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A Statistically-Based Method for Predicting Fog and Stratus Dissipation

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A STATISTICALLY-BASED METHOD FOR PREDICTING FOG AND STRATUS DISSIPATION

THESIS

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AFIT/GM/ENP/04-09

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Abstract

A statistically-based forecasting tool is developed for Dover AFB, McGuire AFB, and Andrews AFB for dissipation times of fog and low stratus. Probability forecasts are produced at hourly increments from 0-6 hours for the most extreme reductions in visibility (less than 0.5 mi) and ceilings (below 200 ft). Forecasts are based on surface observations, upper air observations, and climatological parameters.

Ceiling forecasts at Dover AFB and McGuire AFB show improvements over conditional climatology ranging from 1-51% with an average improvement of 19.2% when verified against an independent data set. McGuire AFB visibility forecasts show an average improvement over conditional climatology of 3%. These findings are of particular importance to the Air Force in general and specifically to the 15th Operational Weather Squadron (15 OWS) who produces forecasts for these airfields. Implementing a method superior to conditional climatology is expected to provide improved forecasts and flight operations for these sites.

The two forecasts for Andrews AFB show relatively low mean square errors, but are unable to consistently improve on conditional climatology, demonstrating an average decrease in forecasting skill of 42%. Small samples of data could be the reason for the decrease in skill. The Dover visibility forecast also shows negative forecast skill, with an average decrease of 39%.

The method is a success in producing forecasts for ceiling and visibility criteria that had never previously been examined. Further research on the technique could produce a powerful tool consistently able to defeat conditional climatology. It is suggested that the 15 OWS incorporate this methodology into their operational forecasting routine.

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Louis L. Lussier III

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A STATISTICALLY BASED METHOD FOR PREDICTING FOG AND STRATUS DISSIPATION

I. Introduction

Weather forecasters in general are unable to consistently beat persistence in short-term (0-6 hour) forecasts of ceiling and visibility. Dagostraro et al. (1995) and Dallavalle and Dagostraro (1995), showed that not only is persistence competitive with National Weather Service (NWS) forecasts, but that NWS forecasts have not improved in the period from 1985-1995. The same inadequacies found in the NWS are experienced throughout Air Force (AF) weather. The standard to beat in the AF is conditional climatology, because it enables forecasters to incorporate knowledge of what has happened in similar situations in the past, thus it is considered a better predictor of future weather than persistence (Hilliker and Fritsch 1999).

A statistical technique based on Vislocky and Fritsch (1997) and Hilliker and Fritsch's (1999) work could provide a tool for the 15th Operational Weather Squadron (15 OWS) to improve forecasts from conditional climatology tables. This research develops an automated statistical data system using an observations-based network for operational implementation.

Conditional climatology combines persistence and climatology by incorporating knowledge of outcomes of similar weather situations in the past in order to provide short-term forecasts of current weather parameters. Because it represents averaged conditions over a long period of time, it is a more difficult tool to beat than persistence (Vislocky and Fritsch 1997). However, conditional climatology tables do exhibit some problems. Murphy and Katz (1995) illustrate that small sample sets in certain cells can lead to unstable probabilities, as would be especially true for the extreme cases examined in this research. It is therefore imperative that the AF develops a more skilled forecasting method for fog and stratus dissipation.

1.1 Statement of the Problem

Accurate predictions of fog and low stratus dissipation (for the purpose of this paper low stratus is defined as clouds at or below 200 ft AGL and the term fog refers to fog and/or low stratus) are essential to all aircraft operations. The 15 OWS is responsible for producing forecasts for 11 airfields throughout the northeastern quadrant of the United States, stretching from North Dakota to Washington DC (Fig. 1). Aircraft supported by the 15 OWS range from large fixed wing aircraft to rotary wing. Among these are transport aircraft, which have critical thresholds for flight cancellations of 200 ft ceilings and 0.5 mile visibility. Accurate ceiling and visibility forecasts are critical to ensure personnel and essential cargo is transferred in a timely manner. Every hour of inaccuracy costs the United States government thousands of dollars and possibly lives (FAS 2003).

There are numerous reasons for the lack of skill in predicting fog dissipation. Fog dissipation is highly variable situation and based on small changes in a variety of

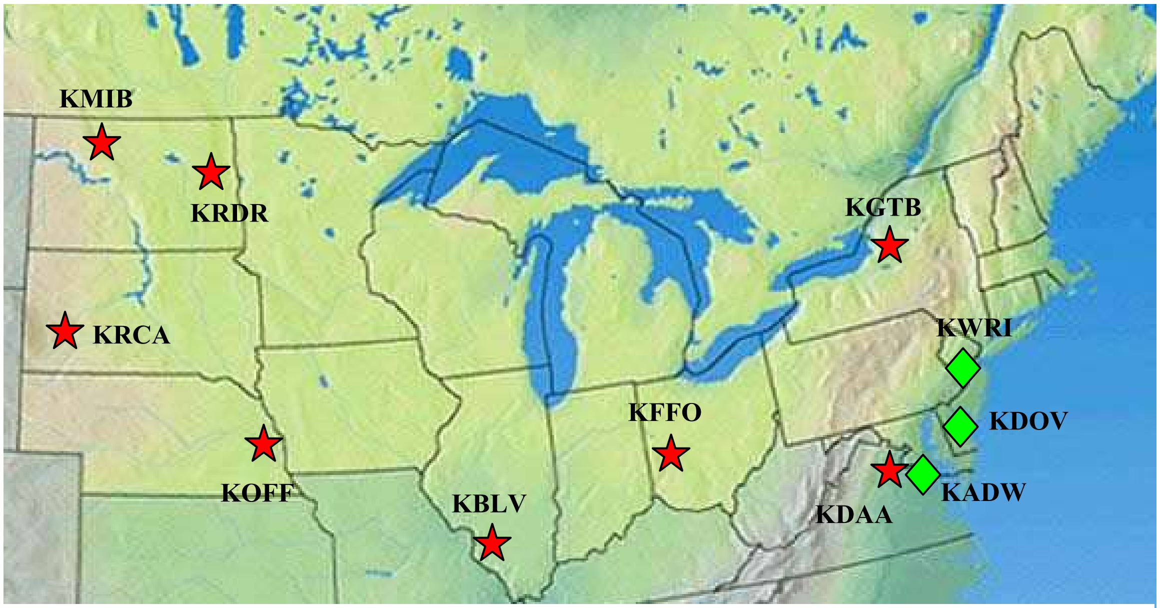

FIG. 1. Location and ICAOs of the 15 OWS Airfields. Airfields with the (♦) symbol are the critical bases, home to aircraft with minimums of 200ft/0.5 mi. Adapted from the 15 OWS homepage (15 OWS 2003).

meteorological parameters (Anthis & Cracknell 1998). Furthermore, the physical environment presents large, localized influences such as snow cover (Johnson 1978), variable terrain and bodies of water that contribute to variability in dissipation rates (Weiss and Gurka 1975). Other important factors that would aid in prediction, such as depth of the fog and height of the inversion layer are not routinely measured nor easily obtained. Vislocky and Fritsch (1997) noted that the single most important factor in short-term forecasting is the latest surface observation. For this reason alone, numerical models are at a disadvantage when it comes to predicting dissipation.

Of these forecast difficulties, the vast differences in terrain, climatology, and relationship to bodies of water among the airfields in the 15 OWS Area of Responsibility (AOR) represent a significant challenges. These variations present forecasters with a

TABLE 1. Annual Number of Days with Reduced Ceiling and Visibility. The three highlighted bases are home to transport aircraft with flight minimums of 200 ft/0.5 mi. (15 OWS 2003).

			Ceiling/Visibility Threshold Criteria (ft/mi)				
Airfield	ICAO	vis < 7	<3000/3	<1500/3	<1000/2	<500/1.5	<200/.5
Minot AFB (ND)	KMIB	71	62	40	26	15	4
Grand Forks AFB (ND)	KRDR	72	66	40	26	15	4
Ellsworth AFB (SD)	KRCA	47	47	33	29	18	7
Offutt AFB (NE)	KOFF	109	73	47	33	15	4
Scott AFB (IL)	KDLV	197	69	40	26	11	4
Wright-Patterson AFB (OH)	KFFO	193	84	47	29	11	1
Fort Drum (NY)	KGTB	117	88	47	33	18	4
McGuire AFB (NJ)	**KWRI**	**192**	**77**	**58**	**44**	**26**	**8**
Fort Belvoir (VA)	KDAA	170	69	55	37	22	7
Andrews AFB (VA)	**KADW**	**170**	**69**	**55**	**37**	**22**	**7**
Dover AFB (DE)	**KDOV**	**187**	**58**	**44**	**29**	**15**	**4**

variety of challenges from different types of fog and/or physical mechanisms contributing to formation and dissipation. Table 1 quantifies some of these difficulties by summarizing the number of days in which fog impacts operations. The data illustrate that low ceilings and visibility are common occurrences throughout the AOR. The eastern seaboard, home of a majority of the cargo aircraft in the AF inventory, experiences reduced ceilings and visibility on average half of the days of the year, significantly impacting military operations.

1.2 Research Objectives

The overall objective of this research is to produce an automated ceiling and visibility forecasting tool for the 15 OWS that will improve on all currently employed methods.

The specific research goals are as follows:

1. Develop a statistically-based system using surface and upper air observations as well as climatological predictors to accurately forecast fog dissipation.
2. Completely automate system to ensure ease of use.
3. Present a viable forecasting tool for the 15th OWS.

The next topic addressed is a summary of past research on successful prediction methods of fog dissipation. Various techniques are examined including numerical weather prediction, conditional climatology, observations-based methods, satellite imagery, and multi-source methods, which combine two or more of the above to produce a dissipation forecast. The third chapter focuses on the methods employed in this research to develop the forecasting tool for the 15 OWS. The fourth chapter provides detailed results of the research, and comparisons to conditional climatology are examined. Finally, conclusions are made which demonstrate the effectiveness of the newly developed method, and suggestions are offered for possible improvements in the future.

Using statistical techniques for forecasting weather is not a new concept, however, with the development of physically-based numerical models, statistical techniques have become less prevalent in short-term forecasting. Chapter two examines the success rate that statistically-based forecasting has produced in the past for short-term prediction of fog dissipation.

II. Literature Review

This research is focused on the dissipation of fog and does not address fog formation or prediction. This section focuses on several different methods to produce fog dissipation. While it focuses mainly on statistically-based methods to predict dissipation, other techniques, such as numerical models, conditional climatology, satellite imagery, and multi-source methods are examined. Advantages and disadvantages are examined, as well as areas where these techniques can be improved.

2.1 Numerical Models

Numerical models are favored by forecasters due to their ease of use, but are often not the best available asset for short-range forecasts. Statistically-based products derived from high-resolution mesoscale models can predict fog dissipation times, but have not proven reliable. Porter (1995) illustrated the fact that persistence is superior to mesoscale numerical model predictions in the short-term. Furthermore, Vislocky and Fritsch (1997) showed that while Model Output Statistics (MOS) can consistently beat persistence and conditional climatology, there are still better methods. The NWS (1981, 1995) concluded that observations are the most important ingredient in producing short-range forecasts, leading Vislocky and Fritsch (1997) to suggest that a surface-based observing network would be more effective than MOS guidance.

2.2 *Conditional Climatology*

As mentioned earlier, conditional climatology offers an advantage over persistence in that it incorporates knowledge of what has happened in past situations to produce an accurate probability forecast. Data are interpreted from tables which are stratified by station, month, time of day, and wind direction and offer probabilities out to 48 hours on the occurrence of select ceiling and visibility criteria. Tables are applied based on the current ceiling criteria already being met. As mentioned, these tables are stratified by time of day and wind direction, therefore, the only required meteorological parameter needed to produce a forecast is the current surface direction at the station.

This methodology is favored by the Air Force for its simplicity and its consistent ability to produce fairly accurate forecasts. The general problem with any climatological model is that it does not take into account the current meteorological event occurring at and around the station. Observations-based networks include this data in statistical methodology to improve on conditional climatology.

2.3 *Observations-Based Statistical Methods*

Enger et al. (1964) introduced the concept of statistical techniques for 2-7 hr prediction of ceiling and visibility in the 1960's. Experiments in Chicago and major cities on the west coast of the US compared objective forecasts to conditional climatology and subjective forecasts. Enger et al. (1964) used 450 binary predictors to forecast future values of 36 ceiling and visibility predictands. The results showed that statistical techniques were superior to conditional climatology, persistence, and subjective forecasts. Improvement ranged from –0.4% to 33.0% with average improvement of 19.2% for ceiling forecasts and 12.8% for visibility forecasts (Enger et al. 1964).

Vislocky and Fritsch (1997) showed more recently that observations-based statistical systems are more effective than MOS and conditional climatology for short-term ceiling and visibility forecasts. Their research focused on 25 major cities along the eastern corridor of the US and used surface observations from a predetermined area around each airfield to forecast future conditions of ceiling and visibility (Vislocky and Fritsch 1997). Hilliker and Fritsch (1999) proved that a similar method could be used to predict fog dissipation at the San Francisco airport.

Vislocky and Fritsch (1997) used a number of predictands (Table 2) based on significant airfield flight restrictions. They embarked on a pilot study to determine the optimal number of surrounding stations and predictors to use in order to eliminate data saturation. The results produced five significant findings:

1. The optimal number of stations to consider increases with desired lead-time and is not constant. Variations exist with season, latitude-longitude, and weather among other factors.
2. The ceiling and visibility predictors were the most important.
3. Non-predictand observations outside the optimal number of stations had very little impact on the forecast.
4. Multiplying, adding, or determining trends among predictors added minimal accuracy.

TABLE 2. List of Predictands. Vislocky and Fritsch (1997) produced forecasts using the surface observational based system for these significant aviation operational thresholds. Adapted from Vislocky and Fritsch (1997).

Variable	Binary Thresholds			
Ceiling Height	< 500 ft	< 1000 ft	≤ 3000 ft	≤ 6500 ft
Visibility	< 1 mi	< 3 mi	≤ 5 mi	≤ 7 mi

5. The optimal number of stations to use for 1, 3, and 6-hr forecasts are 10, 25, and 40 respectively.

Vislocky and Fritsch (1997) determined that 33 surface parameters were operationally significant in forecasting fog dissipation (Table 3). They also concluded that the addition of climatological factors relating to incoming solar radiation produced a more accurate forecast.

TABLE 3. Surface Meteorological Parameters Used as Predictors. These 33 conditions were determined to be the most significant predictors of fog dissipation. Adapted from Vislocky and Fritsch (1997).

Variable	Binary Threshold					
Opaque Cloud Amount	> 1/10	> 5/10	>9/10			
Total Cloud Cover	Clear	Scattered	Broken	Overcast	Obscured	
Precipitation Occurrence	Yes					
Ceiling Height	< 200 ft	< 500 ft	< 1000 ft	≤ 3000 ft	≤ 6500 ft	≤ 12000 ft
Visibility	< 0.5 mi	< 1.0 mi	< 3.0 mi	≤ 5.0 mi	≤ 7.0 mi	≤ 10 mi
Wind Direction	0°	< 45°	< 90°	< 135°	< 180°	< 235°
Wind Direction (cont.)	< 270°	< 315°				
Dew Point						
Dewpoint Depression						
Sea Level Pressure						

Vislocky and Fritsch (1997) used a least squares linear regression model to develop their predictive equations. In this method, each predictand is the result of a combination of predictors. A forward stepwise screening algorithm was used to select the best available predictors (Vislocky and Fritsch 1997). One predictor is added at a time in order to gauge the effect each has on the predictand. This method allows useless or redundant predictors to be discarded (Vislocky and Fritsch 1997).

The results of Vislocky and Fritsch's (1997) findings can be summarized:

1. Observations-based methods on average produced 12% (with a 5-20% range) better results than conditional climatology and 4% better than MOS.
2. Any short-range forecast should rely more heavily on observations than numerical models.
3. At the 6-hour point, the observations and MOS predictands were similar, which verified that the 6-hr point is the time for numerical models to take over.

Two major advantages of an observations-based system are that it is not tied to any numerical model and it can be run in a matter of seconds on any computer as soon as new data becomes available (Vislocky and Fritsch 1997).

Suggested improvements to the observations-based statistical method include incorporation of radar data, satellite imagery, and upper air observations into the equations (Vislocky and Fritsch 1997). Hilliker and Fritsch (1999) added upper air observations to the surface-based observations system in a study at the San Francisco International Airport. They used upper air data from Oakland since it is within the area of interest and developed additional upper air predictors (Table 4). Static stability was added as a predictor in addition to basic upper air parameters.

Hilliker and Fritsch (1999) used a predictand of 3000 ft ceiling height and surface predictors similar to Vislocky and Fritsch (1997) with modifications for local effects. Hilliker and Fritsch (1999) employed a logarithmic regression model with the addition of upper air parameters. Hilliker and Fritsch's (1999) research showed that:

1. Including upper air predictors produced 0-3% improvements over the strictly surface based systems for 0-3 hr forecasts.
2. The longer the forecast time, the less impact the upper air observations had on the forecast.
3. Improvements of up to 32% were shown over MOS forecasts.

Hilliker and Fritsch (1999) proved that even in a region with limited observations, observations-based systems are superior to conditional climatology, persistence, and MOS forecasts for short-term forecasts. Furthermore, including upper air parameters, such as static stability, increased the accuracy of the forecasts. Two additional parameters that could improve the forecast are the inversion height and the thickness of the cloud layer (Hilliker and Fritsch 1999).

Vislocky and Fritsch (1997) and Hilliker and Fritsch (1999) showed success in producing dissipation forecasts using observations-based networks. The next section examines the effectiveness of evaluating satellite imagery to forecast dissipation.

TABLE 4. Upper Air Meteorological Parameters Used as Predictors. Parameters were considered for 8 pressure levels between 1000 mb and 500 mb, with the exception of static stability, which was evaluated in three layers between 1000 mb-850 mb. Adapted from Hilliker and Fritsch (1999).

Parameter	Binary Threshold			
Height				
Temperature				
Relative Humidity	$\geq$ 30%	$\geq$ 50%	$\geq$ 70%	$\geq$ 90%
Wind Direction	23° to < 68°	68° to < 113°	113° to < 158°	158° to < 203°
Wind Direction (cont.)	203° to < 248°	248° to < 293°	293° to < 338°	338° to < 23°
Wind Speed				
Static Stability ($d\theta/dz$)				

2.4 Satellite Imagery

Another method in predicting the dissipation of fog is the use of satellite imagery. Gurka (1974, 1978) showed that high resolution visible imagery can be used to predict fog dissipation because of the strong correlation between fog brightness and duration. Dissipation occurs first on the outer edges of the fog (Gurka 1974), where the ground is heated more intensely along the boundaries than in the interior (Gustafson and Wasserman 1976). Anthis and Cracknell (1999) concluded that the dissipation of fog proceeds inward with time and that it is dissipated according to layer thickness.

Gurka's (1978) work provided significant findings, concluding that enhanced visible satellite imagery could produce effective short-range forecasts of fog dissipation, especially for aviation. Gurka (1978) also realized that computers would be able to ingest and process this data quickly enough to produce real time short-range predictions.

Since all previously mentioned methods had success in predicting dissipation time, the next section examines the possibility of combining parameters into a multi-source method.

2.5 Multi-Source Methods

Reudenbach and Bendix (1998) made progress using multi-source data to predict dissipation in Germany. Their work used four separate types of data for model development: thermodynamic equations, NOAA Advanced Very High Resolution Radiometer (AVHRR) imagery, terrain models, and surface and upper air meteorological observations. Reudenbach and Bendix (1998) focused on multi-source data because single source methods are not able to account for all aspects of dissipation. Of note is that although Gurka (1974) presented a method for nowcasting fog clearance, the method was never standardized, nor proven 100% reliable. Reudenbach and Bendix (1998) also noted that numerical models cannot always account for local effects such as dissipation due to advective processes. They successfully developed a straightforward model for forecasting clearance in 1km by 1km areas.

This chapter summarizes multiple methods employed to accurately predict the dissipation of fog. Vislocky and Fritsch (1997) and Hilliker and Fritsch (1999) showed that an observations-based method produces superior forecasts, while standards such as MOS guidance, persistence and conditional climatology are still regularly employed. Gurka (1974, 1978) and Anthis and Cracknell (1998, 1999) demonstrated that visible satellite imagery could be used to predict duration of fog events. Reudenbach and

Bendix (1998) demonstrated the effectiveness of a multi-source data system on the accurate prediction of fog dissipation times

Each method displayed some degree of success in predicting fog dissipation; however this research focuses on adapting a statistically-based method to forecast dissipation. There are several reasons for this. First, as shown by Vislocky and Fritsch (1997) this methodology is superior to model output and conditional climatology. Second, satellite imagery by itself has not proven to be a single effective tool for predicting dissipation. A multi-source method, that includes an observations-based network and satellite imagery, could produce a superior forecast and should be evaluated in the future. The next chapter details the process of developing and implementing the statistically-based system.

III. Methodology

3.1 Overview

The literature review describes several methods for predicting fog dissipation that prove effective in all geographic areas. Vislocky and Fritsch (1997) showed observations-based systems can be successfully employed along the east coast of the US, while Hilliker and Fritsch (1999) showed that the system is effective for the west coast. Since observations-based networks are superior to conditional climatology and model output (Vislocky and Fritsch 1997), this method is applied to the airfields in the 15 OWS to produce a superior fog dissipation forecast tool.

This research follows Vislocky and Fritsch (1997) and Hilliker and Fritsch's (1999) work into the use of a statistically-based observation network to produce accurate short-term dissipation forecasts. Although this method is a proven success along the east coast, changes are made to fit the needs of the AF. Specifically, a different set of predictands is required in order to meet the need of the 15 OWS, as Vislocky and Fritch's (1997) original work failed to address the critical threshold of 200 ft ceilings and 0.5 mi visibility.

The scope of the problem for the entire 15 OWS AOR may seem large, however, it is not insurmountable and is solved piecewise. The most critical problem, 200 ft ceilings and 0.5 mile visibility on the east coast, is addressed in this research. Once the technique and processes are established, equations tested, and methodology set, other airfields and predictands can be examined in the future.

The remaining portion of this chapter is dedicated to an explanation on the procedures and processes employed to develop the predictive equations. Section 3.2 examines the surface, upper air, and climatological data sets used to develop the equations, while section 3.3 details the statistical approach taken in this research.

3.2 Data

3.2.1 Surface and Upper Air Data. This research is based on a five-year data set (1998-2002), consisting of standard surface observations in METAR format and raw upper air data in formatted ASCII text, provided by the Air Force Combat Climatology Center (AFCCC) in Asheville, NC. The surface data consist of both standard hourly and special observations for stations along the east coast of the US. The upper air data consist of both mandatory and significant levels and are available twice a day, 00Z and 12Z.

The large data set is required for two reasons. First, due to the relatively rare occurrence of the extreme conditions (200 ft ceilings/ 0.5 mile visibility), a large data set ensures a statistically significant number of occurrences. Second, the data are broken into two subsets in order to develop the predictive equations with one set and independently verify the results with another.

The implementation of the Automated Surface Observing System (ASOS) program by the NWS in the middle to late 1990's had a significant effect on this research. The advantages of the automated systems are significant. The density of the surface observation network in the US increased significantly both spatially and temporally. Increased spatial coverage results in smaller surface-based networks, which in turn are more representative of the conditions at the airfield of interest. Increased temporal resolution occurs as many part time observing stations (which were excluded from Vislocky and Fritsch's (1997) initial study) were transitioned into full time observing stations in the late 90's. This positively influences this study in two ways. First, stations which were previously ignored, could now be evaluated, once again increasing the spatial density. Second, more data are available for all hours of the day, resulting in evaluation of more cases of fog occurrence and dissipation. While these advantages assist in this work, problems also arise.

First, the system was not implemented instantaneously at each location. That is, there is a significant difference between the times in which each airfield's system came online. For this reason, stations fitted with ASOS's after 1998 are omitted from this study, even if they fell within the observations-based network, due to their lower data density. Second, the initial period of data received from the ASOS is often missing weather variables. These are two of the main factors for the development and implementation of missing data schemes.

3.2.2 Missing Surface Data. Missing data are broken up into three different categories, each of which is handled in a separate way. The goal of the missing data algorithms is two-fold. First, a scheme is developed to maximize the number of data points available for the study. Second, the replacement data needs to reflect the current meteorological conditions at each station as accurately as possible. For this reason a three step missing data approach is implemented.

Step 1: Missing ceiling data due to the occurrence of fog. One of the most common occurrences of missing data is the lack of sky condition and/or ceiling height when fog is reported. For this reason ceiling, values are represented according to Table 5, data are missing with reduced visibility due to the occurrence of fog.

Step 2: Missing entire observation. If an entire surface observation is missing, a nearest reliable neighbor approach is used. A reliable neighbor is defined as a full time observing station throughout the entire data set. The nearest neighbor approach is used because it is the most physically significant replacement process available. Fog generally occurs in the cold season and is considered more of a synoptic scale rather than mesoscale event. For this reason surface weather conditions at nearby locations are typically similar enough (especially along the data dense east coast) to make this a sound meteorological argument. The exception is reduced visibility or ceiling conditions due to localized convective events or localized terrain influences, which are assumed to occur infrequently enough to not have a significant impact on this study.

TABLE 5. Binary Ceiling Replacement Values. The replacement values used for ceilings when the sky condition is missing from an observation and fog is reported.

Observed Visibility	Binary Ceiling Value
Vis $\leq$ 0.5 mi	Cig < 200 ft
Vis $\leq$ 1.5 mi	Cig < 1000 ft
Vis $\leq$ 3 mi	Cig < 3000 ft

Step 3: Missing individual weather data from an observation. This type of missing data occurs when single or multiple elements from a surface observation are missing. Data are replaced once again using the nearest neighbor approach, but this time only replacing the individual element.

The missing data schemes are only applied to predictors and never to the predictand. If the predictand is missing at any time, that occurrence is not included in the study for either model building or verification purposes. After the surface data is replaced missing upper air data algorithms are implemented.

3.2.3 Missing Upper Air Data. Missing upper air data are handled quite differently than missing surface data due to the relative sparseness of observations both spatially and temporally. Missing data are replaced using data from the upper air observation 24 hours earlier. Therefore, 00Z upper air observations are replaced with 00Z data the day prior. If the data are unavailable 24 hours ago, the event is not included in the study. Data from the previous 24 hours are used in order to best represent atmospheric conditions. Since observations are only taken twice a day, the 00Z data are not typically representative of the 12Z observations and visa versa.

This technique is applied as an accurate representation based on two factors. First, the synoptic situation typically associated with fog events is stable and not rapidly changing. Second, replacement algorithms are used infrequently enough in most cases to not have a significant effect on this research. The Dover AFB and McGuire AFB data sets each have 3.7% missing data rates. The Andrews AFB data set has a 12% missing data rate, this case is a concern heading into equation development. Next examined is the processing of the data.

3.2.4 Data Assimilation and Manipulation. The first step in this procedure is setting up the surface networks for each of the airfields for each of the six hour increments. Vislocky and Fritsch (1997) concluded that the 10, 25, and 40 closest observing stations are the optimal number of stations to be used in 1, 3, and 6 hour forecasts. The optimal number of stations is interpolated as 19, 30, and 35 for the 2, 4, and 5 hour forecasts. Observational networks are built independently for each forecast location and time. The surface observing stations for the observational networks included in this study are for Dover AFB (KDOV), McGuire AFB (KWRI), and Andrews AFB (KADW) and are detailed in the Appendix.

Data processing is the main challenge of this exercise and is summarized in Figure 2. The first step is an evaluation of the airfield of interest for occurrence of the predictand value (e.g. ceiling less than 200 ft). If an observation has an occurrence below one of the predictand thresholds, it is extracted. The same observation may meet multiple criteria (i.e. ceiling below 200 ft and visibility less than 0.5 mi). In this case, the observation is used for all applicable predictand criteria. This experiment is set up to evaluate every case of fog that meets the criteria regardless of time or season.

The next step is an evaluation of network observations. The date time group of each of the 40 stations in the observations network is compared to the main station's date time group. Observations within an hour are extracted to a separate file. If no observation is available within an hour, it is left for missing data algorithms to replace.

The same process is then applied to the upper air and climatological data. With the extraction of the relevant data, the statistical approach is now reviewed.

3.3 Statistical Approach

3.3.1 Predictands. After the network is constructed new predictands are evaluated. As noted earlier, the predictands offered by Vislocky and Fritsch (1997) do not fit the needs

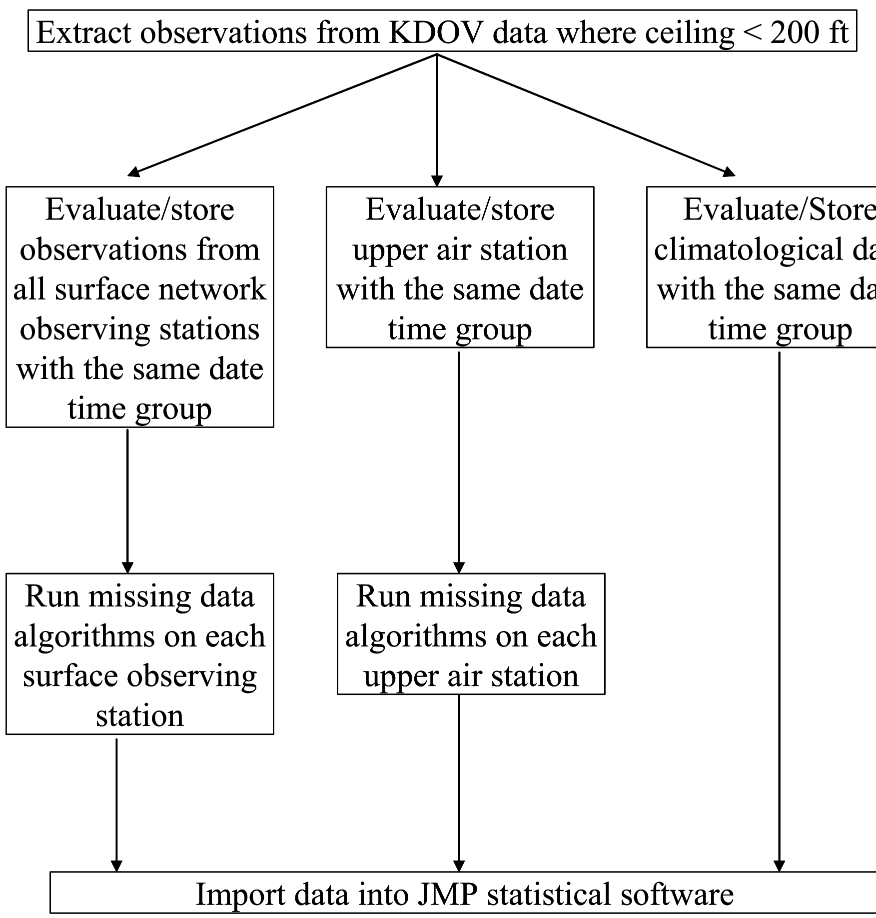

FIG 2. Flowchart for Data Manipulation.

of the 15 OWS, where the critical thresholds (200 ft ceilings and 0.5 mi visibility) are not addressed. This work evaluates predictands of 200 ft ceiling and 0.5 mile visibility at three airfields along the eastern seaboard of the US: McGuire AFB, Dover AFB, and Andrews AFB. Predictands are assigned a binary value of '1' for occurrence of an event and '0' for non-occurrence of event. Predictive equations are developed for each individual predictand at each airfield at hourly increments spanning one to six hours beyond the observation of fog occurrence. The predictors that influence the predictand forecast are now examined.

3.3.2 Predictors. This investigation deviates from Vislocky and Fritsch's (1997) work in terms of surface predictors. The main discrepancy is opaque cloud cover, which is omitted from this study. The reason for this is twofold. First, Vislocky and Fritsch's (1997) work used an earlier data set consisting of surface observations in SA (surface airways) format. These observations include more ceiling information than is currently reported in METAR observations (namely the presence or absence of a ceiling). Furthermore, SA ceilings were more subjective, that is, even if 8/10 of the sky were covered by clouds, an observer could determine it to not be a ceiling due to the lack of opacity. The second reason is inconsistency in remark data, especially reporting the eight and nine cloud groups which detail cloud amount and type. Since these are not present on a majority of observations, it is impossible to determine with the current available data the opacity of the sky.

A second difference in this research from Vislocky and Fritsch's (1997) is the use of altimeter setting rather than sea level pressure. The reason for this is that altimeter is reported in all observations and sea level pressure is not always reported in the remarks of the data set. Since all stations are within a couple of hundred meters of sea level, the approximation of altimeter setting for sea level pressure is valid. Binary predictors are coded with a "dummy" value of '0' representing non-occurrence or '1' representing occurrence, and non-binary predictors maintain their observed values. Each set of 30 predictors (Table 6) is evaluated at each surface observing station within the observing network (the number of stations in each observations network varies with time).

TABLE 6. Surface Predictors for the 15 OWS AOR. The surface meteorological predictors used to create the observations-based forecasts for the 15 OWS AOR. All predictors are evaluated at each airfield in the specific network (which varies depending on the time of the forecast).

Variable	Designator	Binary		Non-Binary
		Occurrence	Non occurrence	
Sky Condition: Clear	SKY (SKC)	1	0	
Sky Condition: Few/Scattered	SKY (FEW/SCT)	1	0	
Sky Condition: Broken	SKY (BKN)	1	0	
Sky Condition: Overcast	SKY (OVC)	1	0	
Sky Condition: Obscured	SKY (OBSCURED)	1	0	
Precipitation	PRECIP	1	0	
Ceiling Height < 200 ft	CIG HT <200 FT	1	0	
Ceiling Height < 500 ft	CIG HT <500 FT	1	0	
Ceiling Height < 1000 ft	CIG HT <1000 FT	1	0	
Ceiling Height ≤ 3000 ft	CIG HT <3000 FT	1	0	
Ceiling Height ≤ 6500 ft	CIG HT <6500 FT	1	0	
Ceiling Height ≤ 12000 ft	CIG HT <12000 FT	1	0	
Visibility < 0.5 mi	VIS < 800 M	1	0	
Visibility < 1 mi	VIS < 1600 M	1	0	
Visibility < 3 mi	VIS < 4800 M	1	0	
Visibility ≤ 5 mi	VIS < 8000 M	1	0	
Visibility ≤ 7 mi	VIS < 9999 M	1	0	
Visibility ≤ 10 mi	VIS >= 9999 M	1	0	
Wind Direction: Variable	WIND DIR (VRB)	1	0	
Wind Direction < 45	WIND DIR (<45)	1	0	
Wind Direction < 90	WIND DIR (<90)	1	0	
Wind Direction < 135	WIND DIR (<135)	1	0	
Wind Direction < 180	WIND DIR (<180)	1	0	
Wind Direction < 225	WIND DIR (<225)	1	0	
Wind Direction < 270	WIND DIR (<270)	1	0	
Wind Direction < 315	WIND DIR (<315)	1	0	
Wind Direction < 360	WIND DIR (<360)	1	0	
Dewpoint	DEWPOINT			X
Dewpoint Depression	DEWPOINT DEPRESSION			X
Altimeter Setting	ALT			X

The upper air predictors follow the work of Hilliker and Fritsch (1999) and are available in Table 7. Each predictor is evaluated at six levels, surface, 1000 mb, 925 mb, 850 mb, 700 mb, and 500 mb, with the exception of static stability, which is evaluated in three layers: 1000 mb-850 mb, 1000 mb-925 mb, and 925 mb-850 mb. The binary predictors are coded in the same manner as the surface predictors. Upper air data from 00Z are used for fog occurrence times of 03Z-15Z (12Z data are used for the hours 15Z-03Z) in order to represent lag times in data availability, ensuring this method can be implemented operationally. The upper air sounding that is closest to each airfield of interest is used (Table 8) and is considered to be representative of the upper air conditions for the entire surface observation network.

Numerous climatological predictors are available for selection by the predictive equations. First among these are climatological frequencies of occurrence of

TABLE 7. Upper Air Predictors for the 15 OWS AOR. The upper air meteorological predictors used to create the observations-based forecasts for the 15 OWS AOR. All predictors are evaluated at each pressure with the exception of static stability, which is evaluated in the three layers.

Variable	Designator	Binary		Non-Binary
		Occurrence	Non occurrence	
Height	HT			X
Temperature	T			X
Relative Humidity ≥ 30%	RH > 30%	1	0	
Relative Humidity ≥ 50%	RH > 50%	1	0	
Relative Humidity ≥ 70%	RH > 70%	1	0	
Relative Humidity ≥ 90%	RH > 90%	1	0	
Wind Direction: 23° to < 68°	WIND N	1	0	
Wind Direction: 68° to < 113°	WIND NE	1	0	
Wind Direction: 113° to < 158°	WIND E	1	0	
Wind Direction: 158° to < 203°	WIND SE	1	0	
Wind Direction: 203° to < 248°	WIND S	1	0	
Wind Direction: 248° to < 293°	WIND SW	1	0	
Wind Direction: 293° to < 338°	WIND W	1	0	
Wind Direction: 338° to < 23°	WIND NW	1	0	
Wind Speed	WIND SPEED			X
Static Stabililty (dθ/dz): (1000-925 mb)	STATIC STABILITY (1000-925 MB)			X
Static Stabililty (dθ/dz): (1000-850 mb)	STATIC STABILITY (1000-850 MB)			X
Static Stabililty (dθ/dz): (925-850 mb)	STATIC STABILITY (925-850 MB)			X

TABLE 8. Upper Air Stations in the 15 OWS AOR. The three upper air stations used in equation development along with the airfield they represent.

Airfield	ICAO	Upper Air Station	ICAO
McGuire AFB (NJ)	KWRI	Brookhaven (NY)	KOKX
Andrews AFB (VA)	KADW	Washington DC	KIAD
Dover AFB (DE)	KDOV	Wallops Island (MD)	KWAL

ceiling and visibility threshold at the airfield of interest. Predictor values including 200 ft/0.25 mi, 500 ft/0.5 mi, 1000 ft/1.5 mi are extracted from the Operational Climatic Data Summary tables available through AFCCC. Sine and cosine of the day of the year are also included as predictors of solar radiation effects per Vislocky and Fritsch (1997).

A better understanding of the effect of solar radiation on the dissipation process is also included. Following the work of Campbell (1977), the maximum amount of incoming solar radiation reaching the surface of the earth for the time of year is calculated. These calculations do not take into account clouds above the fog and stratus; however, for this study it is assumed that all of this radiation is reaching the top of the cloud/fog layer. All of the climatological predictors are non-binary, and a summary is available in Table 9. Now that predictors and predictands are explained the statistical methods behind equation development is examined.

3.3.3 Equation Development. A least squares multiple linear regression model is used to develop six predictive equations for each of the two predictands at each airfield. The first assumption made in order to use linear regression is that errors are uncorrelated random variables with constant variance and zero for a mean (defined as

TABLE 9. Climatological Predictors for the 15 OWS AOR. The climatological predictors used to create the observations-based forecasts for the 15 OWS AOR. All predictors are evaluated at only the airfield of interest (either Dover AFB, McGuire AFB, or Andrews AFB).

Variable	Designator	Binary		Non-Binary
		Occurrence	Non occurrence	
Frequency of Occurrence: 200 ft/0.25 mi	CLIMO < 200/0#25			X
Frequency of Occurrence: 500 ft/0.5 mi	CLIMO < 500/0#5			X
Frequency of Occurrence: 1000 ft/1.5 mi	CLIMO < 1000/1#5			X
Sine of the Day	SIN DAY			X
Cosine of the Day	COS DAY			X
Solar Radiation	SOLAR RADIATION			X

homoscedasticity) (Montgomery and Runger 2003). Analysis of the residuals from each linear model can prove these assumptions valid. The residual of a regression model is defined:

$$e_i = y_i - \hat{y}_i \qquad i=1,2\ldots, n \tag{1}$$

Where y_i is the observed value and $\hat{y}_i$ is the fitted value obtained from the linear regression model. A randomly distributed residual scatter plot, e.g. showing no pattern or trend, verifies the above assumptions.

Figure 3 shows sample residual scatter plots for each of the three data sets. The above characteristic, a random scattering of points around the zero line, is present in the diagrams below. This leads to the conclusion that the models have a mean of zero and constant variance. The above test is performed on each of the 36 models individually.

The second assumption required to use linear regression is that the errors are normally distributed (Montgomery & Runger 2003). First, the Central Limit Theorem states that as a sample size gets larger (typically assumed to be greater than 30), the distribution tends towards normal (Montgomery & Runger 2003). A more precise way to check the distribution is by examining a normal probability plot of the residuals for each

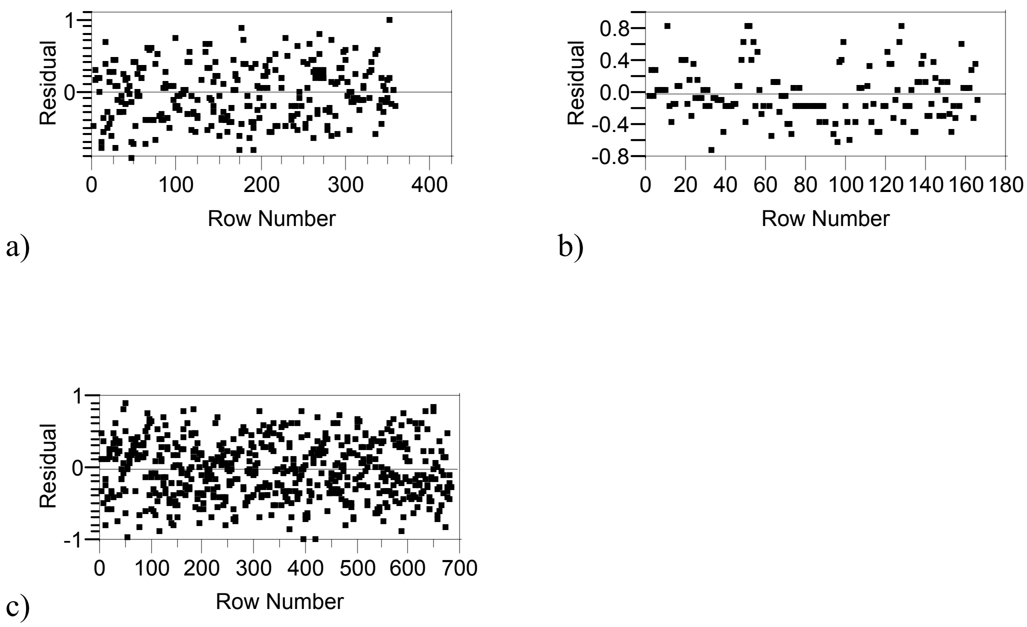

FIG. 3. Residual Plots from Data Sets. Residual plots from the KDOV Cig LT 200 ft (T+2) (a), KADW Cig LT 200 ft (T+2) (b), and KWRI Vis LT 0.5 mi (T+2) (c) data sets. These typical patterns show residual plots scattered and randomly distributed around the zero line, confirming the assumptions necessary to use linear regression.

of the 36 models. To assume normality, the residuals should fall along a straight line. Figure 4 shows two examples of normal probability plots. The first is from the Andrews AFB ceiling less than 200 ft forecast at one-hour (Fig. 4a). Notice the plot is in almost a normal distribution of residuals. The second example is from the Dover AFB ceiling less than 200 ft forecast at two-hours (Fig. 4b). Notice the plot falls essentially along a straight line, allowing the conclusion of normality (Montgomery & Runger 2003).

Table 10 lists the 36 derived models for this work and details the statistical tests run for each. Notice that 10 of the 36 models have errors which are not normally distributed (bold, column 2, Table 10). Six of the non-normal distributions are found in the Andrews AFB data set. Despite these discouraging indicators, regression models are nonetheless

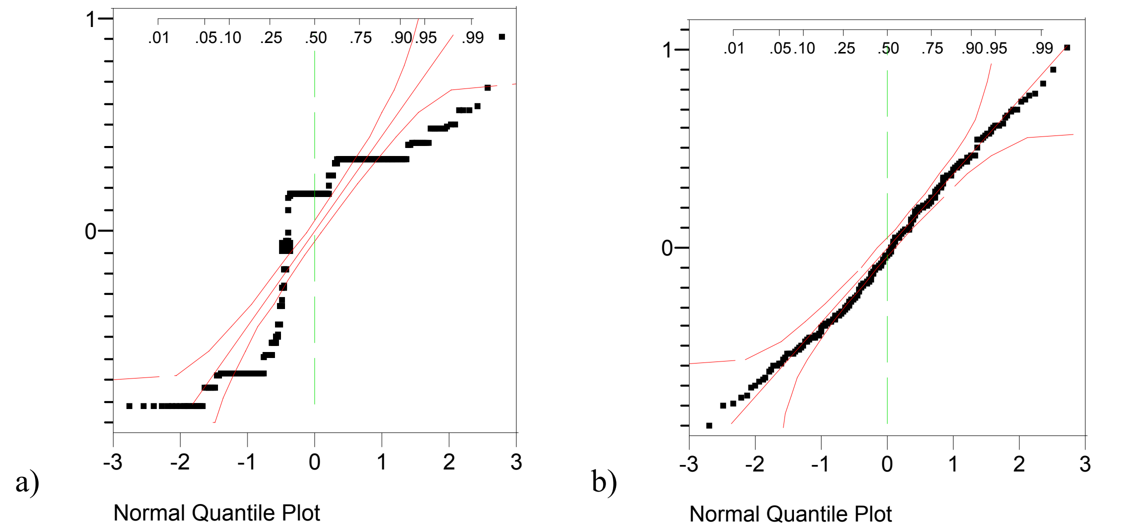

FIG. 4. Normal Probability Plots. Plots for KADW Cig LT 200 ft (T+1) (a) and KDOV Cig LT 200 ft (T+2) (b). Note the non-linear shape of the first model, leading to the conclusion of a lack of normalcy. Panel (b) exhibits a linear pattern, indicating a normal distribution of the residuals, which is a necessary assumption for linear regression.

stair step pattern, not close to resembling a straight line. This is an example of a non-

developed and analysis of effects of the non-normal distributions is found in Chapter IV. A lack of homoscedasticity (e.g. heteroscedasticity) is present in only three of the models (bold, column 3, Table 10). However, as Neter et al. (1990) point out, if heteroscedasticity is inherent, the results obtained are still unbiased, consistent estimators, but no longer possess minimum variance. Since the KWRI Vis LT 0.5 mi (T+1) and KADW Cig LT 200 ft (T+1) possess neither homoscedacity nor normal distributions, these data are of particular concern going into model development.

Multiple linear regression examines the relationship between two or more variables (Montgomery and Runger 2003) with each equation taking the form:

$$Y=\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_nx_n+\varepsilon \qquad (2)$$

TABLE 10. Statistical Tests. Definitions of the 36 models derived in this study along with the results of the statistical tests for normality and heteroscedasticity needed to confirm assumptions necessary to use linear regression.

Forecast	Normal	Homoscedasticity
KDOV Cig LT 200 ft (T+1)	Yes	Yes
KDOV Cig LT 200 ft (T+2)	Yes	Yes
KDOV Cig LT 200 ft (T+3)	Yes	Yes
KDOV Cig LT 200 ft (T+4)	Yes	Yes
KDOV Cig LT 200 ft (T+5)	Yes	Yes
KDOV Cig LT 200 ft (T+6)	Yes	Yes
KDOV Vis LT 0.5 mi (T+1)	**No**	Yes
KDOV Vis LT 0.5 mi (T+2)	**No**	Yes
KDOV Vis LT 0.5 mi (T+3)	Yes	Yes
KDOV Vis LT 0.5 mi (T+4)	Yes	Yes
KDOV Vis LT 0.5 mi (T+5)	Yes	Yes
KDOV Vis LT 0.5 mi (T+6)	Yes	Yes
KWRI Cig LT 200 ft (T+1)	**No**	Yes
KWRI Cig LT 200 ft (T+2)	Yes	Yes
KWRI Cig LT 200 ft (T+3)	Yes	Yes
KWRI Cig LT 200 ft (T+4)	Yes	Yes
KWRI Cig LT 200 ft (T+5)	Yes	Yes
KWRI Cig LT 200 ft (T+6)	Yes	Yes
KWRI Vis LT 0.5 mi (T+1)	**No**	**No**
KWRI Vis LT 0.5 mi (T+2)	Yes	Yes
KWRI Vis LT 0.5 mi (T+3)	Yes	Yes
KWRI Vis LT 0.5 mi (T+4)	Yes	Yes
KWRI Vis LT 0.5 mi (T+5)	Yes	Yes
KWRI Vis LT 0.5 mi (T+6)	Yes	Yes
KADW Cig LT 200 ft (T+1)	**No**	**No**
KADW Cig LT 200 ft (T+2)	Yes	**No**
KADW Cig LT 200 ft (T+3)	**No**	Yes
KADW Cig LT 200 ft (T+4)	Yes	Yes
KADW Cig LT 200 ft (T+5)	Yes	Yes
KADW Cig LT 200 ft (T+6)	Yes	Yes
KADW Vis LT 0.5 mi (T+1)	**No**	Yes
KADW Vis LT 0.5 mi (T+2)	**No**	Yes
KADW Vis LT 0.5 mi (T+3)	**No**	Yes
KADW Vis LT 0.5 mi (T+4)	**No**	Yes
KADW Vis LT 0.5 mi (T+5)	Yes	Yes
KADW Vis LT 0.5 mi (T+6)	Yes	Yes

where Y is the dependant or response variable, in this case, the predictand. Each x is a regressor variable, in this case the predictors, having a correlation with the dependant variable. Each β is a regression coefficient, calculated using a method of least squares, which minimizes the error between the predictand (Y) and each predictor (x). The response variable is interpreted as the expected value of Y for any specific combination of x's, the regressor variables (Neter et al. 1990). For this reason, Y is interpreted as a probability forecast for future occurrence or non-occurrence of a particular meteorological event. Finally, ε is a random error term.

Predictors are added to the regression equations based on a mixed stepwise regression technique. A mixed stepwise technique adds regressor variables to the predictive equation one at a time based on the lowest F-statistic. As more variables are added, F-statistics are recomputed and regressor variables may be removed from the equation if their F-statistic value is increased based on interaction between terms. The major advantage to using a mixed stepwise technique over a forward technique is the ability to remove terms whose F-statistic value has increased after new terms are added. This takes into account interaction between predictors, thereby minimizing the chances of redundant or interactive predictors remaining in the final predictive equation.

The F-test is the criteria for adding a predictor to a stepwise regression (Montgomery and Runger 2003); there is no limit to the number of predictors in each equation, as long as they meet the F-test requirements (which are set stringently at $P<0.001$). The F-statistic is ratio between the sum of the square errors of the coefficients (β) and the mean square error (MSE) of the dependant variables (Montgomery and Runger 2003). For this reason, a minimized F-statistic produces a model with less error and is therefore most desirable. Surface and upper air predictors are added or removed individually to each regression equation based on the above method.

Development of a single equation for one predictand at a specific time in the future occurs as follows (Fig 5). Predictor sets from each network surface observing station, upper air level, and climatological data are first regressed individually against the predictand value (e.g. KDOV CIG LT 200 ft), using an F-test significance of 0.001. Each predictor that meets the strict 0.001 F-test significance level is then combined and regressed against the predictand once again, using a much looser significance level of F<0.1. Since all terms meet the original F-statistic criteria, the larger error rate is accepted simply to remove interactive or redundant terms. This procedure produces one regression equation for each predictand at each time interval.

To produce a single probabilistic forecast, data are fed into the regression equations, which predict a value between 0 and 1 that can be interpreted as a forecasted probability of occurrence (Vislocky and Fritsch 1997). For example, the occurrence of a ceiling less than 200 ft at Dover AFB is coded as a '1'. After the regression equation is calculated, the resulting value is the probability of the 200 ft ceiling existing at some future time. A problem with linear regression, as noted by Wilks (1995) is that in rare cases probabilities can fall outside of the 0 to 1 probability range. However, this is not a significant problem for the operational meteorologist, as forecast values outside of this range can be rounded to 0 or 1 and still produce accurate forecasts (Wilks 1995). All statistical analysis is performed using the JMP statistical software.

After predictive equations are developed, verification is required for each airfield for each predictand at each time period. Verification is accomplished on an independent data set. Each predictive equation is computed and the probability forecast value is compared with the conditional climatology forecast (once again obtained through

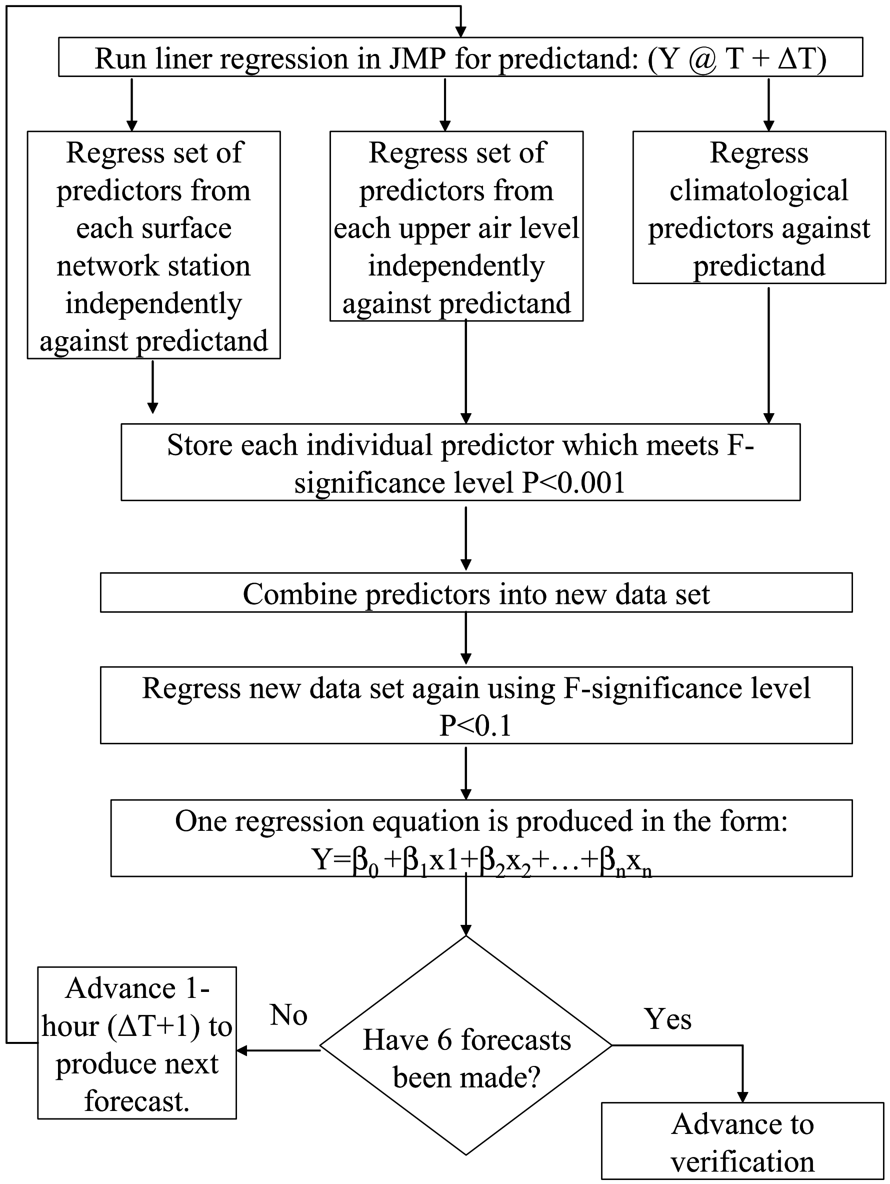

FIG 5. Linear Regression Flowchart.

AFCCC). Forecasts are produced for a one year independent data set for each fog occurrence using both the observations-based method and conditional climatology. This methodology is detailed in Figure 6.

Assessment of forecast accuracy is first made by calculating the mean square errors for both forecast methods. The MSE is the averaged squared difference between the forecast and actual event. The lower the MSE, the higher the accuracy of the forecast. A skill score was then calculated per Wilks (1995) to show the percent improvement of the

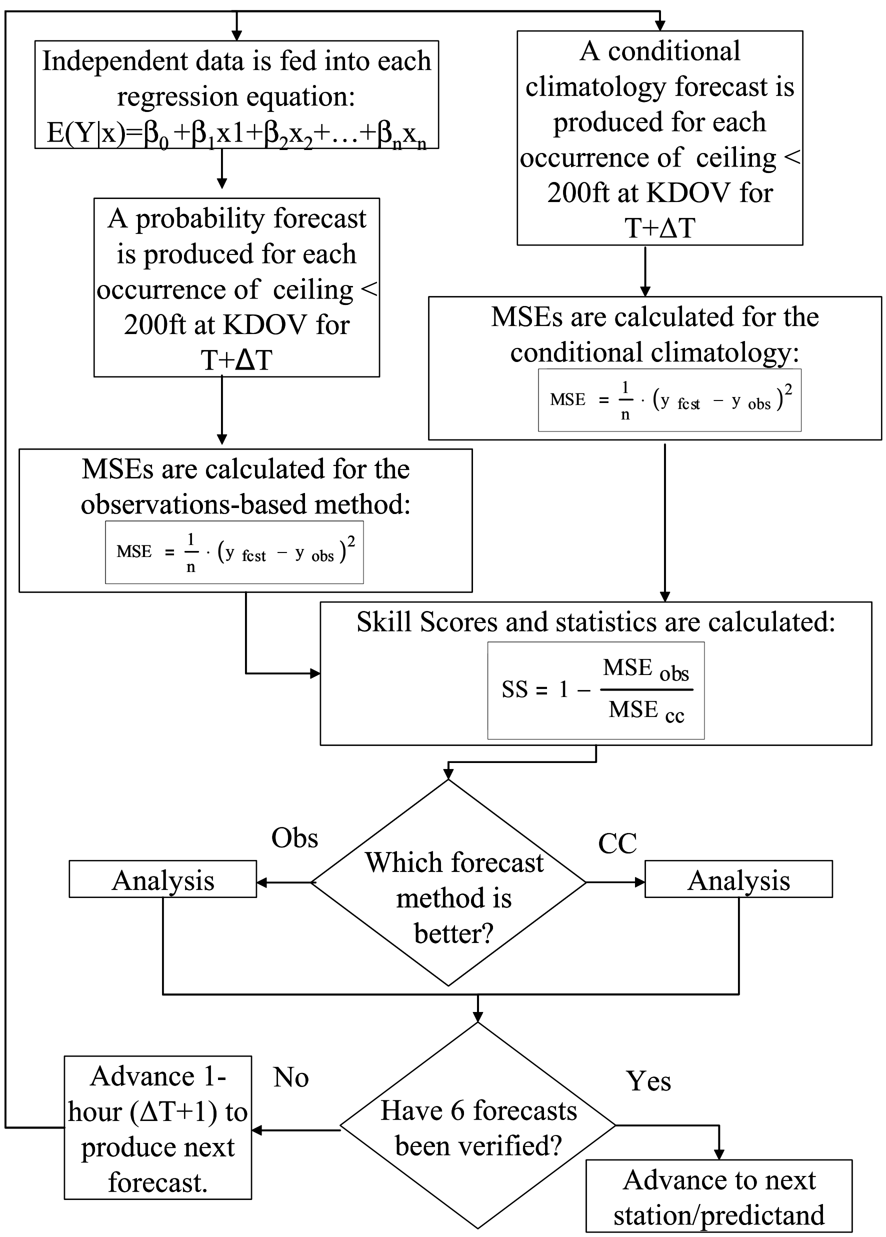

FIG 6. Verification Flowchart.

observations-based network over conditional climatology.

$$MSE = \frac{1}{n} \cdot \left(y_{fcst} - y_{obs}\right)^2 \tag{3}$$

$$SS = 1 - \frac{MSE_{obs}}{MSE_{cc}} \tag{4}$$

Attempts are made to quantify the accuracy of the forecast in an operational environment. The first category evaluated is "bad forecasts," which is defined as a forecast with an absolute error greater than 0.50--e.g. more than 50% error between the forecast and observed conditions. A second assessment is made of "good forecasts." These are defined as having an absolute error of less than 0.30. In order for this methodology to be implemented operationally, good forecast must be the norm. Forecast probabilities between 30-60% have little operational value to the operational forecaster, regardless of the MSE. Mean square errors, number of good forecasts, and number of bad forecasts are computed for both the observations-based network and conditional climatology and are compared.

This chapter details the methodology employed to develop a forecast tool for accurate prediction of fog dissipation. An observations-based network consisting of surface observations, upper air observations, and climatological parameters is developed for the 15 OWS. A multiple linear regression model is implemented for each of the predictands at the three 15 OWS airfields.

The results of the research are now examined. The initial goal is to provide a superior forecast technique to conditional climatology. To accomplish this, 36 probabilistic forecasts are developed for the predictands listed in Table 10. The next chapter details the successes and failures of the observations-based system and examines the characteristics of the predictive equations.

IV. Analysis and Results

4.1 Overview

Predictive equations are developed using the aforementioned statistical technique for two predictands, ceiling less than 200 ft and visibility less than 0.5 mi, at each airfield, for hourly intervals one to six hours in the future, for a total of 36 predictive equations. Of the 36 equations, 16 are able to consistently better conditional climatology when analyzed against an independent data set.

This section provides predictive equations, verification statistics on the independent data set, analysis of the predictive equations, and development of trends. Analysis on the successes and limitations of the technique are examined. Section 4.2 details the results obtained at Dover AFB, with the following sections looking at McGuire AFB and Andrews AFB individually. After each individual airfield is examined, underlying problems persistent throughout the forecast technique are thoroughly examined. Finally, examples of application of the methodology to real world situations are examined.

4.2 Dover AFB

4.2.1 Ceiling Less than 200 ft. Mean square errors are calculated using both conditional climatology and the observations-based network for an independent one year sample of data consisting of approximately 45 occurrences and are graphed in Figure 7a. Note that the MSEs for the observations-based system are superior to conditional climatology at each forecast time. Note also decrease in the MSEs with time. While this is counter intuitive, the set up of the experiment results in this trend. Occurrences of ceilings below 200 ft and visibility less than 0.5 are rare and typically short-lived events, therefore, there is less variability in the observed conditions at the later hours (e.g. the observed condition is coded as a "0" representing non-occurrence for a majority of the events). The observations-based network and conditional climatology typically produce low forecast probabilities at these hours resulting in the decreased MSE with time. Three measures of forecast accuracy, as discussed in the methodology section, are also shown in Figures 7b-d.

First, skill scores for each forecast time are illustrated, with positive values indicating an improvement over climatology of the observations-based network. All six forecast times show significant improvement over conditional climatology. Forecast improvements range from 1.3% to 50%, with an average improvement of 15.8%. The bad forecast category (Fig. 7d) shows that the observations-based network is equal to or superior to conditional climatology at all six hourly forecasts. Bad forecasts range from 2-18 per hour for the observations-based network and 2-26 per hour for conditional climatology. The extreme case demonstrates conditional climatology can be inaccurate on over 50% of the forecasts. The final forecast measure, good forecasts (Fig. 7c), again demonstrates a significant improvement over conditional climatology. The only case where conditional climatology is better is at the 6-hour point where it is favored due to the fact that 200 ft ceilings are typically a short-lived event. On average, the observations-based network produces 15% more good forecasts at each hourly interval.

Predictive equations for Dover AFB ceilings are available in Table 11. The number of predictors selected for each equation varies from 10 at the earliest times to 16 at the latest forecast hours. Standardized beta (std beta) values are included in order to gauge the relative strength of each predictor on each model. The highest absolute value among the standardized betas have the most influence on the forecast. Predictors are now examined for trends.

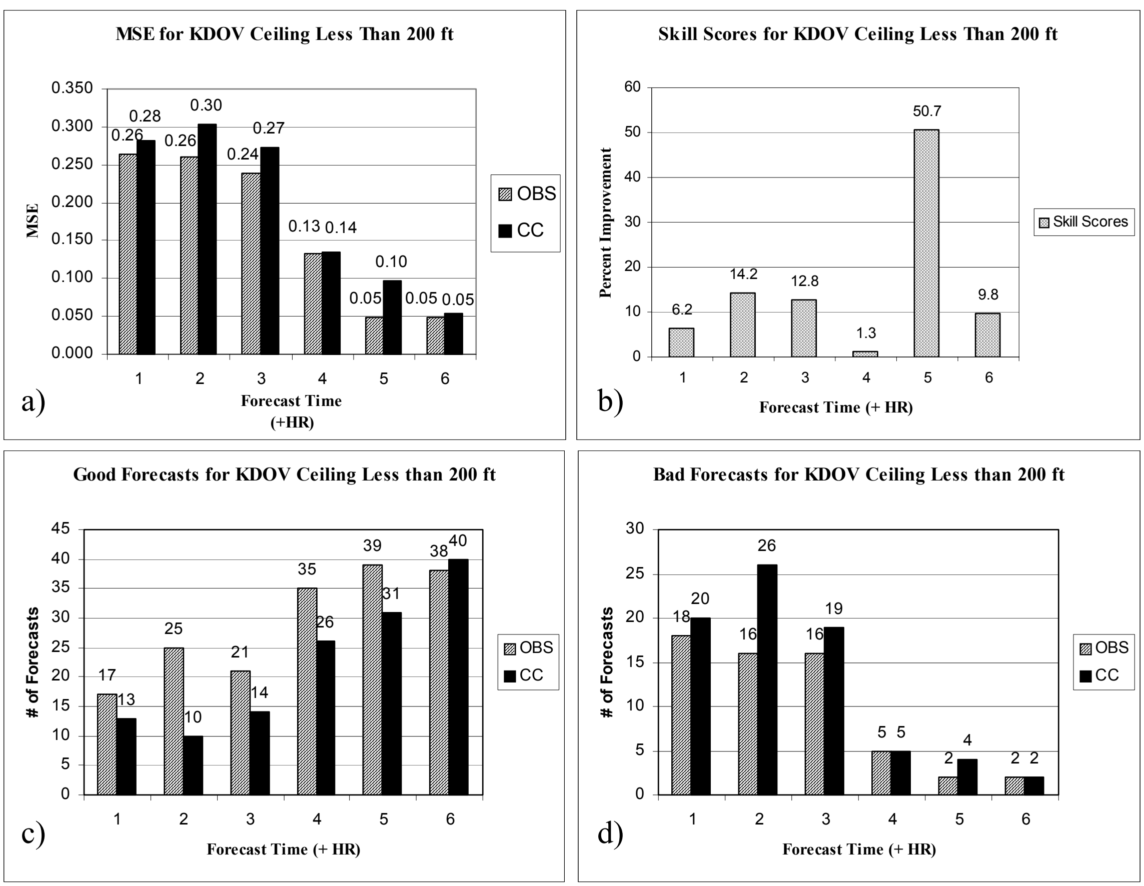

FIG. 7. Forecast Statistics for KDOV Ceiling Less than 200 ft. Panel (a) displays MSE, panel (b) shows skill scores, panel (c) good forecasts, and panel (d) shows bad forecasts for each hour.

TABLE 11. Forecast Equations for KDOV Ceiling Less than 200 ft. The first 3 hours of the forecast (a) and the last three (b).

T+1 HR			T+2 HR			T+3 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	0.700	0.000	Intercept:	0.055	0.000	Intercept:	0.327	0.000
700 MB T	-0.018	-0.148	KDOV SKY (OBSCURED)	0.055	0.120	KDOV SKY (OBSCURED)	0.090	0.085
KWWD CIG HT <3000 FT	-0.410	-0.160	KGED PRECIP	0.085	-0.116	KGED VIS < 1600 M	0.193	0.138
KWWD VIS >= 9999 M	-0.112	-0.097	KWWD VIS < 1600 M	0.063	0.161	**KGED WIND DIR (<90)**	0.173	0.111
KSBY VIS >= 9999 M	-0.121	-0.102	KWWD DEWPOINT DEPRESSION	0.010	-0.089	KWWD VIS < 1600 M	0.155	0.118
KILG VIS >= 9999 M	-0.114	-0.086	KSBY WIND DIR (<270)	0.135	-0.126	KACY VIS >= 9999 M	-0.170	-0.136
KILG WIND DIR (<235)	-0.495	-0.193	KACY SKY (OVC)	0.052	0.119	KMTN SKY (SKC)	0.270	0.123
KMIV WIND DIR (<90)	0.203	0.163	KACY VIS >= 9999 M	0.064	-0.104	KNHK VIS < 4800 M	-0.133	-0.122
KGED CIG HT <3000 FT	-0.383	-0.123	KNHK SKY (SKC)	0.096	0.119	KNHK WIND SPEED	-0.021	-0.167
KDOV SKY (OBSCURED)	0.153	0.139	**KADW WIND DIR (<90)**	0.058	0.118	KWAL WIND DIR (<45)	0.101	0.097
KDOV VIS < 4800 M	-0.139	-0.101	KWAL PRECIP	0.082	-0.099	KWRI WIND DIR (<90)	0.103	0.094
			KWAL VIS >= 9999 M	0.054	-0.144	KABE SKY (SKC)	-0.383	-0.228
			KTTN CIG HT <500 FT	0.049	0.107	KDAA CIG HT <200 FT	0.245	0.121
a)			700 MB T	0.006	-0.212	KDAA CIG HT <3000 FT	-0.155	-0.131
			KLNS PRECIP	0.063	-0.159	KDCA SKY (SKC)	0.349	0.173
			KLNS WIND DIR (<90)	0.054	0.145	**KCXY WIND DIR (<90)**	0.092	0.087

T+4 HR			T+5 HR			T+6 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:			Intercept:	0.005	0.000	Intercept:	-0.219	0.000
KILG WIND DIR (<45)	0.031	0.000	**KGED WIND DIR (<90)**	0.178	0.129	KMTN SKY (SKC)	0.256	0.152
KVAY WIND DIR (<90)	0.074	0.075	**KWWD WIND DIR (<90)**	0.112	0.111	**KVAY WIND DIR (<90)**	0.112	0.141
KNHK WIND DIR (<180)	0.260	0.259	KPNE CIG HT <500 FT	0.137	0.165	KNHK WIND DIR (<360)	0.202	0.128
KADW WIND DIR (<90)	-0.139	-0.101	**KADW WIND DIR (<90)**	0.112	0.115	KWAL SKY (OBSCURED)	0.105	0.113
KMFV VIS >= 9999 M	0.157	0.143	KWAL SKY (OBSCURED)	0.115	0.110	**KWAL WIND DIR (<90)**	0.189	0.189
KNYG CIG HT <200 FT	-0.157	-0.169	KRDG SKY (OBSCURED)	0.231	0.123	KTTN CIG HT <500 FT	0.090	0.128
KNYG VIS >= 9999 M	0.423	0.241	KLNS PRECIP	-0.148	-0.150	KBLM VIS < 9999 M	0.163	0.120
KIAD SKY (FEW/SCT)	0.212	0.231	KBLM VIS < 9999 M	0.323	0.213	KNYG CIG HT <200 FT	0.128	0.090
KIAD WIND DIR (<135)	0.109	0.089	KNYG CIG HT <200 FT	0.285	0.179	KNYG VIS >= 9999 M	0.089	0.125
KEZF VIS >= 9999 M	0.234	0.108	KNYG VIS >= 9999 M	0.093	0.115	**KEZF WIND DIR (<90)**	0.233	0.148
700 MB T	0.138	0.151	**KIAD WIND DIR (<90)**	0.192	0.141	KEWR VIS >= 9999 M	0.111	0.148
500 MB RH > 50%	-0.015	-0.133	KEZF VIS < 4800 M	-0.115	-0.120	KFRG CIG HT <1000 FT	0.101	0.133
	0.167	0.119	KCJR SKY (FEW/SCT)	0.116	0.090	KLFI CIG HT <200 FT	0.108	0.088
			KFRG SKY (FEW/SCT)	-0.214	-0.087	KPTB SKY (OVC)	-0.123	-0.177
b)			700 MB T	-0.014	-0.138	KPTB CIG HT <200 FT	0.097	0.085
			500 MB RH > 50%	0.198	0.156	500 MB T	-0.010	-0.110

A successful trend is the KDOV SKY (OBSCURED) predictor showing up in the first few hours of the forecast. This is important because it is indicates a foggier situation that may persist longer into time. The standardized beta values decrease with time, indicating that this condition has less impact on the forecast as time advances. The least influential region for predictors comes from stations due west of Dover AFB. The early time periods demonstrate a uniformity of direction among the selected network stations, however, as time advances, stations to the southwest become more dominant in the equations. These trends are expected, since weather typically moves from west to east in mid latitudes. All geographical directions influence the earlier hours as the situation is stagnant under typically stable, light wind environment.

Another successful trend is the presence of at least one easterly wind predictor (bold, Table 11), which indicates a higher likelihood of ceilings remaining, due to low-level moisture advection from the Atlantic Ocean. These predictors maintain their strength throughout the six forecast hours. The fact that the only upper air predictors are temperature and moisture predictors, not wind predictors, indicates the model detects ceilings dissipated through lifting processes better than advective processes.

Of concern is the large number of occurrences of unrestricted visibility as a dissipation predictor. While unrestricted visibilities reported at stations close to Dover AFB indicate dissipation, stations further away indicate the persistence of the ceiling. While visibility and ceiling certainly have a correlation, it is a concern that this is one of the most influential predictors, especially in the early forecasts.

Overall, the ceiling forecasts for Dover AFB are very successful in defeating conditional climatology, producing low MSEs, a large number of good forecasts and a small number of bad forecasts. Section 4.2.2 looks at the visibility less than 0.5 mi forecast for Dover AFB.

4.2.2 Visibility Less than 0.5 mi. The forecasts for visibility at Dover AFB are not as successful as the ceiling forecasts. Mean square errors are calculated for each forecast method and are displayed in Figure 8a. The MSEs for the observations-based network, while still relatively low, are higher than those for conditional climatology for each forecast time. While the observations network may still produce accurate forecasts, in this case conditional climatology is more accurate, when verified against the independent data set.

The skill scores and forecast statistics determine if there are any advantages to the observations-based network. Figure 8b shows an average 39% decrease in skill for the observations-based network. The observations-based network averages 8 more bad forecasts (out of a sample size of approximately 150) at each hour. While not a positive result, this is a better percentage of bad forecasts than conditional climatology exhibits on the ceiling forecasts. A positive sign for the observations-based network lies in the good forecasts. In the first hour forecast, the observations-based network produces 19 more good forecasts, and in the second hour they are even. Of the 100 times fog persisted into the one hour forecast, the observations-based network produced a good forecast 78 times. This is positive because the first couple of hours are typically the most critical and often highly variable.

Upon closer examination, the bad forecasts (e.g. higher MSEs) can be explained by the data. The first problem is overestimating non-occurrences of fog through all six

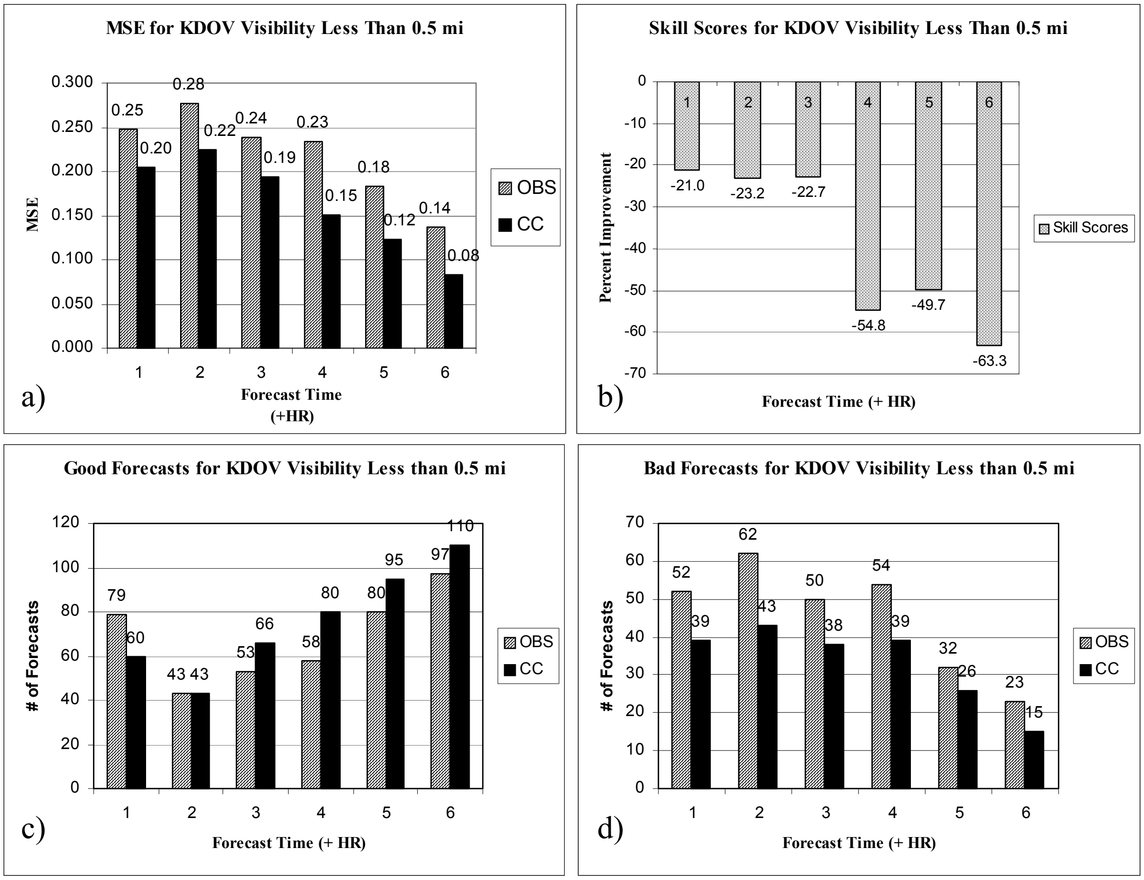

FIG. 8. Forecast Statistics for KDOV Visibility Less than 0.5 mi. Panel (a) displays MSE, panel (b) shows skill scores, panel (c) good forecasts, and panel (d) shows bad forecasts for each hour.

hours of the forecast. This is illustrated by the fact that the average predicted value of occurrence at the one-hour point is 76%. This results in the high number of misses on the situations where fog is not present, essentially driving up the false alarm rate and MSE. This problem of overestimating the probability of occurrence is magnified in the later forecasts as the actual chance of fog is more likely to be zero. The second reason for the higher MSE is a probability forecast of 1 or 0 being produced and the opposite value being observed. This problem is magnified by the set up of the experiment. That is if the observations network is not accurately forecasting fog for a particular event, it is very likely to miss the occurrence of fog at all time intervals. Therefore the MSE is increased for each forecast hour. Examination of the predictive equations as shown in Table 12, could offer a possible physical explanation for the inferior forecasts.

Analyses of the equations reveal two significant factors most strongly influencing a dissipation forecast. This first is in the short-term (one to two hours and to a lesser extent the third hour forecast) and occurs at the Georgetown, DE observing station (KGED, bold in Table 12). Two to three values per forecast predict dissipation among these predictors (the negative estimates in the equations). Of particular note is the influence of broken sky conditions at KGED having one of the strongest correlations with dissipation (based on standardized beta values) at each of the first two hours. Examination of the independent data set reveals that on occasions with inaccurate dissipation forecasts, these conditions are not present at KGED, which in turn keep the probability forecast at a higher level than it should be. With dissipation probability so closely tied to this one station, especially in the early forecasts, slight changes in meteorological parameters (e.g. sky condition broken versus overcast) have significant impact on producing an inaccurate dissipation forecast.

The second predictor subset leading to a dissipation forecast is wind direction between south and northwest (italicized in Table 12). Unfortunately, this condition is not present in a majority of cases where dissipation occurs. This is found throughout all forecasts and is related to these particular wind directions, regardless of station. This finding implies that this method has difficulty detecting dissipation unless the correct wind sector predictors are present.

TABLE 12. Forecast Equations for KDOV Visibility Less than 0.5 mi. The first 3 hours of the forecast (a) and last three (b).

T+1 HR			T+2 HR			T+3 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	0.664	0.000	Intercept:	-8.336	0.000	Intercept:	-18.763	0.000
KDOV SKY (OBSCURED)	0.061	0.067	**KGED SKY (BKN)**	-0.323	-0.170	**KGED VIS < 1600 M**	0.112	0.087
KDOV DEWPOINT	-0.013	-0.149	**KGED PRECIP**	-0.187	-0.121	**KGED PRECIP**	-0.189	-0.122
KGED SKY (BKN)	-0.278	-0.161	**KGED DEWPOINT DEPRESSION**	-0.018	-0.070	KWWD WIND DIR (<90)	0.080	0.072
KGED PRECIP	-0.178	-0.125	KWWD VIS < 1600 M	0.154	0.118	*KMIV WIND DIR (<180)*	-0.145	-0.074
KWWD VIS < 1600 M	0.207	0.175	KSBY PRECIP	-0.232	-0.167	KBWI ALT	-1.831	-0.830
KWWD WIND DIR (<315)	-0.452	-0.138	KNHK CIG HT <1000 FT	-0.196	-0.126	KVAY CIG HT <500 FT	0.069	0.069
KSBY VIS < 800 M	0.134	0.144	KNHK ALT	-2.266	-1.041	KNHK WIND DIR (<45)	0.080	0.078
KACY CIG HT <6500 FT	-0.377	-0.082	*KADW WIND DIR (<315)*	-0.230	-0.089	*KADW WIND DIR (<315)*	-0.262	-0.101
KACY WIND DIR (<180)	-0.184	-0.118	KADW DEWPOINT	-0.023	-0.254	KWAL VIS < 800 M	0.249	0.239
KBWI WIND DIR (<270)	-0.365	-0.127	KWAL VIS < 800 M	0.150	0.145	KWAL WIND DIR (<90)	0.107	0.080
SFC RH > 90%	0.176	0.155	KRDG PRECIP	-0.072	-0.060	KLNS ALT	2.535	1.134
700 MB WIND E	-0.281	-0.128	KRDG CIG HT <1000 FT	0.140	0.133	KABE SKY (OVC)	0.127	0.107
			KRDG ALT	2.561	1.144	KDAA SKY (OBSCURED)	0.159	0.122
a)			SFC RH > 90%	0.255	0.205	SFC RH > 90%	0.182	0.145
						1000 MB HT	0.001	0.173
						925 MB HT	-0.003	-0.344
						850 MB WIND NW	-0.239	-0.078

T+4 HR			T+5 HR			T+6 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	-18.340	0.000	Intercept:	-19.012	0.000	Intercept:	-21.599	0.000
KGED VIS < 1600 M	0.100	0.080	KGED CIG HT <500 FT	0.059	0.059	KDOV SKY (OBSCURED)	0.095	0.106
KWWD SKY (BKN)	-0.179	-0.063	KGED VIS < 1600 M	0.122	0.103	KDOV PRECIP	0.129	0.121
KSBY WIND DIR (<180)	-0.250	-0.191	*KGED WIND DIR (<235)*	-0.128	-0.095	KWWD WIND DIR (<90)	0.159	0.160
KSBY WIND DIR (<235)	-0.166	-0.113	KGED ALT	-3.632	-1.819	KPNE VIS < 1600 M	0.189	0.131
KVAY WIND DIR (<90)	0.095	0.084	KMIV VIS >= 9999 M	0.205	0.132	KVAY WIND DIR (<90)	0.097	0.094
KWAL VIS < 800 M	0.167	0.167	KPNE VIS < 1600 M	0.200	0.133	KNHK WIND DIR (VRB)	0.145	0.079
KWAL VIS < 1600 M	0.166	0.099	KACY WIND DIR (<45)	0.083	0.086	KNHK WIND DIR (<360)	0.125	0.068
KTTN WIND SPEED	0.016	0.129	KNHK WIND DIR (<45)	0.115	0.122	KWRI CIG HT <500 FT	0.101	0.112
KABE SKY (OVC)	0.168	0.147	KNHK WIND DIR (<360)	0.146	0.078	KWRI VIS < 800 M	-0.099	-0.102
KCXY VIS < 9999 M	-0.192	-0.093	KWAL VIS < 800 M	0.146	0.153	KWRI VIS < 4800 M	-0.166	-0.172
KCXY ALT	0.661	0.303	KWAL VIS < 1600 M	0.153	0.097	KLNS VIS < 8000 M	0.205	0.180
KMDT CIG HT <1000 FT	0.088	0.083	KWAL WIND DIR (<90)	0.172	0.140	KDCA VIS < 8000 M	0.116	0.117
KTHV SKY (FEW/SCT)	-0.168	-0.080	KWAL ALT	3.997	1.962	KTHV SKY (FEW/SCT)	-0.188	-0.097
KMFV VIS < 8000 M	-0.110	-0.077	KWRI CIG HT <500 FT	0.131	0.140	KMFV CIG HT <200 FT	0.160	0.142
KNYG PRECIP	-0.122	-0.100	KWRI VIS < 8000 M	0.124	0.083	KNYG CIG HT <12000 FT	0.160	0.095
KNYG VIS < 8000 M	-0.158	-0.124	KTTN VIS < 8000 M	0.145	0.120	KCJR ALT	-1.452	-0.731
KNYG WIND DIR (<235)	-0.135	-0.094	KABE SKY (OVC)	0.177	0.161	KCHO ALT	2.268	1.112
KIAD WIND DIR (<90)	0.141	0.091	KCXY ALT	1.855	0.894	CLIMO < 500/0#50	0.081	0.384
KEZF VIS < 4800 M	-0.110	-0.096	KTHV ALT	-1.565	-0.740	CLIMO < 1000/1#5	-0.080	-0.450
CLIMO < 200/0#25	0.077	0.159	KMFV CIG HT <6500 FT	-0.229	-0.126	1000 MB HT	0.001	0.152
CLIMO < 1000/1#5	-0.044	-0.210	KCHO WIND DIR (<135)	0.218	0.090	925 MB HT	-0.003	-0.395
925 MB HT	-0.001	-0.133	*KCHO WIND DIR (<235)*	-0.167	-0.125			
850 MB RH > 50%	-0.205	-0.110	KRIC VIS < 4800 M	-0.148	-0.141			
b)			925 MB HT	-0.001	-0.115			

Finally, the equations developed for the first two forecast hours exhibit underlying problems in the model data set. Note from Table 10 these two data sets have distributions of errors which are not normal. This statistical problem helps explain some of the inaccuracies the first two models demonstrate.

Overall the forecasts for Dover AFB show promise, especially in the ceiling category. Although conditional climatology has a lower MSE, there are advantages to the visibility forecasts, especially when the good forecasts in the very short term are considered. The predictive equations for McGuire AFB are examined next.

4.3 McGuire AFB

4.3.1 Ceiling Less than 200 ft. Mean square errors for the six forecast hours are illustrated in Figure 9a. The MSEs are smaller for the observations-based network for all six forecast hours. Examination of the skill scores (Fig. 9b) show improvement over conditional climatology for each of the six forecast hours ranging from 3%-49% with an average improvement of 22.5%. The number of good forecasts (Fig. 9c) is consistent with both forecast methods, averaging about 32 good forecasts out of approximately 55 samples. Aside from the skill score, the other distinctive advantage of the method is the minimization of bad forecasts (Fig 9d). Conditional climatology produces an average 6% more bad forecasts per hour.

An examination of the forecast equations (Table 13) leads one to conclude which variables produce the most accurate forecasts. First, as the forecast advances into the

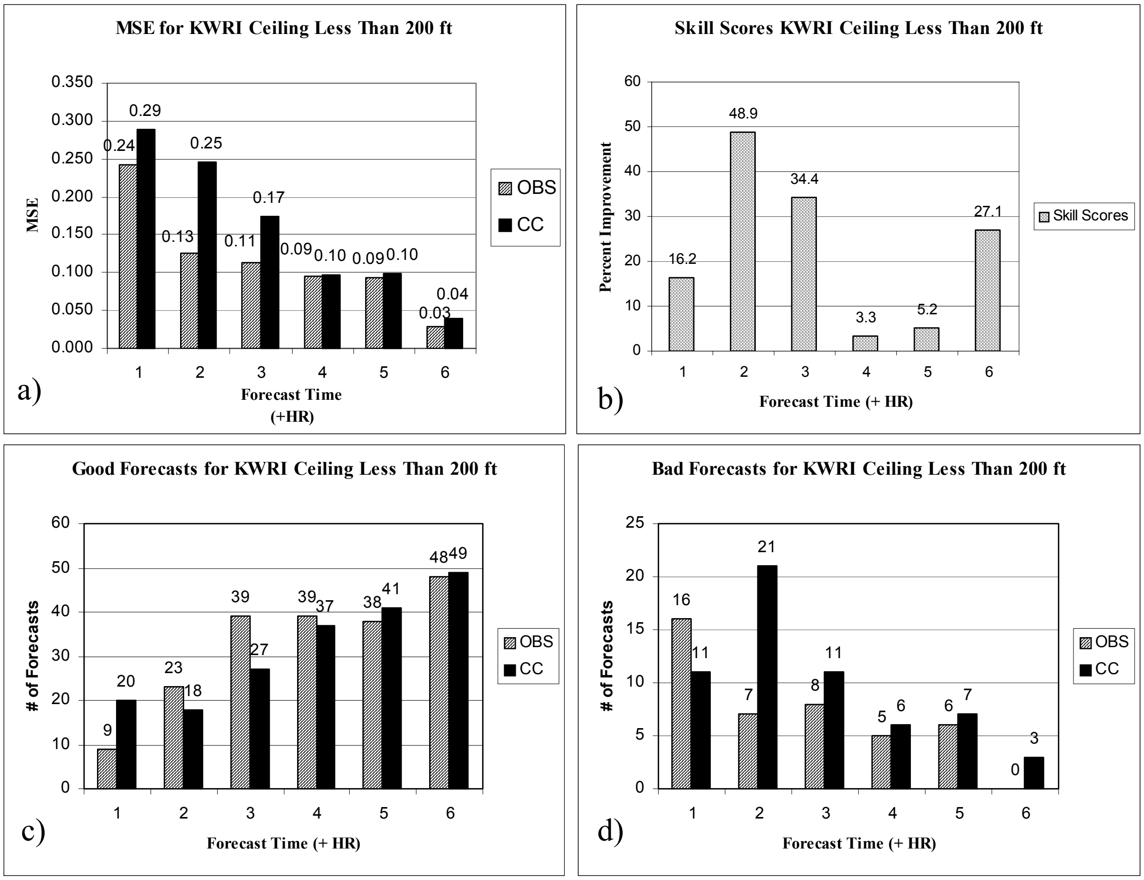

FIG. 9. Forecast Statistics for KWRI Ceiling Less than 200 ft. Panel (a) displays MSE, panel (b) shows skill scores, panel (c) good forecasts, and panel (d) shows bad forecasts for each hour.

future, the climatological factors are among the stronger predictors influencing the equations. This is expected, since in general, as the forecast time increases, the relevance of the current observation decreases. Second, the geographic region of the predictor station relative to McGuire AFB has a significant influence, especially as time increases. Stations from the southwest and west dominate the predictive equations, especially in the later stages. This is consistent with the findings for the ceiling at Dover AFB, where the southwest and west stations dominate the predictive equations at the longer time periods. Of the 96 predictors in the six equations, wind predictors dominate as 43 (indicated in

TABLE 13. Forecast Equations for KWRI Ceiling Less than 200 ft. The first 3 hours of the forecast (a) and the last three (b).

T+1 HR			T+2 HR			T+3 HR		
Predictor	Estimate (β)	St Beta	Predictor	Estimate (β)	St Beta	Predictor	Estimate (β)	St Beta
Intercept:	0.617	0.000	Intercept:	0.439	0.000	Intercept:	0.101	0.000
KWRI VIS < 800 M	0.220	0.220	KWRI VIS < 800 M	0.092	0.094	KBLM SKY (OVC)	0.116	0.125
KPNE CIG HT <1000 FT	-0.258	-0.129	**KACY WIND DIR (<45)**	0.162	0.161	**KBLM WIND DIR (<235)**	0.200	0.149
KACY WIND SPEED	-0.027	-0.170	**KILG WIND DIR (<235)**	-0.166	-0.109	KTTN VIS < 1600 M	0.119	0.101
KACY DEWPOINT DEPRESSION	-0.064	-0.129	**KEWR WIND DIR (<270)**	-0.128	-0.091	KPNE CIG HT <200 FT	0.058	0.061
KMIV VIS >= 9999 M	-0.129	-0.106	**KWWD WIND SPEED**	-0.020	-0.145	KPNE VIS < 800 M	-0.146	-0.141
KMIV DEWPOINT DEPRESSION	-0.056	-0.139	**KTEB WIND DIR (<135)**	0.262	0.156	KACY CIG HT <500 FT	0.190	0.194
KILG WIND DIR (<90)	0.153	0.129	KTEB DEWPOINT DEPRESSION	-0.039	-0.154	**KACY WIND SPEED**	-0.030	-0.210
1000 MB WIND SE	0.183	0.157	KISP PRECIP	0.294	0.154	**KMIV CIG HT <200 FT**	0.128	0.132
850 MB RH > 70%	-0.201	-0.149	KFRG VIS < 800 M	0.254	0.190	KILG SKY (OVC)	-0.181	-0.205
			1000 MB WIND SW	-0.251	-0.167	**KACY WIND DIR (<90)**	-0.274	-0.122
			850 MB RH > 70%	-0.133	-0.100	**KCDW WIND DIR (<180)**	0.387	0.124
			SOLAR RADIATION	-0.004	-0.131	**KFRG WIND DIR (<235)**	-0.249	-0.189
						KRDG WIND DIR (<90)	0.337	0.265
						KLNS WIND DIR (<235)	0.226	0.143
						KMGJ WIND DIR (<135)	0.230	0.169
a)						***1000 MB WIND SE***	0.149	0.151
						1000 MB WIND S	0.112	0.116

T+4 HR			T+5 HR			T+6 HR		
Predictor	Estimate (β)	St Beta	Predictor	Estimate (β)	St Beta	Predictor	Estimate (β)	St Beta
Intercept:	0.284	0.000	Intercept:	0.379	0.000	Intercept:	0.185	0.000
KPNE CIG HT <200 FT	0.088	0.105	KVAY PRECIP	0.131	0.103	KWRI VIS < 800 M	0.054	0.100
KPNE VIS < 800 M	-0.137	-0.153	**KVAY WIND DIR (<180)**	0.166	0.099	KVAY CIG HT <200 FT	-0.085	-0.158
KMIV VIS < 1600 M	0.191	0.159	KVAY DEWPOINT	-0.008	-0.169	KVAY DEWPOINT DEPRESSION	0.010	0.212
KEWR SKY (OBSCURED)	0.147	0.117	KABE DEWPOINT	0.015	0.300	KBLM SKY (OBSCURED)	0.176	0.119
KCDW WIND DIR (<180)	0.468	0.177	KEWR SKY (OBSCURED)	0.153	0.138	KPNE CIG HT <200 FT	0.145	0.243
KLGA WIND SPEED	-0.009	-0.084	**KWWD WIND SPEED**	-0.025	-0.276	KPNE VIS < 800 M	-0.136	-0.213
KDOV CIG HT <200 FT	0.125	0.122	KFRG CIG HT <500 FT	0.069	0.091	KFRG CIG HT <500 FT	0.079	0.127
KFRG CIG HT <500 FT	0.163	0.190	**KRDG WIND DIR (<90)**	0.137	0.142	**KFRG WIND DIR (<135)**	-0.083	-0.098
KRDG WIND DIR (<90)	0.291	0.267	**KLNS WIND DIR (<90)**	0.124	0.159	KLNS DEWPOINT	-0.008	-0.212
KLNS WIND DIR (<90)	0.078	0.089	KDXR CIG HT <1000 FT	0.092	0.128	KAVP PRECIP	-0.135	-0.150
KGED WIND SPEED	-0.019	-0.199	**KDXR WIND DIR (<135)**	0.154	0.138	KAVP DEWPOINT	0.012	0.310
KMGJ CIG HT <3000 FT	0.141	0.180	**KDXR WIND DIR (<180)**	0.138	0.112	**KDXR WIND DIR (<135)**	0.123	0.139
KMGJ WIND DIR (<135)	0.152	0.132	**KMTN WIND DIR (VRB)**	0.440	0.171	**KFOK WIND DIR (<135)**	0.089	0.131
KDXR WIND DIR (<180)	0.155	0.112	**KBWI WIND DIR (<180)**	0.182	0.099	KMTN SKY (OVC)	0.046	0.082
KBWI WIND DIR (<180)	0.274	0.127	KADW CIG HT <200 FT	0.147	0.091	**KBWI WIND DIR (<180)**	0.173	0.117
CLIMO < 200/0#25	0.051	0.191	KDCA VIS < 8000 M	0.070	0.072	KADW CIG HT <200 FT	0.212	0.162
CLIMO < 1000/1#5	-0.025	-0.214	CLIMO < 200/0#25	0.057	0.241	KDCA VIS < 8000 M	0.073	0.091
700 MB WIND S	-0.244	-0.118	CLIMO < 1000/1#5	-0.038	-0.357	KCXY CIG HT <500 FT	0.133	0.194
b)			***700 MB WIND S***	-0.149	-0.081	KTHV SKY (BKN)	0.150	0.156
						CLIMO < 1000/1#5	-0.012	-0.156
						1000 MB WIND SPEED	-0.006	-0.135

bold in Table 13) are based on wind speed or direction. Wind speed and dew point depression, have a significant effect on the prediction of dissipation, especially in the earlier forecast hours. These are positive signs, since they are two of the most important meteorological parameters indicating dissipation. Also of note is the higher number of upper level predictors as compared to the Dover AFB ceiling forecast equations.

A final factor indicating the strength and accuracy of this model is the lack of dependence on erroneous predictors. Whereas the Dover AFB ceiling forecast appears overly dependant on visibility predictors, relatively few are included in McGuire AFB's ceiling forecast. The equations are heavily influenced by wind, moisture, ceiling, and sky condition predictors as would be expected with a ceiling forecast model. Next examined is the McGuire AFB visibility forecast that exhibits some advantages despite not being as strong as the ceiling forecast.

4.3.2 Visibility Less than 0.5 mi. Mean square errors for both forecast techniques are shown in Figure 10a. Half of the forecasts of the observations-based network are superior, while the other three favor conditional climatology. The three-hour forecast shows the largest difference in MSE, likely due to the large difference in number of bad forecasts between the two techniques (Fig. 10d). Removing the three-hour forecast leaves the overall average MSEs almost even. Figure 10b shows a wide variety of range among the skill scores, from an improvement of 34% in the observations-based network to a decrease in skill of 14%, with an average increase of 3%. The observations-based network shows a higher number of good forecasts for the first half of the forecast period while conditional climatology becomes superior at the later forecast hours (Fig. 10c).

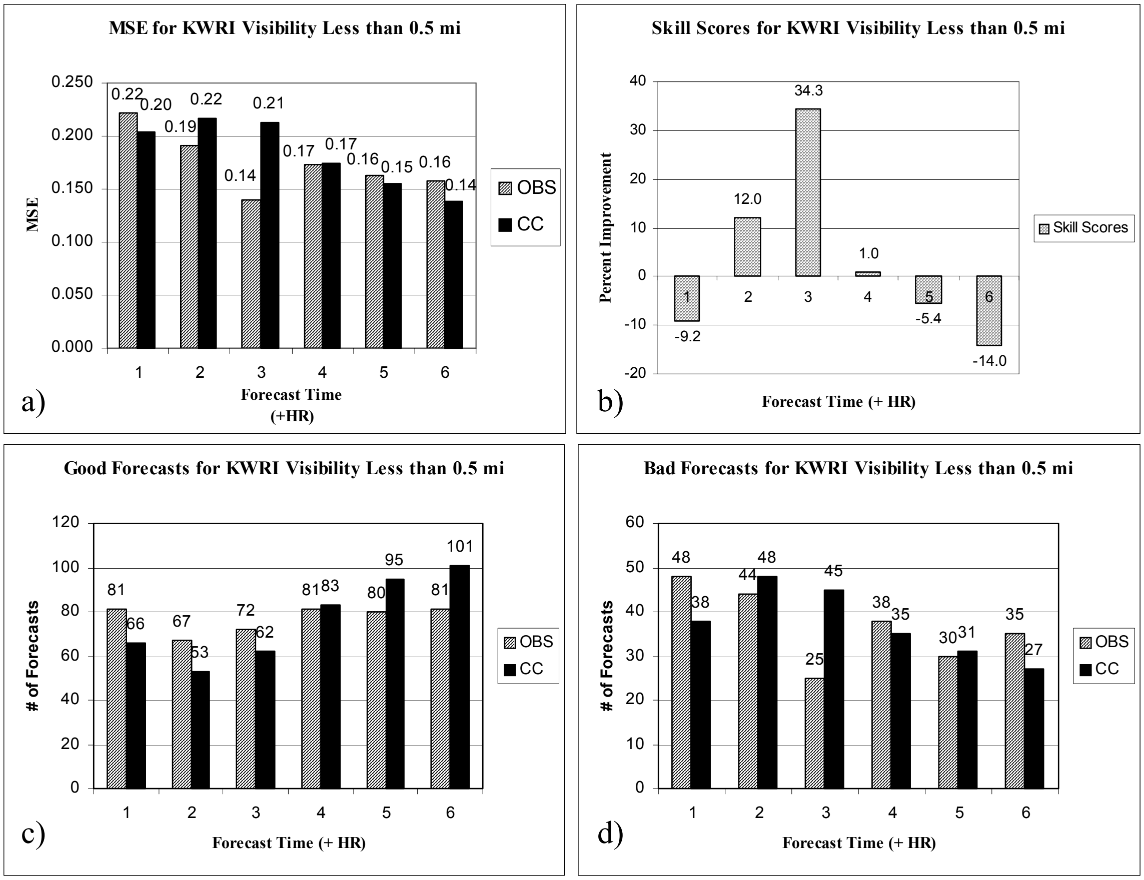

FIG. 10. Forecast Statistics for KWRI Visibility Less than 0.5 mi. Panel (a) displays MSE, panel (b) shows skill scores, panel (c) good forecasts, and panel (d) shows bad forecasts for each hour.

The equations for each forecast are in Table 14. There are two significant differences when comparing the one-hour forecast equation to the 2, 3, and 4 hour forecast equations, which are the successful equations. The first, and least significant, is the absence of any climatological parameters. Climatological parameters are not believed to be the main source of error in equation one because they are typically more influential on the later forecasts. The second major ingredient missing is the presence of any dew point or dew point depression parameters from the one-hour equation. At least one or more of these predictors generally appear in all of the other equations and are the most important factors in fog formation or dissipation. This is believed to be the reason for the low skill score (Fig. 10b) in the one-hour forecast. However, there are still advantages to the one hour forecast, including its producing 81 good forecasts (Fig. 10c) out of 150, significantly more than the 66 issued by conditional climatology.

The five and six-hour equations also have negative skill score, however moisture and climatological parameters are included in them. The reason for the decrease in skill score in this case is over prediction of the event. While bad forecasts (Absolute Error > 50%) are comparable with conditional climatology, forecast values between 30%-50% produce a large forecast error. Due to conditional climatology generally converging to zero at the later hours, it produces lower MSEs in the five to six hour period. For example, in the five hour forecast, the average predicted value using the observations-based network is 21% while the conditional climatology average is 17%. The lower average forecast value produces the lower MSE when over 75% of the observations are for non-occurrence of the event.

The most influential geographical region, as evidenced in the 2, 3, and 4-hour forecasts, is southwest. This is another factor in the degradation of the forecast skill in the 5 and 6-hour forecasts. A more omni-directional sampling of station data is evident at the longer hours, which is contrary to successful forecasts which are typically heavily based on the westerly and southwesterly observations. The lack of influence of the dominant flow on the later hour forecasts likely results in the decreased skill scores at these times.

Note that the upper air predictors are some of the weakest throughout the forecast period, while the climatological predictors, which appear in five of the six equations, are

TABLE 14. Forecast Equations for KWRI Visibility Less than 0.5 mi. The first 3 hours of the forecast (a) and last three (b).

T+1 HR			T+2 HR			T+3 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	0.691	0.000	Intercept:	1.034	0.000	Intercept:	0.971	0.000
KWRI CIG HT <500 FT	0.072	0.077	KWRI SKY (SKC)	0.584	0.122	KWRI WIND DIR (<270)	-0.180	-0.095
KWRI WIND DIR (VRB)	0.069	0.069	KWRI WIND DIR (<135)	-0.102	-0.074	KWRI DEWPOINT DEPRESSION	-0.068	-0.062
KWRI WIND DIR (<90)	0.151	0.119	KVAY PRECIP	-0.101	-0.070	KVAY CIG HT <200 FT	-0.110	-0.111
KVAY CIG HT <200 FT	-0.114	-0.115	KVAY WIND DIR (<270)	-0.358	-0.122	KMIV DEWPOINT	-0.023	-0.382
KVAY CIG HT <3000 FT	-0.341	-0.127	KBLM DEWPOINT	-0.009	-0.146	KMIV SKY (OBSCURED)	0.184	0.159
KBLM WIND DIR (<360)	-0.170	-0.083	KTTN WIND DIR (<315)	-0.212	-0.090	KMIV VIS < 1600 M	0.174	0.145
KTTN WIND DIR (<235)	-0.204	-0.112	KPNE CIG HT <3000 FT	-0.200	-0.086	KCDW CIG HT <6500 FT	-0.221	-0.085
KTTN WIND DIR (<315)	-0.273	-0.123	KPHL WIND DIR (<45)	0.088	0.073	KCDW WIND DIR (<180)	0.242	0.111
KPNE CIG HT <3000 FT	-0.215	-0.100	KACY DEWPOINT DEPRESSION	-0.037	-0.126	KLGA CIG HT <500 FT	0.151	0.143
KPNE CIG HT <6500 FT	-0.209	-0.073	KMIV SKY (OBSCURED)	0.100	0.081	KWWD WIND DIR (<315)	-0.181	-0.088
KACY VIS < 800 M	0.118	0.116	KMIV WIND DIR (<135)	0.123	0.092	KISP WIND DIR (<360)	-0.226	-0.087
KACY VIS >= 9999 M	-0.105	-0.098	KMIV DEWPOINT	-0.027	-0.415	KDOV SKY (FEW/SCT)	0.117	0.109
KMIV VIS >= 9999 M	-0.084	-0.072	KILG SKY (OVC)	-0.068	-0.068	KRDG SKY (SKC)	0.115	0.089
KILG SKY (OBSCURED)	0.091	0.074	KILG CIG HT <200 FT	-0.121	-0.081	KLNS CIG HT <500 FT	0.127	0.116
			KABE WIND DIR (<90)	0.134	0.124	KLNS WIND DIR (<90)	0.093	0.090
			KCDW WIND DIR (<180)	0.209	0.088	KMGJ VIS < 1600 M	0.122	0.068
			KJFK WIND DIR (<135)	0.182	0.134	SOLAR RADIATION	-0.003	-0.093
			KJFK DEWPOINT	0.024	0.375	CLIMO < 200/0#25	0.104	0.331
			KWWD CIG HT <200 FT	0.165	0.153	CLIMO < 1000/1#5	-0.066	-0.484
			KTEB WIND DIR (<360)	-0.220	-0.108	SFC T	0.016	0.298
a)			CLIMO < 200/0#25	0.100	0.296			
			CLIMO < 1000/1#5	-0.054	-0.369			
			SFC WIND E	0.104	0.083			
			925 MB RH > 30%	-0.140	-0.089			

TABLE 14. Cont.

T+4 HR			T+5 HR			T+6 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	-4.283	0.000	Intercept:	0.295	0.000	Intercept:	-3.362	0.000
KVAY CIG HT <200 FT	-0.109	-0.123	KWRI PRECIP	0.069	0.065	KWRI SKY (OVC)	-0.054	-0.076
KVAY CIG HT <12000 FT	-0.185	-0.060	KVAY CIG HT <500 FT	0.057	0.074	KVAY CIG HT <200 FT	-0.090	-0.126
KVAY DEWPOINT	-0.012	-0.235	KVAY DEWPOINT DEPRESSION	0.010	0.134	KVAY DEWPOINT DEPRESSION	0.009	0.133
KTTN VIS < 800 M	0.113	0.121	KBLM SKY (FEW/SCT)	0.067	0.061	KACY SKY (OBSCURED)	0.060	0.074
KACY SKY (OBSCURED)	0.118	0.118	KBLM VIS < 1600 M	0.138	0.109	KILG PRECIP	0.072	0.071
KMIV SKY (OBSCURED)	0.084	0.081	KPHL VIS < 4800 M	0.067	0.073	KABE DEWPOINT DEPRESSION	0.014	0.090
KMIV VIS < 1600 M	0.072	0.066	KACY SKY (OBSCURED)	0.062	0.068	KLGA WIND DIR (VRB)	0.227	0.087
KMIV DEWPOINT	-0.012	-0.226	KMIV SKY (OBSCURED)	0.068	0.073	KLGA WIND DIR (<135)	0.148	0.119
KILG WIND DIR (<45)	0.051	0.052	KILG CIG HT <500 FT	0.051	0.061	KWWD CIG HT <200 FT	0.063	0.087
KILG WIND DIR (<180)	0.128	0.090	KILG WIND DIR (<180)	0.126	0.098	KWWD WIND DIR (<135)	0.076	0.082
KABE DEWPOINT DEPRESSION	0.028	0.141	KABE DEWPOINT DEPRESSION	0.014	0.079	KISP CIG HT <500 FT	0.055	0.077
KCDW WIND DIR (<180)	0.160	0.081	KLGA WIND DIR (VRB)	0.265	0.091	KFRG CIG HT <500 FT	0.065	0.092
KJFK VIS < 8000 M	0.122	0.098	KLGA WIND DIR (<135)	0.145	0.103	KRDG SKY (FEW/SCT)	-0.062	-0.059
KLGA WIND DIR (<135)	0.101	0.065	KWWD WIND DIR (<135)	0.096	0.091	KLNS ALT	0.125	0.066
KWWD WIND DIR (<135)	0.083	0.070	KDOV SKY (SKC)	0.249	0.139	KGED WIND DIR (<135)	0.076	0.064
KISP CIG HT <500 FT	0.083	0.094	KDOV SKY (FEW/SCT)	0.065	0.075	KMGJ SKY (FEW/SCT)	0.171	0.122
KISP CIG HT <1000 FT	0.150	0.140	KRDG SKY (SKC)	0.186	0.179	KDXR WIND DIR (<135)	0.109	0.110
KISP WIND DIR (<360)	-0.138	-0.060	KRDG CIG HT <500 FT	0.086	0.086	KFOK PRECIP	-0.113	-0.119
KFRG CIG HT <500 FT	0.147	0.166	KGED WIND DIR (<135)	0.074	0.054	KFOK DEWPOINT	0.011	0.256
KFRG ALT	0.163	0.077	KDXR WIND DIR (<135)	0.088	0.078	KMSV VIS >= 9999 M	0.077	0.110
KDOV SKY (FEW/SCT)	0.077	0.080	KMSV DEWPOINT DEPRESSION	0.030	0.110	KMSV DEWPOINT DEPRESSION	0.037	0.148
KRDG VIS < 800 M	0.094	0.074	KPOU CIG HT <500 FT	0.111	0.099	KPOU CIG HT <500 FT	0.086	0.087
KRDG WIND DIR (<90)	0.205	0.171	KSBY SKY (OVC)	-0.083	-0.103	KSBY SKY (OVC)	-0.074	-0.103
KSWF VIS < 8000 M	0.115	0.097	KADW CIG HT <200 FT	0.221	0.104	KSBY DEWPOINT	-0.014	-0.297
KSWF WIND DIR (<90)	-0.186	-0.125	CLIMO < 200/0#25	0.033	0.127	KCXY SKY (SKC)	0.086	0.090
COS DAY	-0.081	-0.149	CLIMO < 1000/1#5	-0.036	-0.317	KCXY CIG HT <500 FT	0.106	0.129
CLIMO < 200/0#25	0.068	0.240	SFC RH > 90%	0.056	0.074	KTHV VIS >= 9999 M	-0.135	-0.174
CLIMO < 1000/1#5	-0.053	-0.425	850 MB RH > 50%	-0.061	-0.058	CLIMO < 1000/1#5	-0.026	-0.268
SFC T	0.018	0.371	850 MB WIND S	0.082	0.074	SFC RH > 90%	0.071	0.105
1000 MB WIND NW	0.240	0.124	700 MB RH > 70%	-0.090	-0.096	SFC WIND NW	0.142	0.061
925 MB RH > 30%	-0.104	-0.080				850 MB WIND S	0.098	0.100
850 MB RH > 50%	-0.164	-0.141						
700 MB RH > 70%	-0.090	-0.088						

b)

some of the strongest. Other than the climatological predictors, there are no distinct trends among the meteorological predictor selection.

Of the 12 predictive equations developed for McGuire AFB, nine show superior forecast skill to conditional climatology. The unsuccessful predictive equations produce good forecasts, with slight biases. Overall, the application of the surface-based observing method for McGuire AFB is considered a success. Next, evaluation of the forecast equations for Andrews AFB is examined.

4.4 Andrews AFB

4.4.1 Ceiling Less than 200 ft. The graph of MSEs verified on the independent sample of data is shown in Figure 11a. It is evident in all Andrews AFB cases that the MSE for conditional climatology is smaller than that of the surface-based observations system. Although the one and six-hour forecasts are competitive, the other four clearly are not. The main reason for the variability in MSEs is a small sample size. While the Dover AFB and McGuire AFB forecast parameters have approximately 50 observations for verification, Andrews only has approximately 30. There are a couple of reasons for this. First, the number of occurrences of ceiling below 200 ft at Andrews AFB is significantly lower than the other two stations. Dover AFB and McGuire AFB have approximately 400 observations of fog, while Andrews AFB has only about 200. The second reason is the non-reporting of ceilings. As previously mentioned, forecasts are not verified if ceiling data is not available at the forecast hours. This is especially a problem at

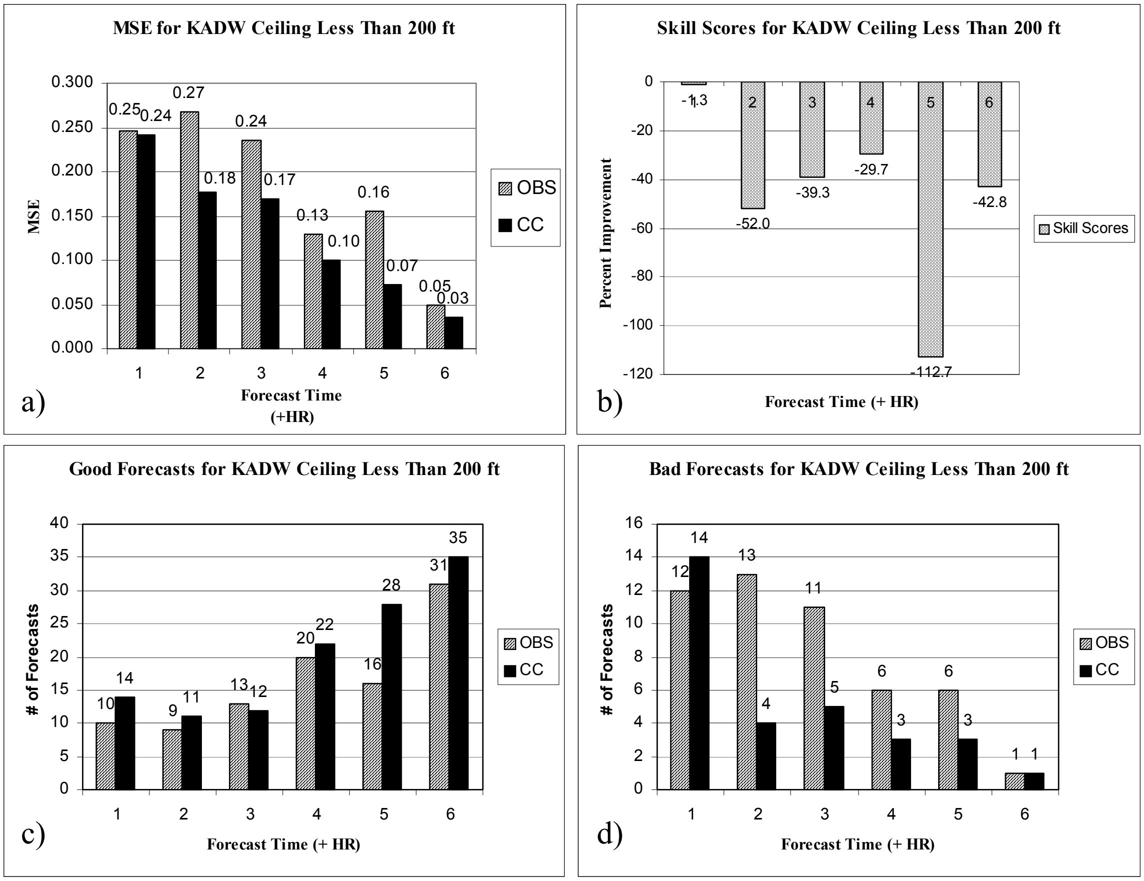

FIG 11. Forecast Statistics for KADW Ceiling Less than 200 ft. Panel (a) displays MSE, panel (b) shows skill scores, panel (c) good forecasts, and panel (d) shows bad forecasts for each hour.

Andrews AFB, where the occurrence of reduced visibility often resulted in no sky condition being reported.

A second problem in the Andrews AFB data set is the large amount of missing upper air data. Section 3.2.3 shows that 12% of the upper air data is missing for Andrews AFB, much higher than the other two data sets. This results in fewer upper air predictors being selected for each forecast. A final problem to note in the Andrews AFB data set is the failure to meet the necessary assumptions required for linear regression. Table 10 in Chapter III illustrates that the first three forecast hours exhibit non-normality, heteroscedasticity, or both. The linear regression model is probably not applicable to this data set and has a strong influence on the excessively high MSEs in the first three hours. The average skill score for the six forecasts is -46% (Fig. 11b). The one-hour forecast is most competitive with conditional climatology, it has a skill score of -1%, but it offers fewer bad forecasts than conditional climatology and almost the same MSE (Fig. 11a & 11d). Aside of the inherent problems with the data, an analysis of the equations produced by the observations-based network (Table 15) provides some insight into why the results from Andrews AFB base differ from Dover AFB and McGuire AFB.

An analysis of the equations reveals significant findings. First, the number of predictors varies from 4-15 throughout the six equations. This is much lower than the previous equations, which typically vary from about 10-25 predictors. The small data set does not adequately detect the dominant atmospheric conditions resulting in dissipation, therefore, the regression is unable to select ample predictors. The smaller number of predictors (which as stated before are mostly binary), unfortunately are not representative enough of the atmosphere surrounding the station. Variations in the atmospheric conditions that could lead to accurate dissipation predictions are therefore not well represented by the model.

Upper air and climatological predictors are also omitted from the equations. These are often the driving forces in the previous successful forecast models. Uniformity of station selection is also evident in the later forecasts. Successful models typically have a majority of the stations used in the prediction from the southwest and west in the later periods. This model has an omni-directional, or uniform geographic distribution in the

TABLE 15. Forecast Equations for KADW Ceiling Less than 200 ft. The first 3 hours of the forecast (a) and the last three (b).

T+1 HR			T+2 HR			T+3 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	0.466	0.000	Intercept:	0.208	0.000	Intercept:	0.120	0.000
KADW SKY (OBSCURED)	0.315	0.315	KNYG VIS < 800 M	0.284	0.275	KDCA SKY (OBSCURED)	0.337	0.190
KDCA VIS < 8000 M	-0.267	-0.185	KBWI SKY (OBSCURED)	0.156	0.132	KNYG WIND DIR (<45)	0.117	0.084
KNYG CIG HT <200 FT	0.178	0.167	KMTN WIND DIR (<90)	0.204	0.173	KBWI SKY (OVC)	-0.165	-0.178
KMTN WIND DIR (<90)	0.325	0.276	KEZF WIND DIR (<90)	0.289	0.170	KMTN WIND DIR (<90)	0.158	0.161
			KOKV CIG HT <12000 FT	0.522	0.337	KCJR SKY (FEW/SCT)	0.373	0.230
			KOKV WIND DIR (<135)	0.202	0.165	KCJR CIG HT <200 FT	-0.166	-0.109
			KMRB WIND DIR (<235)	-0.275	-0.127	KCJR VIS < 1600 M	0.337	0.273
			KNHK SKY (BKN)	-0.234	-0.164	KOKV CIG HT <12000 FT	0.274	0.195
			KLNS WIND DIR (<90)	0.162	0.191	KOKV WIND DIR (<135)	0.226	0.205
						KNHK CIG HT <1000 FT	0.422	0.230
						KGED VIS < 4800 M	0.191	0.190

a)

T+4 HR			T+5 HR			T+6 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	-0.258	0.000	Intercept:	-0.325	0.000	Intercept:	-0.146	0.000
KDCA SKY (OBSCURED)	0.310	0.187	KADW WIND DIR (<45)	0.177	0.112	KDCA SKY (OVC)	-0.111	-0.148
KDAA VIS < 800 M	0.125	0.127	KDCA SKY (OBSCURED)	0.341	0.201	KNYG CIG HT <200 FT	0.098	0.125
KMTN WIND DIR (<90)	0.126	0.122	KNYG CIG HT <200 FT	0.150	0.169	KBWI SKY (FEW/SCT)	0.254	0.167
KCJR SKY (FEW/SCT)	0.582	0.351	KHGR CIG HT <12000 FT	0.342	0.163	KBWI SKY (OBSCURED)	0.103	0.147
KCJR CIG HT <500 FT	0.095	0.099	KCJR SKY (FEW/SCT)	0.203	0.144	KEZF SKY (OBSCURED)	0.276	0.131
KOKV PRECIP	0.431	0.182	KCJR CIG HT <500 FT	0.085	0.115	KNHK SKY (OBSCURED)	0.121	0.148
KOKV WIND DIR (<135)	0.166	0.152	KNHK SKY (OBSCURED)	0.116	0.127	KGED VIS < 4800 M	0.072	0.099
KDOV WIND SPEED	0.013	0.106	KSBY SKY (OVC)	0.083	0.111	KWAL VIS < 1600 M	0.093	0.111
KLNS WIND DIR (<135)	0.122	0.117	KCHO CIG HT <500 FT	0.139	0.178	KPNE WIND DIR (<45)	0.161	0.209
KGED VIS < 4800 M	0.112	0.107	KCHO DEWPOINT DEPRESSION	0.059	0.185	KPNE WIND SPEED	0.018	0.220
KPTB SKY (OBSCURED)	0.240	0.033	KPNE WIND DIR (<45)	0.089	0.111	KWWD VIS < 1600 M	0.112	0.124
KCHO CIG HT <500 FT	0.126	0.120	KPNE WIND SPEED	0.018	0.199	KLFI CIG HT <12000 FT	0.106	0.092
KCHO DEWPOINT DEPRESSION	0.065	0.177	KWWD WIND DIR (<90)	0.180	0.218	KTTN VIS < 9999 M	0.135	0.086
KPNE PRECIP	-0.253	-0.219	SFC WIND N	0.125	0.160	KBLM CIG HT <1000 FT	0.171	0.182
KPNE WIND SPEED	0.023	0.226				1000 MB WIND N	0.151	0.184

b)

later forecast hours, which is also troublesome in the Dover AFB and McGuire AFB cases where it appears. The predictors selected by the model do not appear ambiguous. That is, the model focuses mainly on sky conditions and ceiling predictors and veers away from the visibility predictors. Overall, it is believed that with a larger, normally distributed sample and some fine tuning this model could be made to accurately represent the forecast conditions. Examined next is the visibility forecast for Andrews AFB.

4.4.2 Visibility Less than 0.5 mi. The MSE (Fig. 12a) for the one-hour forecast is superior in the observations-based system; however, it is the only case that illustrates the superiority of this methodology. The MSEs are significantly better for conditional climatology for the other five forecast hours. This is also evident in the skill scores (Fig. 12b) where the average decrease in skill score of the observations-based network is 45%. The other forecast statistics (Fig 12c, 12d) significantly favor conditional climatology, with the observations network competitive on only a few occasions.

Once again, it is believed that the largest problem for the Andrews AFB visibility forecasts is the data itself. The number of occurrences is about one third the number of occurrences for both Dover AFB and McGuire AFB. Also note from Chapter III (Table 7) that the first four forecast hours exhibit errors that are not normally distributed. This violates the assumptions required for linear regression. This is the main reason for the inadequacies in the Andrews AFB forecast.

Examining the equations (Table 16) provides further insight on the problems with the visibility forecast. The best forecast time, at one hour, has relatively few predictors, but is geographically uniform around the station. The model remains consistent in its

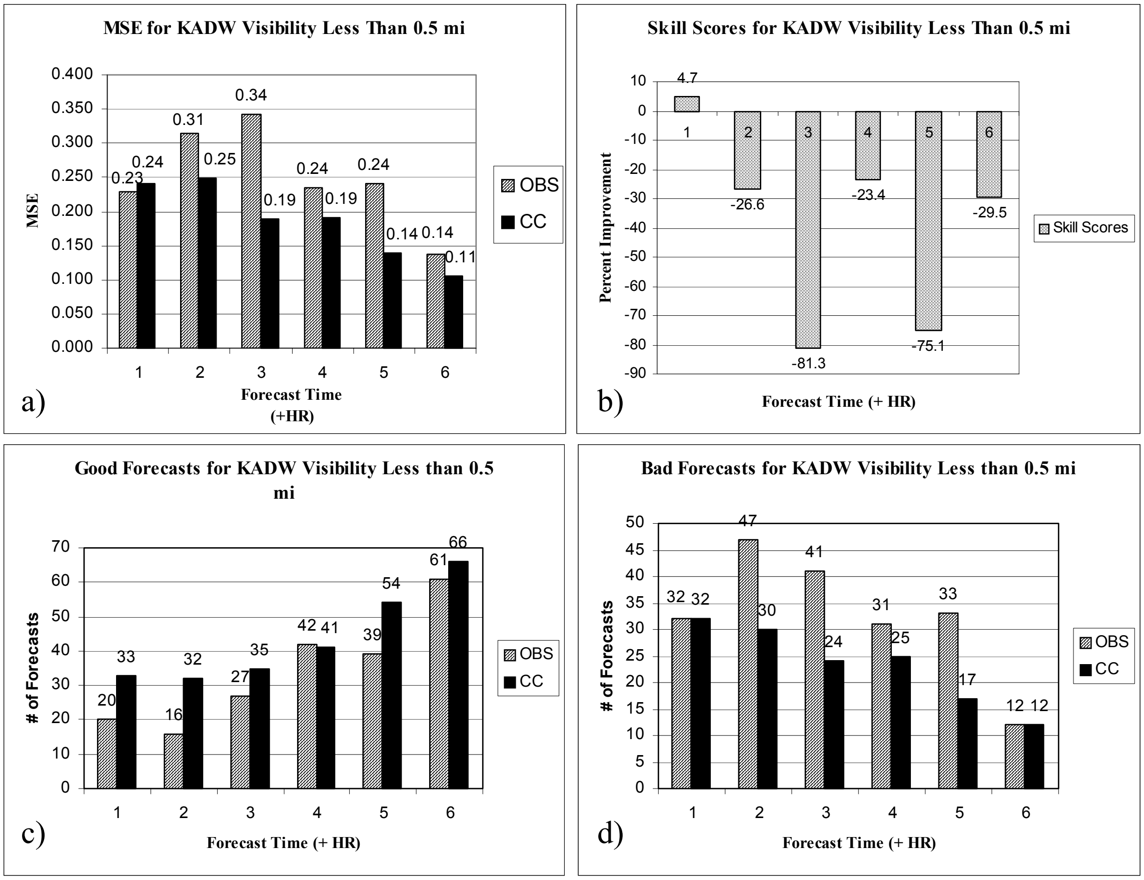

FIG 12. Forecast Statistics for KADW Visibility Less than 0.5 mi. Panel (a) displays MSE, panel (b) shows skill scores, panel (c) good forecasts, and panel (d) shows bad forecasts for each hour.

selection of parameters throughout the six hours, and also appears to hone in on the meteorological processes that lead to dissipation. For example, at least one moisture parameter is present in all six forecasts (bold in Table 16) and the standard beta values show that they are one of the most influential factors predicting dissipation. Another noticeable trend is the strong presence of northeasterly to southeasterly winds, which would intuitively indicate moisture advection from the Atlantic Ocean. In the first hour's forecast, the easterly wind term indicates dissipation, while the other five forecasts

TABLE 16. Forecast Equations for KADW Visibility Less than 0.5 mi. The first 3 hours of the forecast (a) and last three (b).

a)

T+1 HR			T+2 HR			T+3 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	0.652	0.000	Intercept:	0.340	0.000	Intercept:	0.250	0.000
KNYG WIND DIR (<45)	0.160	0.162	KNYG WIND DIR (<45)	0.139	0.136	KDAA SKY (OVC)	-0.135	-0.142
KBWI DEWPOINT DEPRESSION	-0.085	-0.160	KMTN WIND DIR (<90)	0.143	0.118	KDAA CIG HT <1000 FT	0.254	0.218
KMTN SKY (SKC)	-0.477	-0.116	KEZF CIG HT <200 FT	0.179	0.150	KHEF VIS >= 9999 M	-0.095	-0.081
KHGR VIS >= 9999 M	-0.145	-0.108	KHGR WIND DIR (<135)	0.260	0.153	KNYG CIG HT <500 FT	-0.181	-0.184
SFC WIND SW	-0.343	-0.111	KNHK WIND DIR (<135)	-0.416	-0.232	KNYG VIS >= 9999 M	-0.177	-0.121
			KNHK DEWPOINT DEPRESSION	-0.052	-0.141	KNYG WIND DIR (<45)	0.074	0.075
			KLNS WIND DIR (<90)	0.149	0.140	KMTN WIND DIR (<90)	0.100	0.084
			1000 MB WIND SW	-0.314	-0.104	KNHK VIS < 800 M	0.146	0.140
			700 MB WIND NW	-0.245	-0.130	KNHK WIND DIR (<135)	-0.300	-0.171
						KLNS CIG HT <500 FT	0.090	0.093
						KLNS WIND DIR (<90)	0.170	0.165
						KCXY WIND DIR (<90)	0.121	0.114
						KWAL VIS < 800 M	0.194	0.164
						1000 MB RH > 30%	-0.204	-0.096

b)

T+4 HR			T+5 HR			T+6 HR		
Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta	Predictor	Estimate (β)	Std Beta
Intercept:	0.407	0.000	Intercept:	0.573	0.000	Intercept:	-5.842	0.000
KNYG WIND DIR (<45)	0.107	0.117	**KADW DEWPOINT**	-0.022	-0.310	KNYG CIG HT <200 FT	0.228	0.166
KIAD CIG HT <200 FT	-0.194	-0.150	KNYG CIG HT <200 FT	0.173	0.114	KBWI VIS < 4800 M	0.169	0.204
KCJR SKY (FEW/SCT)	0.261	0.133	KNYG WIND DIR (<45)	0.064	0.075	KHGR WIND DIR (<360)	0.158	0.148
KRIC WIND DIR (<135)	0.164	0.137	KBWI VIS < 4800 M	0.129	0.140	KOKV SKY (FEW/SCT)	0.136	0.091
KLNS DEWPOINT	-0.013	-0.178	KMTN SKY (OVC)	0.106	0.128	KNHK VIS < 800 M	0.079	0.098
KGED CIG HT <500 FT	0.067	0.073	KMTN CIG HT <1000 FT	-0.148	-0.140	KLNS WIND DIR (<90)	0.086	0.107
KILG DEWPOINT DEPRESSION	-0.037	-0.169	KHGR WIND DIR (<360)	0.165	0.141	KCXY SLP	0.185	0.112
KSBY VIS < 800 M	0.274	0.261	KMRB VIS >= 9999 M	-0.112	-0.091	KGED VIS < 8000 M	-0.085	-0.076
KRDG WIND DIR (<90)	0.145	0.122	KTHV WIND DIR (<90)	0.097	0.093	KSBY SKY (OVC)	0.079	0.107
KPNE VIS >= 9999 M	-0.091	-0.093	KNHK SKY (OBSCURED)	0.160	0.162	KSBY VIS < 800 M	0.200	0.228
KPNE WIND SPEED	0.009	0.087	KDOV SKY (OBSCURED)	-0.119	-0.133	KWAL CIG HT <200 FT	0.101	0.092
CLIMO < 1000/1#5	-0.024	-0.148	KSBY VIS < 800 M	0.296	0.305	KPHL WIND SPEED	-0.015	-0.166
STATIC STABILITY (925-850MB)	14.577	0.137	KWAL VIS < 1600 M	0.174	0.127	KWWD WIND DIR (<90)	0.077	0.094
			KCHO WIND DIR (<135)	0.220	0.124	KMIV SKY (OVC)	0.057	0.074
			KWWD WIND DIR (<90)	0.200	0.220	KMIV WIND SPEED	0.020	0.203
			KWWD DEWPOINT	0.007	0.140	KLFI SKY (SKC)	0.115	0.082
			KLFI WIND SPEED	-0.020	-0.199	KLFI WIND DIR (<135)	0.079	0.078
			CLIMO < 1000/1#5	-0.029	-0.189	KEWR CIG HT <1000 FT	0.113	0.138
			850 MB RH > 30%	0.233	0.166	SIN DAY	-0.050	-0.096
						1000 MB RH > 90%	0.139	0.188
						850 MB RH > 30%	0.302	0.237

remain consistent in indicating the presence of reduced visibility with these wind conditions. This discrepancy is left unexplained in the statistical analysis.

The later forecast hours again show neither climatological predictors, nor a dependence on westerly or southwesterly stations for predictors. These could be two contributing factors to the lack of skill shown later in the period.

Although the Andrews AFB forecasts overall fail to verify well on independent data, there are positive trends, such as the lack of erroneous predictor selection indicating that success could be achieved in the future. The small number of predictors, due to the smaller data set, has a large influence on the negative skill scores of the model. However, the most significant problem in the models is the failure of the data set to meet the assumptions required for linear regression. Underlying problems throughout the models are examined next.

4.5 Underlying Model Problems. There are inherent problems that persist through all the models that are addressed. The first is the linearity of the model. In linear regression, an R^2 value is calculated, this is the coefficient of determination and represents the adequacy of fit of the regression model, or the variability in the data accounted for by the model (Montgomery and Runger 2001). The R^2 values range from 0 to 1 with 1 being a perfect fit. The R^2 values for the forecast models presented in this work typically are between 0.25 and 0.6. Although these values may seem low, they are not of major concern for the following reasons. First, R^2 values can be erroneously inflated by adding an excessive amount of terms (Montgomery and Runger 2001). This study keeps with the strict F-test criteria to minimize the number of predictors added to the equation. Second, this is a linear model of the atmosphere, an entity that usually behaves non-linearly, making high R^2 values difficult to obtain. Third, according to Montgomery and Runger (2003) large R^2 values do not necessarily imply accurate predictions of future events. Finally, as Wilks (1995) points out the goal of the statistical methodology is to produce an accurate forecast, not a perfect model. Therefore, this work focuses on developing accurate dissipation forecasts, regardless of the model's linear relationship to the data set.

A second issue is the absence of sky conditions in observations. Although replacement data are used to fill in the missing values, sky condition is never used as a predictand value. This reduces the sample size considerably for both equation development and verification, especially in the Andrews AFB data set.

Third, this system is designed independent of time of day so that one forecast equation could suffice for the airfield. This varies from Vislocky and Fritsch's (1997) work that focused on two short time intervals for their forecasts. Breaking the data into intervals (2-4 hours) would be more representative of diurnal differences in weather patterns and could produce improved equations for fog dissipation. Furthermore, it eliminates some of the advantages conditional climatology has. That is, as fog is primarily a nocturnal/early morning event conditional climatology has an advantage in the afternoon cases in that probabilities decrease to zero much faster, typically mirroring the observations. Many of the over forecasting occurrences occur in late morning or afternoon situations, where the observations-based network is working regardless of time. While the observations network is based on the physical mechanisms that lift the fog, different processes are at work in the overnight versus daylight hours. Breaking into time blocks could allow the equations to pick different predictors, e.g. different physical mechanisms for afternoon versus nocturnal events.

A final remark is the impact automated observing systems employed by the NWS had on this study. Vislocky and Fritsch's (1997) original work used abundant full time manual reporting stations along the east coast, many of which no longer exist. The disadvantage of the ASOS observations is missing data due to staggered implementation and spin-up times. These two factors cause many of the observations from ASOS stations to be strongly influenced by missing data techniques. Examples of the how this technique is applied to real world events follow.

4.6 Applications of the Observations-Based Method. To implement this method operationally, each equation is calculated to produce a probability forecast. Forecast probabilities range from '1' representing a 100% chance of occurrence of the event (e.g. ceiling below 200 ft). to '0' representing a 0% chance of the event occurring.

Table 17 provides an application of this process to produce a prediction forecast for 1-hour in the future at Dover AFB. The first column represents the predictor labels (the physical meaning of the response variable) with the regression coefficients (β) in the second column. The third column is the actual or observed value of the predictor (x). Notice that a majority of the predictors are binary values, coded as either a '0' for non-occurrence or a '1' for occurrence. The values are multiplied, and then summed, per Eq. 2 (including the intercept, β_0) to produce the forecast of 76.9% probability of occurrence. Probabilities are calculated for each of the six hourly forecasts for each of the two network versus conditional climatology on actual observed events. The first event took

Table 17. Example Predictive Equation.

Predictor	Estimate (β)	Observed Value	Equation Result
Intercept:	0.6999357		0.6999357
700 MB T	-0.018243	4.6	-0.0839178
KWWD CIG HT <3000 FT	-0.4099	0	0
KWWD VIS >= 9999 M	-0.11243	0	0
KSBY VIS >= 9999 M	-0.120956	0	0
KILG VIS >= 9999 M	-0.11369	0	0
KILG WIND DIR (<235)	-0.494969	0	0
KMIV WIND DIR (<90)	0.2029688	0	0
KGED CIG HT <3000 FT	-0.382974	0	0
KDOV SKY (OBSCURED)	0.1530178	1	0.1530178
KDOV VIS < 4800 M	-0.139053	0	0
Forecast Probability:	0.7690357		

place on 24 Jan 01 at 0627Z at Dover AFB and the forecast is for ceiling below 200 ft. Figure 13 illustrates the two probability forecasts for the six valid times along with the actual observed event. Notice at the one-hour point, the observations-based network produces a forecast of over 80% probability of occurrence, while conditional climatology has probabilities in the 60-65% range. As the low ceiling lifts, slightly after 0800Z, the two-hour observations-based forecast accurately detects dissipation, generating a probability forecast of 17% compared to 33% for conditional climatology. The observations forecast remains in sync with the actual observation at the three-hour point. The four-hour point shows both methods producing forecast probabilities of 25%, still within the good forecast range. Finally, the observations-based network accurately forecasts the last two hours, while conditional climatology lags behind in its prediction.

The second example (Fig. 14) is from 26 Oct 00, 0500Z at McGuire AFB, with visibility less than 0.5 mi as the forecasted predictand. This situation persists for over six

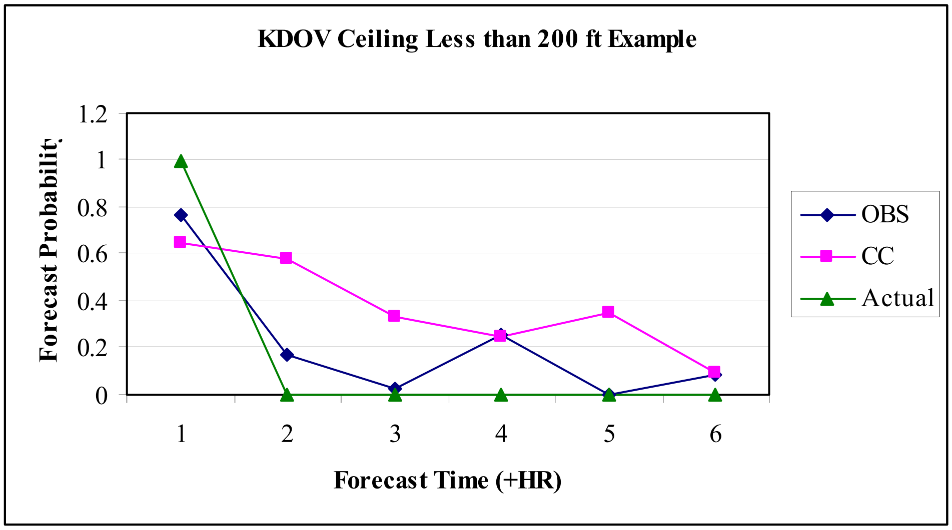

FIG. 13. Forecast Comparison for Dover AFB. Each forecast method is plotted for a six hour forecast beginning at 0627Z, 24 Jan 01 at Dover AFB. Note that the observations-based network predicts dissipation faster and more accurately than conditional climatology.

hours and is forecasted more accurately by the observations-based network. The one-hour forecast is accurate for both forecast techniques, with a 92% probability for the observations-based network and an 81% probability for conditional climatology. The second hour illustrates the strength of the observations-based forecast, where conditional climatology almost always decreases probabilities with time; the observations network adjusts and produces a more accurate forecast based solely on the current conditions. Thus the two-hour forecast is actually more accurate than the one-hour forecast and significantly better than conditional climatology. Although the probabilities decrease as time goes on, the observations-based method continues to produce a superior forecast. As far as five hours out, this method is still forecasting a 64% probability of occurrence, which may be below the good forecast criteria, but is still a solid forecast for five hours in the future based solely on the current conditions and is significantly better than conditional climatology.

Overall these two examples illustrate the effectiveness of an observations-based system to accurately forecast timing of dissipation, as well as event duration. Conclusions arising from this research along with recommendations on implementation and future work follow.

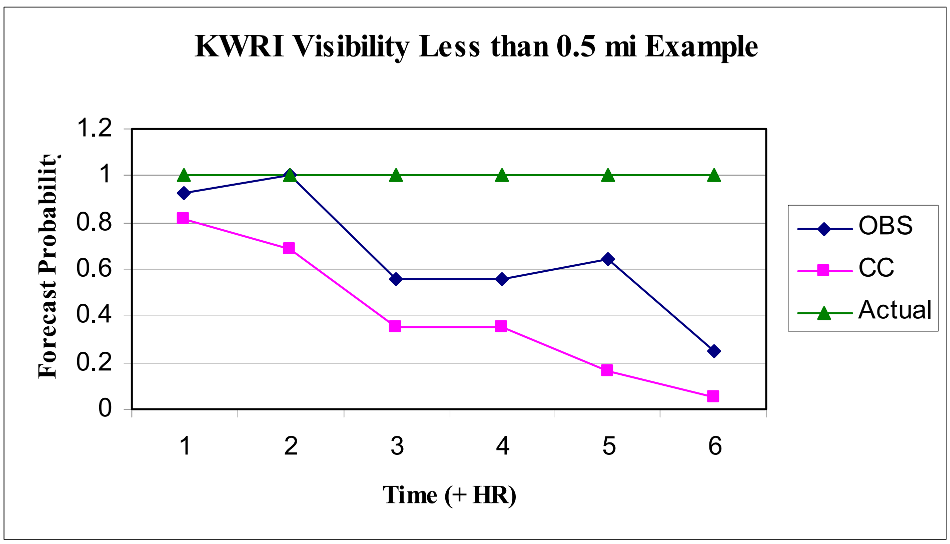

FIG. 14. Forecast Comparison for McGuire AFB. Each forecast method is plotted for a six hour forecast beginning at 0500Z, 26 Oct 00 at McGuire AFB. Note that the observations-based network more accurately predicts the continued presence of the low ceiling through the duration of the event.

V. Conclusions and Recommendations

5.1 Conclusions

The goal of this research is to develop a forecast tool for the 15 OWS to predict dissipation of fog more accurately than their current methodology, conditional climatology. To accomplish this, 36 probabilistic forecast equations are developed, 12 for each of the three main airfields along the east coast, Dover AFB, McGuire AFB, and Andrews AFB. Short-term forecast equations are developed at hourly intervals from 0-6 hours beyond the initial time for each of two predictors, ceiling less than 200 ft and visibility less than 0.5 mi.

The overall results of this research are mixed. Of the 36 predictive equations, 16 perform better statistically than conditional climatology when compared against an independent sample of data. Of the forecasts that are better, a 17.6% average improvement is made over conditional climatology. Some of the improved forecasts are the ceiling less than 200 ft criteria at both Dover AFB and McGuire AFB where all 6 hourly forecasts had positive skill scores. Also notable are the McGuire AFB visibility forecasts, which show a positive average skill score. The two most successful forecasts, for ceilings less than 200 ft at Dover AFB and McGuire AFB both show large increases in skill score, a high number of good forecasts, and few bad forecasts.

In the cases where the observations-based network is superior, the predictive equations have similar characteristics. First, is geographic influence. The early forecasts have little dependence on the geographic location of the network station selected. As the forecast lead time increases dependence on predictors from the southwest especially dominate the equations. Second, many of the successful longer term forecasts (5 or 6-hours) contain climatological parameters. A strong dependence on wind predictors, both at the surface and upper levels is evident throughout the equations.

With these similarities examined, it is noted that each of these forecasts is independently produced and validated for each station at each hour. Although there appear to be trends, switching a predictor from one model to another will not produce a more accurate forecast. Just because one predictor works at McGuire AFB does not mean it will be effective at Dover AFB.

The most disappointing conclusions of this study are the Andrews AFB forecasts, which show large negative skill scores. A majority of the forecast times for Andrews AFB fail the tests of normality and/or heteroscidacity required to meet the assumptions necessary to employ linear regression, indicating that a linear model is not the best representation of this data set. Problems contributing to this include the Andrews AFB data set being smaller than the others, especially in the verification data set where missing observations dominate. As a result, the Andrews AFB data set is unable to account for variability in surface observations (in fog cases), which prevents the production of an accurate forecast. More research, with a larger, more complete data set may correct these forecasts for operational implementation.

Despite forecast scores below conditional climatology, the negative forecasts do show some advantages. First, the number of forecasts with absolute error less than 30 percent (e.g. good forecasts) often exceeds the number of good forecasts produced by conditional climatology. Second, the MSEs in these cases are typically, with a few exceptions, low and very competitive with the climatology forecasts. Many of the errors and decreased forecasting skill from the poor forecasts in the observations-based network are similar and shown to have bias. The most common bias among the forecasts is an overestimate of event occurrence when the fog has already dissipated. In the later forecast hours of the forecast this is especially significant and results in the higher degradation of skill scores.

A final success noted is the overall application of the methodology to new "extreme" predictand values, representing the worst cases of fog. The lowest values studied before now were 500 ft ceilings and 1 mi visibility (Vislocky and Fritsch 1997). This is encouraging as this allows the method to have significant impact on operations in the most marginal weather conditions. Recommendations for implementation of this technique by the 15 OWS and possible future research to improve the shortfalls follow.

5.2 Recommendations for the 15 OWS

It is recommended that the 15 OWS implement this program for the following cases: KDOV ceiling less than 200 ft, KWRI ceiling less than 200 ft, and KWRI visibility less than 0.5 mi. For both of the ceiling forecasts, all six hourly forecasts show significant improvement over conditional climatology and are the superior forecast model. The six hourly visibility forecasts for KWRI only have three hours that are consistently better than conditional climatology; however, it has two advantages. First, the earlier hours consistently produce the better forecasts; only the first hour had a negative skill score. Second, the first hour had a distinct advantage in producing good forecasts--forecasts with an absolute error of less than 30%. Therefore, this model can be used successfully in an operational environment.

Implementation of the other three models could be used on a trial basis. Although the verification results are not optimal, the technique has some merit in these cases based on both previous work and this current research. Implementation of these methods on a trial basis could produce better results than in the confined scope of this research. Realizing the shortfalls of each particular model is crucial for successful implementation. For example, the Dover AFB visibility forecasts, which all have negative skill scores do a solid job of forecasting occurrences in the short-term, however, the oveforecasting tendency is tied to the reliance on southwesterly winds to advect the fog from the area. Analysis of the presence or absence of these conditions could lead the forecaster to an accurate dissipation forecast. Using these models on any type of basis could provide valuable information on the ability of the model to produce successful forecasts.

5.3 Recommendations for Future Research

The observations-based method is successful for many areas, including the area currently researched for the 15 OWS. This researcher believes that with some tweaking of the system, this methodology could be applied across the AF. There are factors that must be accounted for in future research to make this work operationally.

First, forecasts should be broken up temporally. Forecast increments of 2-4 hours should be looked at individually in order to focus on the exact physical mechanisms that dissipate the fog. This allows diurnal cycles to be taken into account, capitalizing on the advantages conditional climatology offers. Distinct time periods would be more representative of different observed parameters predicting dissipation.

Vislocky and Fritsch (1997) suggest inclusion of satellite imagery into the system. This is a key element to determine spatially how large the extent of the fog area is. Although the statistical method is cut and dry, the input of both the spatial extent of the fog coverage, as well as how close the airfield of interest is to the outer edges of the fog (as suggested by Gurka 1978) would add considerable predictive ability to the model.

Additionally, further research is necessary to apply this technique throughout the remainder of the 15 OWS AOR. The original intent of the research was to apply this methodology to all 11 airfields throughout the 15 OWS. With some modification to the methodology, this could be a successful application for any site within the AOR. It is envisioned that this methodology, with a significant amount of additional work, could be applied to airfields throughout the AF as an effective alternative to conditional climatology.

This study's observations-based methodology could benefit significantly from the inclusion of mesonet data in regions where available. States such as Oklahoma and Colorado currently have mesonets. This spatially denser observing platform could provide more insight, data, and information on the dissipation process and as a result produce more accurate forecasts.

Lastly, another process that could produce accurate forecast equations is the use of a logistic regression model as opposed to the linear model. The advantage of the logistic model is that it always produces a value between 0 and 1 and is able to reduce forecast error (Hilliker and Fritsch 1999). A comparison between linear and logistical regressions could demonstrate the advantages of the logistical regression and further improve forecasts.

Appendix: Surface Observing Networks

This appendix outlines the 40 surface observing stations used to produce the dissipation forecasts for the three airfields. The 10, 19, 25, 30, 35, and 40 station networks used to produce the 1-6 hour forecasts are listed.

Dover AFB

TABLE A1. Surface Network Observing Stations for Dover AFB.

Observing Station	ICAO	LAT	LON	Elevation (m)
	10 Station Network			
Dover AFB (DE)	KDOV	39 08	75 28	9
Georgetown Suffox County (DE)	KGED	38 41 24	75 21 45	15
Wilmington (DE)	KILG	39 40 22	75 36 03	24
Wildwood (NJ)	KWWD	39 01	74 55	7
Millville (NJ)	KMIV	39 21 58	75 04 42	26
Philadelphia (PA)	KPHL	39 52 06	75 14 37	6
Philadelphia NE Airport (PA)	KPNE	40 04 44	75 00 49	36
Salsbury (MD)	KSBY	38 20 21	75 30 15	15
Atlantic City (NJ)	KACY	39 27 53	074 35 12	23
Baltimore, Washington International (MD)	KBWI	39 10 00	076 41 00	44
	19 Station Network			
Baltimore, Martin (MD)	KMTN	39 20	076 25	7
Mount Holley (NJ)	KVAY	39 56 26	074 50 28	16
Patuxent River NAS (MD)	KNHK	38 16 43	076 24 50	12
Andrews AFB (MD)	KADW	38 49	076 51	86
Wallops Island (VA)	KWAL	37 56 26	075 27 47	12
McGuire AFB (NJ)	KWRI	40 01	074 36	41
Trenton, Mercer County Airport (NJ)	KTTN	40 16 35	074 48 59	64
Reading Regional Airport (PA)	KRDG	40 22 24	075 57 34	105
Lancaster Airport (PA)	KLNS	40 07 13	076 17 40	123
	25 Station Network			
Allentown (PA)	KABE	40 39 03	075 26 57	120
Fort Belvoir (VA)	KDAA	38 43	077 11	21
Washington, Reagan National (VA)	KDCA	38 50 54	077 02 03	4
Harrisburg, Capitol City Airport (PA)	KCXY	40 13 13	076 51 14	105
Harrisburg International Airport (PA)	KMDT	40 11 46	076 46 23	94
York Airport (PA)	KTHV	39 55 22	076 52 41	146
	30 Station Network			
Belmar-Farmsdale (NJ)	KBLM	40 11	074 08	48
Melfa/Accomack Airport (VA)	KMFV	37 39	075 46	15
Quantico, MCAF (VA)	KNYG	38 30 45	077 17 30	3
Washington-Dullus (VA)	KIAD	38 56 05	077 26 51	95
Shannon Airport (VA)	KEZF	38 16	077 27	26
	35 Station Network			
Culpeper County Airport (VA)	KCJR	38 31 36	077 51 32	95
Newerk International Airport (NJ)	KEWR	40 40 57	074 10 10	5
Caldwell, Exxex County Airport (NJ)	KCDW	40 52 35	074 16 59	52
Charlottesville-Abermarle Airport (VA)	KCHO	30 08 18	078 27 21	195
Richmond International Airport (VA)	KRIC	37 30 40	077 19 24	51
	40 Station Network			
Farmingdale Republic Airport (NY)	KFRG	40 44 03	073 25 01	24
New York City, JFK (NY)	KJFK	40 38 19	073 45 44	3
Langly AFB (VA)	KLFI	37 05	076 21	6
New York, LaGuardia (NY)	KLGA	40 46 45	073 52 48	6
Petersburg (VA)	KPTB	37 11	077 31	59

McGuire AFB

TABLE A2. Surface Network Observing Stations for McGuire AFB.

Observing Station	ICAO	LAT	LON	Elevation (m)
	10 Station Network			
McGuire AFB (NJ)	KWRI	40 01	074 36	41
Mount Holley (NJ)	KVAY	39 56 26	074 50 28	16
Belmar-Farmsdale (NJ)	KBLM	40 11	074 08	48
Trenton, Mercer County Airport (NJ)	KTTN	40 16 35	074 48 59	64
Philadelphia International Airport (PA)	KPHL	39 52 06	075 13 52	6
Philadelphia, NE Philadelphia Airport (PA)	KPNE	40 04 44	075 00 49	36
Atlantic City (NJ)	KACY	39 27 53	074 35 12	23
Millville Municipal Airport (NJ)	KMIV	39 21 58	075 04 42	26
Wilmington (DE)	KILG	39 40 22	075 36 03	24
Allentown (PA)	KABE	40 39 03	075 26 57	120
	19 Station Network			
Newerk International Airport (NJ)	KEWR	40 40 57	074 10 10	5
Caldwell, Exxex County Airport (NJ)	KCDW	40 52 35	074 16 59	52
New York City, JFK (NY)	KJFK	40 38 19	073 45 44	3
New York, LaGuardia (NY)	KLGA	40 46 45	073 52 48	6
Wildwood ASOS (NJ)	KWWD	39 01	074 55	2
Teterboro Airport (NJ)	KTEB	40 51 32	074 03 24	2
Islip, Long Island (NY)	KISP	40 47 38	073 06 06	30
Farmingdale Republic Airport (NY)	KFRG	40 44 03	073 25 01	24
Dover AFB (DE)	KDOV	39 08	075 28	9
	25 Station Network			
Reading Regional Airport (PA)	KRDG	40 22 24	075 57 34	105
Lancaster Airport (PA)	KLNS	40 07 13	076 17 40	123
Georgetown, Suxxex County Airport (DE)	KGED	38 41 24	075 21 45	15
Montgomery, Orange County Airport (NY)	KMGJ	41 30 33	074 15 54	111
Newburgh/Stewart (NY)	KSWF	41 30	074 06	150
Wilkes-Barre-Scranton International (PA)	KAVP	41 20 20	075 43 36	293
	30 Station Network			
Bridgeport (CT)	KBDR	41 09 30	073 07 44	3
Danbury Municipal Airport (CT)	KDXR	41 22 18	073 29 04	139
Westhampton Beach (NY)	KFOK	40 51 03	072 37 14	20
Baltimore, Martin (MD)	KMTN	39 20	076 25	7
Baltimore, Washington International (MD)	KBWI	39 10 00	076 41 00	44
	35 Station Network			
Monticello (NY)	KMSV	41 42	074 48	428
Poughkeepsie (NY)	KPOU	41 37 32	073 52 55	50
Salsbury (MD)	KSBY	38 20 21	75 30 15	15
Andrews AFB (MD)	KADW	38 49	076 51	86
Washington, Reagan National (VA)	KDCA	38 50 54	077 02 03	4
	40 Station Network			
Fort Belvoir (VA)	KDAA	38 43	077 11	21
Washington-Dullus (VA)	KIAD	38 56 05	077 26 51	95
Harrisburg, Capitol City Airport (PA)	KCXY	40 13 13	076 51 14	105
Harrisburg International Airport (PA)	KMDT	40 11 46	076 46 23	94
York Airport (PA)	KTHV	39 55 22	076 52 41	146

Andrews AFB

TABLE A3. Surface Network Observing Stations for Andrews AFB.

Observing Station	ICAO	LAT	LON	Elevation (m)
	10 Station Network			
Andrews AFB (MD)	KADW	38 49	076 51	86
Washington, Reagan National (VA)	KDCA	38 50 54	077 02 03	4
Fort Belvoir (VA)	KDAA	38 43	077 11	21
Manassas Municipal (VA)	KHEF	38 43	077 31	59
Quantico MCAF (VA)	KNYG	38 30 45	077 17 30	3
Washington-Dullus (VA)	KIAD	38 56 05	077 26 51	95
Baltimore, Washington International (MD)	KBWI	39 10 00	076 41 00	44
Baltimore, Martin (MD)	KMTN	39 20	076 25	7
Shannon Airport (VA)	KEZF	38 16	077 27	26
Hagerstown (MD)	KHGR	39 42 21	077 43 48	214
	19 Station Network			
Culpeper County Airport (VA)	KCJR	38 31 36	077 51 32	95
Winchester Regional (VA)	KOKV	39 09	078 09	222
Martinsburg (WV)	KMRB	39 24 14	077 58 30	169
York Airport (PA)	KTHV	39 55 22	076 52 41	146
Patuxent River NAS (MD)	KNHK	38 16 43	076 24 50	12
Richmond International Airport (VA)	KRIC	37 30 40	077 19 24	51
Dover AFB (DE)	KDOV	39 08	75 28	9
Lancaster Airport (PA)	KLNS	40 07 13	076 17 40	123
Harrisburg, Capitol City Airport (PA)	KCXY	40 13 13	076 51 14	105
	25 Station Network			
Harrisburg International Airport (PA)	KMDT	40 11 46	076 46 23	94
Georgetown Suffox County (DE)	KGED	38 41 24	75 21 45	15
Wilmington (DE)	KILG	39 40 22	75 36 03	24
Salsbury (MD)	KSBY	38 20 21	75 30 15	15
Wallops Island (VA)	KWAL	37 56 26	075 27 47	12
Melfa/Accomack Airport (VA)	KMFV	37 39	075 46	15
	30 Station Network			
Petersburg (VA)	KPTB	37 11	077 31	59
Charlottesville-Abermarle Airport (VA)	KCHO	30 08 18	078 27 21	195
Reading Regional Airport (PA)	KRDG	40 22 24	075 57 34	105
Philadelphia International Airport (PA)	KPHL	39 52 06	075 13 52	6
Philadelphia NE Airport (PA)	KPNE	40 04 44	75 00 49	36
	35 Station Network			
Wildwood ASOS (NJ)	KWWD	39 01	074 55	2
Millville Municipal Airport (NJ)	KMIV	39 21 58	075 04 42	26
Langly AFB (VA)	KLFI	37 05	076 21	6
Staunton/Shenandoah (VA)	KSHD	38 16	078 54	366
Atlantic City (NJ)	KACY	39 27 53	74 34 02	23
	40 Station Network			
Trenton, Mercer County Airport (NJ)	KTTN	40 16 35	074 48 59	64
Newerk International Airport (NJ)	KEWR	40 40 57	074 10 10	5
Belmar-Farmsdale (NJ)	KBLM	40 11	074 08	48
Allentown (PA)	KABE	40 39 03	075 26 57	120
McGuire AFB (NJ)	KWRI	40 01	074 36	41

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14. ABSTRACT

A statistically-based forecasting tool is developed for Dover AFB, McGuire AFB, and Andrews AFB for dissipation times of fog and low stratus. Probability forecasts are produced at hourly increments from 0-6 hours for the most extreme reductions in visibility (less than 0.5 mi) and ceilings (below 200 ft). Forecasts are based on surface observations, upper air observations, and climatological parameters. Ceiling forecasts at Dover AFB and McGuire AFB show improvements over conditional climatology ranging from 1-51% with an average improvement of 19.2% when verified against an independent data set. McGuire AFB visibility forecasts show an average improvement over conditional climatology of 3%. These findings are of particular importance to the Air Force in general and specifically to the 15th Operational Weather Squadron (15 OWS) who produces forecasts for these airfields. Demonstrating a method superior to conditional climatology is expected to provide improved forecasts and flight operations in this region. The two forecasts for Andrews AFB show relatively low mean square errors, but are unable to consistently improve on conditional climatology, demonstrating an average decrease in forecasting skill of 42%. Small samples of data could be the reason for the decrease in skill. The Dover visibility forecast also shows negative forecast skill, with an average decrease of 39%. The method is a success in producing forecasts for ceiling and visibility criteria that had never previously been examined. Further research into the forecasts could produce a powerful tool consistently able to defeat conditional climatology. It is suggested that the 15 OWS incorporate this methodology into their operational forecasting routine

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