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Assessment and Interpretation of En Route Weather Avoidance Fields from the Convective Weather Avoidance Model*

Michael P Matthews† and Rich DeLaura‡
MIT Lincoln Laboratory, Lexington, MA 02420, USA

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This paper presents the results of a study to quantify the performance of Weather Avoidance Fields in predicting the operational impact of convective weather on en route airspace. The Convective Weather Avoidance Model identifies regions of convective weather that pilots are likely to avoid based upon an examination of the planned and actual flight trajectories in regions of weather impact. From this model and a forecast of convective weather from the Corridor Integrated Weather System a probabilistic Weather Avoidance Field can be provided to automated decision support systems of the future impact of weather on the air traffic control system. This paper will present three alternative spatial filters for the Convective Weather Avoidance Model, quantify their performance, address deficiencies in performance, and suggest potential improvements by looking at the ATC environment and common situational awareness between the cockpit and air traffic control.

I. Introduction

The future Air Traffic Management (ATM) system will require decision support tools capable of translating the impact of convective weather into application specific parameters, such as the expected delay of individual flights, on the air traffic control system[1]. The Convective Weather Avoidance Model (CWAM)[2] is a statistical model to correlate observable weather parameters with pilot behavior in the en route airspace. This model has been under development at Lincoln Laboratory, sponsored by NASA, with the goal of defining avoidance polygons[3] that can be used by ATM decision support tools to support real-time trajectory automation during times of weather impact. The observable weather information currently being employed by CWAM are the ground-based radar derived echo top height and vertically integrated liquid (VIL) available from the Corridor Integrated Weather System (CIWS)[4]. CIWS also provides forecasts of the future location and intensity of VIL out to a two hour time horizon in five minute increments along with a prediction of the echo top location and height. Combining a probabilistic prediction of pilot behavior from CWAM with a deterministic prediction of convective weather from CIWS a probabilistic Weather Avoidance Field (WAF) can predict the likelihood a pilot would chose to avoid the weather at each grid point in space.

The ability of CWAM to correlate pilot behavior with weather parameters begins with defining a database of aircraft trajectories encountering convective weather along a planned flight trajectory. The flight trajectories were obtained from the Enhanced Traffic Management System (ETMS). Each aircraft's planned and actual trajectory are then examined to determine if the pilot decided to avoid the weather along the planned trajectory by maneuvering some normal distance from the planned path that is greater than a 'deviation threshold'. The deviation threshold was defined by examining the mean and maximum normal distances on a day without any weather impact. Finally, each weather encounter is defined as a deviation or non-deviation in the CWAM database.

This paper quantifies the performance of the WAFs in predicting the likelihood of pilot deviations due to weather by generating a deterministic deviation prediction from the WAF for each flight in a test data set. Scoring results for the deviation prediction are presented as a function of forecast lead time, weather type, and other variants. This paper also discusses identified limitations in the CWAM and WAF products as well as how decision support tools might consider performing post-WAF processing identifying constraints to the preferred trajectories with knowledge of the ATC environment.

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† Associate Technical Staff, Weather Sensing Group, 244 Wood Street.
‡ Technical Staff, Weather Sensing Group, 244 Wood Street.

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II. CWAM Methodology

A. Creating Deviation Database and Weather Avoidance Fields

The basic component of CWAM is a database of flight trajectories consisting of weather encounters along a planned flight path with each encounter identified as either a deviation or a non-deviation. An automated process has been developed that classifies each flight trajectory that encounters significant weather along the planned path based upon a comparison of the planned and actual trajectories. Each deviation computes the starting point of the deviation, an ending point, and a decision point. Figure 1 depicts several illustrations of the methodology to classify planned flight trajectories encountering weather. The algorithm identifies when the actual flight trajectory has deviated from the planned by a distance larger than a parameter called the mean deviation threshold (nominally 20km). If the distance between the two paths remains larger than the threshold for a period of at least two minutes a deviation is declared. The algorithm limits the time between the first encounter with the weather and the decision point to no longer than 15 minutes. Weather encounters along the planned flight path after this limit are excluded from the database with the assumption that other factors may have been more relevant. For example, pilots routinely take ‘short cuts’ in air space with little congestion and pilots that have deviated due to the first weather encounter along a flight path may have had little information about the subsequent weather encounters along the planned path. Once a deviation has been declared the end time will be determined by the time the aircraft returns to the planned trajectory or the time the weather encounter ends; whichever comes last.

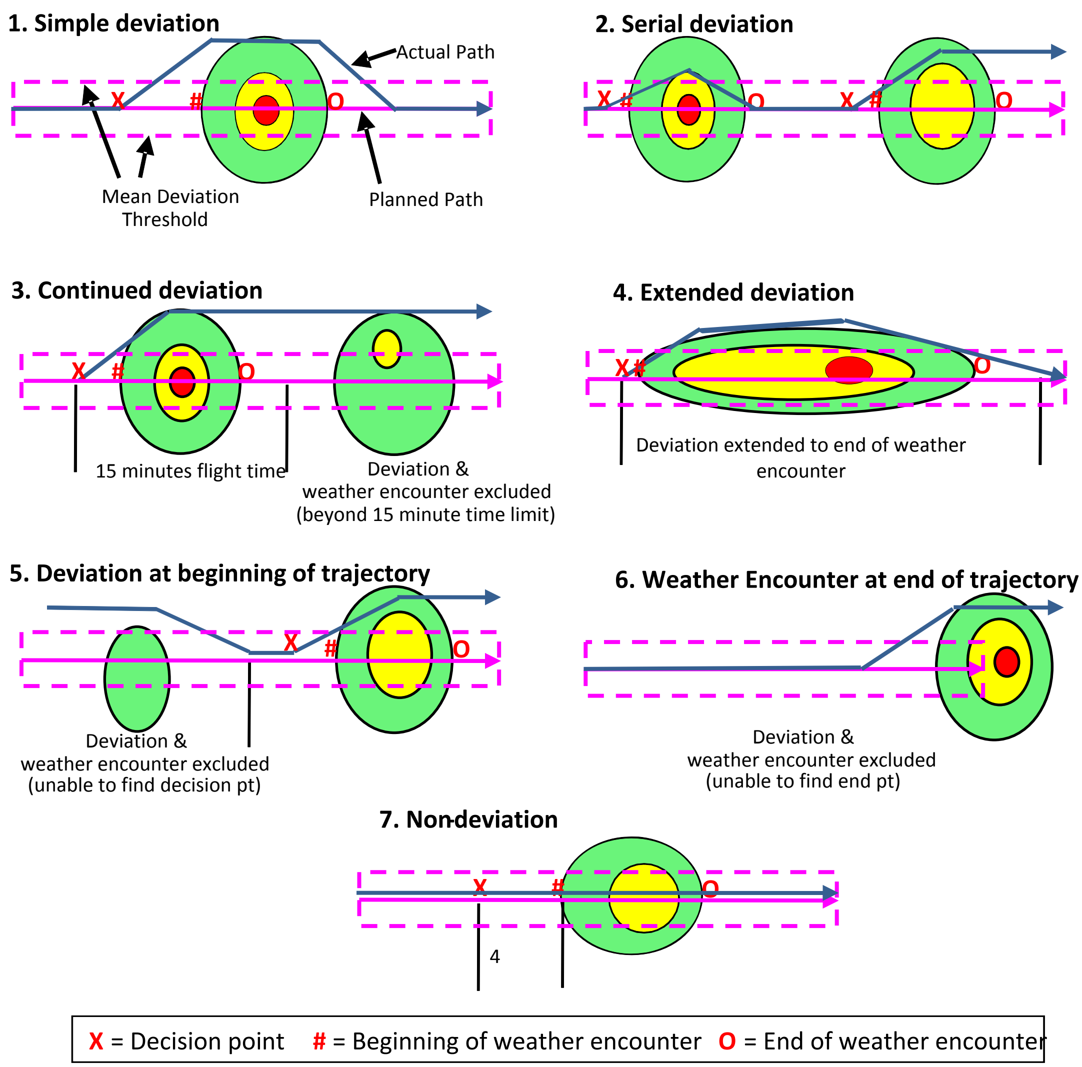

Figure 1: Methodology to classify planned flight trajectories encountering weather

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The main component of CWAM is to translate the deterministic weather information from CIWS into an estimate of the likelihood of pilot deviation. The final output of CWAM is a three-dimensional Weather Avoidance Field which estimates the probability (0 to 100%) that a pilot will deviate around convective weather at each WAF grid point. Figure 2 shows the steps involved with generating a WAF within CWAM. The CWAM deviation database described above and depicted in the figure is limited to aircraft above 25kft that encounter level 2 or higher VIL or 25,000 foot echo tops for at least one minute. Spatial filters are run on the observed VIL and echo tops to generate deviation predictors. The best predictors of deviation are identified using a Gaussian classification algorithm. Two-dimensional histograms of the deviation statistics are used to generate the probability of deviation as a function of the two best predictors. Finally, the deviation probability lookup table that is used to create the WAF is produced by smoothing and filling the two-dimensional deviation probability histogram.

The original CWAM identified the difference between flight altitude and echo top height as the primary predictor of deviation to avoid convective weather, and the percent of area covered by VIL>=level 3 as a secondary predictor. The echo top height used in the difference calculation was the 90^{th} percentile calculated over a 16 x 16 km kernel. The VIL coverage kernel was 60 x 60 km. Logically, these two filters represent the regional coverage of heavy weather and whether the flight was above or below the tallest nearby echo tops.

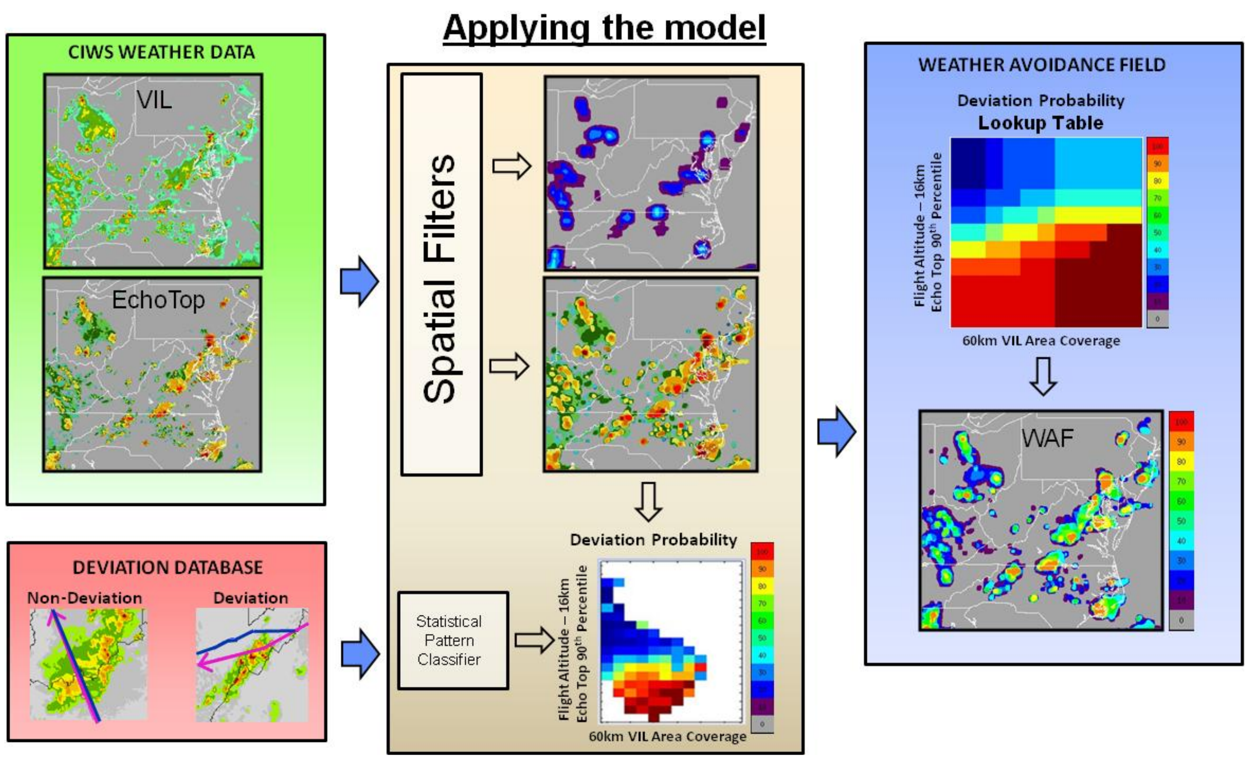


Figure 2: Generation of the Weather Avoidance Field using the Convective Weather Avoidance Model.

B. Scoring the Weather Avoidance Fields

The CWAM deviation predictions can be evaluated by converting the WAF into a deterministic deviation prediction. First, a deviation probability threshold (WAF_{dev}) is applied to the WAF field to identify regions that pilots are most likely to avoid. Next, each trajectory in the database is analyzed to find the maximum WAF (WAF_{max}) along the planned path for each weather encounter. Finally, for each trajectory the deviation prediction can be classified as a correct prediction or hit ($WAF_{max}>=WAF_{dev}$), an incorrect prediction or miss ($WAF_{max}<WAF_{dev}$), or a false prediction ($WAF_{dev}<WAF_{max}$). To evaluate CWAM, the probability of correct deviation prediction (PoD), probability of incorrect deviation detection (false alarm rate, or FAR), and critical skill index (CSI) are calculated for different values of WAF_{dev}. These quantities are defined as:

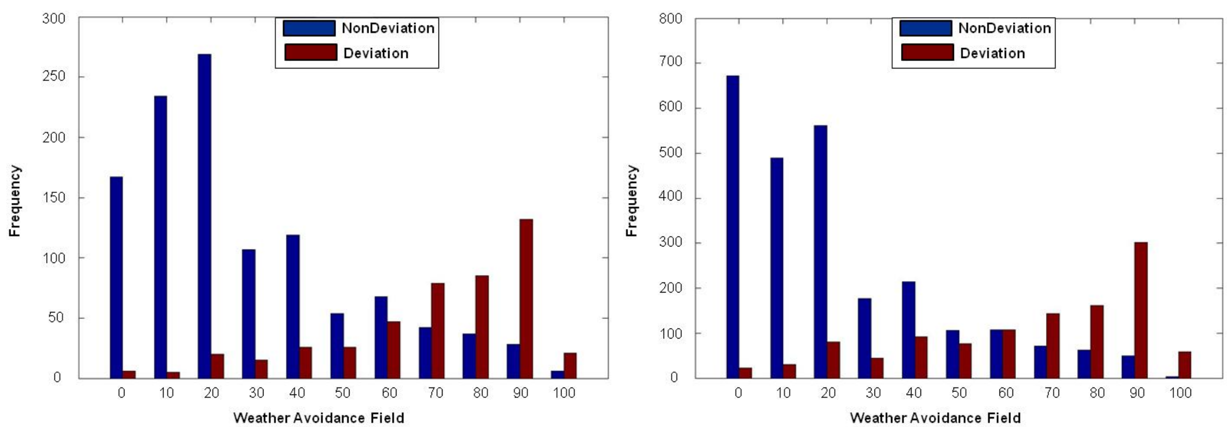
$$\text{PoD} = \text{hits} / (\text{ hits} + \text{misses })$$
$$\text{FAR} = \text{false} / (\text{ hits} + \text{false })$$
$$\text{CSI} = \text{hits} / (\text{ hits} + \text{misses} + \text{false })$$

POD vs. FAR plots can be created, with the optimum performance being the closest point to the top left corner. The highest WAF threshold of 100 will be in the lower left hand corner (low false rate and low detection rate) and the lowest WAF threshold of 10 will be in the upper right hand corner (high false alarm rate and high detection rate). The CSI, which provides one number to identify the optimum performance, allows easy identification of the best WAF threshold (WAF_{dev}) for deviation predictions.

III. CWAM Evaluation Results

A. Performance quantification

The original CWAM was created using a data set consisting of six case days from the summer of 2006. A total of 1,955 weather encounters were used with 668 causing pilot deviations. A recent expansion of the database using five case days from the summer of 2007 and one from the winter of 2008 allows an independent evaluation of the CWAM performance. These case days added another 3,280 weather encounters to the dataset with 896 of those causing a pilot deviation. Figure 3 depicts the deviation and non-deviation probability distributions as a function of maximum WAF deviation probability encountered along the planned trajectory for the two different data sets. Probability distributions are similar and well-calibrated, suggesting that CWAM may be applied to a wide range of weather regimes with consistent results. With this in mind, all evaluations here-forward will be performed on the complete trajectory dataset (2006, 2007, and 2008).



(a) (b)

Figure 3: Deviation and non-deviation probability distributions from 2006 (a) and 2007/2008 (b) datasets.

The greatest errors in the CWAM deviation predictions are where the probability of deviation is in the 30 – 70% range, this represents the greatest uncertainty in the model. Figure 4 illustrates the region with the highest uncertainty in the two-dimensional deviation probability histogram (shown in the inset of figure 4; the x-axis is area coverage of VIL>= level 3 in a 60 x 60 km window, the y-axis is flight altitude minus 90th percentile echo top in a 16 x 16 km window). The best deviation predictors, resulting in the lowest CWAM prediction error, are characterized by the smallest range of uncertainty.

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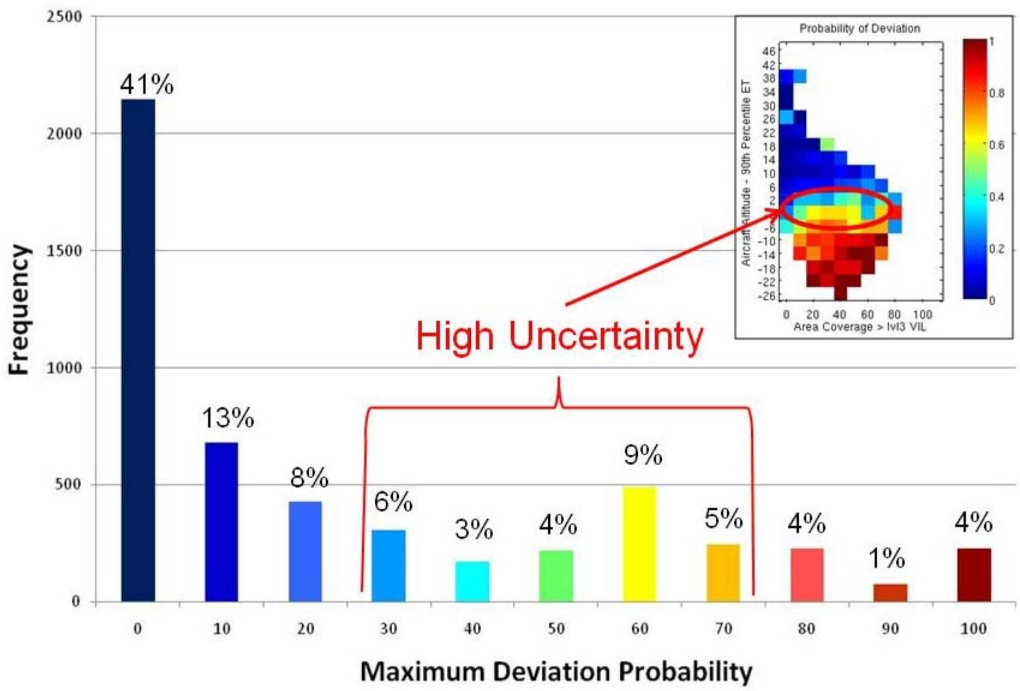

Figure 4: Maximum Deviation Probability distributions for CWAM from the 2007/2008 data set denoting the region of uncertainty for the deviation prediction model. Percentages give the percent of total encounters in the dataset whose planned trajectories encountered the specific maximum deviation probability.

In an effort to further improve CWAM performance, three variations were defined, and their deviation prediction errors were compared to the original CWAM (CWAM-ORIG). The first, CWAM-ORIG-LITE is based on the same two deviation predictors as CWAM-ORIG, but uses smaller spatial filter kernels on the echo top (4 x 4 km) and VIL (16 x 16 km) fields. A smaller kernel size will reduce the processing time which is a concern for real time operations of CWAM and potentially improve performance. The second, CWAM-1KM does not apply spatial filters to either weather input; WAF deviation probabilities at each grid point are based on echo top and VIL values at that grid point only. Finally, CWAM-16KM-MAX uses the 90^{th} percentile value of both echo top and VIL in a 16 x 16 km kernel as deviation predictors. CWAM-16KM-MAX attempts to capture the observation that pilots appear to provide a buffer of approximately 10km to severe weather. Figure 5 shows the results for the four different CWAM 2-D histograms, the WAF lookup table created from the 2-D histograms and a subsequent WAF for weather impacted airspace. Figure 6 is the POD vs. FAR and CSI results for the four CWAM versions at 10 WAF thresholds.

A comparison of the four CWAM versions shows the performance of the CWAM-1KM does not perform as well as the three versions using a spatial filter indicating that a spatial filter is required for optimum results. Any differences between the three versions using a spatial filter appear to be negligible. The results also indicate that the optimal WAF deviation probability threshold of 70 produces a POD of ~65% and a FAR of ~25% for CWAM-16KM-MAX.

The creation of a deviation prediction model is dependent upon comparing the actual weather encountered by pilots with the deviation database generated for CWAM. However, for evaluation purposes the true impact of the operational usefulness of the model is dependent upon the forecasts of convective weather. This is due to the fact that for planning purposes, air traffic control managers need to know which regions will be impacted by weather well in advance. ATC makes use of weather forecasts provided by CIWS and other sources and ultimately, the CWAM will be combined with convective weather forecasts from CIWS to predict future regions that will be closed or impacted due to the weather. The deviation prediction error observed in operations will be the convolution of the CWAM deviation prediction error and weather forecast errors.

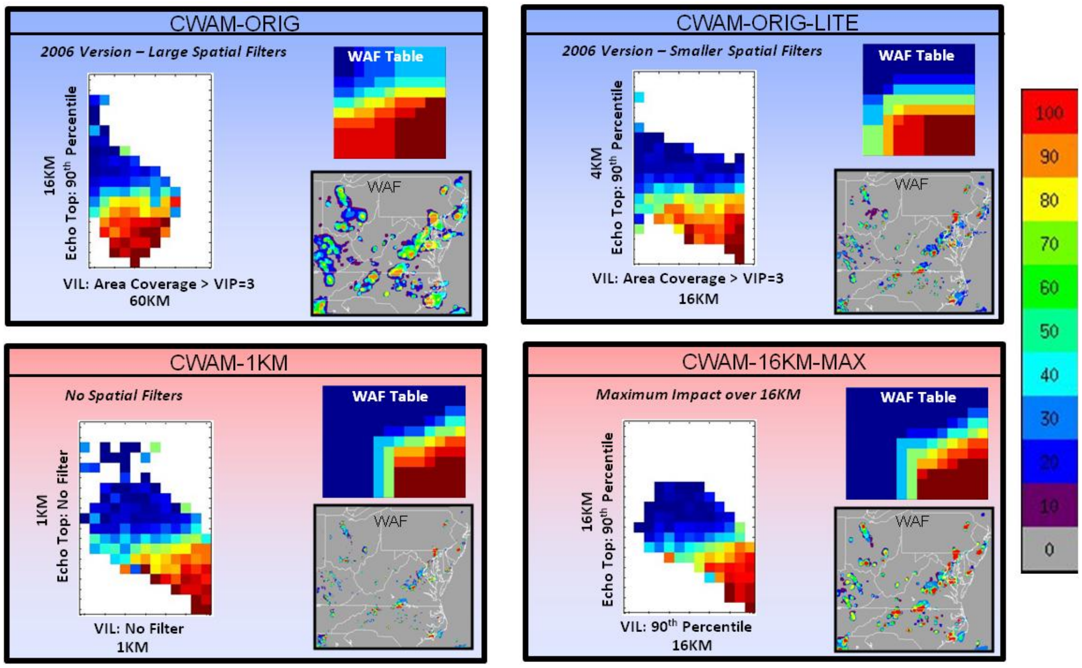

Figure 5: 2-D histograms, WAF lookup table and WAF output for four versions of the Convective Weather Avoidance Model.

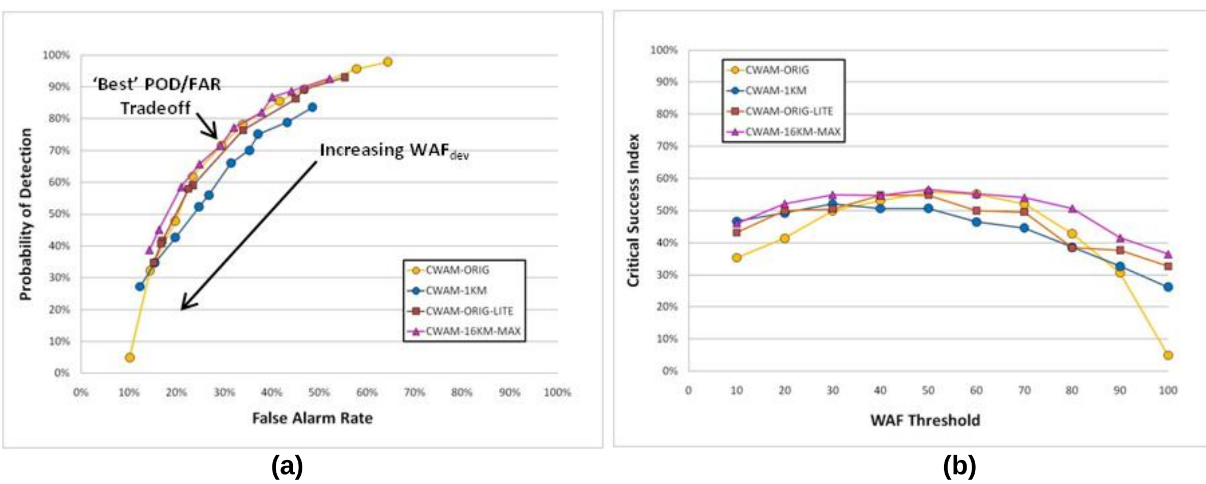

Figure 6: Probability of Detection vs. False Alarm Rate (a) and Critical Success index (b) for four versions of CWAM using the CIWS VIL and echo tops.

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In an effort to identify factors that may influence the deviation prediction accuracy the data set can be partitioned by region and case day. Figure 7a partitions the data set into the three different ARTCCs that were selected for the CWAM database. Clear differences in predictive skill for weather impacts in different ARTCCs are evident but the reasons for these differences are not readily evident. A speculation could be made about different factors that may be related to these results, such as; differences in the predominant weather type in each ARTCC (e.g. severe thunderstorm cores vs. weak or moderate high topped convection), differences in the geometric relationship of the route structure and weather orientation (e.g., do routes cross or parallel major weather features), the perceived willingness of air traffic control to accommodate deviations (possibly affecting pilot behavior), or the availability of acceptable alternatives (i.e., if there are readily accessible avoidance routes in the airspace). Figure 7b partitions the data set into the 12 case days chosen in the CWAM deviation database. Clear variations in performance are also evident on different case days with three days showing particularly high false alarm rates. The difference in POD vs. FAR results by case day of CWAM suggests a possible correlation between the type of weather and the algorithm performance.

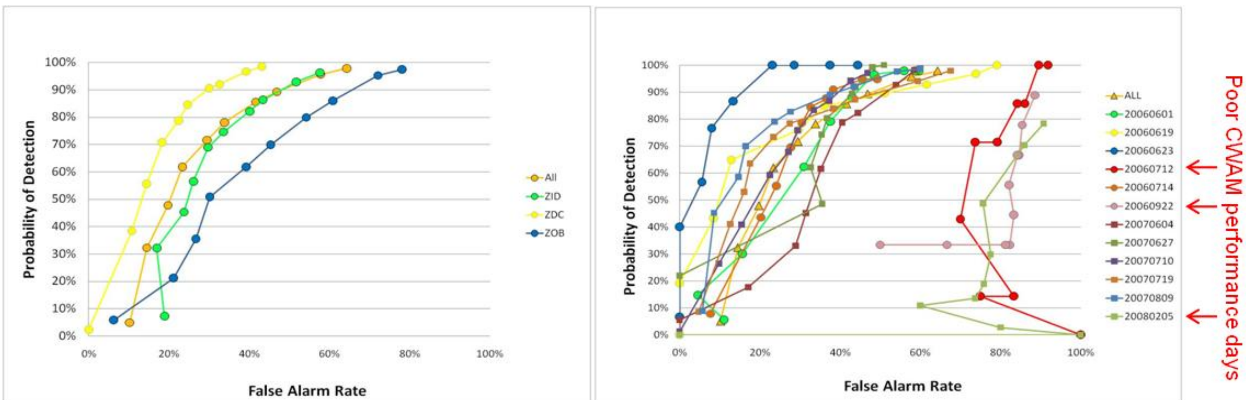

Figure 7: Probability of Detection vs. False Alarm Rate for the original CWAM partitioned by ARTCC (a) and case day (b).

With the expanded data set used in this study, CWAM cases can be partitioned into one of three weather types; Cellular convection (small scale cells, short life cycle), synoptic scale events (low pressure systems, warm fronts, weak cold fronts), and strong organized convection (strong cold fronts, MCCs). Figure 8 shows the 2D deviation probability histograms from the 1km CWAM regenerated using the entire data partitioned by weather type. The cellular convection consists of all valid weather encounters on June 4, 2007. The synoptic scale events are all encounters from July 12, 2006, September 22, 2006 and February 5, 2008. The eight remaining case days were typical days with strong organized convection. The results from days with strong organized convection are similar to the overall results presented in the original study. However, very different results are observed in the cellular convection and synoptic scale event days. The region highlighted with a red box shows the most significant difference. This region covers the cases with VIL greater than level 3 and flight altitudes at or slightly above the echo tops. For the cellular convection weather type pilots are more likely to deviate even when well above the echo tops. In fact, on days with cellular convection the likelihood of pilot deviation is roughly 50% over a large segment of the 2D probability of deviation histogram, suggesting that the current CWAM predictors are a poor choice in cellular convection. For synoptic scale events, the histogram suggests that the pilots are unlikely to deviate at the echo top height. However, for synoptic scale events these results may require further evaluation due to the limited number of encounters at echo top height and the pilots preference to avoid these areas altogether during preflight planning. The results do suggest that weather characteristics that differentiate between typical and high false alarm days could be incorporated directly into CWAM to improve its performance, or to identify days when CWAM will perform poorly.

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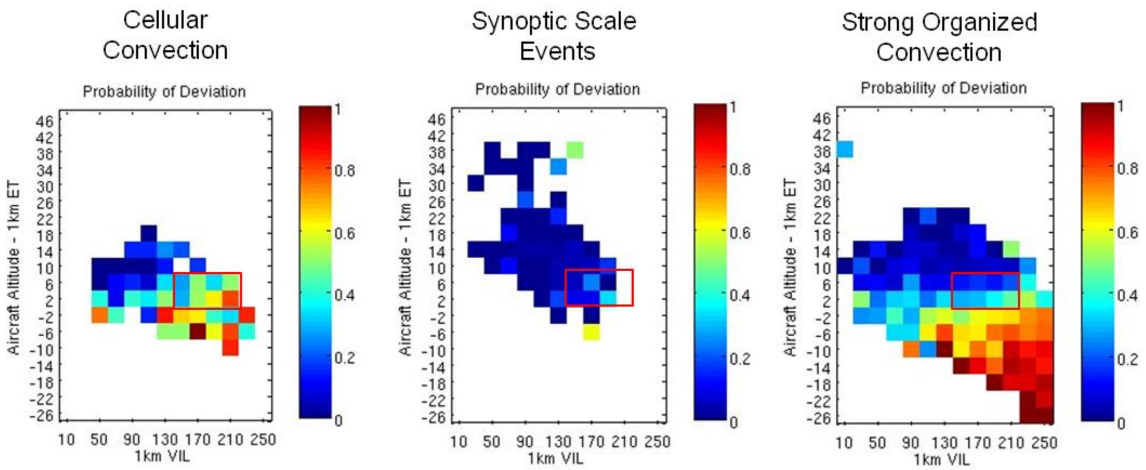

Figure 8: 2D histograms of observed probability of deviation (percentage of flights in each histogram bin that deviated) for (a) cellular convection, (b) synoptic scale events, and (c) strong organized convection. The region of the 2D histogram with the most significant differences is highlighted in red.

The same methods used to measure the performance of CWAM using actual weather can be applied to estimate the deviation prediction error based on forecasted weather. Figure 9 compares the POD vs. FAR and CSI curves calculated for all four CWAM using 60 minute and 120 minute forecasted WAF. As the forecast time horizon increases, the differences in deviation prediction errors associated with the different CWAM variants decreases. The deviation prediction performance of the three spatially filtered CWAM variants is virtually identical for the two hour forecasts. This finding suggests that the characteristics of the forecast – spatial smoothing and forecast error – have a greater impact on CWAM deviation prediction accuracy then the choice of spatial filter applied in the CWAM itself.

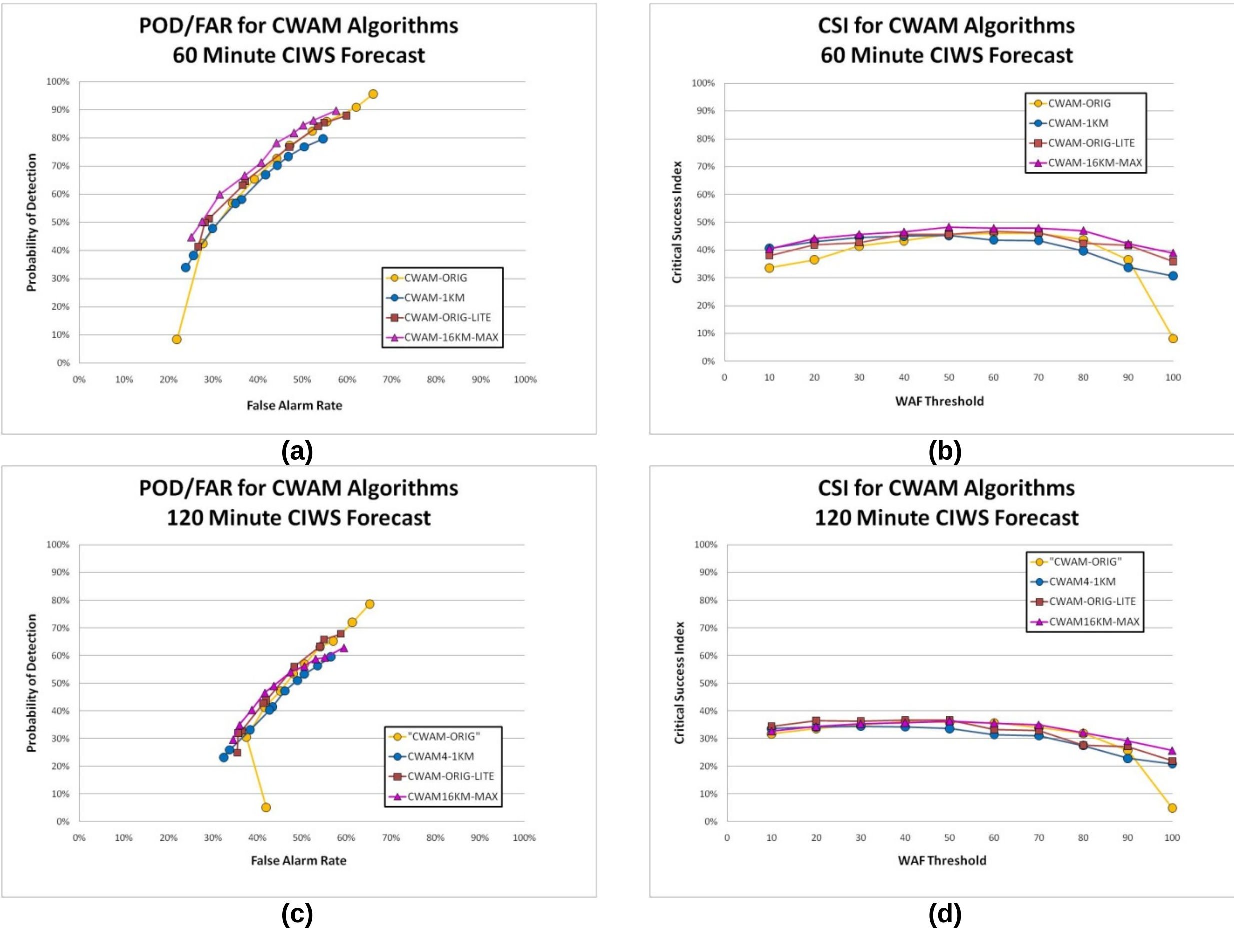

Figure 9: Probability of Detection vs. False Alarm Rate and Critical Success index for four versions of CWAM using the 60 minute CIWS VIL and echo tops forecasts (a,b) and the 120 minute CIWS VIL and echo tops forecasts (c,d).

The comparison of CWAM accuracy, based on both true and forecast weather, also provides some insight into what may be operationally meaningful measures of uncertainty. The CWAM forecast error is a convolution of two terms: deviation prediction errors in the CWAM itself (based on deviation probabilities calculated using true weather as the CWAM inputs), and weather forecast errors. The comparison of CSI scores for CWAM based on true and forecast weather provides a basis for the assessment of the relative contributions of CWAM prediction error and weather forecast error to the total deviation prediction error that is observed in operational use. In essence, the comparison of CWAM performance based on forecast and truth may be used as a weather forecast uncertainty metric. Figure 10 shows the deviation prediction CSI scores for true weather, one hour and two hour weather forecasts, for each of the 12 case days. Figure 10a shows 'typical' forecast behavior: deviation prediction skill decreases as the forecast time horizon increases. Figure 10b shows examples of excellent weather forecasts: deviation predictions based on one and two hour forecasts are as accurate as those based on the actual weather. It may be desirable to develop a forecast scoring model based on weather characteristics that correlate well to deviation prediction forecast performance.

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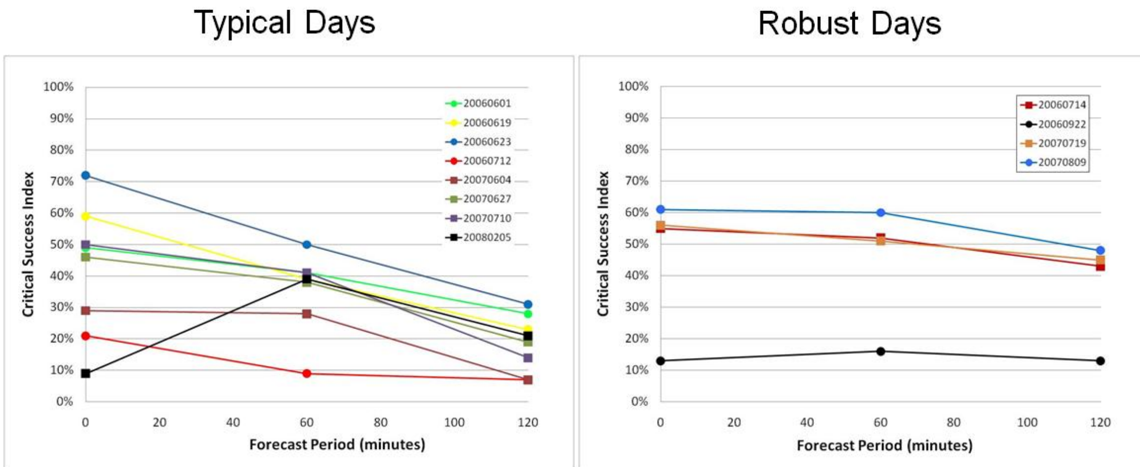

Figure 10: CSI for deviation prediction (WAF >= 70) using original CWAM, as a function of forecast time for (a) typical forecast performance days and (b) robust forecast performance days.

B. CWAM Deviation Prediction Error Mode Analysis

To date, the focus on improvements to the CWAM have been modifications to the spatial filters used on the VIL and echo tops products or adjustments to the thresholds used to define a deviation. This has resulted in limited gains with the model, especially as the forecast horizon increases from the weather forecasts. To better understand where potential improvements could be made an analysis was conducted on the false deviation predictions and the missed deviation predictions from the actual weather encountered. For this study, a deviation prediction will be defined as an aircraft encountering a threshold of 70 or greater from the original CWAM version. A total of 1,312 deviations predictions were made with 998 being validated by the deviation database resulting in 314 false deviation predictions and a false alarm rate of 25%. An analysis of the 314 false deviation predictions identified seven common error modes shown in Table 1.

Table 1. Frequency of false deviation prediction error modes.

Error modes	Count	Percent
Small deviation or active maneuvering	80	26%
Stratiform rain	73	23%
Storm orientation	39	12%
Aircraft climbing or descending during encounter	31	10%
Low altitude flight	31	10%
Unknown	31	10%
Planned path skirts edge of storm	26	8%
Data problems	3	1%
TOTALS	314	100%

The most common false deviation prediction error mode was identified as aircraft making small deviations or actively maneuvering around storms. However, in all of these cases the aircraft were not designated as deviations in the database because the aircraft did not deviate from the planned path by a distance greater than the mean deviation threshold for at least two minutes. Figure 11 shows two examples of aircraft that have been classified as non-deviations and thus result in false deviation predictions from the model. In each of these examples the aircraft's actual trajectory encountered observed weather that was significantly less severe than the weather along the planned trajectory, suggesting that the model correctly predicted pilot deviation to avoid weather, but that the actual deviation was too small to meet the 'operationally significant' threshold in the deviation definition.

The second common false deviation prediction error mode was identified as aircraft encountering stratiform rain. Stratiform rain originates from stratus clouds that are flat and featureless with weaker upward motions and less intense precipitation. However, stratiform rain on radar can have very high echo tops and large regions of level three precipitation. With tops above aircraft altitude and large area coverage over the 60km VIL kernel stratiform

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can have very high WAF values but are not typically avoided by pilots. On days with convective weather, stratiform will typically trail behind the convective cells in the decaying region of the storms. Figure 12 depicts two examples of aircraft penetrating stratiform rain regions.

Another common false deviation prediction error mode is associated with the orientation of the storm to the aircraft flight trajectory. In these instances, pilots are encountering storms with a large cross section perpendicular to the aircraft trajectory and a relatively short along-track encounter time. It is speculated that the pilot is deciding to accept a short period of potential turbulence rather than make a lengthy deviation that will cost a significant amount of delay. Figure 13 depicts two flights encountering storms with a large cross section relative to the encounter time. The first example is a flight leaving Chicago, Illinois enroute to Charlotte, North Carolina. The storm encountered is orientated southwest to northeast or perpendicular to the planned flight trajectory. The second example is a flight from Los Angeles, California to New York City. The planned trajectory takes this aircraft into JFK airport using the northwest ATC routes. The short encounter with this north-south orientated storm is most likely a better option to the pilot than deviating several hundred miles into Canada or the southeastern US. This type of situational awareness of constraints to the preferred trajectory versus cost of alternative trajectories will be discussed later in this paper.

The next two false deviation prediction error modes are related to mode of flight operations. Aircraft in the ascending or descending stage of flight may not react to convective weather in the same manner as those at flight altitude. This may be due to ATC restrictions that are different than those for level flight at en route altitude, differences in pilot concerns during ascent or descent, or perhaps an altered view of the storm while in this stage of flight. Figure 14a depicts an aircraft ascending out of Detroit that penetrated a storm with high WAF values. Also, aircraft at lower altitudes (below 30kft) have a high false deviation prediction alarm rate. This may because the difference between echo top height of weak convection and aircraft at lower flight altitudes falsely predicts a deviation from the probability of deviation histogram. Figure 14b depicts an aircraft at a flight altitude of 28kft penetrating a storm that is not convective but has a region of level three precipitation and echo tops near flight altitude.

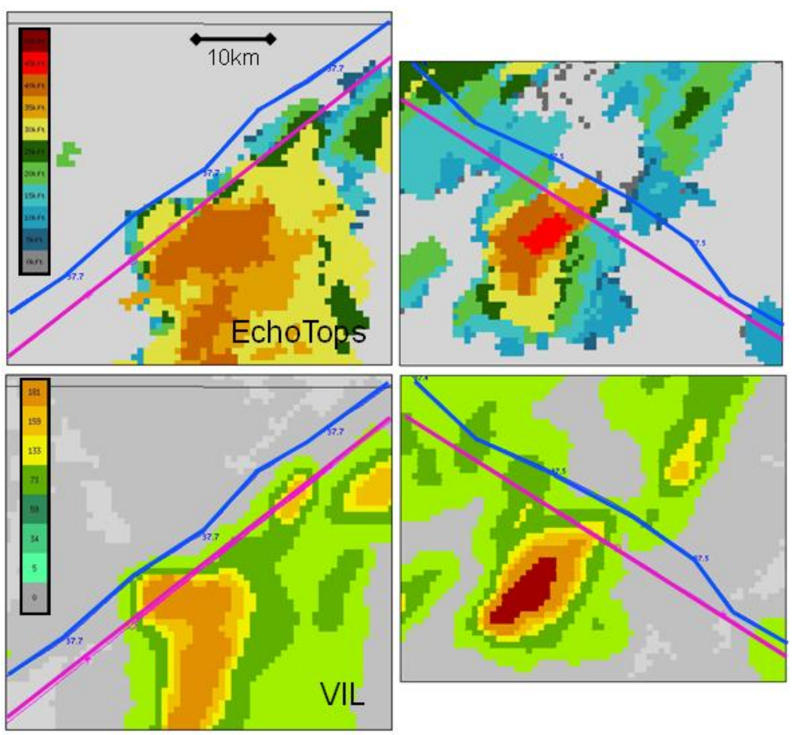

Figure 11: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on June 1, 2006 (left column) and June 4, 2007 (right column) classified as non deviations in the deviation database. The aircraft maneuver less than 20km to avoid to convective weather.

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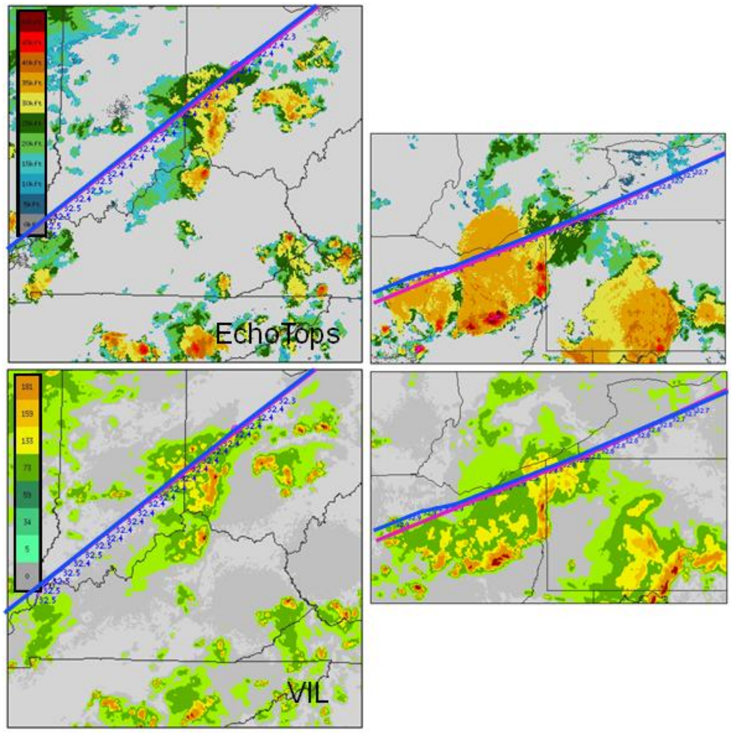

Figure 12: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on June 1, 2006 (left column) and August 9, 2007 (right column) classified as non deviations in the deviation database. The aircraft depicted encounter regions of stratiform rain.

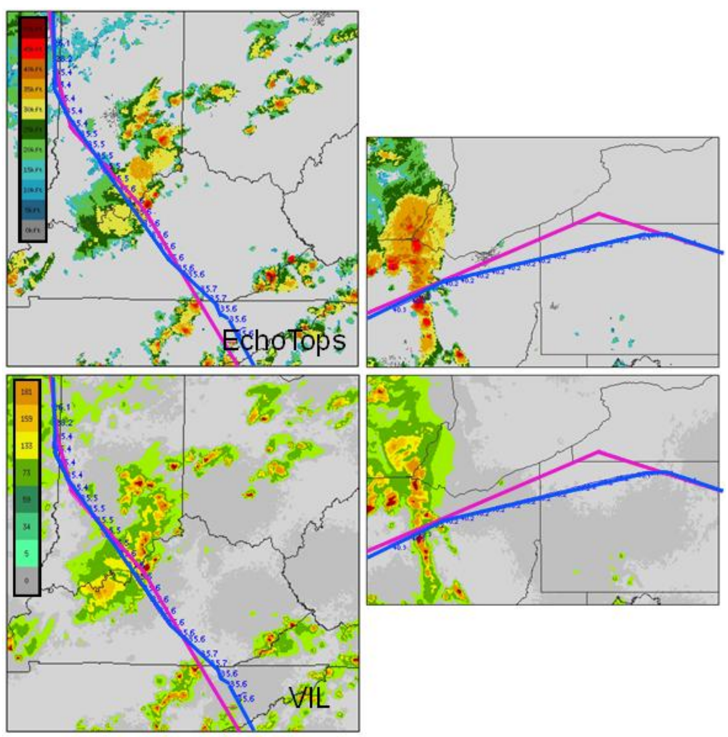

Figure 13: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on June 1, 2006 (left column) and July 14, 2006 (right column) classified as non deviations in the deviation database. The aircraft depicted encounter storms with a large cross section perpendicular to the flight path.

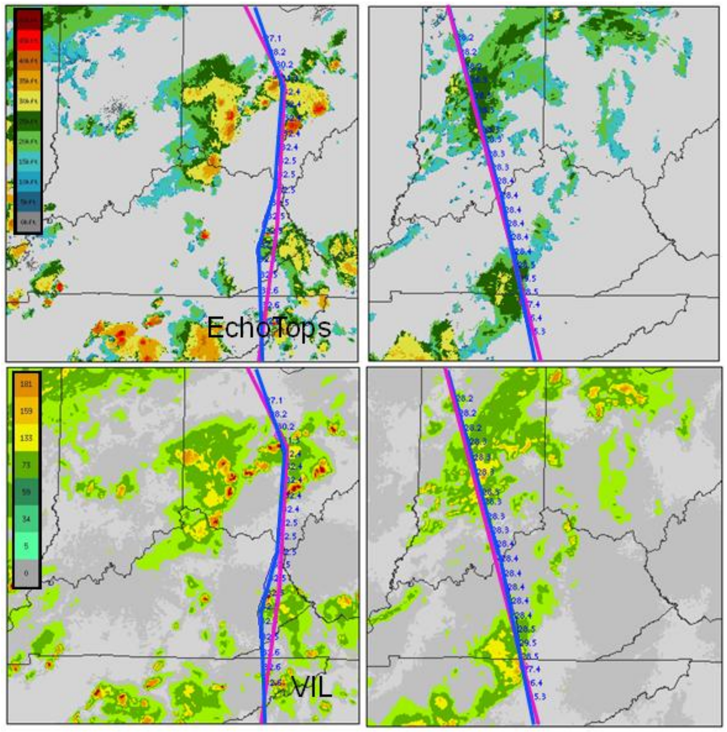

Figure 14: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on June 1, 2006 (left column) and June 19, 2006 (right column) classified as non deviations in the deviation database. The aircraft on June 1st is ascending out of Detroit during the encounter and the aircraft on June 19th is at a flight altitude of 28,000 feet.

An error mode analysis was also performed on the missed deviation predictions. Out of the 1,564 deviations in the database, this model correctly predicted 998 deviations leaving a total of 566 missed deviation predictions. Table 2 shows seven common error modes that were identified for the missed deviations. The most common missed deviation prediction error mode accounting for 57% of the cases involved aircraft maneuvering around small isolated cells or all weather in regions that may not have strict ATC restrictions. For most of these cases knowledge of the ATC environments (route density, ARTCC operations, etc.) may provide insight into methods to improve the improve performance. Some possibilities may be lowering the WAF threshold or performing additional post-WAF processing. Figure 15 shows three examples of aircraft deviating around small storms that do not meet the 70% WAF threshold to declare a deviation prediction.

Table 2. Frequency of missed deviation prediction error modes.

Error modes	Count	Percent
Avoid small isolated cells or all weather	323	57%
Thunderstorm anvil	120	21%
Aircraft climbing or descending during encounter	26	5%
Data problems	25	4%
Severe weather is beyond 15 minute limit of deviation	21	4%
Unknown	21	4%
Storm orientation	18	3%
Shortcut avoiding weather within ARTCC	13	2%
TOTALS	566	100%

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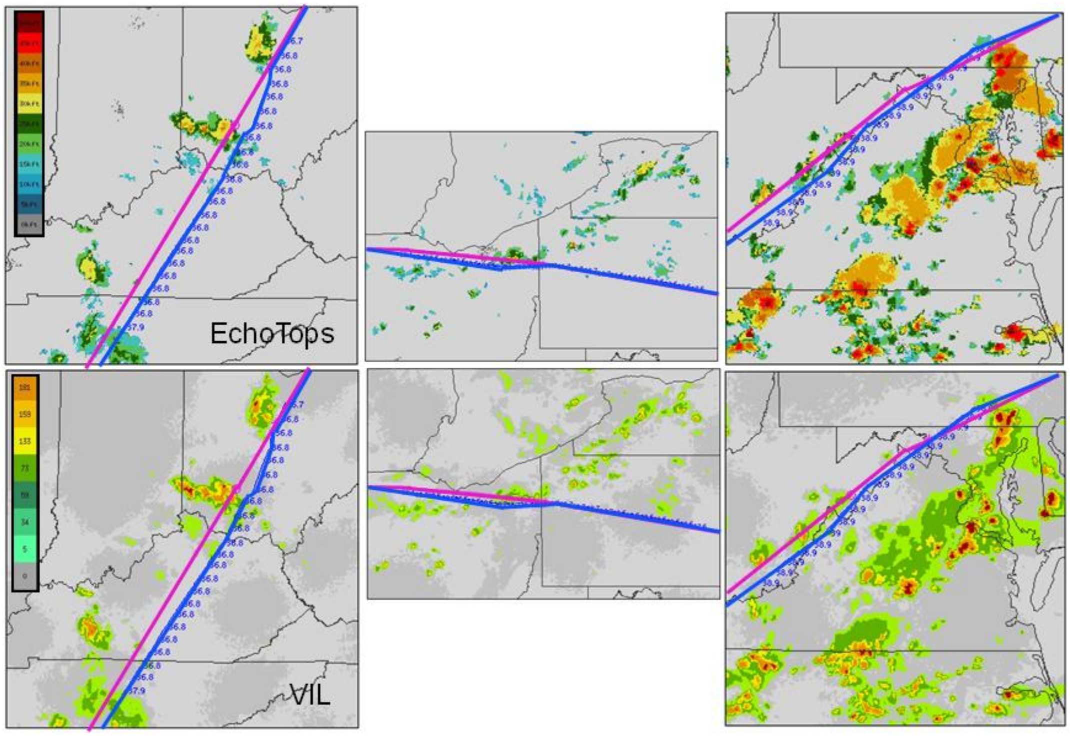

Figure 15: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on July 10, 2007 ZID ARTCC (left column), June 1, 2006 ZOB ARTCC (center column) and July 10, 2007 ZDC ARTCC (right column) classified as deviations in the deviation database. These aircraft are deviating around weather that does not meet the 70% WAF threshold.

Another common missed deviation prediction error mode was identified as aircraft encountering the thunderstorm anvil. The anvil is a region downwind from the main storm where the tops of the convective cells have reached the tropopause and are being blown out ahead of the storm. This region is recognized by pilots to be very turbulent and is desirable to avoid. On radar, these regions will have low VIL values and the echo tops may not represent the true vertical extent of the anvil cloud. Without any level 3 VIL and with echo tops below the flight altitudes these regions will have very low WAF values thus not representing the high probability of pilot avoidance. Figure 16 depicts two aircraft avoiding the anvil region of thunderstorms.

Two missed deviation error modes are similar to the error modes observed in the false deviation predictions, aircraft climbing or descending and the storm orientation. Missed deviations that are due to storm orientation would have lengthy storm impact along the planned trajectory. In these cases, accepting a few minutes of delay may avoid several minutes of potentially turbulent flight. Figure 17a depicts an aircraft avoiding a storm that does not meet the 70% WAF threshold but is severe enough to warrant avoiding a lengthy impact. Figure 17b depicts an aircraft descending into the Chicago terminal airspace. In this case the descending aircraft is being vectored along a different arrival corridor than was originally intended in the aircraft's flight plan. These type of deviations are more likely associated with the ATC operations and not weather avoidance.

The remaining missed deviation error modes are related to the way the deviation database was defined. First, while defining deviations in the database a limit of 15 minutes was placed on the time difference between when the deviation began (decision point) and when the weather encounter began. This was done to prevent multiple encounters from being merged together into one deviation. However, in a few instances the deviation began earlier than this 15 minute limit. Also, the short cut error mode was observed when aircraft were performing shortcuts within the ATC airspace and the planned path encountered fairly benign weather. These errors do not necessarily represent CWAM errors, and filtering of events to edit out such occurrences should be performed when defining the database.

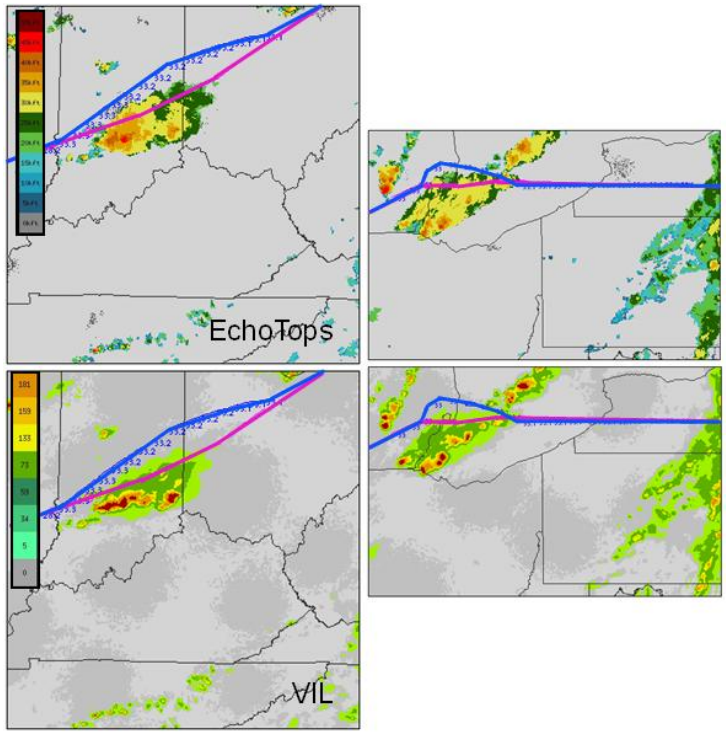

Figure 16: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on June 19, 2006 ZID ARTCC (left column) and June 19, 2006 ZOB ARTCC (right column) classified as deviations in the deviation database. These weather features are anvils associated with rigorous thunderstorm development.

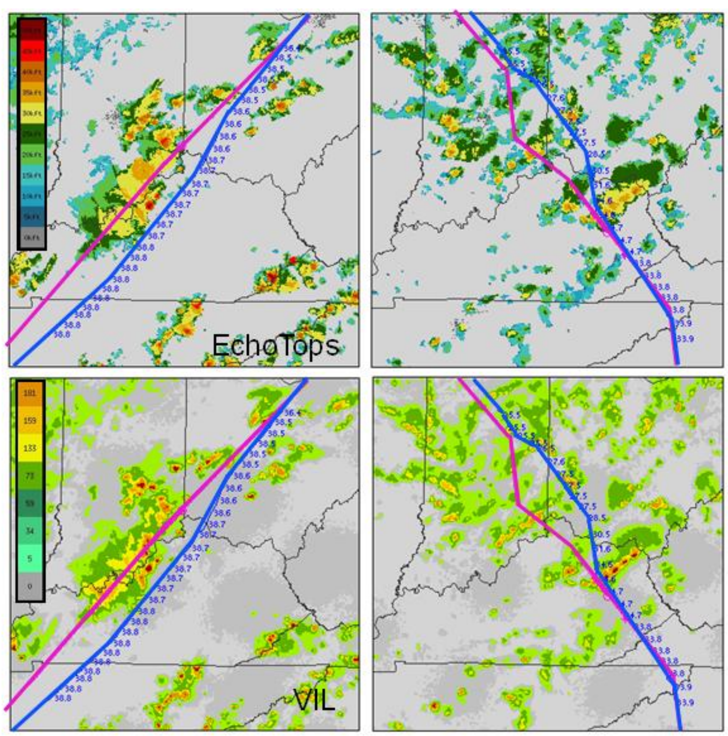

Figure 17: Planned (magenta) and actual (blue) trajectories of aircraft encountering weather on June 1, 2006 (left column) and June 4, 2007 (right column) classified as deviations in the deviation database. The aircraft on June 1st is avoiding a lengthy storm impact. The aircraft on June 4th is being vectored for landing at ORD.

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The error mode analysis suggests areas for potential CWAM improvement and application-specific factors that should be considered when using WAF in different decision support applications. CWAM performance will be improved by developing algorithms to identify weather phenomena that are treated differently by pilots, such as thunderstorm anvils and stratiform rain that are not easily differentiated using echo tops, VIL and the current spatial filtering approach. It is also apparent that the en route, level flight CWAM may not be directly applied to predict pilot behavior during flight ascent and descent. Finally, in applying WAF probabilities to predict individual pilot behavior, it may be important to examine other factors, such as the relative cost of different weather-avoiding or weather-penetrating trajectories or the influence of ATC restrictions that may influence an individual pilot's decision.

IV. WAF Interpretation

The interpretation of the WAF requires an understanding that the field is a probability of pilot deviation. In some instances pilots will penetrate very high WAF probabilities and in others, pilots may avoid weather with lower WAF values. Some of these variations in behavior may be due to the spatial characteristics of the WAF that arise from the CWAM spatial filters, or to pilots identifying different types of weather phenomena and making decisions based upon the perceived threat of these phenomena. However, as was shown in the error mode analysis, in some instances pilots are faced with the need to evaluate the cost of delay with the risk of turbulent flight. For instance, an aircraft that anticipates a lengthy impact of weather with a WAF below threshold may deviate if the deviation does not require excessive delay. To the contrary, an aircraft encountering a WAF above threshold for a relatively short period of time (1- 2 minutes) compared to a lengthy delay to avoid all of the weather may decide to penetrate and accept the risk of turbulent flight. In order to improve the accuracy of WAF in predicting the behavior of individual pilots, it is necessary to consider the perception of risk versus the cost of significant delays that may affect the decision to deviate around weather.

Figure 18 depicts two different aircraft encountering the same storm at very similar altitudes on June 1, 2006. The storm was a strongly convective event with peak echo tops over 50kft and a broad region of tops greater than 30kft. The VIL peaked at level 6 in growing regions with large areas covered by VIL greater than level 3. The first trajectory (shown on the left panels) was flying on a northeast-southwest course at 38kft. The planned trajectory would have required the pilot to fly along the length of the storm, through an extended region where echo tops ranged between 30 and 40 kft. The pilot decided to deviate from the planned trajectory and fly along the front edge of the storm. The second trajectory (shown on the right panel) was flying on a northwest-southeast course at 36kft. The planned trajectory was to fly across the storm encountering 50kft tops and level 6 VIL. This pilot decided to penetrate the storm and make a small maneuver away from the most intense tops.

The difference in pilot behavior when encountering this storm of very high WAF values may be attributed to the relationship between the constraints on the preferred deviation trajectory and the cost of a lengthy delay. The pilot who deviated at 38kft was able to minimize the additional flying time by making a small maneuver to the left and ahead of the storm. The increased flying time (less than one minute) was small but the amount of potentially turbulent weather encountered (several minutes) was large in comparison. The pilot who decided to penetrate the storm at 36kft was climbing out of the Chicago terminal airspace when the weather was encountered along the planned trajectory. In order to avoid the storm, a large deviation was required and would have resulted in a significant increase in flight time. A penetration of the storm would create a potentially turbulent flight for a time period that may have been deemed acceptable by the pilot.

Airspace constraints may also play a part in pilot decision making in convective weather. In densely packed, highly structured airspace, there may be few options for deviating flights and the cost of deviation may be a significant reroute onto a completely different arrival stream or cornerpost. For instances, northbound arrivals flying up the east coast into New York metro airports that wish to deviate to avoid weather are often constrained by nearby departure airspace to both the east and west, and as a result, may be required to reroute far to the west and north over eastern Ohio in order to join the eastbound New York arrival stream. Also, high demand on the northbound arrival streams require aircraft merging onto a route to arrive at the merge point within a minute or two of the expected time. Any delay due to weather will require additional workload on the air traffic controllers and possibly additional delay to wait for the next available slot.

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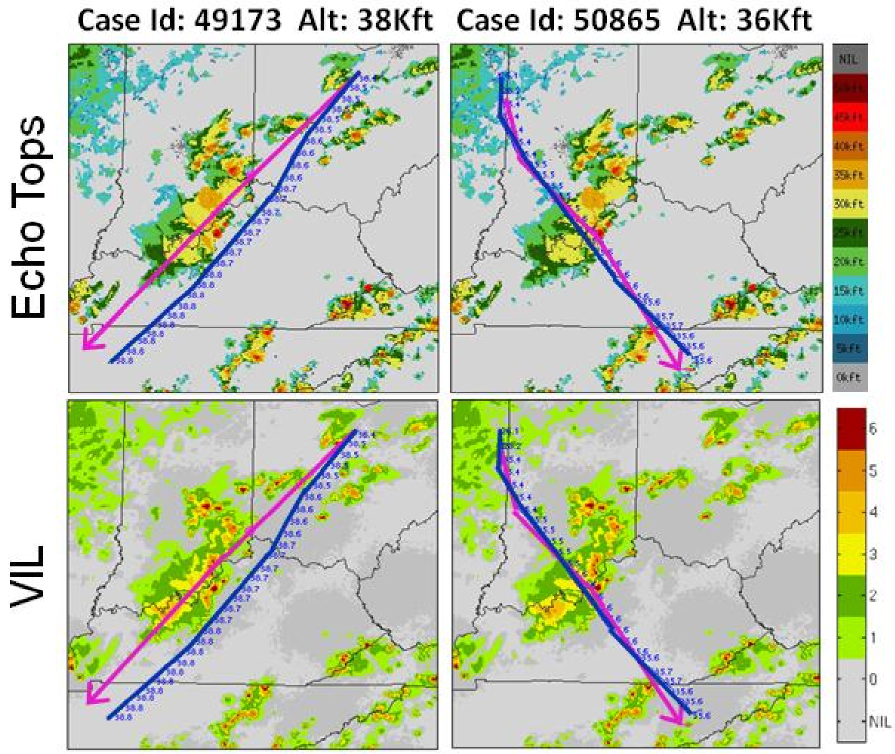

Figure 18: Echo Tops (top panel) and VIL (bottom panel) on June 1, 2006 at 19:40Z showing planned (magenta) and actual (blue) trajectories for two flights encountering a convective storm.

Figure 19 illustrates a scenario where the highly structured air space and the cost of a deviation may have impacted the pilot's decision making. A flight from DFW to LGA maneuvers around and through several large, level 5 and 6 thunderstorm cells along its original flight plan. A short, weather-avoiding reroute to the north is unavailable because it would conflict with busy New York metro departure streams. A commonly used reroute option through eastern Ohio requires both a large deviation and significant coordination to implement. With the final weather avoiding option of holding, the pilot elects to continue on the original flight plan and penetrate large WAF values. This pilot is also merging into the busy northbound ATC routes and may be trying to maintain a slot within the flow.

Figure 20 illustrates just how different the pilot's behavior may be due to the ATC operational environment. This figure shows the weather on July 14, 2006 at 09:00Z and 09:05Z along with four aircraft trajectories encountering the weather. The aircraft inbound to ZNY are false deviation predictions encountering WAF values larger than the deviation threshold. These aircraft are not deviating possibly due to the same airspace restrictions discussed previously; deviations in either direction will result in the arriving aircraft entering airspace used by southbound New York metro departures. The two outbound aircraft are missed deviation predictions because the weather did not meet the WAF criteria for a deviation. However, aircraft departing ZNY to the southwest have greater flexibility to avoid weather due to the airspace structures; in this instance, the aircraft are deviating toward airspace used for other New York metro departures streams to the west and southwest. When weather impacts one of these routes, ATC can take advantage of the available nearby departure airspace to avoid the weather, and then maneuver the aircraft towards the original destination once the aircraft has cleared the weather.

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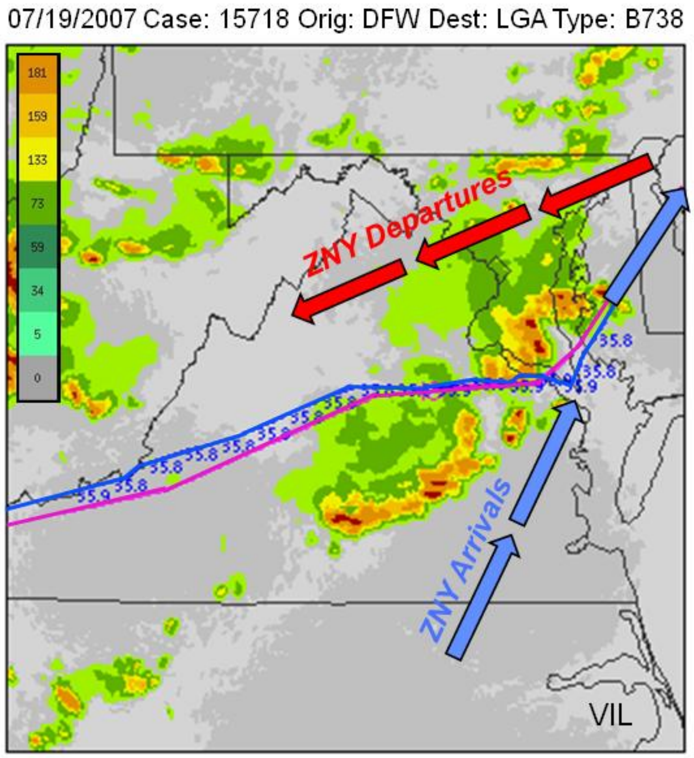

Figure 19: Planned (magenta) and actual (blue) trajectories of an aircraft penetrating intense weather on July 19, 2007 destined for LGA.

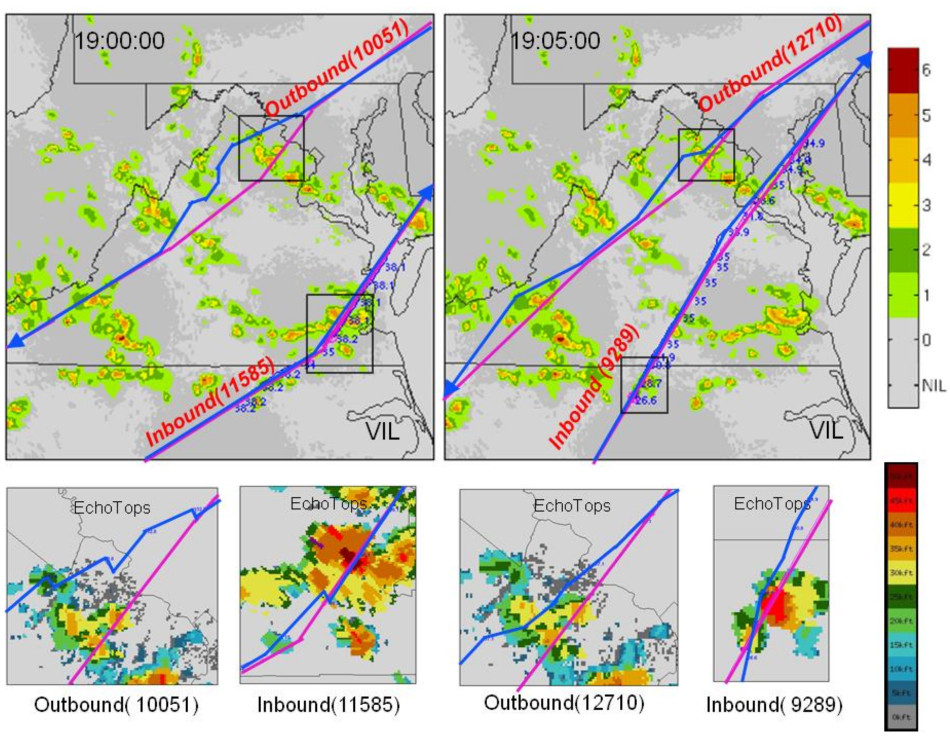

Figure 20: VIL on July 14, 2006 at 19:00Z (top left) and 19:05Z (top right) showing planned (magenta) and actual (blue) trajectories of aircraft inbound and outbound from ZNY. Echo tops at the time of weather encounter are shown (bottom row) for the four trajectories.

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V. Conclusion

This paper presents the results of work to evaluate and improve the performance of the Convective Weather Avoidance Model. CWAM was developed to correlate pilot behavior with observable and predictable weather parameters from a system such as the Corridor Integrated Weather System. The evaluation of several different CWAM versions was presented and the performance was shown for the model in various weather and air traffic impact scenarios. The accuracy of the model was compared with both the true and forecasted weather information.

Modeling pilot behavior in the vicinity of convective weather from observed and forecasted weather is a very complex challenge. A significant amount of uncertainty is observed within the CWAM data set due to factors not yet understood or modeled by CWAM. To this end, a deviation prediction error mode analysis was performed on the false deviation predictions and missed deviation predictions and the results suggest several potential improvements to the CWAM. These include improving the methodology of the original model and expanding the model to identify different weather phenomena and incorporating additional knowledge of the interaction between ATC and pilots. Ultimately, an evaluation of the relationship between the constraints on the pilot's preferred trajectory and the cost of the potential deviation trajectories along with an understanding of the ATC environment (route planning, sector capacity estimates, proximity to destination airport) must be included in the interpretation of the Weather Avoidance Fields for optimum performance.

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