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A Stochastic Network Model for Uncertain Spatiotemporal Weather Impact at the Strategic Time Horizon

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Abstract

Motivated by challenges in flow-contingency management, we introduce a stochastic network model for the spatiotemporal evolution of weather *impact* at a strategic time horizon. Specifically, we argue that a model that represents weather-impact propagation using local probabilistic *influences* can capture the rich dynamics and inherent variability in weather impact at the spatial and temporal resolution of interest. We then illustrate that such an influence model for weather impact is simple enough to permit a family of analyses that are needed for decision-support, including 1) model parameterization to meet probabilistic forecasts at time snapshots, 2) fast simulation of representative weather trajectories and impact probabilities, and 3) computation of correlations and higher-order statistics in weather impact. Also, lower-order representation of the stochastic dynamics at critical locations in the airspace is considered. Finally, a brief exploratory discussion is given on how the weather-impact model may eventually be used in tandem with network flow models to study flow contingency management.

1. Motivation and Goals

As the Next Generation Air Transportation System (NextGen) comes into operation, a wide array of new decision-support tools for traffic flow management (TFM) are needed, in order to meet the performance requirements of the new system and to take advantage of its new hardware capabilities. Although decision-support for tactical TFM has been advanced significantly during the last few years, TFM *design* at the *strategic* and *planning* time horizons (2hrs – 1day, and days – months/years, respectively) remains challenging. A major obstacle in current TFM operations is the often overly conservative actions taken when demand exceeds capacity in either predicted or impending operations. A lack of information availability and integration, as well as grave limitations in decision support systems that assist decision makers in identifying and alleviating potential congestion in a way that minimizes the impact on the National Airspace System (NAS), are understood to be current deficits in the system. *However, the details on exactly what decision support system capabilities are necessary, and the resulting products from these decision support systems, are not clearly defined.* The work that we present here is motivated by this need for decision-support at the strategic time frame.

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1.1. Broader Motivation: An Operational Framework for Flow Contingency Management

To carefully motivate and position the research presented here, let us begin with an overview of the relevant aspects of and technical challenges in strategic TFM (see e.g. [1-4]). The NextGen Mid-Term Concept of Operations [1] defines activities in the strategic timeframe as two separate, yet intertwined components for developing effective TFM decisions: Capacity Management (CM) and Flow Contingency Management (FCM). Briefly, CM refers to the long-range to flight -day airspace design planning in order to define airspace and routing to best match capacity with demand. FCM is the strategic planning of actions that result when the demand is predicted to exceed the planned capacity. FCM must yield NAS-wide guidance for traffic flows to achieve efficient resolution of capacity excesses under significant weather uncertainty, while also seamlessly translating to tactical management (TM) actions (i.e., to regional management efforts at a 2 hour time horizon). It is the FCM component of TFM decision support that we are primarily interested in here.

Developing FCM for NextGen requires addressing a range of challenges in modeling uncertainties in the NAS, achieving practical decision-support in the face of these uncertainties, and allowing transition to TM solutions. With these challenges in mind, we are developing an operational concept for strategic FCM in the NAS. Let us give a brief overview of this proposed operational concept, to better motivate the particular research pursued here:

The FCM operational concept described here is motivated by the desire to provide a scientific basis for strategic operational decisions. As such, we propose using formal analysis methods that capture uncertainty in the available data in order to produce accurate plans that can be understood and utilized effectively by decision makers. The overall concept evolves in three stages: predicting weather impacts, developing mitigation approaches, and defining a strategic operations plan. The remainder of this section provides a brief overview of these three components.

Weather impact predictions are essentially propagations of TFM impacts due to weather, or any such event that limits the available capacity. We propose that by predicting the scope of weather impact we can better understand how an event may evolve and disrupt TFM operations. As such, our operational concept begins by analyzing how flows are potentially impacted by reductions in capacity and how this capacity reduction propagates through the system. Representative weather impact scenarios are aggregated from the set of potential outcomes, with associated statistics, to inform decision makers on the likely outcomes arising from an event.

The second component of the FCM operational concept develops the mitigation plans linked to the weather impact forecasts. Mitigation plans comprise the set of actions, such as ground delays, sector or flow controlled area rate restrictions, rerouting, or other necessary initiatives that must be taken to alleviate the congestion due to an imbalance between predicted capacity and predicted demand. A mitigation plan outlines where and when these actions need to be implemented and how to best regain use of available capacity to reduce the overall impact on the system. When developing the mitigation plans, metrics of utility such as throughput or delay are assessed to ensure that the mitigation plans suggested provide efficient traffic management initiatives.

However, as there are multiple weather impact outcomes, there are multiple mitigation plans and integrating these multiple plans into a single Current Decision Point Plan (CDPP) is the final step in the FCM process. The CDPP reflects both the likelihood of the different weather-impact outcomes developing and their associated mitigation strategies being necessary, as well as input from both NAS users and service providers as to the relative priority of different disparate goals, given the situation. The CDPP is developed using a risk management decision framework which both weighs the benefits, costs, probabilities, and value of different actions to determine the necessary actions that should be settled upon now as well as the likely actions that will be recommended later.

It is important to note here that the CDPP represents the agreed upon plan of action; however it is possible and even likely that the actions included in the CDPP at a given time will not be enacted until later and simply represent impending actions. Airspace users, empowered with both the knowledge of impending actions as defined in the CDPP as well as the recommendations of all the mitigation plans, can adjust their schedules as they see fit. The updated demand information, in combination with updated capacity predictions derived through the evolving weather impact updates, are then utilized to repeat the strategic decision process.

1.2. The particular goal of this study

Our operational concept for FCM (and the underlying challenges motivating this approach) highlights that tools for predicting and modeling weather impact at the strategic time frame are badly needed, as a key component of a FCM decision-support system. Weather *uncertainty* is particularly critical in understanding weather impact at the strategic timeframe, as small changes in weather realities can drastically impact TFM operations while in fact weather prediction capabilities leave open the possibility for not small but significant variability in weather.

The aim of this work is to introduce a promising stochastic (probabilistic) spatiotemporal model for the impact of weather on traffic flows at the strategic time frame for use in FCM. Developing such models is challenging, because they must be accurate enough to capture the complex and uncertain evolution of weather impact at a multi-hour time scale, and yet simple enough to permit evaluation and eventually design of flow contingencies. In our view, modeling weather at the strategic time frame for FCM must be based on the following observation: at the level of traffic flows, the *uncertain time-evolution of a few critical weather events disproportionately impact the flows, capacities, and management actions, and hence hugely impact FCM performance*. The time-evolution of these critical weather uncertainties, and in particular their impact on traffic flows, must be modeled. For instance, on a particular day, uncertainties regarding stratus-clearing times at San Francisco International Airport (SFO), the locations of a couple of convective-weather systems, and the duration of high winds at several terminals may critically impact traffic flows. Thus, we need to accurately model these critical uncertainties over time.

The literature on weather impacts at the strategic time horizon is quite sparse. A couple of recent works [5,26] have identified weather-impact modeling needs, and specifically have considered translating weather-model outputs to probabilistic forecasts of TFM-relevant parameters, like Sector capacities, at particular future times. *However, to be used in design, we believe that weather-impact modeling must be enhanced to allow representation of 1) the onset and completion (or duration) of key weather events and 2) temporal and spatial correlations in flow-impacting weather events.* For instance, in summer time in the Southeastern United States, it is common that there may be a diffuse probability for convective weather over a fairly long period of time (e.g. due to a slowly-progressing and weak dry line or during a period of unfocused convective activity); in this case, finding the probability that a convective-weather event happens at all at a terminal (e.g. Dallas Fort-Worth International Airport (DFW)) and the probability density of the event duration (or start/finish times), will enhance TFM-performance prediction and hence design as compared to finding capacity-reduction probabilities at particular times. In such highly uncertain settings, temporal and spatial correlations in weather become important. For instance, the chance of convection at DFW may be small, but if it occurs, Love Field is also likely to be impacted shortly before or after. These needs in modeling weather at the strategic time frame are illustrated in Figure 1.

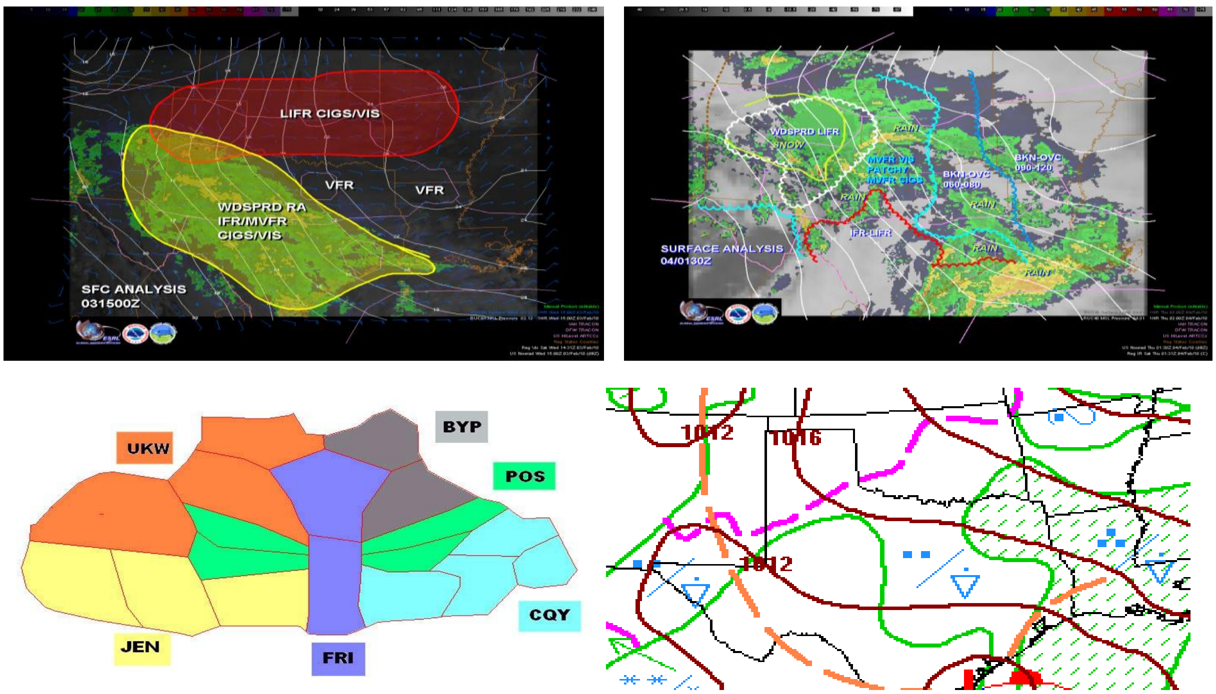


Figure 1 – Actual evolution of weather in Fort Worth Center (ZFW) during a half-day time period, along with concurrent impacts on air traffic (*upper plots)*. The weather displays complex temporal and spatial correlations, which impact traffic flow and capacity in a complicated and correlated way in the Sectors in ZFW (*bottom left plot*) and hence require consideration in FCM. Unfortunately, even at one-day (strategic) time horizon, weather forecasts fail to capture the complex evolution of weather impact, instead providing crude aggregate descriptions of weather (*bottom right plot*), or at best probabilistic forecasts of weather/impact at a few time instances (see, e.g., [5,10]). Our work aims to model the complex evolution of weather impact on airspace regions at a strategic time horizon, while respecting the inherent uncertainty in weather at that horizon. These maps were obtained from the Fort Worth Center Weather Service Unit, on February 3, 2010 [11].

With FCM design in mind as an eventual goal, this work introduces a model for the uncertain spatiotemporal evolution of weather impact. Our core viewpoint is that, in order to capture the spatial and temporal correlations that are central to weather impact, we need a tractable spatial model that generates time-trajectories or *scenarios* of weather-impact, at airspace-relevant locations (e.g., Sectors, other regions, or at points like airports). Here, we pursue modeling of weather impact using a tractable stochastic network model known as the *influence model* [9]. This influence model representation is compelling because it appears to capture the rich family of correlated dynamics observed in weather impact at the strategic time frame, and yet is especially tractable in several ways: 1) it can be parameterized to match probabilistic weather-impact forecasts at particular times such as those developed in [5]; 2) subsequently, it can be used to simulate weather impact and interpolate the probabilistic forecasts; and 3) it permits fast analysis of correlations and higher-order statistics of weather impact. Furthermore, promising tools are available for condensing the full spatiotemporal model into low-order Markov models for weather impact at a few critical locations. Finally, we believe the model is promising in that it can be interfaced with dynamic models for traffic flow [6] using the *jump-Markov* modeling framework [7-8].

In this paper, we focus on conceptualizing the influence-model representation of weather impact, and presenting results on the parameterization and the simulation/analysis of the model, using representative examples. We omit general mathematical formulations of the models and details of analysis techniques, both for the sake of giving an uncluttered presentation and because we continue to obtain more refined results on these aspects. The reader is kindly asked to see the Appendix, as well as our previous and concurrent work on the influence model [9,12-15], for many of the details.

2. An Influence Model for Weather Impact: Formulation, Parameterization, and Analysis

In this section, we develop a stochastic network model for weather impact. This effort enhances weather-impact forecasting at the strategic time frame (see [5]), to capture the *dynamics* (time-evolution) of weather impact in a way that can be incorporated into aggregate models for traffic flow dynamics, and can permit analysis of temporal and spatial correlations in weather impact. We approach weather-impact modeling in two steps.

Specifically, we first introduce the *networked-Markov-process* model for the spatial and temporal evolution of weather impacts (Section 2.1); the model that we develop falls in a class of models known as influence models. We take advantage of the special structure of the influence model to 1) parameterize the model based on current weather impact and a weather-impact forecast at a future time, such as would be generated by the methodology in [5] (Section 2.2); and 2) simulate and achieve statistical analysis of weather impact.

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 (see for instance [5]), 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 our goal is to develop 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 Sectors (see Figure 1) or may be lattice squares in the airspace (see e.g. Figures 2 and 3 below. 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 given in e.g. [16]. 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. In particular, we model the weather-impact states' evolutions as a *networked Markov process*: at each time, 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 particular time instances 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. 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*, 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 and [12-15] 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. 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 its predicted weather impact matches current weather impact, as well as probabilistic forecasts of weather impact at one or more future time snapshots (see [5] and [26] for some preliminary ideas on how weather impact forecasts can be obtained from ensemble weather forecasts). We note that these probabilistic forecasts 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. Thus, the problem of parameterizing the weather-impact model 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 addressed this snapshot-design problem in our concurrent work [15], and here propose using 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 in that information is available at only a few time snapshots. Fundamentally, our method for snapshot design [15] derives from the core tractability of the influence model, enabling individual sites' state probabilities (in our case, individual regions' weather-impact probabilities) to be found over time using a low-order recursion. The snapshot-design problem thus can be viewed as a problem of designing the low-order recursion to achieve desired state probabilities at particular times, while maintaining the specified graph structure of the model (in our case, reflecting that influence interactions occur between geographical neighbors). This design problem is solved using both iterative methods and explicit computations in [15]; we ask the reader to see that paper for details (see also [17] 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 features of the weather-impact dynamics.

Beyond the systematic parameterization developed 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 further 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 scaling linearly with the number of regions and the duration of the simulation). Multiple representative spatiotemporal trajectories can be easily obtained based on the probabilistic description, and so the range of possibilities in weather impact can be obtained. These 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. 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. 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 (see e.g. [18]) 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. In this paper, we have excluded these details, and ask the reader to see the theses [12-14] for them.

2.4. Examples

We conclude the development of the weather-impact model with several examples, in order to illustrate the parameterization, simulation, and analysis of the model. We stress that these examples are meant to illustrate modeling concepts rather than to capture all the intricacies involved in using the model in practice. For the examples, we define regions as lattice squares in the airspace rather than based on actual Sector boundaries, for convenience (and analogously with [18]). However, the modeling paradigm naturally permits use of actual Sector maps instead.

Example 1: We have developed a lattice model for capacity-reduction due to convective weather in a narrow strip along an Eastward-moving front over an 11-hour time horizon, see Figure 2. Two simulations of the model in the front-progression example both indicate an Eastward-moving line of capacity reductions due to convection, but with significant differences at a fine temporal and spatial scale in the locations of capacity reduction. This variability is reflective of the actual inaccuracy in weather-impact prediction at the strategic time horizon. We also illustrate the analysis of weather-impact probabilities for individual regions for this example, see Figure 3. In this example, we see that the location of the weather-impact becomes increasingly uncertain as time passes, in reflection of the increasing uncertainty in the front location and extent/structure of convection. This increasing variability is reflected in the generated weather-impact scenarios, as shown in Figure 2.

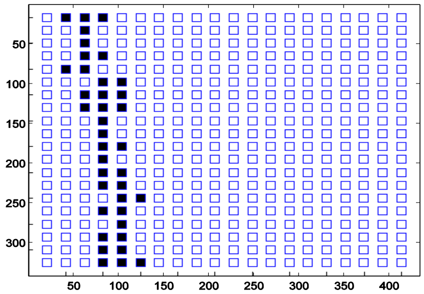
Example 2: We pursue development and analysis of a weather-impact model in a 20x20 grid of regions over a 15-hour period, which captures diffuse thunderstorm activity near a dry-line. We model each region as having two weather-impact states, full capacity (F) and reduced capacity (R), which evolve in time according to a networked Markov process.

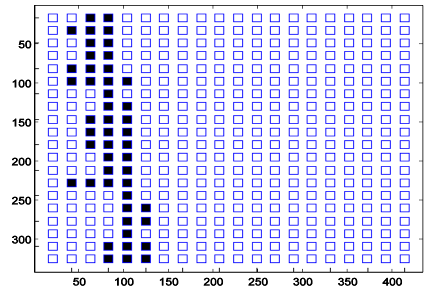
At the initial time, a band of convection (and consequent capacity reduction) is present at the Western end of the grid. As time progresses, this band of storms is expected to transition to a large area of scattered thunderstorms, with the densest concentration of storms shifting Eastward and Southward through the time period; individual storms are expected to move in a West-to-East direction, with a significant chance of storms re-forming repeatedly in the same place. A weather-impact forecast is available at 7.5 hours, which predicts the highest probability for capacity reduction along an axis from South-Central part of the grid to the North-East part, with decreasing but still significant probabilities away from this axis.

We have developed and parameterized a weather-impact model that matches the probabilistic forecast at 7.5 hours (as given in Figure 4a) and has West-to-East moving-storms. Once the model has been developed, it can be used to simulate weather impact and also to give probabilistic forecasts at other times. We have obtained a forecast at another time (Figure 4b), and also show the state at two times (Figure 4c and 4d) during a simulation of the model.

Simulation Set a)

Simulation Set b)





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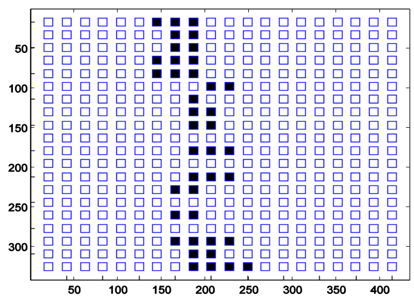

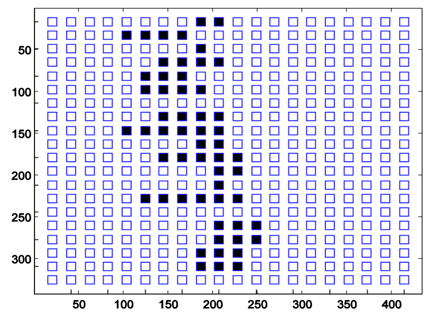

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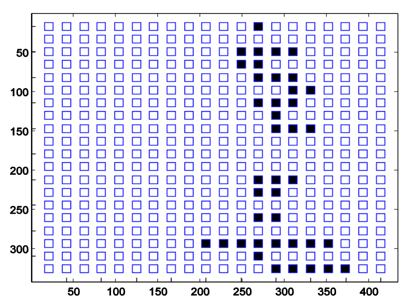

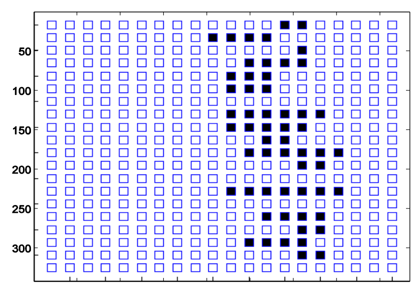

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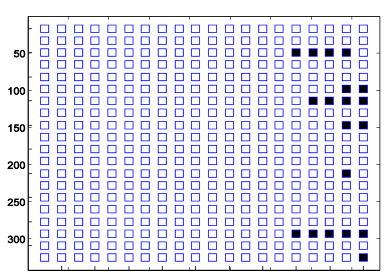

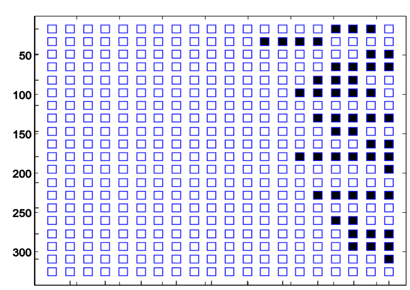

a: 10.5 hrs)   b: 10.5 hrs)

Figure 2 – A Stochastic Weather-Impact Model for Strategic FCM: Two simulations (set a) and set b))of a spatiotemporal weather-impact model for convective weather impact during a cold-front passage at the strategic time horizon are shown, with the dark squares representing regions that are subject to capacity reduction due to the convection. In each simulation, the capacity map is shown at 1.5 hours, 4.5 hours, 7.5 hours, and 10.5 hours in the future. The model captures the significant uncertainty at this time horizon. We note that, although we have defined regions as squares in a grid in this simulation, an arbitrary network of regions (e.g., one corresponding to Sectors and airports) can be used.

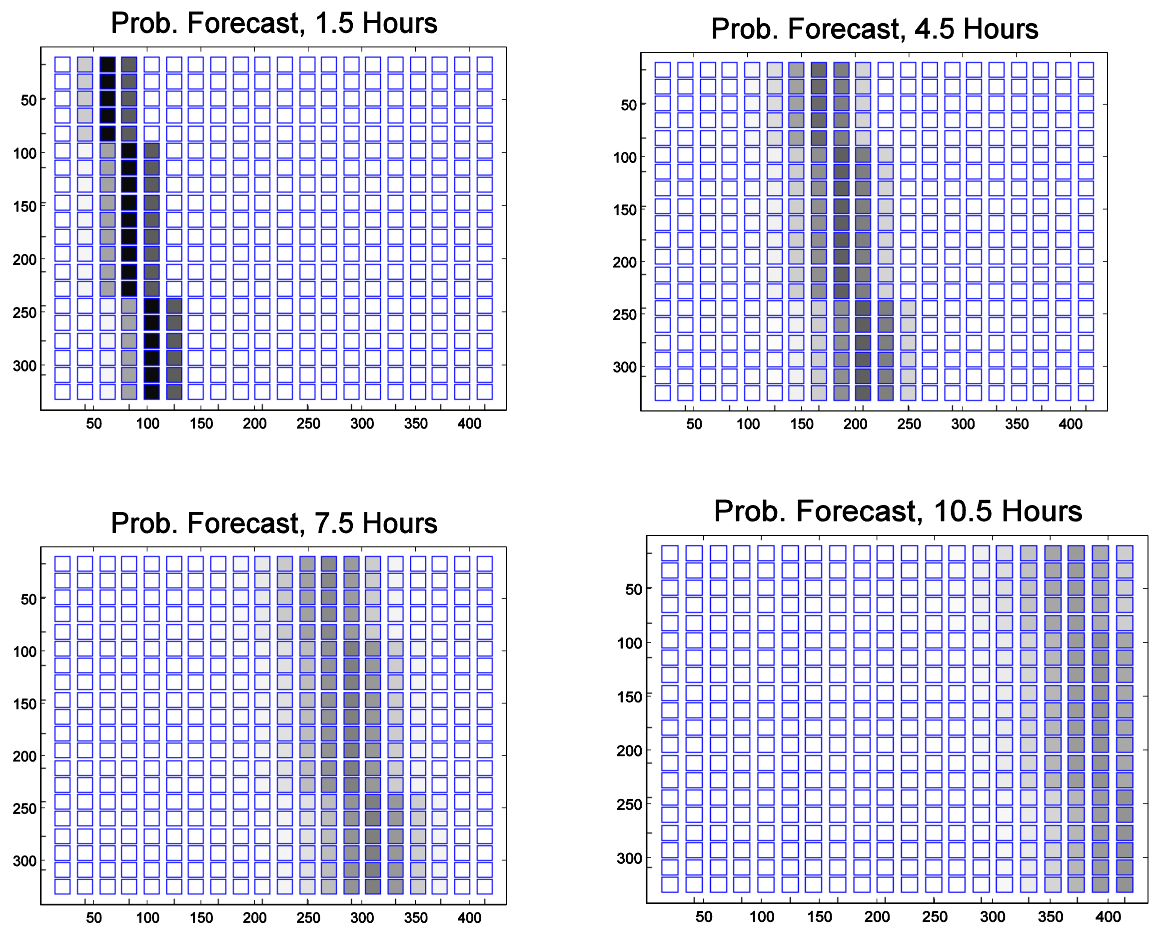

Figure 3 – Probabilistic Analysis of the Weather-Impact Model: A statistical analysis of the spatio-temporal weather-impact model allows calculation of probabilistic forecasts of weather impact at arbitrary times. Here, we have used this analysis to find regional probabilities of capacity-reduction with time in the cold-front passage example introduced in Figure 2. In this example, the narrow band of weather impact due to convection evolves toward a wider but more diffuse region of weather impact.

We are especially concerned about capacity reductions in the airspace near two major airports corresponding to nearby cities (for convenience, let's call them Yanville—located at the 16th row from the top and the 15th column from the left—and Craigsburg – located at the 16th row from the top and 13th column from the left). Let us use the model to analyze the duration of the capacity reduction at Yanville. Through multiple simulations of the model, we have approximated the probability density function (pdf) of the duration, see Figure 4; meanwhile, the mean and variance of this duration can be found with very little computational effort, by exploiting the special tractability of the influence model. Specifically, we find that the mean duration is 3.2 hours and the standard deviation in the duration is 2.1 hours. The pdf suggests that long periods of capacity reduction are possible during this weather event, and that capacity-reduction durations are quite variable at the time horizon of interest.

We can also use the model to characterize the correlation between weather impact (capacity reduction) at Yanville and Craigsburg. Given the close proximity between the two cities, we might expect the duration of capacity reduction for the two associated airspaces to be highly correlated. In fact, analysis of the network model demonstrates that this is the case: the durations of capacity reduction at the two terminals have a correlation coefficient of 0.359. We have also included a scatter plot of the two capacity-reduction durations taken from over 5000 simulations, which illustrates the strong correlation.

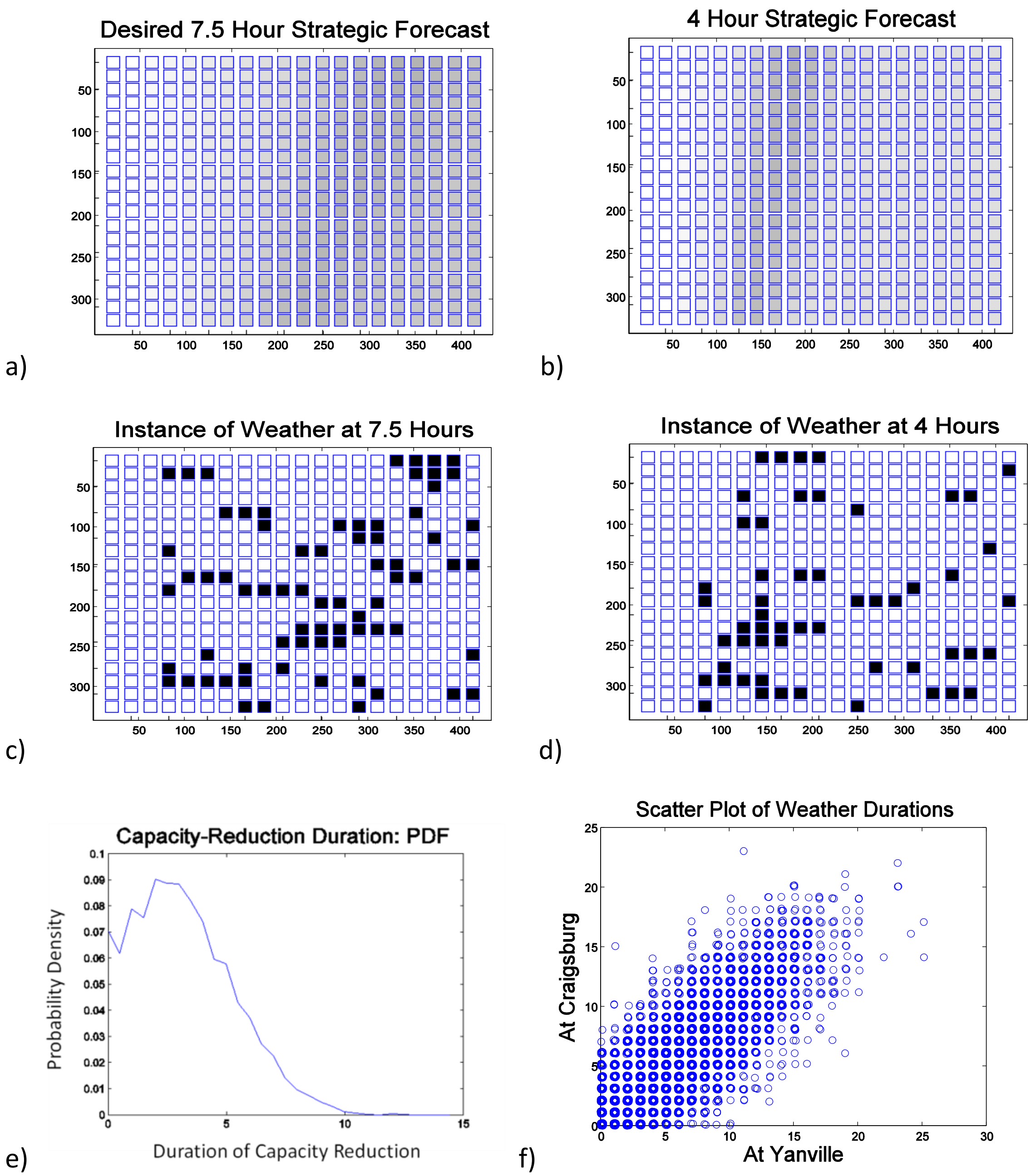

Figure 4 – Comprehensive Design and Analysis of the Spatiotemporal Model: A spatio-temporal stochastic weather model is designed to match current weather impact and a probabilistic forecast at 7.5 hours, in this case one that predicts a large area of moderate convective activity concentrated along a Southwest-Northeast axis (a). The model can then be used to analyze weather impact (capacity reduction) probabilities at other times (b), to simulate weather (c and d), to analyze weather-impact characteristics in one important region (e), and correlations among weather impact in two regions (f).

Example 3: We model a winter-weather event. The particular example that we considered is roughly inspired by a predicted weather event in the Pacific Northwest, on the weekend of December 12th, 2009. An advance forecast for the weather event predicted a surface low-pressure center moving along a east-west stationary weather front, producing a period of rain/sleet/snow along this trajectory. There is significant uncertainty about the location of the front, with two possibilities roughly equally likely: a southern front location (in central Oregon), with a (relatively) weaker low pressure system moving along it; or a more northerly track with a stronger storm system. Additionally, pop-up snow showers are possible, especially after passage of the low-pressure system.

We show several plots. We first show the time-course of weather-impact probabilities on the map, in Figure 5. (Note that the plots roughly capture from Central Oregon to the Canadian border in the vertical direction, and from slightly off the coast to Western Idaho in the horizontal direction.) We then show two simulations of the weather model (Figures 6 and 7). We note that one of the simulations (by chance) captures the southern low track, while the other one displays the northern track. It is also evident from these simulations and others that, even when one low track occurs, significant variability in the weather impact itself is observed. Also, we stress that the stochastic modeling approach can permit analysis of spatial correlations in weather. For instance, in this example, at the 1.5 hour time horizon, Portland (5th column from left, 5th row from bottom) and Seattle (4th,14th) both have significant probability of weather impact (>25%), but the probability that they both have weather impact turns out to be less than 1%.

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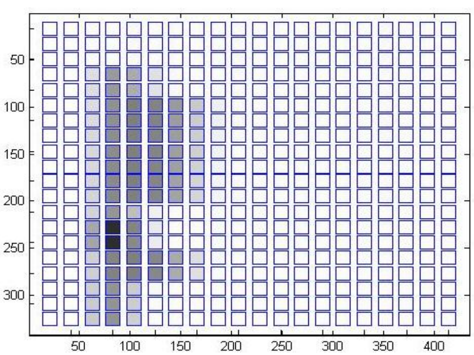

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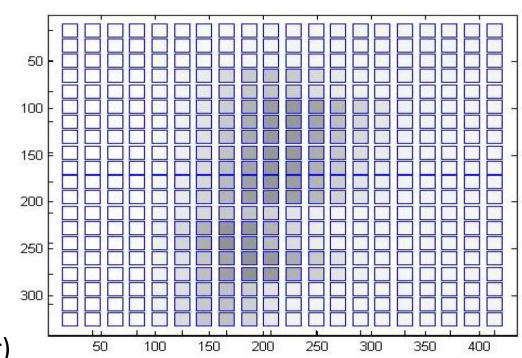

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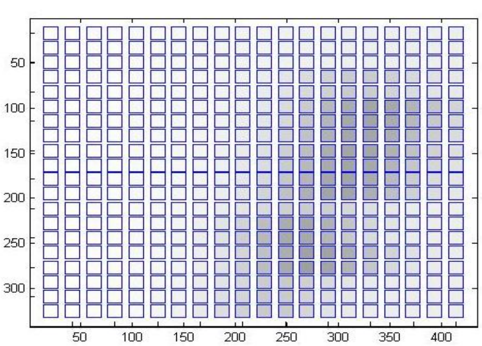
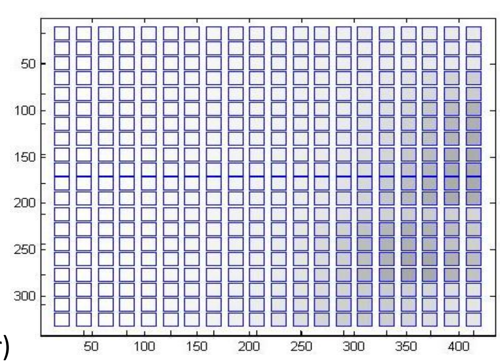


10.5hr)



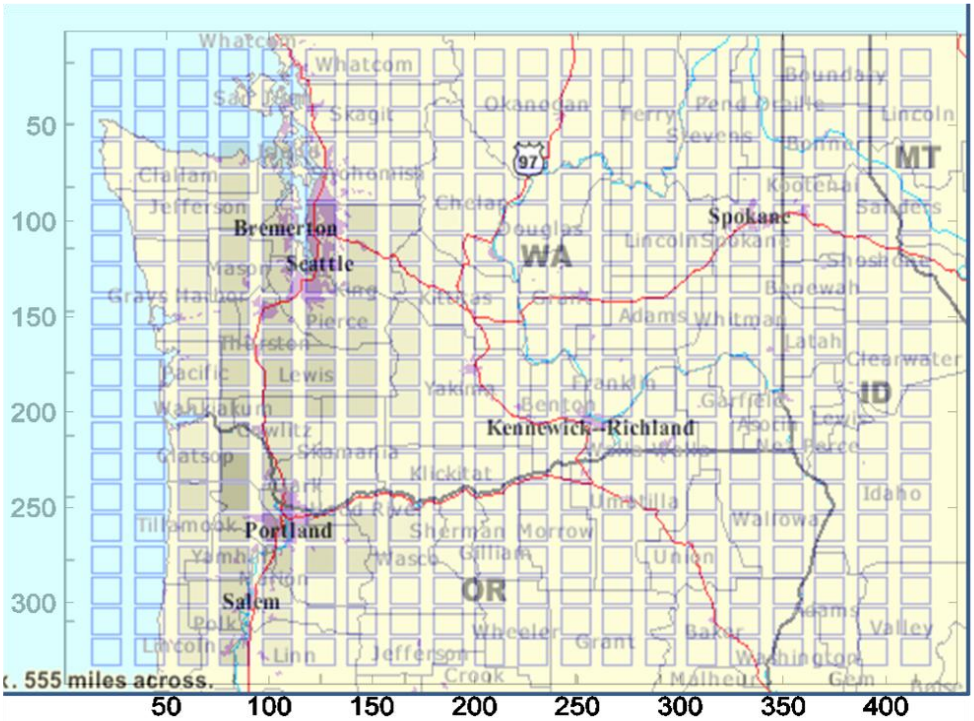


Figure 5 – Weather-Impact Probabilities, Winter-Weather Example. For the reader's convenience, we have also overlayed the weather-impact probabilities at 1.5 hours on a map of the Pacific Northwest, to illustrate the geographical extent and resolution of the example (lower plot).

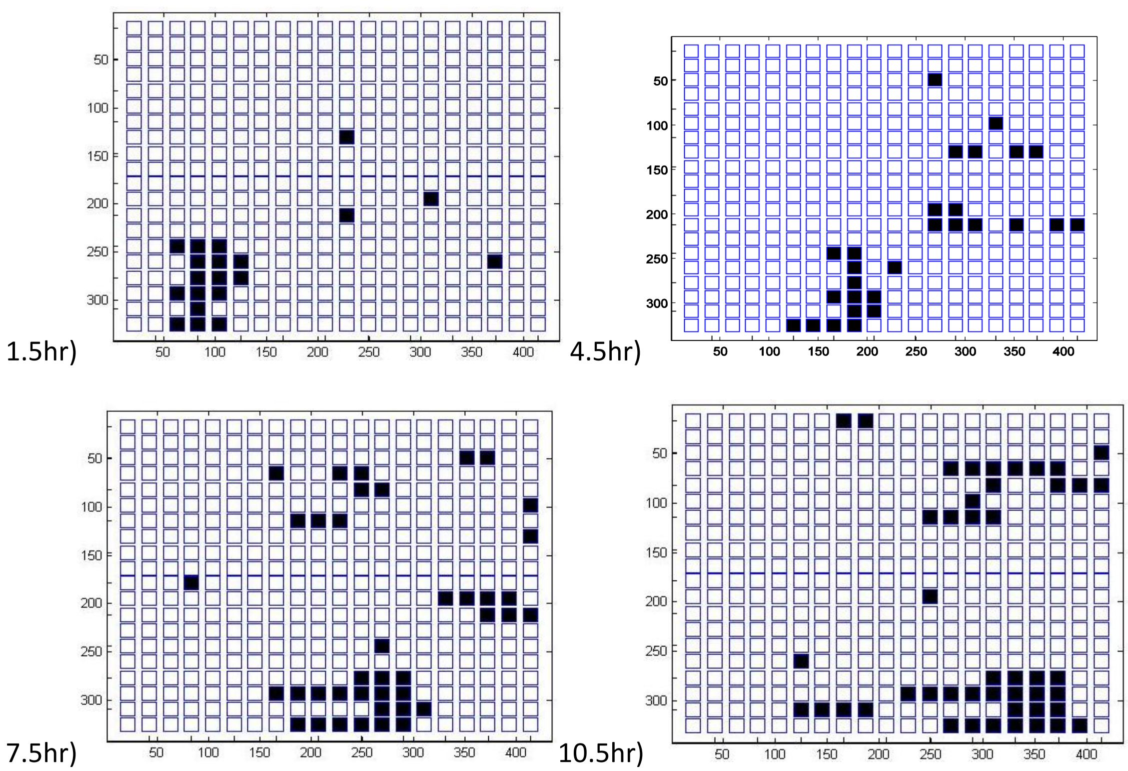


Figure 6 – Simulation, Winter-Weather Example: the storm takes a Southern track

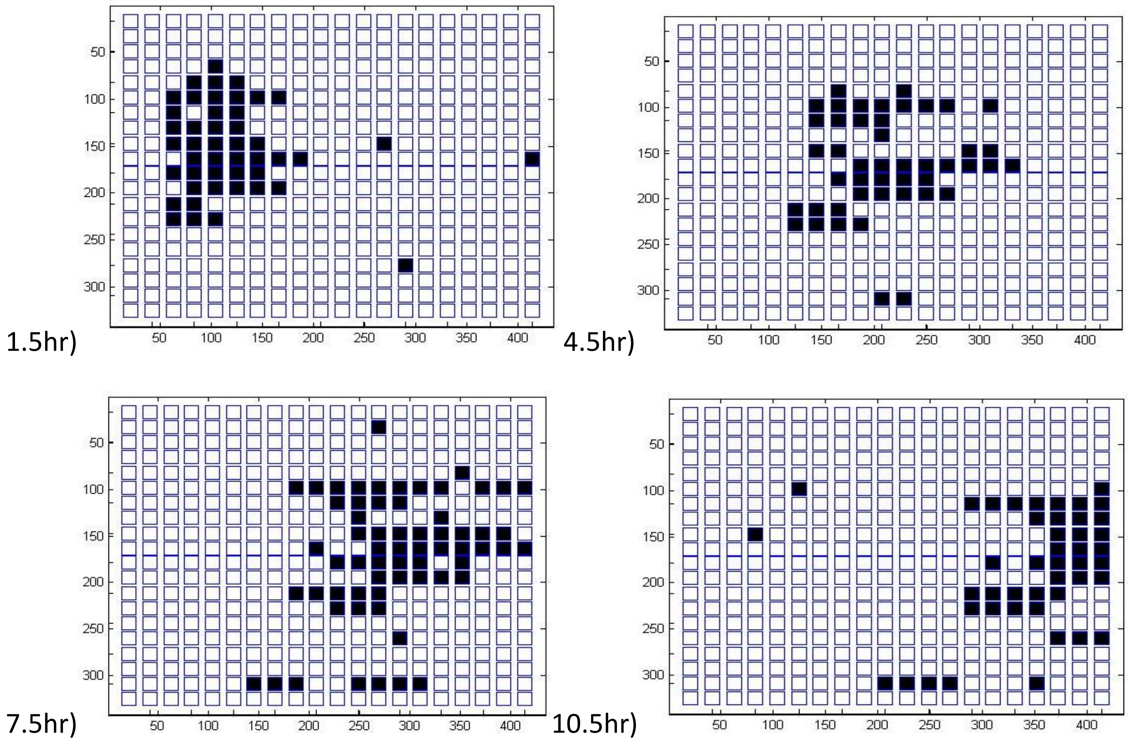


Figure 7 – Simulation, Winter-Weather Example: the storm takes a Northern track

3. Lower-Order Markov Models for Critical Weather-Impact Uncertainties

Our eventual goal is to analyze and design traffic flow under weather uncertainty. Given that a relatively small set of geographically-distant bottleneck points often play a dominant role in flow restriction and delay, it may sometimes be cumbersome to model weather impact throughout the entire NAS when only a few critical uncertainties are of importance. It is often possible to obtain much simpler (lower-order) representations for weather uncertainties at these locations, since only a portion of the full spatial model may play a significant role in deciding the local weather, and further because geographically-distant locations often have uncorrelated uncertainties. Thus, we are seeking lower-order models for critical uncertain weather-impact events. We propose developing such models in two ways: first, through approximation and reduction of the spatiotemporal model; and second, directly using weather forecasting tools such as the fog forecast for the San Francisco area. As a very first analysis in this direction, we note that the pdf of weather-impact duration at Yanville in Example 2 can be approximated well using only a four-state Markov chain, see Figure 8 for the approximation. We are in the process of developing systematic tools for approximating the weather-impact model with lower-order Markov chain models.

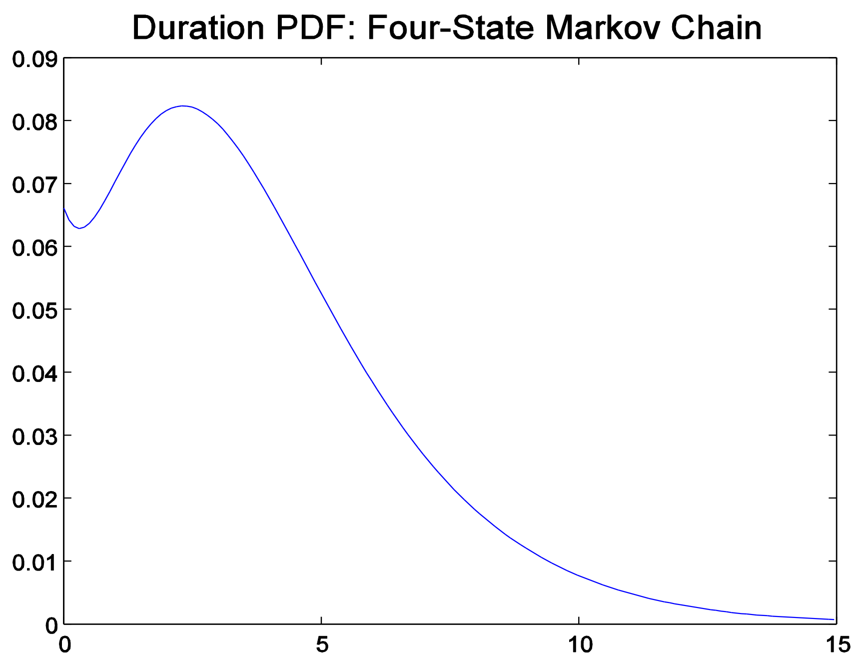


Figure 8 – Low-Order Models for Critical Weather Uncertainties: Interestingly, a Markov-process model with only four states can be used to generate weather-impact events at one location (Yanville) which statistically match the durations predicted by the spatiotemporal model, as seen by comparing the above PDF with that in Figure 4e.

4. Future Work

We stress that the weather-impact model developed in this paper is only one component in a comprehensive methodology for evaluating and designing FCM. In pursuing a full solution to the FCM problem, a range of tasks involving the weather-impact model will need to be completed. The following are some first tasks that need to be addressed in applying the weather-impact model to FCM.

1) Motivated by the need for collaborative traffic flow management tools, we have been developing aggregate models for traffic flow and management as well as tools for simulation of the NAS under uncertainty [6,19-22] (see also e.g. [23-25]). The weather-impact model needs to be meshed with these aggregate flow models and simulation tools at the strategic horizon. To do this, parameters in the aggregate-flow and queueing models (like capacities) must be represented by stochastic-process models for weather uncertainties which are derived from the weather-impact model. Additionally, some simplicity/abstraction in modeling is helpful, to permit analysis of the meshed weather and flow models.

2) The problem of FCM design under weather uncertainty must be formulated, perhaps by using a *jump-Markov model* formalism [7-9]. We expect this problem of design under uncertainty to lead to a family of rather ugly (and technically interesting) distributed resource-allocation problems. We will need to advance our ongoing work on network design to address these problems.

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Appendix: Mathematical Formulation of the Influence Model

A mathematical formulation of the influence model is given, to supplement the conceptual development in the main text. This formulation is drawn directly from our concurrent work on parameterizing the influence model [15]. For ease of presentation, each site (or region in our case) is assumed to have two states. We refer the reader to [9,12] for a complete formulation allowing more than two and varying numbers of states throughout the network. These documents also extensively describe the tractabilities of the influence model.

The influence model [9,12-15] comprises a network of n components or nodes or **sites** (which represent airspace regions in this article). We label these sites as $1,\ldots,n$. Each site has a binary **status** (which captures the weather-impact state of the region in this article) evolving in discrete time. We find it convenient to represent the status of each site I at a time k using a two-element 0--1 indicator vector, which we call the **local status vector** or simply **status vector** for site i and denote as $\mathbf{s}_i[k]$. The sites' statuses evolve in time due to probabilistic influences from neighboring sites (possibly including the site itself), as specified by a directed **network graph** Γ. (Notice that we permit self-loops, i.e., edges directed from vertices back to themselves, in the network graph). Specifically, a site j's next- (or time $k+1$) status is influenced by a site i's current (time-k) status (where i may equal j), if there is an edge from i to j in Γ.

This influence is codified with two parameters: a scalar interaction strength or **weight** d_{ji} that indicates the frequency with which *i* influences *j* (where the weights to *j* are between *0* and *1* and sum to *1*) , and a row-stochastic **local transition matrix** A_{ij} that specifies the probabilistic rule by which site *j*'s next status is determined by site *i*'s current status. Precisely, the sites' next-statuses are determined from their current statuses according to the following two-step procedure:

1) For each site *j*, a (neighboring) site *i* is chosen as its influencing or **determining** site independently with probability d_{ji}.

2) Each site's next-status is generated independently, according to a probability mass function (or probability vector) specified by its determining site's current status. Specifically, the next-status of site *j* is chosen according to the probability mass function (pmf) specified in the vector $\mathbf{s}_i[k]' A_{ij}$. That is, if $\mathbf{s}_i[k]'=[1,0]$, the entries in the first row of A_{ij} specify the probabilities that $\mathbf{s}_j[k+1]'$ equals *[1,0]* and *[0,1]*, respectively. Similarly, if $\mathbf{s}_i[k]'=[0,1]$, the entries in the second row of A_{ij} specify the probabilities that $\mathbf{s}_j[k+1]'$ equals *[1,0]* and *[0,1]*, respectively. We have thus specified the time-evolution of the influence model.

We have thus specified the stochastic dynamics of the influence model.

The influence model is a promising tool for abstractly representing various stochastic network dynamics, because it can capture *heterogeneous* stochastic influences (e.g., in our case, translation, generation, or decay of weather impact) in a network with general graph structure [12]. Specifically, although the model is very specially structured in certain senses (e.g., in each site's selection of a determining site at each time step), the model also permits wide latitude in capturing stochastic influences in networks – including in allowing arbitrary graphical structures for influence, and in permitting generic and heterogeneous local-influence rules (e.g., copying or anti-copying influences as well as more general stochastic influences). Because of the model's ability to capture varying influence structures, it encompasses a diversity of stochastic network dynamics, including both ergodic and non-ergodic dynamics; settling, periodic, and apparently chaotic responses; and long-range spatial correlations and persistences in the asymptotics. This wide representation capability makes the influence model suitable for numerous applications, including in modeling voting and decision-making processes, abstractly modeling failures in infrastructure networks, and (as developed here) capturing weather evolution; and in graph partitioning and distributed-agreement computations [14].