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SHORT-TERM FORECASTING OF CLOUD CEILING CATEGORIES AT KENNEDY SPACE CENTER FOR THE SPACE SHUTTLE PROGRAM

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1. INTRODUCTION

The forecast cloud ceiling over the Shuttle Landing Facility (SLF) at Kennedy Space Center (KSC) is a critical element in determining whether a GO or NO GO should be issued for a Space Shuttle landing. However, the Spaceflight Meteorology Group (SMG) forecasters at Johnson Space Center (JSC) in Houston, TX indicate that the ceiling at the SLF is challenging to forecast, even in the short-term (0-6 hours) when persistence is assumed to be a reliable predictor. The Applied Meteorology Unit (AMU) was tasked to develop a statistical cloud ceiling forecast technique to aid forecasters in this critical area.

Two recent studies, Vislocky and Fritsch (1997, hereafter VF) and Hilliker and Fritsch (1999, hereafter HF) have shown success using statistical methods to improve the short-term ceiling forecast of the standard Federal Aviation Administration (FAA) Flight Rules (FR). In these studies, equations were developed that used conventional surface and upper-air rawinsonde data from the forecast site as well as surrounding stations. Their observations-based equations consistently out-performed the benchmark persistence climatology equations. These studies provided the basis for the AMU task methodology.

The AMU task differed from VF and HF in two ways. First, the previous studies used data from areas where persistent ceilings were known to exist. Such conditions are not the norm in the subtropical environment of east-central Florida. Second, the studies used standard FAA FR cloud ceiling categories as predictands. The predictands in the AMU task were the ceiling thresholds as defined by the Space Shuttle FR (NASA/JSC 1997):

- < 5000 ft (Return to Launch Site)
- < 8000 ft (End of Mission)
- < 10 000 ft (Navigation Aid Degradation)

This paper will present the data and methods used in the equation development, a discussion on the predictors chosen and their importance in the equations, the results of equation performance testing, and a description of possible improvements to the methods used.

2. DATA

Hourly surface observational, rawinsonde, and buoy data were collected and examined for potential use in the equation development. The stations considered are shown in Figure 1. The data from each station were examined to determine period of record (POR), the amount of missing data, and the quality of the data. Those stations with inadequate PORs or an insufficient amount of quality data were eliminated from consideration.

The stations whose data were used in the equation development are surrounded by squares in Figure 1. They include the Daytona Beach (DAB), Orlando (MCO), Patrick Air Force Base (COF), Melbourne (MLB), and SLF (TTS) hourly surface observations over a 20-year POR (1978 – 1997).

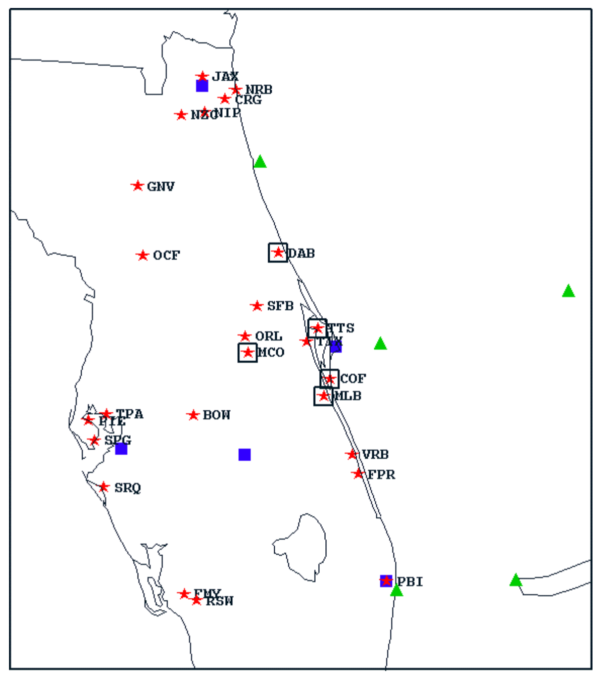

Figure 1. Map of stations whose data were considered for the equation development. The stars are hourly surface observations, the squares are rawinsondes, and the triangles are buoys. The stations surrounded by squares were used in the equation development.

Quality control routines were developed to remove gross outliers in the data, and then the data were analyzed to determine ceiling climatologies, temporal trends, and relationships between data types. This analysis revealed that the largest number of ceilings at the SLF occurs in the cool season months of October through March, with a maximum at and just after sunrise in December and January. On the other hand, very few ceilings were reported during the warm seasons (April – September). As a result, the data were stratified by these two seasons. Only the cool season data set was used to develop the equations.

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The data were further stratified into dependent and independent data sets. Equation development was done with the dependent data, and equation verification wasdone with the independent data. The dependent data set had to be sufficiently large in order to develop stable equations (WMO 1992). There were 19 cool seasons in the POR and 16 were chosen randomly for the dependent data, leaving 3 cool seasons for the independent data set. The equations were tested using the independent data to ensure that they were not strongly fitted to only the dependent data with which they were developed.

3. EQUATION DEVELOPMENT

Two types of equation sets were developed to forecast the probability of occurrence of the Shuttle FR ceiling height thresholds at TTS: observations-based (OBS) equations that incorporate data from TTS and all surrounding stations, and persistence climatology (PCL) equations to be used as the benchmark against which the OBS equations would be tested. The binary observations (0 or 1) of the Shuttle FR ceiling height thresholds at TTS were the predictands, or weather element to be predicted, for both equation types. Least squares multiple linear regression (MLR) was used as the statistical model for all the equations. MLR equations have the form

$$P = C_o + C_1x_1 + C_2x_2 + \ldots C_nx_n,$$

where P is the forecast probability, C_n represents the coefficient values and x_n represents the predictor values Equations were developed using the cool season data for each of the three ceiling thresholds at 1-, 2-, and 3-hour lead times, and for each hour of the day. This procedure resulted in 216 equations for each equation type (3 lead times * 3 ceiling categories * 24 hours).

3.1. Observations-based Equation Development

The OBS equation development began with predictor selection from a list of potential predictors as shown in Table 1. The choice of these predictors were based on those used in VF and HF combined with results from preliminary testing to determine which variables could be useful in cloud ceiling forecasting. Most of the predictors were binary values of several cloud parameters.

The predictors were chosen using a forward stepwise regression utility in S-PLUS® (Insightful, Corp. 1999). The cutoff at which no additional predictors were selected was controlled by the change in the explained variance (R^2) as each predictor was added to the equation. If the predictor did not change R^2 by more than 0.05% (Wilks 1995), the predictor was not added to the equation and the forward stepwise procedure was stopped.

This procedure yielded an average of four to five predictors per equation, ranging from one to nine predictors. In 212 of the 216 OBS equations, the predictor that explained the most variance was the observation of the predictand at the initial time. In other words, the TTS ceiling height threshold observation was the most important predictor in forecasting the ceiling height threshold for every lead time. This result is consistent with the findings in VF and HF.

Table 1. List of potential predictors used for the OBS equation development. The predictor value is 1 if the observation satisfies the binary threshold otherwise it is 0. "Continuous" means that the actual value of the variable was used.

Variable	***Binary Threshold***
Ceiling Height	< 10 000, < 8000, or < 5000 ft
Total Cloud cover	> 1/10, > 5/10, or > 9/10
Wind Direction	N (315-45°), E (45-135°), S (135-225°), W (225-315°)
Precipitation	Yes
1st Cloud Deck	< 10 000, < 8000, or < 5000 ft
2nd Cloud Deck	< 10 000, < 8000, or < 5000 ft
3rd Cloud Deck	< 10 000, < 8000, or < 5000 ft
4th Cloud Deck	< 10 000, < 8000, or < 5000 ft
Wind Speed	Continuous
Temperature	Continuous
Dew Point Temp	Continuous
Dew Point Dep	Continuous

Other predictors chosen include the ceiling height category observations, cloud cover, and cloud deck observations from TTS and the other stations. Wind direction, precipitation, and the continuous variables were rarely, if ever, chosen as an important predictor of cloud ceiling at TTS.

Once the predictors were chosen, the MLR equations were developed using an S-PLUS® function. This function determined the constant (C_o) intercept value and the coefficient (C_n) values for the predictors.

3.2. Persistence Climatology Equation Development

The PCL equations were developed to provide a benchmark against which to test the OBS equations. According to VF, PCL is a formidable benchmark for very short-range prediction of cloud ceiling.

The PCL equations have only two predictors: 1) the observation of the predictand at the initial time, and 2) the climatology of the predictand at the forecast valid time. The second term is a simple mean calculation of the number of ceiling events of each threshold for each hour of every day of the cool season. Because the predictors were known a priori, a forward stepwise procedure, as used in the OBS equation development, was not needed. The same S-PLUS® function developed to create the OBS equations was used to calculate the constant (C_o) intercept value and the coefficient (C_1 and C_2) values for the predictors.

4. RESULTS

After the OBS and PCL equations were developed, they were used to make forecasts from all records in the independent data set. The OBS forecasts were then tested against the PCL forecast for each hour of the day, lead time, and ceiling height threshold to determine if the OBS equations produced improved forecasts over those of the PCL equations.

4.1 Quantitative Performance

The mean square error (MSE) between the forecasts and observations were calculated using the equation

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(f_i - o_i\right)^2 ,$$

where n is the number of forecasts, f_i is the OBS or PCL probability forecast and o_i is the binary (0 or 1) observation of the ceiling height category at TTS. The MSE values were then used in the following equation to determine whether the OBS equations produced a quantifiable improvement over the PCL equations:

$$\text{PI} = \left[\left(E_{OBS} - E_{PCL} \right) / \left(E_0 - E_{PCL} \right) \right] \times 100,$$

where PI is the percent improvement, E_{OBS} is the OBS equation MSE, E_{PCL} is the PCL equation MSE and E_0 is the MSE for a perfect forecast, which is zero in this case. If PI is positive, the OBS equations produced an improvement over the PCL equations, and if PI is negative the OBS equations worsen the forecast.

In order to test the performance of the OBS equations, the probability of detection (POD) and false alarm rate (FAR) were calculated for each equation. The POD and FAR were computed using the values from a standard contingency table, as shown below (Wilks 1995). The observations were binary, 1 for Yes and 0 for No. However, the forecasts were probability values between 0 and 1, inclusive, so values ≥ 0.5 were considered Yes forecasts and those < 0.5 were No forecasts.

		Observed	
		Yes	No
Forecast	Yes	a	b
	No	c	d

$$\text{POD} = \frac{a}{a+c}$$

$$\text{FAR} = \frac{b}{a+b}$$

The PI, POD, and FAR values for all 24 (each hour of the day) equations in each lead time/ceiling category were averaged and shown in Table 2. All of the PI values are positive, indicating that the OBS equations produce an improvement over the PCL equations. The smallest improvements were found for the 1-hour forecasts where it is assumed that persistence climatology is a strong performer. Larger improvements were produced with the 2- and 3-hour forecasts, time periods over which persistence is likely to be less of a factor. In general, PI also decreases as ceiling height decreases.

The actual performance of the OBS equations is indicated by the POD and FAR values. The POD values decrease rapidly with lead time and the FAR values increase rapidly in each ceiling category. This may indicate that the observation at TTS is becoming less valid as a predictor for increasing lead time, as well as the observations at the other stations. The values also degrade with decreasing ceiling height. This may be a result of fewer cases of the lower ceiling categories available for the equation development. The 0.5 threshold may also be an inappropriate value in determining a Yes/No forecast, although not tests were done to determine what value should be used. The appropriate value would depend on whether the user wished to maximize POD or minimize FAR.

Table 2. Average values of I, POD, and FAR for the OBS forecasts using the independent data. Each average was calculated from the 24 values generated by each hourly equation.

Lead Time by Ceiling Height	***PI***	***POD***	***FAR***
10 000 ft			
1-Hour	11.9	0.83	0.16
2-Hour	15.2	0.73	0.21
3-Hour	14.9	0.67	0.25
8000 ft			
1-Hour	10.0	0.83	0.17
2-Hour	13.5	0.70	0.23
3-Hour	13.6	0.63	0.27
5000 ft			
1-Hour	8.8	0.80	0.18
2-Hour	11.9	0.65	0.24
3-Hour	13.4	0.54	0.27

4.2 Hypothesis Testing

A hypothesis test was used to determine whether the OBS equation improvement, PI, was statistically significant. The null hypothesis was that the mean of the differences between the OBS and PCL equation MSE values is zero. This implies that the two equation types produced forecasts of equal value. If the improvement of the OBS equations over the PCL equations was significant, the null hypothesis could be rejected.

Several charts of MSE differences (not shown) showed non-Gaussian distributions, therefore the non-parametric Wilcoxon Signed Rank test (Wilks 1995) was chosen to determine statistical significance. For every lead time and ceiling category, the improvement in skill created by the OBS equations was significant at the 99% confidence level. Therefore, the null hypothesis can be rejected and the OBS equations can be used knowing that they produce a more accurate forecast than the PCL equations.

5. RECOMMENDATIONS

Based on successful results found in the literature, the AMU developed observations-based short-range ceiling forecast equations that outperform persistence climatology. However, the success achieved as described in the previous section must be tempered with other findings during the development. The predictors in the OBS equations were only able to account for 55-60% of the variance in the data for the 1-hour equations to 35-40% for the 3-hour equations. The VF equations were able to explain 85-90% of the variance with their predictors. There are several possible explanations for the “missing variance”.

One possible deficiency is that only hourly surface observations were used to develop the equations. Rawinsonde data were shown to improve the forecast in HF, but only by 0-3% and only in the hours immediately after the data were collected. Other data, such as Geostationary Operational Environmental Satellite (GOES) images or soundings, radar, or input from data assimilation software may be needed to fill the gap.

Another issue is that the data were grouped into a cool season data set, stratified only by time of day. This means that the equation used to make a 1-hour forecast of ceilings < 8000 ft at 1500 UTC will be applied every day from the beginning of October to the end of March. This stratification was necessary to ensure that the number of ceiling events was large enough to develop robust equations valid for each hour of the day. In the period from October to March, several meteorological phenomena could be responsible for the development of ceilings in east-central Florida. A phenomenological stratification of the data would be time-consuming, but may be useful in developing more accurate forecast equations.

Nonetheless, the OBS equations developed in this study are still useful in that they are an improvement over persistence climatology. They provide the forecasters at SMG another tool with which to make the ceiling forecasts critical to safe Shuttle landings at KSC. Combined with other observational and model data, as well as forecaster experience, these equations will likely help to improve the ceiling forecasts at the SLF.

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