weather forecasting and transportation network engineering.

In sum, this article aims to 1) introduce the weather forecasting community to needs in flow contingency management and the weather-impact simulator concept, 2) evaluate weather forecasting capabilities from the perspective of their use in FCM, and 3) illustrate the parameterization of the weather-impact simulator using ensemble/probabilistic forecast data. To this end, we progress as follows:

- In Section 2, we introduce the weather-impact simulator.
- In Section 3, we conceptualize how several ensemble and probabilistic weather-forecasting products can be used to construct the weather-impact simulator, and more generally to inform weather-impact modeling for FCM. In the process, we also highlight the need for further insight from the weather forecasting community in impact modeling.
- In Section 4, we present an example illustrating the parameterization of the weather-impact simulator using ensemble- or probabilistic- forecast data.

2. The Weather-Impact Simulator: Review

In (Roy, 2010), we developed a *stochastic network model* for the spatial and temporal evolution of weather impacts, which is promising as a tool for FCM. Specifically, this work enhanced previous efforts that examined weather-impact forecasting at the strategic timeframe, see (Steiner and Krozel, 2009) and (Ren et al., 2007), to capture the *dynamics* (time-evolution) of weather impact. This dynamic model is promising for FCM because it 1) can permit fast generation of weather-impact scenarios with realistic levels of uncertainties, 2) can be incorporated into aggregate models for traffic flow dynamics, and 3) can permit computationally-efficient analysis of temporal and spatial correlations in weather impact. In (Roy, 2010), we argued for using a particular *networked-Markov-process* model, called an *influence model*, for the spatial and temporal evolution of discrete-valued weather impacts. The influence model is promising for weather-impact modeling because it can capture a rich set of stochastic evolutions as needed for weather-impact modeling, yet its special structure allows us to 1) parameterize the model based on current weather impact and a weather-impact forecast at a future time and 2) simulate and achieve statistical analysis of weather impact. In (Xue, 2010a), we provided a detailed conceptual/mathematical introduction to the weather-impact model, and explained at a conceptual level how parameterization and simulation/analysis could be undertaken using the model. We also gave several illustrative examples of the model's use. *However, critically, we did not demonstrate construction of the model for a real historical weather scenario, based on weather-forecast data.* In Section 4, we will construct a weather-impact model for propagation of convective weather during a bad-weather day in Atlanta using probabilistic forecasts. This concrete example is of importance in that it indicates the feasibility of the weather-impact modeling approach in capturing real weather events, while also highlighting challenges in constructing and using the model.

Here, for the reader's convenience, we repeat the development of the weather-impact model given in (Roy, 2010). Specifically, we first formulate the influence model for weather impact (Section 2.1), then overview the approach to model parameterization (Section 2.2), and finally give an overview of scenario-generation and statistical analysis of the model for FCM (Section 2.3). Compared to our previous development, we extend the model-parameterization discussion to list concrete challenges in parameterization from real weather forecasts, which then will be addressed in Sections 3 and 4. We also briefly highlight recent progress in interfacing the weather-impact model with queuing models for FCM in Section 2.3.

2.1. Model Formulation

At the strategic time frame, prediction of fine weather structure and its consequent impact on air traffic is probabilistic. That is, weather prediction capabilities are accurate enough to yield probabilities of weather-impact events (Steiner, 2009), but not to predict these events with certainty. For instance, weather models may be able to predict the passage of a cold front through a terminal, but most likely will not be able to predict the precise locations of capacity-reducing convective cells along the front, nor pin down the front-passage time exactly. Given this fundamentally probabilistic description of weather impact at the strategic time horizon, our goal is to develop a model for weather-impact dynamics (time evolution) that is stochastic but matches the probabilistic descriptions that have been obtained from weather forecasts at one or several times. In other words, we are seeking a model that provides a different sample of weather-impact dynamics (time-evolution) on each simulation (reflecting the inherent uncertainty at this time frame), but with statistics that match probabilistic forecasts at one or several times. Such a stochastic model for weather impact is valuable because it can permit statistical evaluation of flow-management performance, through simulation and mathematical analysis (if the model is sufficiently tractable). Let us describe a class of models that can capture stochastic weather-impact evolution, and then discuss selection of model parameters to match forecast probabilities.

Let us consider modeling weather-impact states in regions of the airspace. These may be selected according to the user's preference, for instance the regions may be air traffic control sectors (see Figure 3.6) or may be lattice squares in the airspace (see e.g. Figures 3.9 and 3.10). Specifically, we view each region of the airspace (or **site** in the model) as having a discrete-valued **weather-impact state** evolving in time, which reflects the operational characteristics of the airspace region resulting from weather events during a strategic (one-day) time horizon. For instance, en route airspace may be simply modeled as having three possible weather-impact states, Full Capacity (F), Reduced Capacity (R), and No Capacity (N), or more precisely modeled with multiple levels based on characterizations of capacity (Song, 2007). We note that the modeling framework allows different cardinalities of weather-impact states in different regions, so for instance terminal-area airspaces could be represented at higher fidelity than en-route ones.

Each region's weather-impact state is viewed as evolving stochastically. The state evolution is modeled as occurring in discrete time, but we note that the time-step of the model may be chosen at our convenience (with the understanding that the computational complexity of model analyses are inversely proportional to the time-step); here, we will choose a time-step that matches the temporal granularity of flow-management actions (e.g., 15 minute intervals). In particular, we model the weather-impact states' evolutions as a *networked Markov process*: at each time (time-step), each region's next state is generated based on probabilistic influences that are modulated by its neighbors' current states. More precisely, we model each region at a particular time instance as being probabilistically influenced through weighted random selection of a single neighboring upstream region (possibly including itself). Specifically, each site in the network is viewed as selecting one among several upstream neighbors (as specified by a **network graph**) with some probability, whereupon the current weather-impact state of the upstream neighbor specifies the probability of the site's next state. We notice that this type of stochastic update can be interpreted as follows: first, each site's selection probabilities can be viewed as capturing spatial influence rates/strength (and hence we call them **network influence rates** or **probabilities**); second, the stochastic update from the selected neighbor's current weather-impact status captures the nature of weather-impact propagation due to these influences (and hence is specified by **local influence matrices**). Stochastic update equations of this form can be used to capture typical weather-impact progressions, including generation, dissipation, persistence, and drift of weather impact, while still capturing the significant variability in weather at the strategic time frame. Furthermore, the model for weather impact that we have given falls in the class of *influence models* (Asavathiratham, 2001), a sub-class of stochastic network models whose statistics are especially tractable, and easy to parameterize and simulate.

We kindly ask the reader to see the Appendix of (Roy, 2010) for a brief mathematical formulation, and to see (Asavathiratham, 2001; Asavathiratham, 2000; Roy, 2003; Wan, 2009; Xue 2010a) for a thorough formulation and analysis of the influence model. Very briefly, these studies show that the influence model has the following core tractability: statistics of individual sites and small groups of sites can be found with little computational effort, using low-order linear recursions. Of relevance to our development here, we note that the computational complexity of finding individual sites' status probabilities is quadratic in the number of sites and the number of statuses, while the complexity of correlation-analysis exhibits a quartic (fourth-order) dependence. The methods used in the context of the weather-impact model fundamentally derive from this special tractability. Now that the model has been formulated, let us summarize results on its parameterization, simulation, and analysis, before developing three examples.

2.2. Parameterization

To permit quantitative prediction using the weather-impact model, we must first parameterize the model. We propose to parameterize the model so that it's predicted weather impact matches current weather impact at zero prediction time, and matches probabilistic forecasts of weather impact at one or more future time snapshots. To achieve such a parameterization, two advances are fundamentally needed: as a preliminary step, weather forecasts must be translated to weather-impact forecasts (upon selection of a proper weather forecast, see Section 3); and second, the influence model parameters must be designed to match the forecasts at times of interest. The problem of translating weather to weather-impact has begun to been considered in the air transportation literature: we ask the reader to see (Steiner, 2009) and (Ren, 2007) for some preliminary ideas on how weather impact forecasts can be obtained from ensemble weather forecasts, and we also note that methods for capacity estimation can be brought to bear for translation. The probabilistic weather-impact forecasts obtained through such translation may themselves provide value for traffic management, but 1) only indicate weather-impact probabilities in individual regions and not correlations among weather impacts in several regions, and 2) are valid at only certain widely-spaced time snapshots. Once these forecasts have been obtained, we are thus required to find parameters for the dynamic weather-impact model that we have proposed so as to match the forecasts. This problem can be viewed as that of designing an influence model's interaction parameters, so that individual sites' state probabilities meet forecasts at one or a few time-snapshots. We have partially addressed this snapshot-design problem in our concurrent work (Xue, 2010a), and here propose using and extending the developed methodology to parameterize the weather-impact model.

Although our focus is on motivating and using the weather-impact model, let us briefly discuss the mathematics underlying the snapshot-design method, to give the reader some intuition into the model's parameterization. The snapshot-design problem is related to numerous problems on *inference* of stochastic network models, but differs from the bulk of these problems in that the parameters are being obtained from a probabilistic forecast rather than from data, and therefore information is available at only a few time snapshots. Fundamentally, our method for snapshot design (Xue, 2010a) derives from a core tractability of the influence model. Let us discuss this tractability and hence the method for parameterization, using terminology specific to the weather-impact model for the reader's convenience. Specifically, the relevant tractability of the weather-impact model is that individual regions' weather-impact probabilities can be found over time without considering correlations and other higher-order statistics, and hence can be computed using a low-order linear recursion (one whose dimension is on the order of the number of regions). The snapshot-design problem thus can be viewed as a problem of designing the low-order linear recursion to achieve desired weather-impact probabilities at particular time-steps, while maintaining the specified graph structure of the model (in our case, reflecting that influence interactions occur between geographical neighbors). This design problem has been solved for various cases using both iterative methods and explicit computations in (Xue, 2010a); we ask the reader to see that paper for details (see also (Xue, 2010b) for a related method). It is worth noting that model parameters may remain free even after the probabilistic forecast is matched, and this additional freedom can be used to capture further qualitative and quantitative features of the weather-impact dynamics. In the example given in Section 4, we will discuss how these additional degrees of freedom can be exploited to tune the extent of spatial and temporal correlation of the weather-impact trajectories.

Beyond the systematic parameterization discussed above, a couple of ad-hoc approaches are worth noting. Of interest, if probabilistic forecasts are not available and instead only some aggregate predictions about weather-impact are available (e.g., location of a cold front), model parameters can be inferred so that the weather propagation has certain basic characteristics (e.g., a drift speed or a growth or decay characteristic over the time horizon). Weather model outputs such as wind-field maps can also aid in constructing the networked Markov models. We will explore this possibility in future work. We will also continue to study the automated translation of weather forecasts to weather-impact snapshots, so as to best leverage forecasting capabilities in parameterizing the weather-impact model.

2.3. Simulation and Analysis

The special structure of the influence model dynamics permits fast simulation and significant analysis of weather impact, once the model has been parameterized. Let us list several of the key analyses of weather impact that are permitted by the model's special structure:

1. **Simulation** of weather impact over a one-day time horizon, with very little computational and storage effort; specifically, effort scales linearly with the number of regions and the duration of the simulation. Individual scenarios can be generated very quickly, in less than 1 second of computation time. Multiple spatiotemporal trajectories can thus be easily obtained based on the probabilistic description, and so the range of possibilities in weather impact can be characterized. We are currently developing a procedure for *representative scenario selection* using a quadrature-based clustering algorithm, whereby a small number of scenarios representing qualitatively-different weather outcomes are selected and assigned probabilities.

These weather-impact scenarios (and/or representative weather-impact scenarios) may be valuable for both designing and evaluating FCM strategies.

2. **Low-order analysis of the time-evolution of weather-impact probabilities in each region**, using the linear recursion for individual regions' state probabilities. Specifically, the computational effort required is that of simulating a sparse linear recursion whose dimension is equal to the number of regions; even for a large-scale example with several thousand regions, the computational complexity is low. This basic analysis serves to interpolate the snapshot forecasts that are being matched through the parameterization, as may be needed in evaluating the performance of FCM strategies (in terms of e.g. delays).
3. **Low-order analysis of spatial and temporal correlations in weather impact at several locations**, with the complexity of the analysis growing gracefully with the number of regions whose joint statistics must be ascertained. Of particular interest, the computational complexity of finding pair-wise correlations (joint probabilities that pairs of sites have certain weather-impact statuses) is roughly the square of the computational complexity of finding individual regions' weather-impact probabilities. This correlation analysis is necessary for the design and evaluation of FCM, since it can be used to indicate patterns in weather impact at critical locations in the airspace.
4. **Analysis of several other temporal statistics of weather impact**, for instance the duration or start/end time of a weather-impact event at a critical location in the airspace (e.g., in a terminal airspace). Characterizing these temporal statistics of weather impact can aid in fast simulation of FCM strategies (Wan, 2011) and in designing non-conservative FCM strategies.

These various tractabilities of the weather-impact model readily follow from the core analysis of the influence model. We have excluded these details, and ask the reader to see the theses (Asavathiratham, 2000), (Roy, 2003), and (Wan, 2009) for them.

The weather impact simulator produces stochastic weather impact dynamics that can guide decision-making for FCM under weather uncertainty. Specifically, the generated stochastic weather impact is interfaced with flow dynamic models, so as to evaluate and design management strategies based on statistical performance measures. We are in the process of developing dynamic queuing network models and the associated analytical and design tools that permit the seamless integration of the weather and flow models, e.g. (Wan, 2011; Zhou, 2011). In (Wan, 2011), we developed a queuing network model, in which stochastic weather impact is considered as modulating the parameters (e.g., capacity constraints) of the queuing network model. In (Zhou, 2011), we introduced two analytical approaches---the integrated Markov chain approach and the jump-linear approach that allow the systemic evaluation of dynamic delay performance under stochastic weather.

3. Using Probabilistic Forecasts to Inform Weather-Impact Simulation

The probabilistic weather-impact scenario generator requires parameterization to match forecast weather predictions, where a major goal of the simulation will be to provide weather impact scenarios that are consistent with the input weather forecasts. Parameterization of the weather-impact model requires weather data including current weather conditions, weather forecasts, and possibly historical data. Historical data can help verify the simulator and parameterization, but it is the weather forecasts that are both critical to parameterization and perhaps the limiting resource in achieving accurate parameterization.

Parameterization can use any type of weather phenomenon that can be hazardous to aircraft and can be translated into capacity impacts, either in en route or terminal areas. Convective weather has historically been the largest weather-related contributor to delay in the NAS (DeLaura, 2008), and is the initial focus of this research. Also, there are several studies of the impact of convective weather on airspace capacity (Davis, 2005; Song, 2007; Krozel, 2007; Klein, 2008; Weber, 2005; Martin, 2006).

Other weather phenomenon including turbulence, icing, winter weather, stratus, surface wind (at runways) can disrupt operations and their forecasts may eventually be incorporated into the impact scenario generator. Storm altitude information, such as storm or echo tops forecasts, may also be included to help predict the altitude impact of storms.

Weather forecasts are needed that adequately cover the strategic FCM decision making time horizons, from 2 hours to at least 8 hours and potentially to 24 hours in the future.

3.1 Candidate Probabilistic Weather Forecasts

Any forecasts used for parameterization must convey information about multiple possible weather outcomes. Probabilistic forecasts convey these possibilities, although in a very basic way. And there are multiple probabilistic forecasts routinely generated that can provide the data needed for this research.

The probabilistic Very Short Range Ensemble Forecast System (VSREF) and Short Range Ensemble Forecast (SREF) forecasts have been selected for the initial parameterization. These forecasts provide a gridded field of weather probabilities for different weather phenomenon, including convection. The VSREF is produced by National Center for Environmental Prediction (NCEP) with forecasts out to 12 hours at 1 hour intervals, and hourly updates (Zhou, 2010). The VSREF is focused on weather that impacts aviation and air traffic management. The SREF is produced by the Storm Prediction Center (SPC) with forecasts out to 87 hours at 3 hour intervals, and updates every 6 hours (Bright, 2009). Our ability to obtain historical forecast data for these forecasts has been a major factor in selecting them.

The High Resolution Rapid Refresh (HRRR) model is an alternate forecast candidate. This is a 12 hour probabilistic forecast produced by the Earth System Research Laboratory (ESRL) (Smith, 2008).

Other forecasts will also be considered for use in parameterizing the simulation, including new forecasts as they are implemented. Weather forecasts must adequately cover the strategic look-ahead times and convey as much information as possible about this range of possible weather outcomes. These forecasts must also forecast the types of weather phenomenon that impact aviation and air traffic management and can be translated to reductions in capacity.

3.2 Ensemble Forecasts

Ensemble forecasts, where each ensemble member can be treated as a possible weather outcome, could also be used to inform the simulation. However, forecasts that include individual members are not widely available. One of the easiest ways to obtain ensembles is to use time lagged forecasts (Zhou, 2010; Bright, 2009); however this technique produces a limited number of members and the members may not be widely varied. Other techniques for generating ensembles include initial perturbation (Wei, 2008; Steiner, 2008). These can produce a wide variety of ensemble members but can be very expensive to generate. Also, there is limited historical data available from ensemble forecasts using initial perturbation.

In addition to the computational expense and lack of data availability, there are other issues associated with using ensemble forecasts. First, it is difficult to estimate the probability of occurrence of each ensemble member and to estimate how well the set of all members covers the potential outcome space given that the real outcome will usually not be an exact match to any of the members. Also, if clients are processing each member instead of using a probability field derived from the members (as is common in today's forecasts), this places a higher accuracy requirement on each member and makes unrealistic outliers less tolerable.

As a result of the aforementioned issues, our initial research effort does not use ensemble forecasts; however future research will continue to investigate their inclusion as ensemble forecasts can have advantages. The ensemble members provide a great deal of additional information beyond what is in a probabilistic forecast. For example, inferring the forecast storm type, speed, and the degree of storm organization may be possible using the ensemble members. This information can be hard to derive from a probability field where the uncertainties in storm location, movement, initiation, growth, and decay are combined.

Finally, if sufficient ensemble members could be cost-effectively generated to adequately cover the outcome space with sufficient lateral and temporal resolution then it may be possible to use these directly to generate impact scenarios. However, this is a difficult and expensive undertaking and it may be a long time before this could be implemented. As such, the probabilistic weather impact scenario generator can delay or replace the need for large expensive ensemble forecasts, while supporting near-term research.

3.3 Forecast requirements for FCM

In order to select the weather forecasting products to be utilized in FCM, it is necessary to carefully consider the weather-impact models and parameterization requirements. For the weather-impact simulator, three sets of parameters need to be identified: initial conditions that drive the simulator, stochastic interactions among regions, and stochastic transitions among weather impacts. The requirements for all three parameters are essentially defined by how accurately the weather-impact simulator is able to produce outcomes that match the probabilistic forecasts and reflect the real physical environment.

Existing weather systems usually provide probabilistic predictions at longer intervals, such as the hourly probabilistic convection forecast in the VSREF. In contrast, the weather-impact simulator can produce impact scenarios using a time step resolution based on the FCM decision making needs. For example, the simulation can generate impact forecasts at every 15 minutes look-ahead. These generated impact forecasts will be consistent with the weather forecast at each hour, and will evolve smoothly through the intermediate forecasts. One advantage of this is that near-term FCM research can be supported without needing changes in the temporal resolution of weather forecasts.

Even though we have identified the desired probability weather impacts at certain time steps, parameterization still requires additional information in order to refine the model to represent the real physical environment. First, current weather conditions are needed to provide initial conditions to the weather-impact simulator. Second, climatic factors can affect how weather evolves among regions of interest. For example, wind, pressure, and temperature can change from region to region and these factors influence storm motion. As such, this data may provide insightful information on weather-impact evolution.

Weather forecast resolution is important in determining whether a forecast can be used effectively. This includes horizontal grid resolution, number of forecast times, and update frequency. This research will help to refine the spatial and temporal resolutions needed to adequately inform the simulation.

Including additional information in probabilistic weather forecasts could be beneficial. Potentially useful information may be provided as inputs to the forecasting system but not conveyed in the forecasts. The convective probability fields combine the uncertainties in storm location, movement, initiation, growth, and decay. Because of this, an area of low probability can be interpreted in many ways. One interpretation could be an area where popcorn convection is likely, and the locations of these small cells are unpredictable. An alternate interpretation of the same result may be an area where an organized line of thunderstorms is predicted, but the speed of movement is uncertain, or the combination of a modest speed inaccuracy with a long forecast time leads to a wide range of possible storm locations. Additional forecast information could include the predicted type of storm, characteristics of storm movement, and degree of organization. These characteristics may vary with location and forecast times, since there may be several storms in the forecast coverage area, and storm properties may evolve with the forecast time. Any information that could help the weather-impact simulation generate more appropriate and realistic scenarios would be valuable.

Unique and accurate parameterization may be possible if enough historical forecast data is available. However, the amount of historical data we currently have is limited. Whether or not current weather forecasts provide enough information to permit accurate generation of weather scenarios using the proposed simulator is an open question. It is possible that forecast data limitations will lead us to alter our proposed scenario-generation methodology, or to tailor it to different types of forecasts.

4. Example: A Parameterized Weather-Impact Model

So far, we have developed a theory for the weather-impact simulator, including formulation and analysis of underlying structure and dynamics, and identification of methods and challenges in parameterizing the simulator. To further support our development and better evaluate the appropriateness of the weather-impact model for use in FCM, we present an example here. In the example, we first choose a particular historical day and a geographical region, consisting of high-altitude Air Route Traffic Control Centers (ARTCCs, referred to from now on as “Centers”) and sectors, for study. We also decide which probabilistic weather-forecast data we will use for the selected area on the selected day based on requirements for parameterization. We then parameterize a weather-impact simulator that matches the weather-forecast data. Once the weather-impact simulator has been constructed, we can implement the simulator, and hence produce a family of stochastic weather-impact scenarios. We organize the rest of this section as follows: (1) we list all the accessible data/information required and used for parameterization, (2) we give a detailed description of the actual simulator parameterization, with a particular focus on identifying challenges in real applications, and show some weather-impact simulation results, and (3) we discuss potential uses of simulation results in FCM and possible improvements of the simulator parameterization.

We note that a full tutorial on the parameterization method requires a technical understanding of the mathematics of the influence model. For the sake of readability, we do not introduce the influence-model mathematics in detail here. Consequently, we largely present the parameterization method at a conceptual level rather than in full mathematical detail. We kindly refer the reader to our tutorial on the weather-impact model for the specifics.

4.1 Data and Preliminary Processing

As discussed in Section 3, we believe that simulator parameterization primarily requires probabilistic weather forecast data (e.g., convection probability or winter-weather probability) on a ground map, and over a time span of interest. Although assisting information (e.g. wind direction, ground terrain) may yield more accuracy and precision in the simulator, in this first example we focus on a simple model construction where such assisting information is not considered. To have some credence as a realistic weather-impact simulator, we note that the probabilistic weather forecast data should generally meet the following two criteria: 1) the represented weather should have a significant impact on air traffic; and 2) the forecast should provide enough information on weather dynamics during the selected time span.

Here we consider convective weather for a region that includes the airspace managed by three Centers, in particular the Atlanta, Memphis, and Jacksonville ARTCCs (denoted ZTL, ZME, and ZJX respectively) during September 26^{th} and 27^{th}, 2010 as our study example. We aim to build the weather-impact simulator based on probabilistic weather-forecast data for this example. Specifically, we will use probabilistic weather data from an ensemble-forecast product, namely the *SPC Short Range Ensemble Forecast (SREF)*, to parameterize the simulator (see (Du et al., 2003) and (Bright and Grams, 2009) for more information about SREF).

Before we illustrate how we will use the selected weather product (SREF), let us give a brief overview of the relevant aspects of SREF here. SPC SREF is an ensemble weather forecast product which uses a post-processing method, e.g. (Raftery et al., 2005; Gneiting and Graftery, 2005). Its primary goal is to predict/analyze high-impact and severe weather, including thunderstorms, hazardous winter weather, and other types of weather that may have a great impact on the air traffic system. Its output is an hourly probabilistic weather prediction across the United States, which is updated (generated) every 6 hours (03, 09, 15, 21 UTC). For example, below (Fig. 1) is one probabilistic thunderstorm forecast output of SREF for the time 11 UTC, 09/26/2010, which was generated at time 09 UTC, 09/26/2010. The spatial resolution of this product is 20 km, and the data resolution is one hundredth of a percent. In this figure, ten different color shades represent ten different probabilities (from 0.03 to 0.66 with common difference 0.07) of having convective weather within the grid square).

In our example development, we will use a set of 25 such hourly probabilistic weather forecasts (from time 09 UTC, 09/26/2010 to time 09 UTC, 09/27/2010), and aim to parameterize the weather-impact simulator to match these probabilistic weather forecasts.

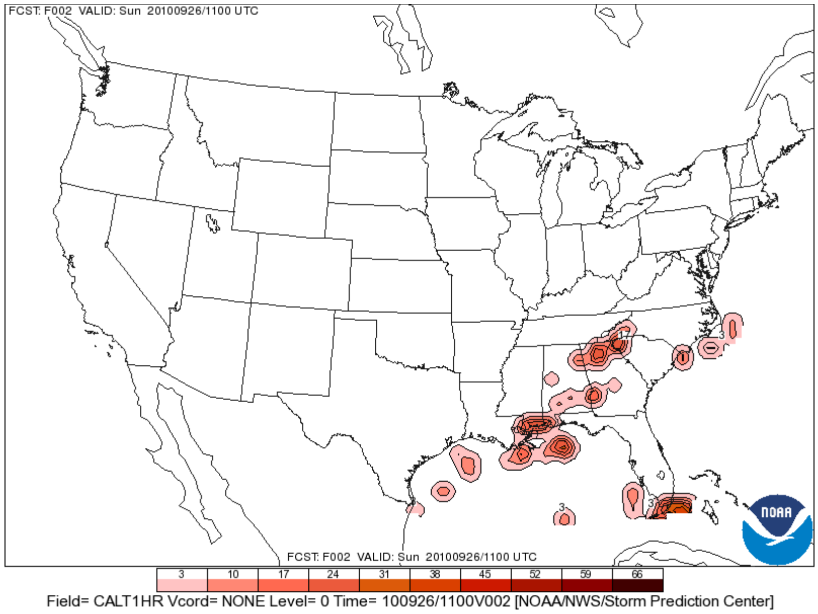

Figure 1: SREF Output at 11 UTC, 09/26/2010.

- **Desired Influence-Model Simulator: Times, Regions, and States**

As introduced above, the influence-model-based weather-impact simulator is a discrete-time Markovian model. We would like to develop a model for a full-day time span (starting at time 09 UTC, 09/26/2010, ending at time 09 UTC, 09/27/2010). Here, we choose 15 minutes as the discrete time interval of the simulator. Thus, the simulator has 97 time steps in our example, with initial condition at time step $k = 0$ (or time 09 UTC, 09/26/2010). In this first simple example, we will also assume that each airspace region has two weather-impact states: full capacity (represented in white in the simulation) and reduced capacity (represented in below). Also, since the weather data contain 25 hourly convective probability weather forecasts, the regional weather-impact probabilities of the simulator (i.e., probabilities of low capacity due to weather impact) at these time steps $(4(n-1)$,for $n = 1, \dots ,25)$ should match the weather-impact probabilities obtained from these forecasts.

In this example, we limit the model to ZTL/ZME/ZJX airspace, both because these three Centers have a higher probability of convection according to the data on the day of interest, and because we plan to use the simulator as part of a more extensive example of flow-contingency management for Atlanta-bound traffic on that day (Fig. 2-a). Because of the procedural difficulty of overlaying an actual Sector map on the weather-forecast map, and the complexity in describing influence model sites for a general Sector map, we simply assume a grid geometry for the model weather-impact region(see Fig. 2-b). As shown in Fig. 2-b, we divide the ZTL/ZME/ZJX centers into 128 (16 by 8) grids (in blue color), each of which represents a square area with size ~50 miles by ~50 miles. We believe that the grid size is small enough to capture the weather-impact variability that is of importance for traffic flow management, yet large enough to meaningfully match and translate the weather-forecast data for this example. As for the influence-model-based simulator, each site of the influence network therefore represents a grid square. Each site has associated with it at each time a binary weather-impact status, which captures whether the corresponding region has nominal or low capacity due to weather. We also assume that each site of the network can be only impacted by its geographically surrounding sites and itself. Such an assumption is sufficient to characterize influence from other areas since weather-impact propagation should be relatively slow compared to the time-step duration used; this assumption can simplify the parameterization process. For example, the top left grid squares can only be influenced by three neighboring squares (sites) and itself. We note here that, although some edge sites may receive some influence from outside (e.g., the top left site may get some impact from left or above areas), we will not consider those situations in this example and instead will capture such influences as local generations of weather-impact[2]. (For this particular example, from the data, we also notice that convection is mostly focused inside this region, and hence the influence from outside of the region is likely not very significant.)

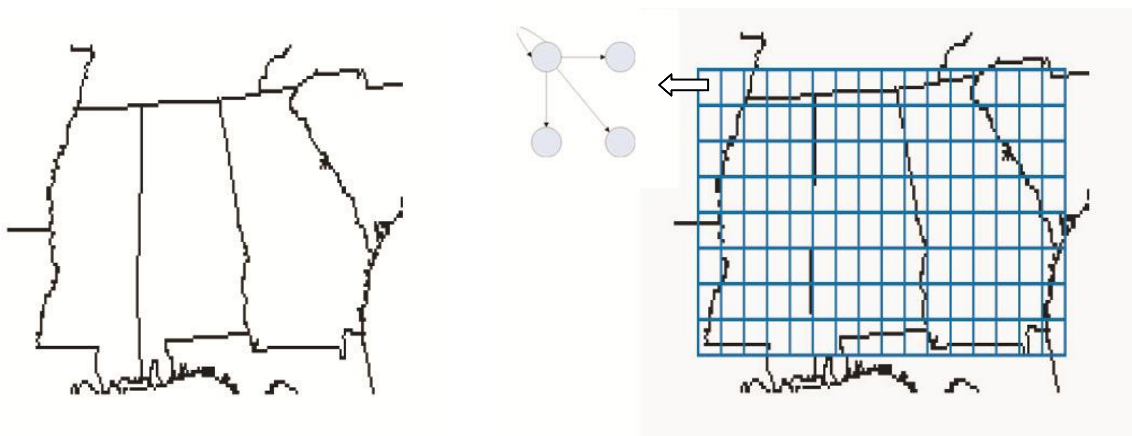

Figure 2: a. Geographical region of interest; b. Gridded region map.

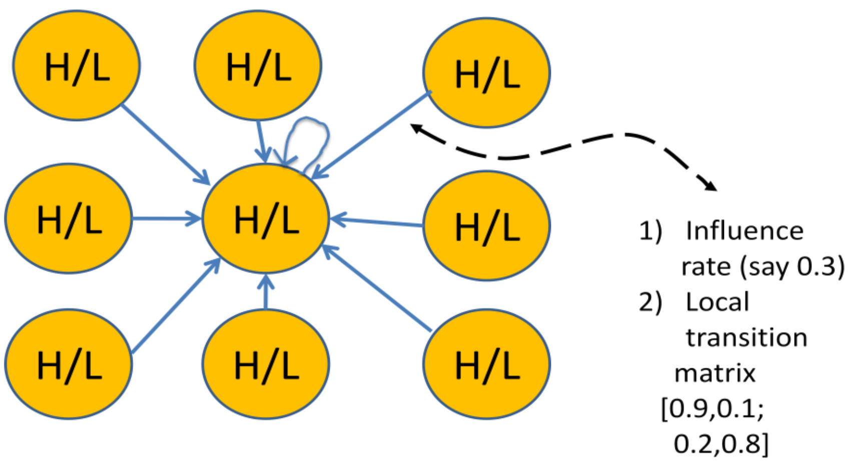

Figure 3: An illustration of the weather-impact model (influence model) parameterization task. Each grid square's weather impact status (capacity level) is influenced by its own past status and that of its eight geographical neighbors: this yields an influence structure for each influence-model site (which takes on two statuses, H for high capacity and L for reduced capacity), as shown above. We stress that each possible influence is defined by two parameters at each time step: a network influence rate that describes the frequency or chance of the particular network interaction, and a local transition matrix whose rows specify the next-status probability of the influenced site for each possible current status of the influencing site.

We have thus introduced a structure for the weather-impact simulator, including defining discrete time steps and constructing the network structure. Our next task is to parameterize the simulator so that certain of its snapshots match the given probabilistic weather information. Before doing this, let us

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[2] The arrow direction from one site to another is inverse to the influence direction.

summarize several aspects of the simulator here (and in the process define relevant terminology). For convenience, let us use notation Γ to refer to the underlying network of the simulator, which contains 128 sites representing the 128 grid squares (labeled as $i = 1, \ldots, 128$), and horizontal/vertical/diagonal network edges (i, j)[3] connecting two sites i and j corresponding to geographically neighboring grid squares$j$. The 25 forecast maps from SREF provide probabilistic weather information at 25 snapshot times: $k = 0,4,8, \ldots, 96$. More specifically, at times $k = 0,4,8, \ldots, 96$, each site is associated with a probability of having weather-impact (low capacity due to convection) in the corresponding area, which should match weather-impact probabilities obtained from the SREF forecasts. In the following, we use the information to parameterize the influence model, by designing the network influence rates (i.e. the rate of influence by each site j on neighboring site i, which we denote $d_{ij}[k]$ in coherence with standard influence-model terminology, see Fig. 3) and the local transition probabilities (which are captured by row-stochastic matrices which we denote as A_{ij} for each pair of neighboring sites).
In this example, we define two statuses for each site (or grid area) at each time step, reduced capacity due to weather impact and nominal capacity, and use a status-indicator vector $\boldsymbol{s}_i[k]$ to represent the statuses (i.e. $\boldsymbol{s}_i[k] = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ represents reduced capacity and $\boldsymbol{s}_i[k] = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ represents high capacity).
We use the notation $p_i[k]$ to represent the probability of having weather-impact (reduced capacity due to convection) at time k for site i (and $1 - p_i[k]$ indicates the probability of not having convection). These notations are consistent with the ones defined in our previous work (Xue, 2010a).

4.2 Parameterization and Simulation

In this section, a detailed description of how to parameterize the simulator for our example will be presented. Two major steps of the parameterization process are: converting weather (i.e. thunderstorm) probabilities to weather-impact (i.e. airspace capacity) probabilities, and computing the influence-model parameters $d_{ij}[k]$ and $A_{ij}[k]$. Once parameterization has been completed, we will also illustrate simulation of the weather-impact model.

- **Conversion of ensemble weather forecast to weather-impact forecasts:**

It is important to recall that the simulator captures weather impact rather than weather itself. Therefore, probabilistic weather forecasts must be converted to predictions of the weather impact on the capacity of airspaces and airports at the times when forecasts are available (time-steps k=0,4,8,12,…). Here, we use a very simple weather to weather-impact translation. Prior to discussing this simple translation, it’s worth introducing some literature relevant to the problem. Several approaches for estimating the impact of weather on airspace capacity have been developed (Davis et al., 2005; Song et al., 2007; Krozel et al., 2007; Klein et al., 2008; Weber et al., 2005; Martin et al., 2006). Much of this research assumes deterministic forecasts. However, at the forecast times needed for FCM decisions, deterministic forecasts are not sufficient since many weather outcomes are often possible when weather is forecast. Forecasts with probabilistic information that convey the possibility of multiple weather outcomes are required.

[3] (i, j) is an ordered pair of sites that indicates that the edge direction is from site i to site j, while the influence direction is from site j to site i.

Methods for obtaining probabilistic capacity forecasts from probabilistic weather forecasts have also been proposed (Mitchell et al., 2006; Michalek and Balakrishnan, 2009). Broadly, these studies consider proposed functional relationships between weather and capacity and aim to characterize probability distributions or statistics of capacity from these relationships assuming stochasticity in the forecasted weather. We envision using similar methods, or simple insights derived from these methods, to translate probabilistic weather forecasts to weather-impact maps for FCM; however, we stress that the resolution and details of weather forecasts (as well as the necessary accuracy for decision-making) may differ at the strategic time horizon, so some refinement of this methodology may be needed. Finally, the recent work of Krozel has directly studied weather-impact generation from forecasts, albeit using a somewhat heuristic approach.

A brief discussion of geographic structure of the model as it pertains to parameterization is also relevant. Airspace resources can include air traffic control sectors, which motivates representing sectors (as an alternative to grid squares) as the regions of interest in the weather-impact model. An advantage of using sectors is that sector capacity has been widely studied (EUROCONTROL, 2003; Majumdar et al., 2005; Stamp, 1990; Song, 2006), and many of the weather impact studies mentioned above focus on the impact to sector capacity. One issue is whether the sizes of sectors are large enough to tolerate the spatial inaccuracies in weather forecasts at the longer forecast times needed for strategic decisions. The fact that the weather impact simulator will produce many impact scenarios can help mitigate this issue, but we may also need to consider larger resources such as sector clusters at the longer look-ahead-times. Airports are also key resources, and the impact of weather on airport capacities is frequently a major disruption. Other weather factors besides convection, particularly ceiling and visibility, can have major impacts on airport capacities. We also note that weather-impact may be measured using constructs other than capacities, although our focus here is in capacity representation.

In this example, we assume that capacity reduction is simply caused by sufficient presence of convective weather. On this basis, we propose an (extremely simplified) computation of weather-impact maps from the SREF weather forecasts. Specifically, we argue that the weather-impact probability for a particular grid square at a particular time is equal to the expected convection coverage fraction in the grid square at the time, as given by the SREF forecast. Based on this intuition, we compute the weather-impact probability for the grid square as the average of the convection probabilities for SREF points within the grid square. Specifically, we note that each grid square contains 100 SREF forecast probability points; we simply average these 100 probability values to obtain the weather-impact probabilities. We note that we obtain 128 such probability values (for the 128 grid squares) for each time, and 25 sets of these values in total (for the 25 forecasts). Here, we use notation $q_i[k]$ to represent the weather-impact probabilities at time $k = 0,4, \ldots ,96$, for each site i. Once we have established on the conversion from weather to weather impact, the probabilistic weather forecast data can be applied to the parameterization process.

- **Influence-Model Parameterization:**

Let us rephrase the parameterization task as follows. We consider the weather-impact simulator as described above. Our goal is to design the network influence rates $d_{ij}[k]$ and the state transition probability matrices $A_{ij}[k]$, such that $p_i[k] = q_i[k]$ at the time steps $k = 0,4,8, \ldots ,96$. As stressed in (Xue, 2010a), we may have quite a bit of freedom in parameterizing the influence model, given the limited available information (only local statistics, and only at some time-steps). The parameterization will be unique only when certain very special network structures are assumed. In our example, since the simulator is constructed in a fairly general form, we may expect more than one parameterization solution, and in fact that is the case here. Note that we allow the parameters to be time-varying, which yields even more freedom in design. In other words, for each hourly time span, we aim to design a new set of parameters such that the two snapshots at the beginning and the end match the desired ones. For example, between $k = 4$ and $k = 8$, we individually design $d_{ij}[5], \ldots, d_{ij}[8]$, and $A_{ij}[5], \ldots\ A_{ij}[8]$, such that given $\boldsymbol{p}_i[4] = \begin{bmatrix} q_i[4] \\ 1 - q_i[4] \end{bmatrix}$, we have $\boldsymbol{p}_i[8] = \begin{bmatrix} q_i[8] \\ 1 - q_i[8] \end{bmatrix}$; while for other hourly time spans, we may obtain different values for $d_{ij}[k]$ and $A_{ij}[k]$. The time-varying parameters also have the physical interpretation that the interactions among all sites may change as the actual weather environment changes. Here, we only present a parameterization process for a single hourly time span (say between time step k and $k + 4$), and explain how to design the parameters $d_{ij}[k + n]$ and $A_{ij}[k + n]$ for $n = 1, \ldots, 4$. Such a process can be simply repeated for other hourly time spans.

In introducing the parameterization process, it is important to highlight that a family of designs for the *network interactions* $d_{ij}[k + n]$ and the local *influence matrices* $A_{ij}[k + n]$ match the snapshot probabilities: we have considerable freedom to choose among possible designs that achieve the snapshot weather-impact probabilities obtained from the SREF forecast. Our philosophy is thus to identify a family of appropriate designs, and then choose one among them (by tuning certain parameters) that matches other qualitative features of the weather impact – most notably, the extent of spatial and temporal correlation in the weather-impact propagation. Specifically, we will argue in the ensuing discussion that, for an appropriately-chosen set of network interactions parameters, the local influence (transition) matrices can be tuned to set the extent of spatial and temporal correlation. Let us now delve into the model parameterization based on this philosophy. The approach that we take is connected with the parameterization methods described in (Xue, 2010a), and the reader is referred there for more details and justifications of influence-model parameterization methods; however, our work here considerably extends the effort in (Xue, 2010a), especially in the sense of deciding how to select among multiple possible valid parameterizations. For the sake of simplicity, we do not include all the mathematical details (which are considerable), but aim to give a sufficiently-detailed presentation to provide the reader with insight into the methods.

To begin this parameterization, in this example we first compute the 3 snapshots in between that will be approximately met by the parameterization. We know that $\boldsymbol{p}_i[k]$ and $\boldsymbol{p}_i[k + 4]$ are fixed (since $p_i[k] = q_i[k]$ and $p_i[k + 4] = q_i[k + 4]$), and weather generally has a slow motion relative to the time axis of interest (hence weather impact does also). Therefore, based on the time differences, we assume the snapshots in between to be a linear combination of both known impact forecasts, or

$\boldsymbol{p}_i[k + 1] = 0.75\, \boldsymbol{p}_i[k] + 0.25\, \boldsymbol{p}_i[k + 4]$, or $p_i[k + 1] = 0.75\, q_i[k] + 0.25\, q_i[k + 4]$,
$\boldsymbol{p}_i[k + 2] = 0.50\, \boldsymbol{p}_i[k] + 0.50\, \boldsymbol{p}_i[k + 4]$, or $p_i[k + 2] = 0.50\, q_i[k] + 0.50\, q_i[k + 4]$,
$\boldsymbol{p}_i[k + 3] = 0.25\, \boldsymbol{p}_i[k] + 0.75\, \boldsymbol{p}_i[k + 4]$, or $p_i[k + 3] = 0.25\, q_i[k] + 0.75\, q_i[k + 4]$.

We note here that, although the above three values are not constrained to be the actual probabilities for site i, comparing the difference between two consistent time steps can still provide useful information for the simulator design. Generally, we set the network influence probabilities (rates) to reflect trends in these probabilities (and hence to achieve an evolution of the local weather-impact probabilities that match the desired ones), and then set the state transition matrices to achieve the temporal and spatial correlation that is desired. Specifically, the state transition matrices can be set to achieve different degrees of memory of the current state on the past ones (i.e. the degree to which $\boldsymbol{s}_i[k + n]$ is dependent on the past), which decides the level of spatial and temporal correlation.

Let us now describe computation of the network influence rates for various sites in the influence network, and then describe the computation of the local state transition matrices. First of all, let us describe how to parameterize for the boundary grids (i.e. grids that are adjacent to outside region). For simplicity, we set $d_{ii}[k+n] = 1$, for all boundary sites, implying that each boundary site can only influenced by itself. As for each$A_{ii}[k+n]$, we compare the two values $p_i[k+n-1]$ and $p_i[k+n]$: if $p_i[k+n] \geq p_i[k+n-1]$, we set $A_{ii,11}[k+n] = 1$ and $A_{ii,21}[k+n] = \frac{p_i[k+n]-p_i[k+n-1]}{1-p_i[k+n-1]}$; otherwise, we set $A_{ii,11}[k+n] = \frac{p_i[k+n]}{p_i[k+n-1]}$ and $A_{ii,21}[k+n] = 0$. It is easy to see that this solution yields local evolution of the boundary sites' weather impact (with the motivation that this weather impact reflects generation of weather and/or imposition from outside), while the state transition matrices have been designed to achieve maximum temporal correlation of the weather impact at these sites.

The interior sites have a more complex design rule in our example since each site can be influenced by 9 sites (including itself). Again, here we compare the two values $p_i[k+n-1]$ and $p_i[k+n]$:

1) For the simple case that $p_i[k+n-1] = p_i[k+n]$, we assume that weather (hence weather impact) does not evolve spatially between time $k+n-1$ and time $k+n$, and set $d_{ii}[k+n] = 1$.
2) For the much more common case that $p_i[k+n-1] \neq p_i[k+n]$, we need to consider several sub cases as follows.
   2-a) For each interior site i, if all its 9 neighboring sites have the same probability of having a low capacity at time $k+n-1$, and m ($m \leq 9$) sites of them still have the same probability at time $k+n$, we then set the influence rates from these m neighboring sites as $1/m$.
   2-b) Otherwise (and in the most common case), we determine the influence neighbors and the corresponding influence rates based on how the probabilities change between time $k+n-1$ and time $k+n$ for all 9 sites: a weighted influence is determined for each neighbor, that reflects whether or not the neighbor's current weather impact probability is higher or lower than the desired probability at site i, and based on the trends of these probabilities.

Once the influence rates are fixed, we design the state transition probabilities according to the changes in the weather-impact probabilities. In fact, it is straightforward to identify a family of local transition matrices that achieve the desired weather-impact probabilities at the next step (independent of the network-influence rate selection). These local influence matrices can then be tuned to achieve varying degrees of spatial and temporal correlation (ranging from complete independence from the past to the strongest possible correlation permitted by the probability evolution). In this example, we have tuned the state transition matrices simply based on a visual comparison with typical convective weather. In future work, we expect to determine typical extents of spatial and temporal correlation for storm-system types, and to choose the state-transition matrices based on these.

In sum, the whole parameterization process is to first set the influence rates and then come up with certain feasible state transition matrices such that the desired weather-impact probabilities are matched and desired spatial/temporal correlation is achieved.

- **Simulation results:**

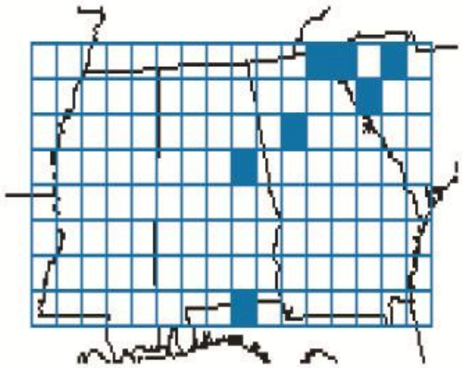
Once we have parameterized the weather-impact simulator between the initial time 0 and time step 96, we can use it to generate weather-impact scenarios. Each individual simulation run will generate one weather-impact scenario (independent of scenarios generated from other runs). Here, we will present some simulation results (illustrations of generated scenarios) based on the parameterization.

In our example, the simulator generates one weather-impact scenario at each time, which contains 97 snapshots (from time step 0 up to time step 96). At these time steps $k = 0,4,8, \ldots ,96$, the generated snapshots should statistically match the given weather-impact probabilities (i.e. $p_i[0], p_i[4], \ldots, p_i[96]$): that is, the probability of each site having weather impact (low capacity) should match those obtained from the forecasts. Since we allow time-variant parameters for the influence model, we individually parameterize the model for each hourly time span. However, for the simulation, since we want to capture a temporal and spatial correlation, we need to process the full-day time span together. First, we need to generate an initial weather impact at time 0 based on the give $p_i[0]$ (e.g. simply a realization for each grid square based on a probability distribution). Then, we need to generate each site's next status: 1) for each site i, we choose an influence neighbor based on the current influence rates, as site i's copying source; 2) given the chosen neighbor's current status, we compute site i's status probabilities at next time step, based on the state transition matrix from this neighbor to site i. By repeating this process, we eventually obtain a sequence of 97 weather impacts (i.e. capacity statuses) for the whole region.

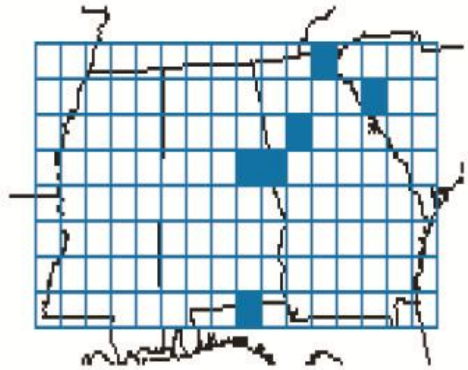
For example, Fig. 4 contains two given probabilistic weather forecasts (15 UTC, 16 UTC) for ZTL/ZME/ZJX centers, with a 1h time difference. For our simulator model, the corresponding time steps are from 0 to 4. Fig. 5 shows these 5 generated weather-impact snapshots, for one simulation run. The snapshots at time steps 0 and 5 statistically match the weather forecasts at times 15 UTC and 16 UTC, respectively, but with a spatial and temporal correlation between each other.

a) 15 UTC, 09/26/2010; b) 16 UTC, 09/26/2010.

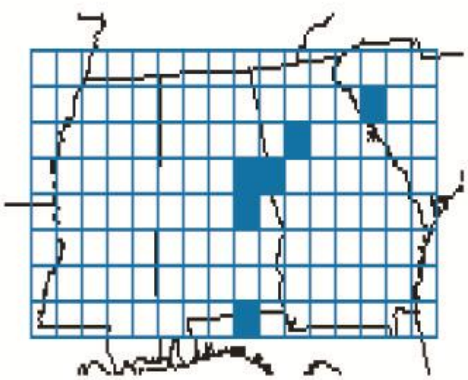
Figure 4: Weather probability information above ZTL/ZME/ZJX centers.



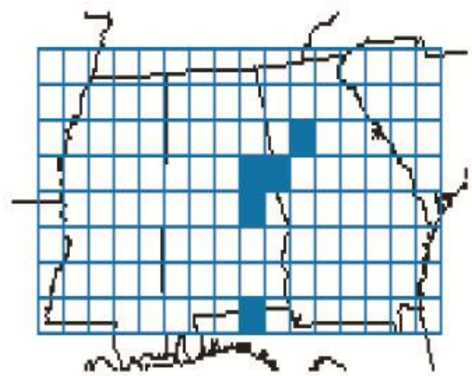
a) time step 0;



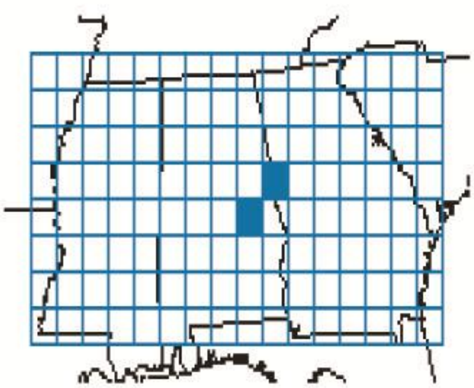
b) time step 1;



c) time step 2;



d) time step 3;



d) time step 4.

Figure 5: Five snapshots (within one hour) of a scenario from one simulation example.

It is also instructive to compare the weather-impact predictions of multiple different scenarios at a particular time. In Fig. 6, we show three possible weather-impact scenarios at time step 30. The three scenarios show significant differences, but have similar weather-impact patterns (that match forecast data) and display some spatial correlation.

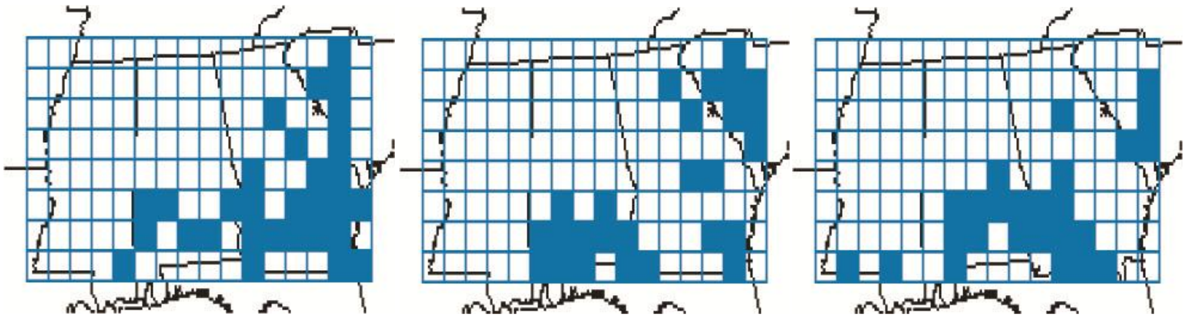


Figure 6: Three different weather-impact scenarios at time step 30.

In sum, we have presented a specific example illustrating the construction of a weather-impact simulator. We note here that, other atmospheric or terrain information may help to reduce the solution space and refine the simulator. For example, we may obtain more realistic influence rates if information about air motion is used in parameterization. However, the example in its current form is quite promising in that it shows the spatial and temporal correlations among weather-impact throughout the airspace, as achieved by a Markovian generation process, which also matches currently-available probabilistic weather forecasts. Moreover, the simulator can also generate snapshots at a strategic time horizon (i.e. 15 min interval), which weather forecasts cannot provide. Also, we stress that the influence model permits fast generation of scenarios, as well as fast computation of important statistics (e.g., correlation between weather-impact at two critical locations).

In concluding, let us reiterate what we have achieved through construction of the weather-impact simulator (for this example and more broadly), and also stress that much is left to be done. We believe that the example developed here illustrates why the weather-impact simulator is so promising for air traffic management: fundamentally, it allows us to generate alternate realistic realizations of a weather events impact, and to quickly analyze statistics of these weather-impact events; this information, if even roughly accurate, may inform a wide range of decision-making tasks in the airspace system. Yet, even as the example shows promise, it highlights that parameterizing the weather-impact model to generate realistic scenarios (and to validate/evaluate whether they are realistic) is a challenging and open-ended endeavor. To this end, and more broadly to properly leverage the weather-forecasting capabilities in the air traffic management arena, it is essential that the weather-forecasting community advise and collaborate with traffic-management engineers on weather-impact modeling, and also that extensive data analysis be performed to validate and evaluate promising methodologies. We hope that this article begins to foster such discourse and evaluation.

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Notice:

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