7.2

GRIDDED CLOUD LAYER GUIDANCE TO SUPPORT THE TAF

Bob Glahn*
Meteorological Development Laboratory
Office of Science and Technology Integration
National Weather Service, NOAA
Silver Spring, Maryland
and
Adam D. Schnapp
KBRwyle Science Technology & Engineering Group
Silver Spring, Maryland

1. INTRODUCTION

Station based and gridded MOS (Dallavalle et al. 2004; Glahn et al. 2009) and LAMP (Ghirardelli and Glahn 2010) guidance has been provided for many years to assist in the preparation of forecasts by the National Weather Service (NWS) forecasters and for use by private companies and the academic community. However, less emphasis has been placed on the production of guidance for aviation forecasts than for public and related forecasts. In particular, the TAF (Terminal Aerodrome Forecast) includes information about cloud amounts and heights, but the cloud guidance provided by MOS and LAMP is only ceiling height and total opaque sky cover. There is no guidance on whether the ceiling is obscured, broken, or overcast or other possible cloud layers. In addition, the LAMP forecasts for ceiling, visibility, sky cover, and wind go out to only 25 h, while international TAFs contain forecasts out to 36 h.

The current LAMP ceiling height product, the LAMP/HRRR Meld, is a combination of basic LAMP probability forecasts of ceiling height, HRRR (High Resolution Rapid Refresh; Benjamin et al. 2016) forecasts of ceiling height, and observations (persistence) (Glahn et al. 2017). MOS probability forecasts of each of eight **discrete** categories of ceiling are produced by regression equations; the categories are shown in Table 1.[1] Forecasts of cumulative categories are made from the discrete forecasts, and feed directly into LAMP.

LAMP probability forecasts of each of seven **cumulative** categories of ceiling height are produced by regression equations; the categories are also shown in Table 1. The approach of using categories was taken because of the highly non-normal distribution of ceiling and the importance of the very infrequent low values. Using ceiling as a continuous variable, even a transformed one to stretch the low values with respect to the high values, has not proved productive (Bocchieri and Glahn 1972 and extensive unpublished work by David Unger and Glahn circa 1980).

This paper demonstrates that the LAMP/HRRR ceiling guidance can be extended to 38 h and explores the specification of ceiling as either obscured, overcast, or broken. The forecasting of few or scattered layers is left for another study.

Table 1. Category definitions of basic LAMP and MOS ceiling height. Ceilings are observed (reported) in hundreds (hd) of feet (ft).

Category Number	Ceiling height (hd of ft)	
	Discrete	Cumulative
1	<2	< 2
2	2-4	< 5
3	5-9	< 10
4	10-19	< 20
5	20-30	≤ 30
6	31-65	≤ 65
7	66-120	≤ 120
8	>120	

2. THE CEILING HEIGHT PREDICTAND

The original LAMP forecasts were designed to be disseminated via text messages, and the breakdown in Table 1 seemed sufficient. Later, the forecasts were gridded, and both the categorical and probability values were used in the BCDG analysis process (see Glahn and Im 2015). Now, the primary purpose is to produce a gridded product, so more definition is desirable. Table 2 shows the 24 categories used for development and when that category is forecast, the value that is put onto the grid. For some categories, the value put on the grid is the only reportable value (e.g., <400 ft); for others it represents a range of values (e.g., < 4,000 ft).

3. DATA SAMPLE

The data sample was largely determined by the availability of recent HRRR data produced in a reasonably consistent framework. We chose the cool season period October through March, 2015-2016 and 2016-2017. The 4 months used for test data were October 2015, February and December 2016, and March 2017, the other 8 months being used for development. In order to produce a forecast in a timely manner, and on a schedule commensurate with the basic LAMP, we use the HRRR from the previous run cycle. We used for these tests the 0100 UTC cycle, so that the HRRR is

*Corresponding author address: Bob Glahn, Meteorological Development Laboratory, 1325 East West Highway, Silver spring, MD 20910; email: harry.glahn@noaa.gov.

[1] This process has changed little since Bocchieri and Glahn (1972) first applied MOS to ceiling height prediction.

from the 0000 UTC cycle. For the sample period, HRRR was running to 36 h four times per day, including at 0000 UTC.

Table 2. The 24 Meld ceiling height categories. The definitions in bold indicate the LAMP categories. The definitions of IFR (Instrument Flight Rules), VLIFR (Very Low IFR), LIFR (Low IFR), and MVFR (Marginal Visual Flight Rules) are also shown.

Category Number	Category Definition (ft)	Value on Grid (hds ft)
1	< 100	0
2	**< 200 (VLIFR)**	1
3	< 300	2
4	<400	3
5	**< 500 (LIFR)**	4
6	< 600	5
7	< 700	6
8	< 800	7
9	< 900	8
10	**<1,000 (IFR)**	9
11	< 1,200	11
12	<1,500	13
13	< 1,700	15
14	**< 2,000**	18
15	< 2,500	22
16	**≤ 3,000 (MVFR)**	27
17	≤ 4,000	35
18	≤ 5,000	45
19	**≤ 6,500**	58
20	≤8.000	73
21	≤9,000	85
22	≤10,000	95
23	≤ 11,000	110
24	**≤ 12,000**	120

The development points were 1552 locations where we had "ground truth," the METAR (OFCM 1995) observation points. All data were available at, or interpolated to, these points.

4. PREDICTORS AVAILABLE

MOS forecasts are those produced by the Meteorological Development Laboratory (MDL) based primarily on the Global Forecast System (GFS) run at NCEP (National Centers for Environmental Prediction). REEP regression equations (Miller 1958) were developed for each of the discrete categories in Table 1. The MOS probabilities were converted to cumulative for input to LAMP. The MOS forecasts used in this study were produced by the operational equations in use for the sample.

Basic LAMP forecasts are produced by MDL based on MOS ceiling probability forecasts (above), observations (persistence), and the output of simple advective models. REEP regression equations were developed for each of the cumulative categories in Table 1 and put into operations several years ago. (Equations are currently in the process of being redeveloped and will be implemented this year.)

The HRRR model produces forecasts of ceiling height, which have been used previously in the production of the LAMP/HRRR Meld (Glahn et al. 2017). The HRRR output also includes the relative humidity at specific heights above the surface; these values did not appear to be useful for cloud layer prediction over and above the HRRR ceiling height. Also, a variable called the "cloud base height" was available.

The METAR observations were used to compute ceiling heights (which are not directly reported), and these were used for both the ceiling predictand and as predictors in binary form. METARs were also used to provide predictors and predictands of total obscuration, overcast, and lowest broken layer.

5. EXTENSION OF THE LAMP/HRRR MELD OUT TO PAST 36 HOURS

The LAMP/HRRR Meld described by Glahn et al. (2017) furnishes forecasts out only to 25 h, the extent of the basic LAMP forecasts. For this extension, we persisted the 25-h LAMP forecast to 30 h; this means we used the 25-h forecast as input to all projections 25 to 30 h. MOS is available, by interpolation from 3-hourlly values, out past 36-h. HRRR was available to 36 h (actually, 35 h because of our using the previous cycle). For the first 17 h, we used a 3-lag HRRR ensemble; we produced a MOS equation based only on HRRR predictors for each of 12 categories of ceiling, and forecasts from these equations were probabilistic predictors for the Meld. For the projections 18-38 h, we used only the most recent run of the HRRR. Because of the lag, HRRR forecasts end at 35 h, so we persisted the 35-h forecast to 38 h. For the Meld, we pool the data for all stations to get a "generalized operator" equation for each ceiling height category and each projection that can be used for all stations or all gridpoints.[2]

Table 3 indicates the regression runs were broken into three groups. The first group was for the projections we first developed 3-lag HRRR probability equations. The second group picked up at 17 h and went out a few hours past where LAMP was available. The regression program, written especially for LAMP (see Glahn and Wiedenfeld 2006 for details), puts the same predictors (with matching projections except for the observations) into all the equations for the projections in the run; this is to foster temporal continuity in the forecasts. Most basic LAMP runs are for all 25 projections

[2] Some pooling of data is necessary, because there are not enough instances of the low ceiling categories to develop stable regression equations for each station. An earlier test showed that slightly better results could be achieved by using four "regions" for development—the Pacific coast, the intermountain west, the central states, and the Atlantic region, but for this work, we used only one region (generalized operator).

together. As the importance of a predictor, such as an observation, decreases with projection, the coefficient for that predictor becomes small and may go to zero. On the other hand, it may not be desirable to use the same predictors for all projections, and breaking the development into parts lets the best predictors for groups of projections be chosen. The tradeoff to that is that there may be a hiatus of sorts at the projection interface of the individual runs. International TAFs contain forecasts out to 36 h; the Meld is extended here a couple of hours after that to allow for production and dissemination time and perhaps a missing cycle so that the last cycle's forecast could be used and still cover the entire 36-h TAF period.

Table 3. The predictors available for selection by the screening regression program, the types, and those selected.

Projections	Source	Type of Predictor	Number of Predictors	Number Selected	
				By Source	By Projection
1-16 h	LAMP	Cumulative Probs	7	7	22
	MOS	Cumulative Probs	7	3	
	HRRR	3-lag Cumulative Probs	14	4	
	OBS	Cumulative Binaries	16	8	
17-30 h	LAMP	Cumulative Probs (25 h used to 30h)	7	5	19
	MOS	Cumulative Probs	7	5	
	HRRR	Cumulative Binary	12	7	
	OBS	Cumulative Binaries	16	2	
31-38 h	LAMP	None	-	-	10
	MOS	Cumulative Probs	7	4	
	HRRR	Cumulative Binary (35 h used to 38 h)	12	4	
	OBS	Cumulative Binaries	16	2	

As shown in Table 3, the number of predictors chosen dropped for the longer projections. The observations (obs) were very important initially, and then faded out. MOS was important for all projections. The HRRR was also important for all projections, being most important at the mid-projection range. LAMP contributed heavily when available. For all three projection groups, the reductions of variance (RV) for the first predictand category (the one with the lowest heights) were anonymously high, indicating overfitting because of the low number of cases.

The regression equations produce probability forecasts of each of the 24 cumulative categories, and there is a category 25 which is 1.- the probability of category 24. This category includes both clouds above 12,000 ft and no clouds. While forecasts are useful in probabilistic form, most users want a categorical value. We devise thresholds for each of the 24 categories such that if the forecast is $\geq$ the threshold, that category will be forecast, starting from the bottom and working up. We devise the thresholds in an iterative fashion and require the bias be within a prescribed range, and within that range, the threat score (TS; Palmer and Allen 1949; Wilks 2011)[3] for that category is maximized. This makes it possible to form categorical forecasts from the probability forecasts. The bias range is normally approximately 1.0 to 1.1. For the first category, for which the regression equation showed signs of instability, we used a bias range of 0.0 to 0.25; this allowed us to use the equations, but make a categorical forecast only for the relatively "sure" cases. These categorical forecasts are what we verified.

[3] The TS is the same as the critical success index (CSI) introduced by Donaldson et al. (1975) and discussed by Shaffer (1990).

Figs. 1 and 2 show the TS for < 1,000 ft on the dependent and independent data, respectively. The scores follow the same pattern as was shown in Glahn et al. (2017) out to 25 h. These graphs show the skill out past 25 h, the maximum extent of LAMP, to 38 h. The scores drop off more past about 25 h on dependent data than on independent data. The "bump" at 24 h for the independent data shows up in most scores. This is an artifact of sample size, which dropped from about 77,000 at 23 h to 33,000 at 24 h. Evidently, the HRRR did not run past 24 h for much of the sample.

The TS focuses on one category; the one shown here is for IFR. That is, if the ceiling is < 1,000 ft, it is IFR, an important definition for the aviation industry. However, other categories are also important, and a good overall score is the Gerrity formulation of the matrix weights for the Gandin-Murphy family of proper scores (Gerrity 1992). This score considers all categories, gives more weight for a hit of the rarer categories than for the more frequent categories, and gives some credit for near misses. Fig. 3 shows the Gerrity scores computed on the 7 categories for which LAMP and MOS forecasts are available (see Table 1 for the category definitions).

Figs. 1 through 3 show that LAMP and the Meld rival persistence at 1 h, but persistence drops rapidly after that. For both TS and Gerrity scores, the Meld is clearly better than the rest. LAMP and HRRR are rivals, except for projections < 5 h, where LAMP scored better.

The process for making a ceiling height grid for LAMP is to apply the regression equations at stations, then to analyze those values onto a grid commensurate with the NDFD (Glahn and Ruth 2003) grid. The Meld grid is produced differently. The generalized equations, developed at stations, are evaluated at each gridpoint, making the analysis of the forecasts unnecessary. However, in so doing, the predictors have to be on the grid. This means the initial observations, used as persistence, have to be gridded, as well as each category of MOS and LAMP probability used in the equations. Overall, fewer analyses have to be done with the Meld process, but the main reason for making the forecasts directly on the grid is to allow the fine-scale detail of the HRRR to be maintained. Figure 4 shows the 8-h ceiling height forecast from March 5, 2017, 0100 UTC.

6. FORECASTING TOTAL OBSCURATION, BROKEN, AND OVERCAST AS COMPONENTS OF CEILING

The definition of ceiling height is the height of either a total obscuration, the lowest layer of broken clouds, or overcast clouds. The METAR observations were used to define each of these components of ceiling, which became the predictands, and the initial values were also used as predictors. Overcast and broken cumulative binary predictands were the 24 shown in Table 2. Obscuration was limited to the lowest 13 of those categories. Partly because of the LAMP and HRRR availability and partly due to computer limitations, the 38 projections were divided into 6 segments; the projections in each are indicated in Table 3. The number or predictors selected was limited to 24. A minimum RV of 0.5% was required for another predictor to be selected, and there were also predictor collinearity constraints on selection. The < 1,000 ft category for each of the obscured, broken, and overcast groups was forced for the 1-7 h projection interval because of the operational importance of that category. LAMP was not available past 25 h, but was persisted to 28 h. The 3-lag HRRR was computed only to 17 h but was persisted to 21 h, then the last HRRR run was used out to 35 h.

As expected, the initial obs were heavily used in the early projections, faded quickly, but lingered. LAMP was heavily used for all projections it was available. MOS was used for all projection intervals except the first. HRRR played an important role. The broken predictors were not important past the first projection interval. This seems reasonable because there can be little difference in synoptic situation to produce broken, overcast, or scattered or few clouds. That is, the transition from one to another can happen over short spans in time and space. On the other hand, obscured or overcast may exist for long periods of time, and at least for overcast, over large distances.

Table 3. The predictors, types, number available, and the number selected for each of the six projection intervals. Probs stands for probabilities.

Predictor	Type	No. available	Predictors Selected by Projection Interval (h)					
			1-7	8-14	15-21	22-28	29-35	36-38
MOS	Cumulative probs	7	0	3	4	3	5	5
LAMP	Cumulative probs	7	4	5	6	4	-	-
HRRR	3-lag cumulative probs	14	2	4	3	-	-	-
HRRR	Last run binary	12	-	-	-	4	4	-
Obs (broken)	Binary	16	3	0	0	1	0	0
Obs (overcast)	Binary	16	11	3	1	1	2	1
Obs (obscured)	Binary	11	4	2	3	3	2	1
Total		83	24	17	17	16	13	7

The only predictors that really had a bearing on the type of ceiling was the initial observations. Because of this, one would not expect good discrimination except for the early projections. In related work, the HRRR relative humidity at specific levels was not useful. Also, the HRRR cloud base variable was erratic, sometimes being below the HRRR ceiling and sometimes above.

Figures 5 and 6 show graphically the 8-h forecast from March 5, 2017, 0100 cycle of overcast and broken ceiling heights, respectively. The forecast of obscuration was of only small areas, predominantly over mountain tops (not shown). Each of the components has been designed to be relatively unbiased for each category (bias near unity) and verify that way. For the points where two or three of the components are forecast, one must decide which forecast to make. A hierarchy of obscured, overcast, and then broken seems reasonable. Very few points are forecast as obscured, on the order of 2%, and obscured tends to persist. Overcast is more frequent than broken and has more forecast skill than broken. Using this method, and looking at the lower mid-west, we see a large area which is forecast as both overcast and broken. The major problem is that when all components are put together, the ceiling height is considerably low biased. This is because of the strong overlap of broken and overcast. For instance, large areas with ceiling in the northwest (Fig. 4) have no broken or overcast (Figs. 5 and 6) Because ceiling height is of such importance to aviation, it must be relatively unbiased.

In order for the ceiling as made from the combination of the three components to be unbiased, we did the following:

1) Removed the stations and times for which obscured forecasts were made from the developmental sample.
2) Developed thresholds for the overcast ceiling categories for a bias near unity with those obscured cases removed.

3) Removed the stations and times for which obscured or overcast forecasts were made from the sample.

4) Developed thresholds for the broken categories for a bias near unity with those obscured and overcast cases removed.

This improved the combined ceiling bias somewhat but not nearly enough. The obscured cases were so few as to not affect the result much, and since they were made “first” in the selection, they would remain relatively unbiased. Also, again because the number of obscured was small, the overcast forecasts were relatively unbiased. So, new thresholds were developed for broken to give higher than unity bias. This was done by trial and error. It was found a different bias had to be used for different categories of bias, and it was not possible to get very satisfactory biases by category. Also, to get reasonable biases for all height categories, when more than one component was forecast, the lowest height was used.

7. DIVIDING CEILING INTO ITS COMPONENTS

Because the approach of forecasting the components and producing a ceiling from them was not satisfactory, we took an alternate approach, and divided the ceiling forecasts into its three components. The steps in doing that were:

1) Obscured was forecast where there was also a ceiling with the height of the ceiling.

2) Overcast was forecast where there was a ceiling but not obscured with the height of the ceiling.

3) All ceiling forecasts, but not forecast as obscured or overcast were forecast as broken with the height of the ceiling.

In this way, the ceiling is preserved exactly as directly forecast (e.g., Fig. 4). Fig. 7 shows the TS for overcast < 1,000 ft for developmental and test data. The red lines are for the overcast forecasts coming directly from the equations, and the blue lines are for cases where both overcast and ceiling was forecast. The forecast scores held up well on independent data and the differences between requiring the ceiling be forecast (blue lines) or not (red lines) was in the noise level.

Figures 8, 9, and 10 are similar to Fig. 7, except they show the Gerrity score; Fig. 8 is for overcast, Fig. 9 is for obscured, and Fig. 10 is for broken. Figure 8 shows a similar pattern to Fig. 7, except there is a tendency for better overcast scores when it is required a ceiling be forecast and the ceiling height is taken as the forecast. Both Figs. 7 and 8 show the persistence score to be considerably different past about projection 18 on the dependent and independent cases. The number of cases decreases as the projection increases due to lesser HRRR data; for this reason the independent sample is too small to be a reliable indicator past 23 hour and scores are not shown.

Figure 9 shows that the equations, even for the rare obscured category, hold up on independent data, but the skill is lower than for overcast. Figure 10 shows the broken skill to be much lower than it is for overcast and even obscured. Importantly, the skill when it is required a ceiling be forecast is not as good as persistence. Evidently, the hierarchy of decision—obscured, overcast, broken—does well for obscured and overcast but not for broken.

For the same case as shown previously, the resulting obscured, overcast, and broken maps from this process are shown in Figs. 11, 12, and 13, respectively. The patterns look generally reasonable. Obscured is forecast predominantly over the higher mountain tops in the west. In the west and northwest, the higher elevations tend to be overcast with the lower areas being broken with higher heights. The large cloud-covered area in the lower mid-west is predominantly overcast, with broken around the edges, and in some areas (e.g., Arkansas and Louisiana) overcast and broken are interspersed.

8. CONCLUSIONS

The goal of this study was two-fold, to demonstrate that the ceiling height Meld methodology could be extended to at least 36 h with skill, and to specify for ceiling height the three components: Total obscuration, overcast, and broken. On the first, we were successful, as shown in Figs. 1-3. On the second, the second approach was reasonably successful, and could eventually furnish the basis for an operational product. With further development and with other data samples, we could determine whether using the forecast ceiling height for the obscured, broken and overcast components was better than using the individual heights forecast for the components, all being forecast only when there was a ceiling forecast. Other more involved decision-making processes could be explored.

Not all information available from the HRRR was tried for predictors, although some attempt at using relative humidity at various levels above the surface and the “lowest cloud height” were tried without success. It may be that the information from numerical models must be improved before substantially better results will result than are shown here in differentiating ceiling height into obscured, broken and overcast.

9. REFERENCES

Benjamin, S. G., S. S. Weygandt, J. M. Brown, M. Hu, C. R. Alexander, T. G. Smirnova, J. B. Olson, E. P. James, D. C. Dowell, G. A. Grell, H. Lin, S. E. Peckham, T. L. Smith, W. R. Moninger, J. S. Kenyon, and G. S. Manikin, 2016: A North American hourly assimilation and model forecast cycle: The rapid refresh. *Mon. Wea. Rev*., **144**, 1669-1694.

Bocchieri, J. R., and H. R. Glahn, 1972: Use of Model Output Statistics for predicting ceiling height. *Mon. Wea. Rev*., **100**, 869-879.

Dallavalle, J. P., M. C. Erickson, and J. C. Maloney III, 2004: Model output statistics (MOS) guidance for short- range projections. Preprints, *20th Conf. on Weather Analysis and Forecasting/16th Conf. on Numerical Weather Prediction*, Seattle, WA, Amer. Meteor. Soc., **6.1**.

Donaldson, R., R. Dyer, and M. Krauss, 1975: An objective evaluator of techniques for predicting severe weather events. Preprints, *Ninth Conf. on Severe Local Storms, Amer. Meteor. Soc.*, Norman, OK, 321-326.

Gerrity, J. P., 1992: A note on Gandin and Murphy's Equitable Skill Score. *Mon. Wea. Rev*., **120**, 2709-2712.

Ghirardelli, J. E., and B. Glahn, 2010: The Meteorological Development Laboratory's aviation weather prediction system. *Wea. Forecasting*, **25**, 1027-1051.

Glahn, B, and D. P. Ruth, 2003: The new digital forecast database of the National Weather Service. *Bull. Amer. Meteor. Soc*., **84**, 195-201.

_____, A. D. Schnapp, J. E. Ghirardelli, and J.-S. Im, 2017: A LAMP/HRRR MELD for Improved Aviation Guidance. *Wea. Forecasting*, **32**, 391-405.

_____, and J. Wiedenfeld, 2006: Insuring temporal consistency in short range statistical weather forecasts. Preprints, *18th Conf. on Probability and Statistics in the Atmospheric Sciences*, Atlanta, GA, **6.3**.

_____, K. Gilbert, R. Cosgrove, D. P. Ruth, and K. Sheets, 2009: The gridding of MOS. *Wea. Forecasting*, **24**, 520-529.

____, and J.-S. Im, 2015: Objective analysis of visibility and ceiling height observations and forecasts. *MDL Office Note* **15-2**. Meteorological Development Laboratory, National Weather Service, NOAA, U.S. Department of Commerce, 17 pp.

Miller, R. G., 1958: Regression estimation of event probabilities. U.S. Weather Bureau, Contract Cwb-10704, *Tech. Rep. No*. **1**, The Travelers Research Center, Inc., Hartford, CN.

OFCM, 1995: Surface weather observations and reports. *Federal Meteorological Handbook* **1**, NOAA/Office of the Federal Coordinator for Meeorological services and Supporting Research, 104 pp.

Palmer, W. C., and R. A. Allen, 1949: Note on the accuracy of forecasts concerning the rain problem. Weather Bureau Manuscript, Washington, D. C., 2 pp.

Shaffer, J. T., 1990: The Critical Success Index as an indicator of warning skill. *Wea. Forecasting*, **5**, 570-575.

Wilks, D. S., 2011: *Statistical Methods in the Atmospheric Sciences*. Academic Press, 676 pp.

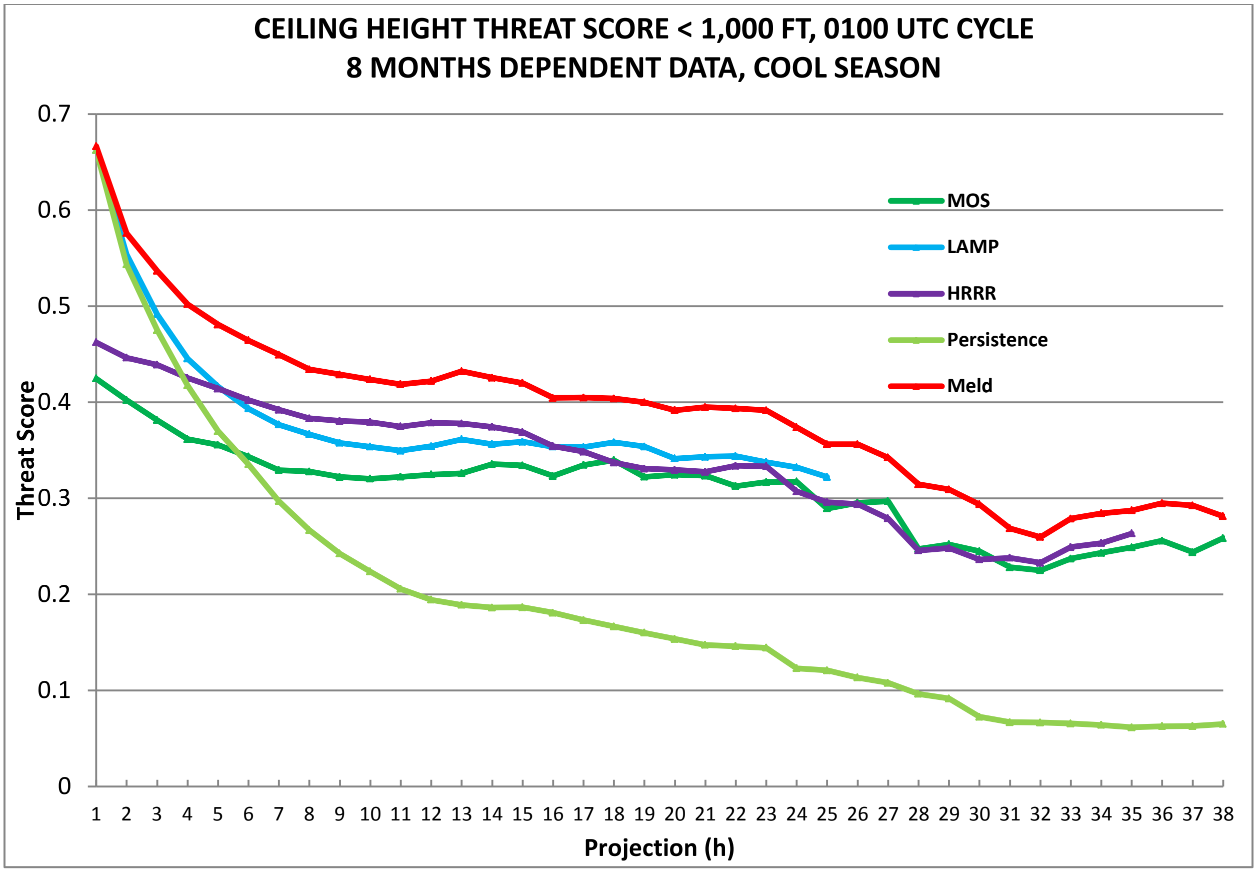


Figure 1. Threat score for < 1,000 ft for the systems verified on 8 months of dependent data.

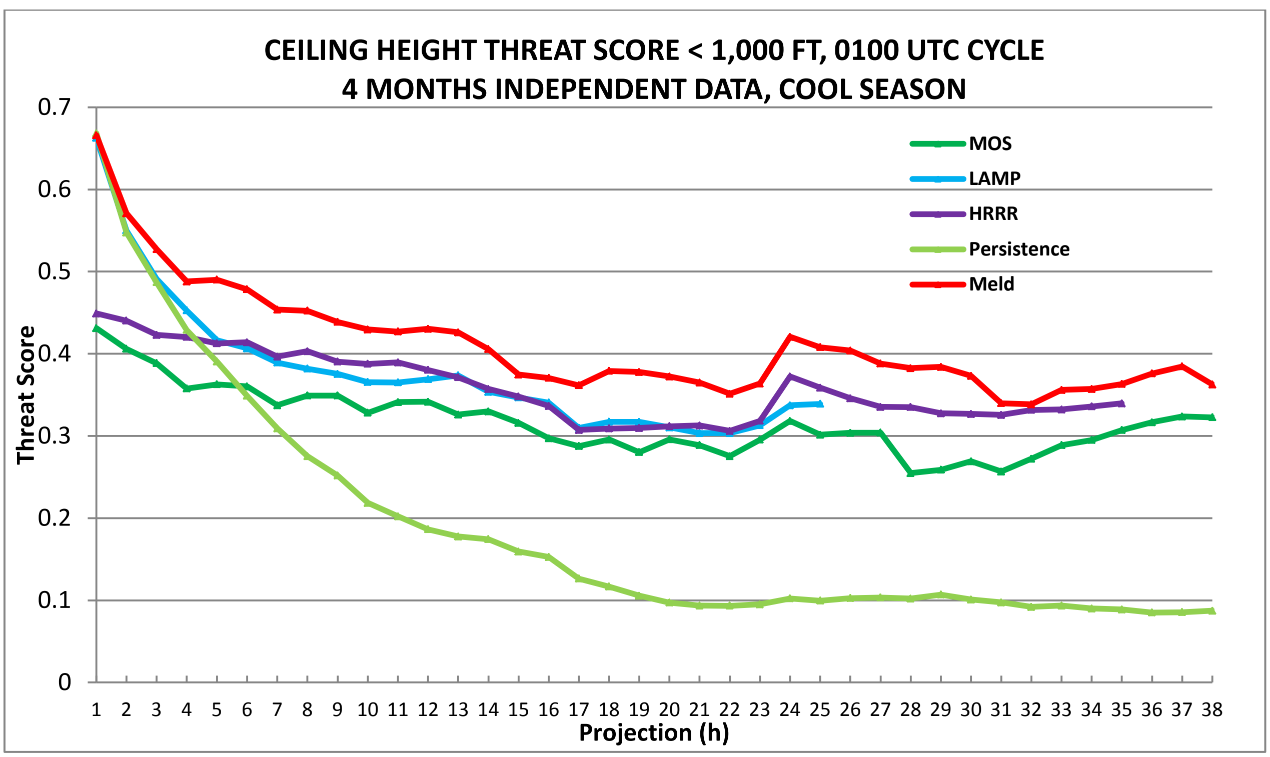


Figure 2. The same as Fig. 1, except on 4 months of independent data.

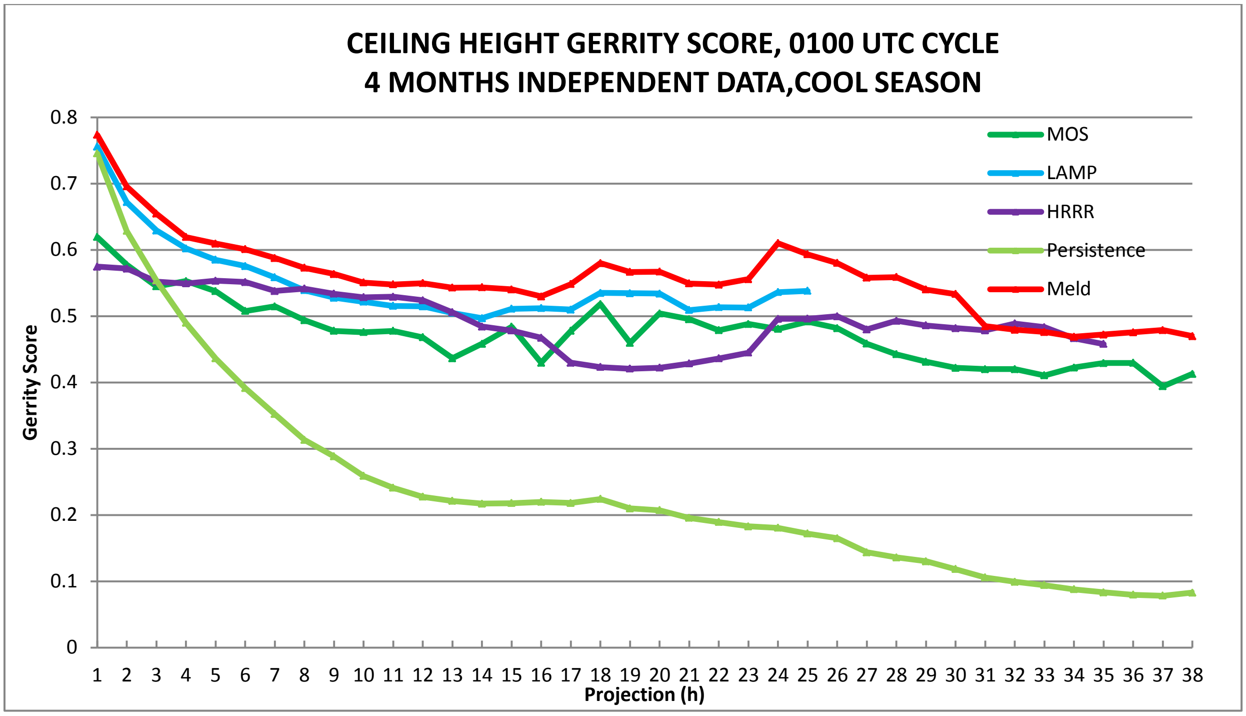


Figure 3. Gerrity score for the systems verified on 4 months of independent data.

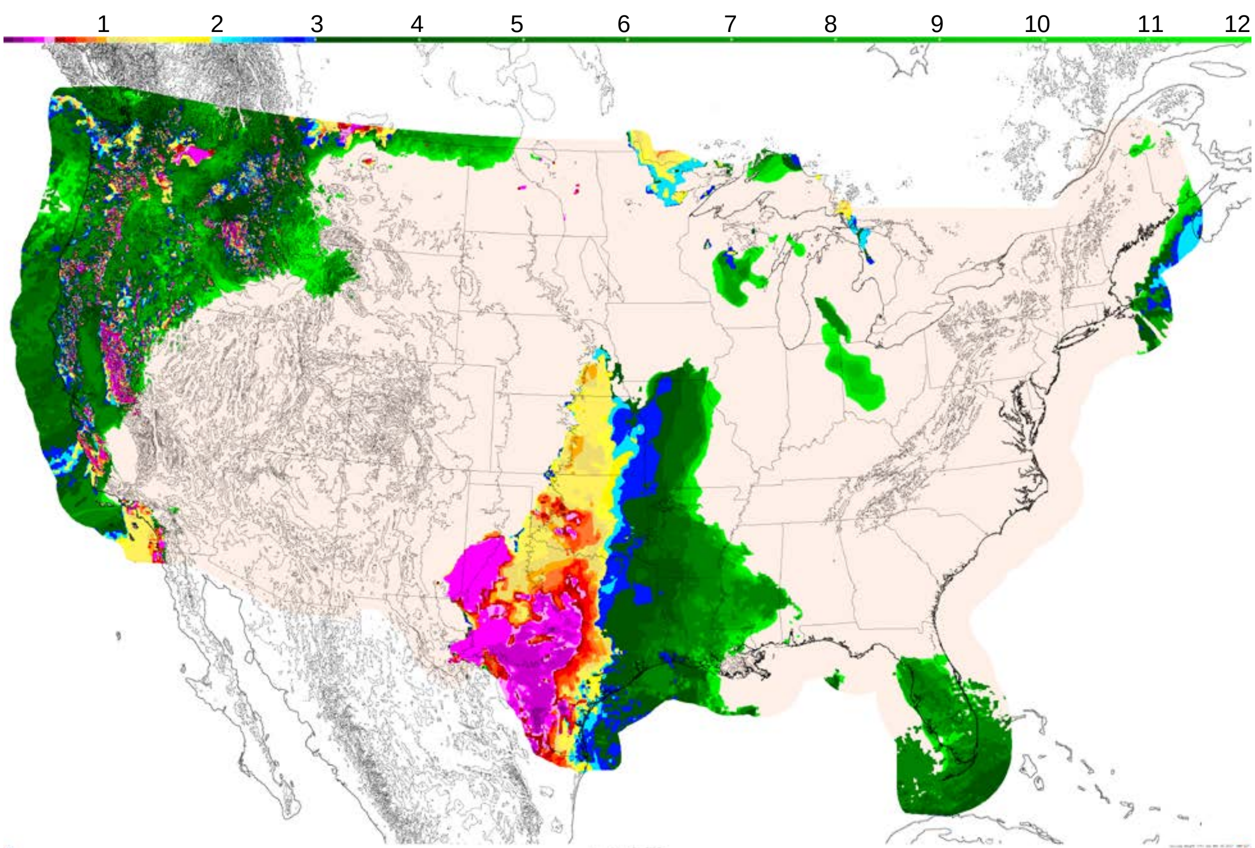


Figure 4. The LAMP/HRRR Meld ceiling height forecast (color bar, thousands of ft) 8-h projection from 0100 UTC March 5, 2017.

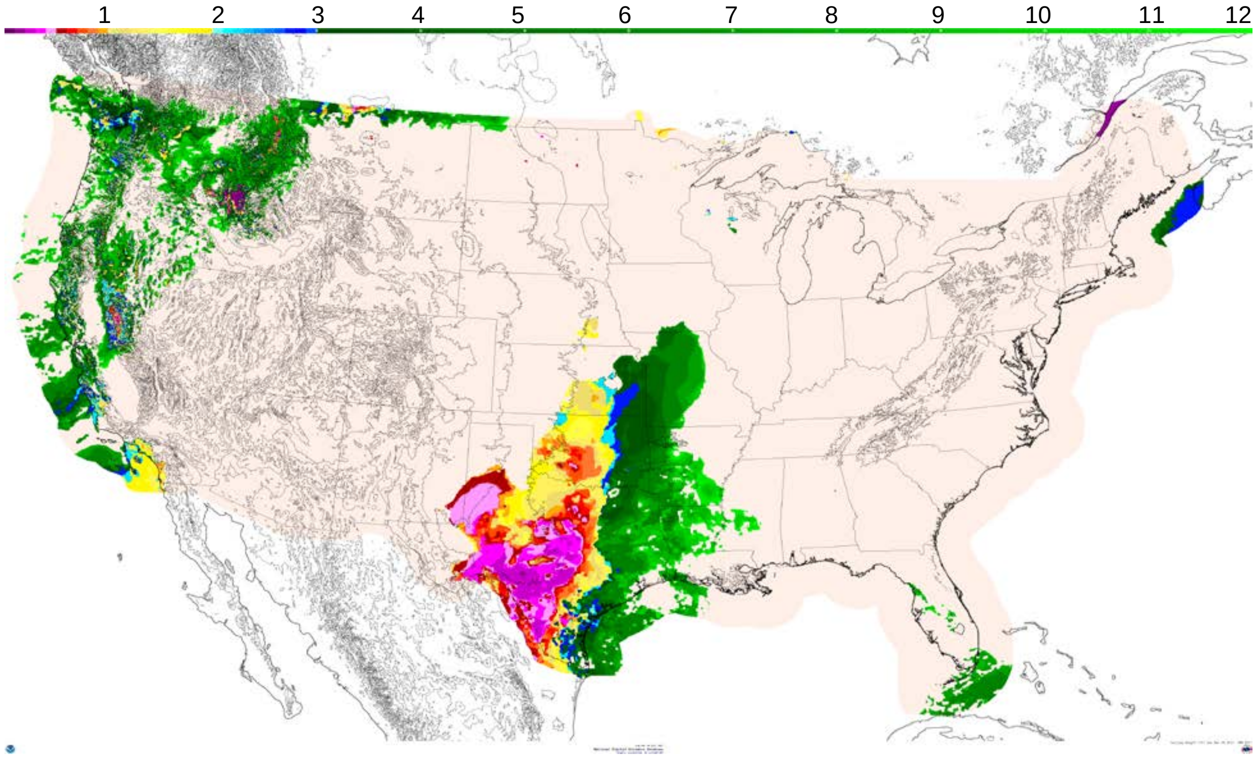


Figure 5. Eight-hour forecast from March 5, 2017, 0100 UTC of overcast ceiling height.

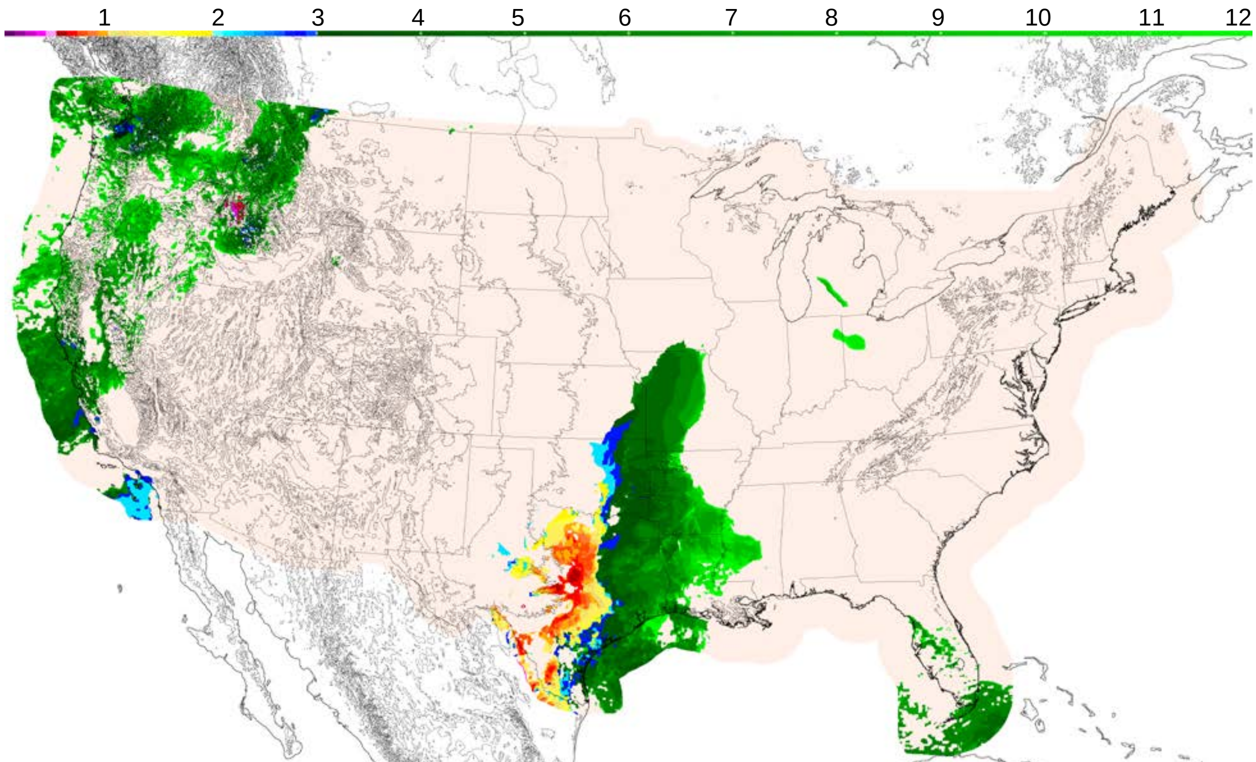


Figure 6. Eight-hour forecast from March 5, 2017, 0100 UTC of broken ceiling height.

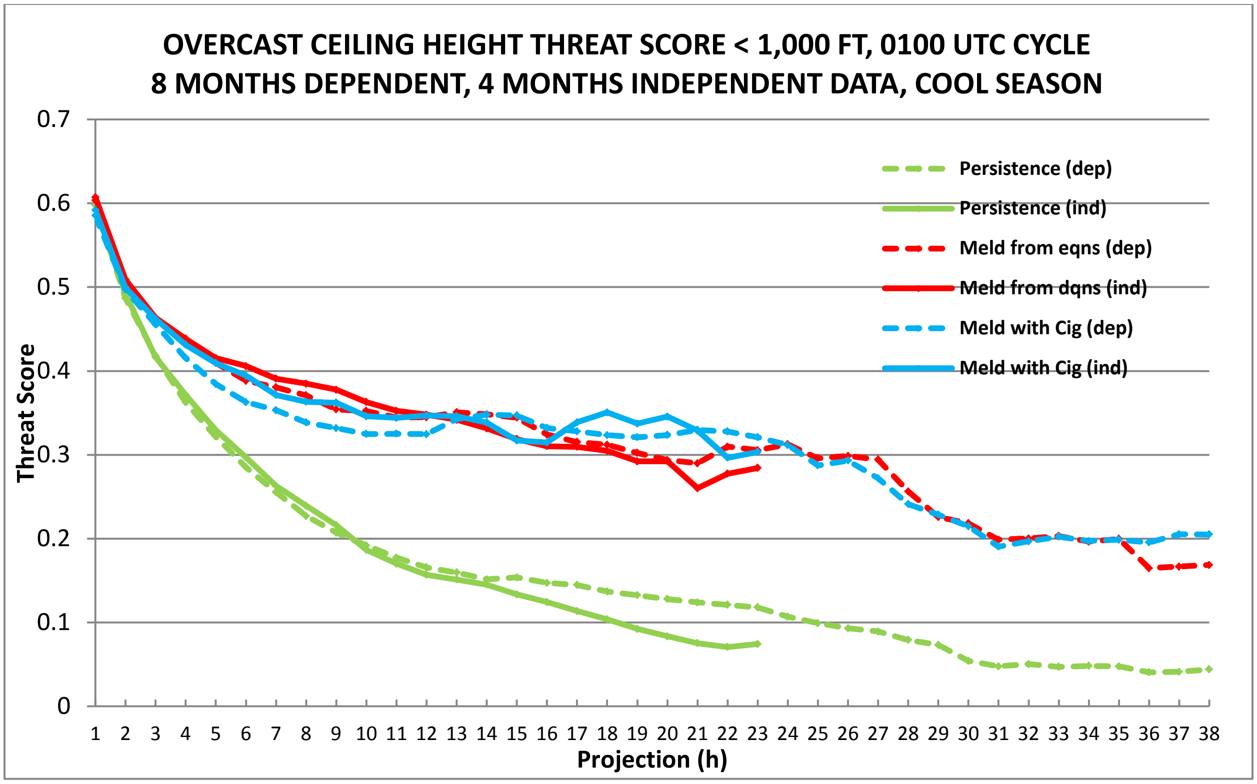
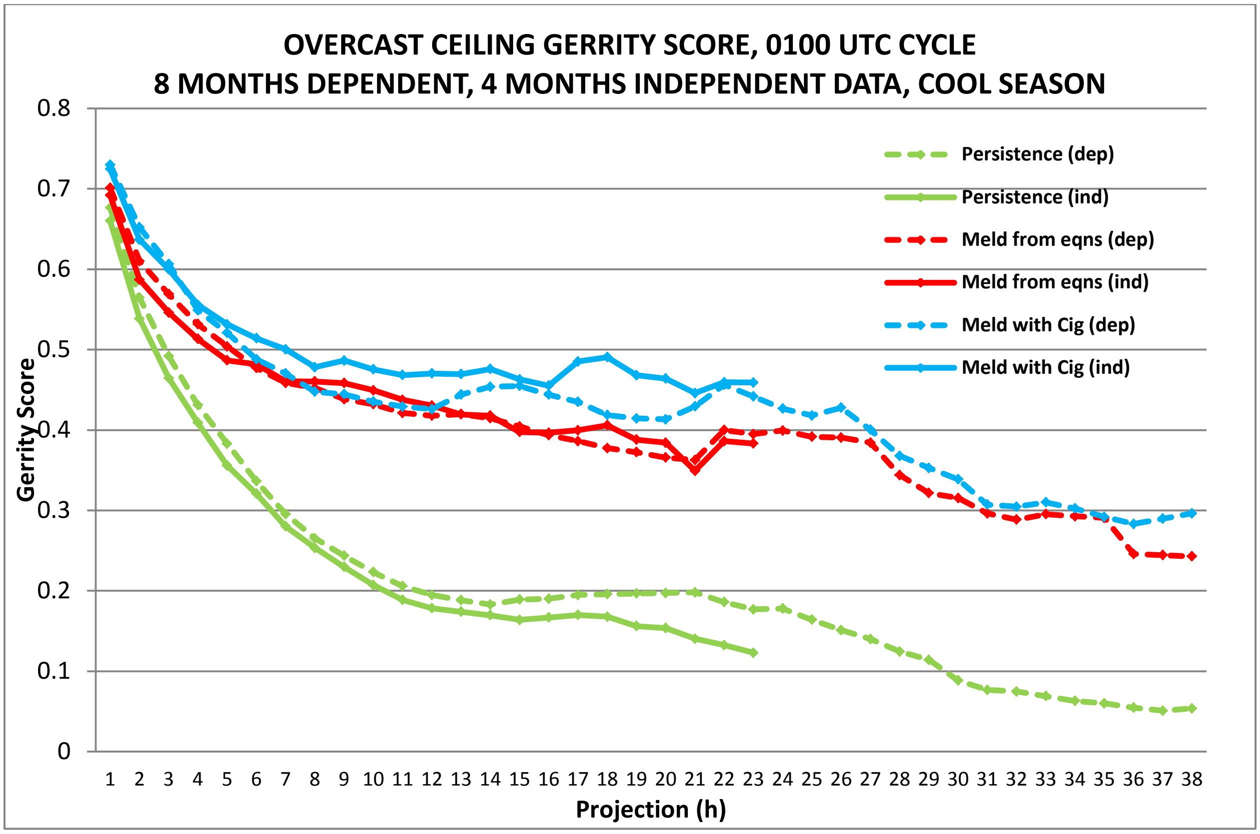


Figure 7. Threat score for < 1,000 ft for dependent and independent data for overcast.



0Figure 8. Gerrity score for overcast ceiling for dependent and independent data.

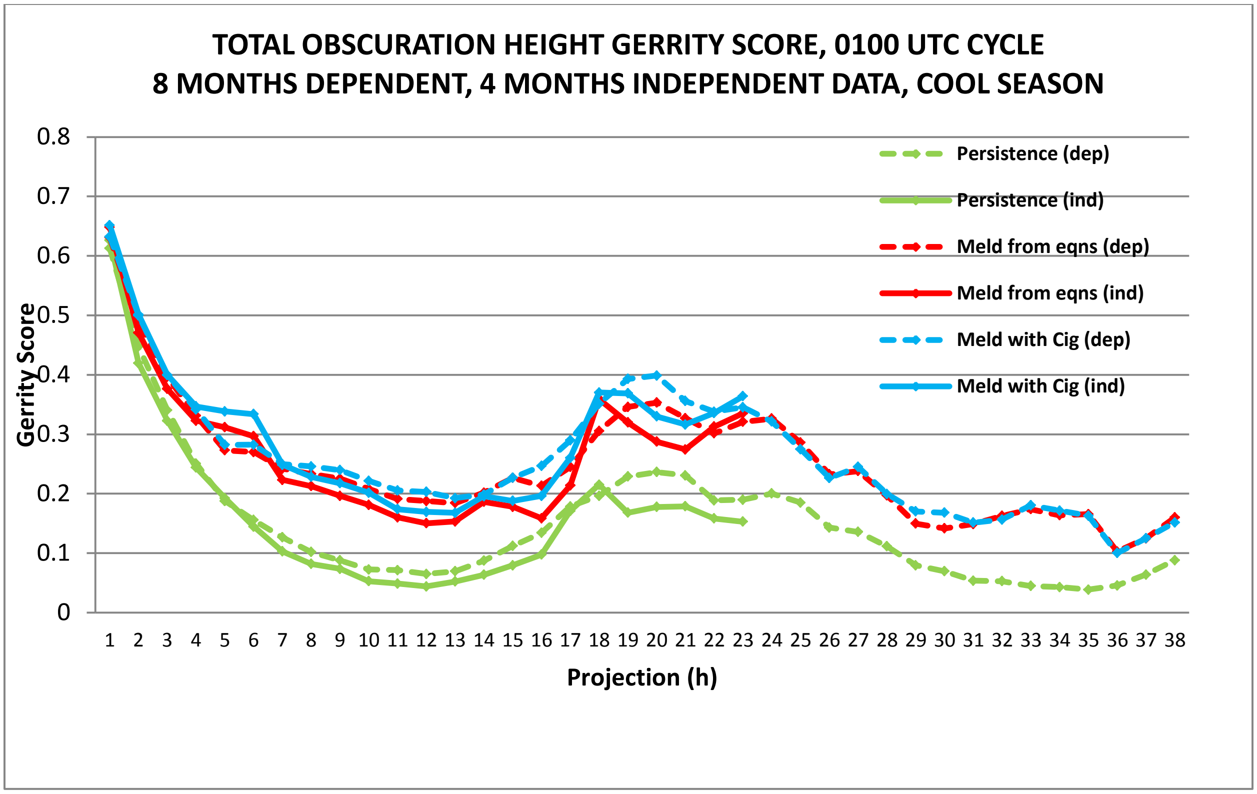


Figure9. Gerrity score for total obscuration ceiling for dependent and independent data.

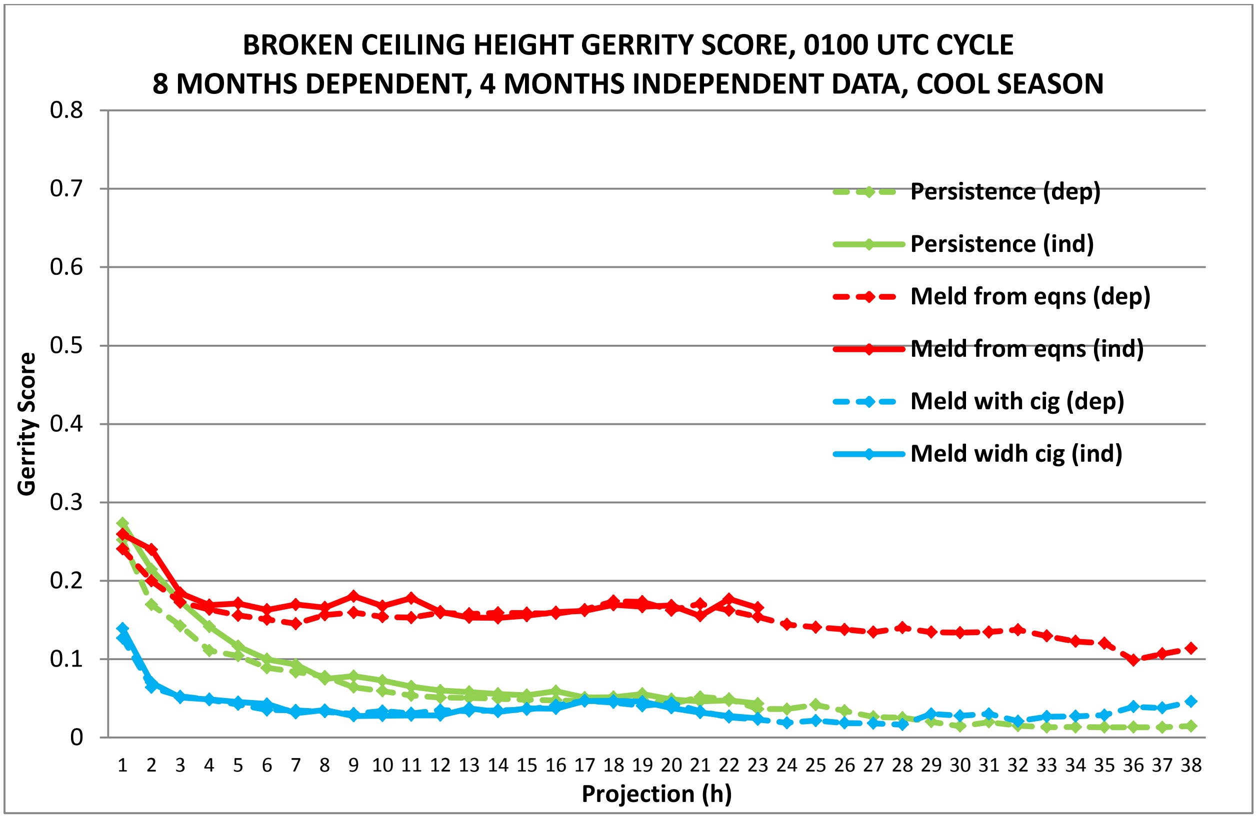


Figure 10. Gerrity score for broken ceiling for dependent and independent data.

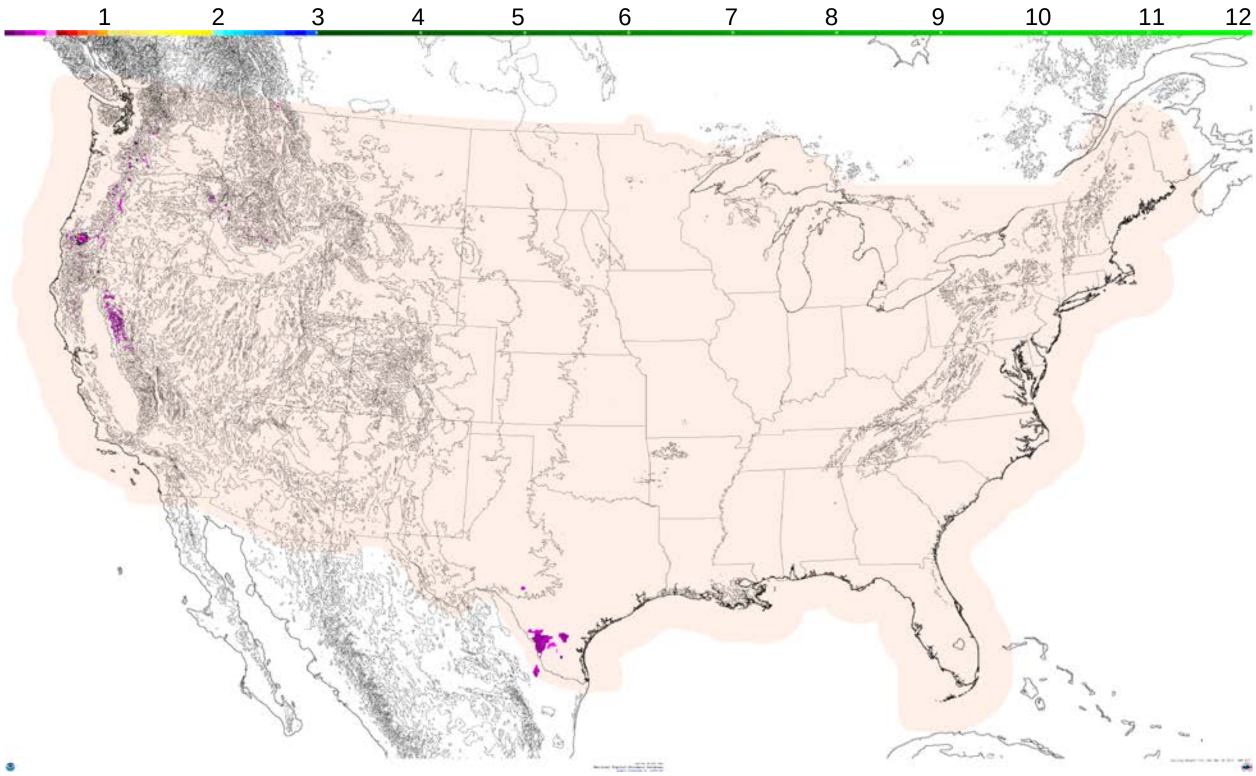


Figure 11. Eight-hour forecast from March 5, 2017, 0100 UTC of obscured when a ceiling height was forecast.

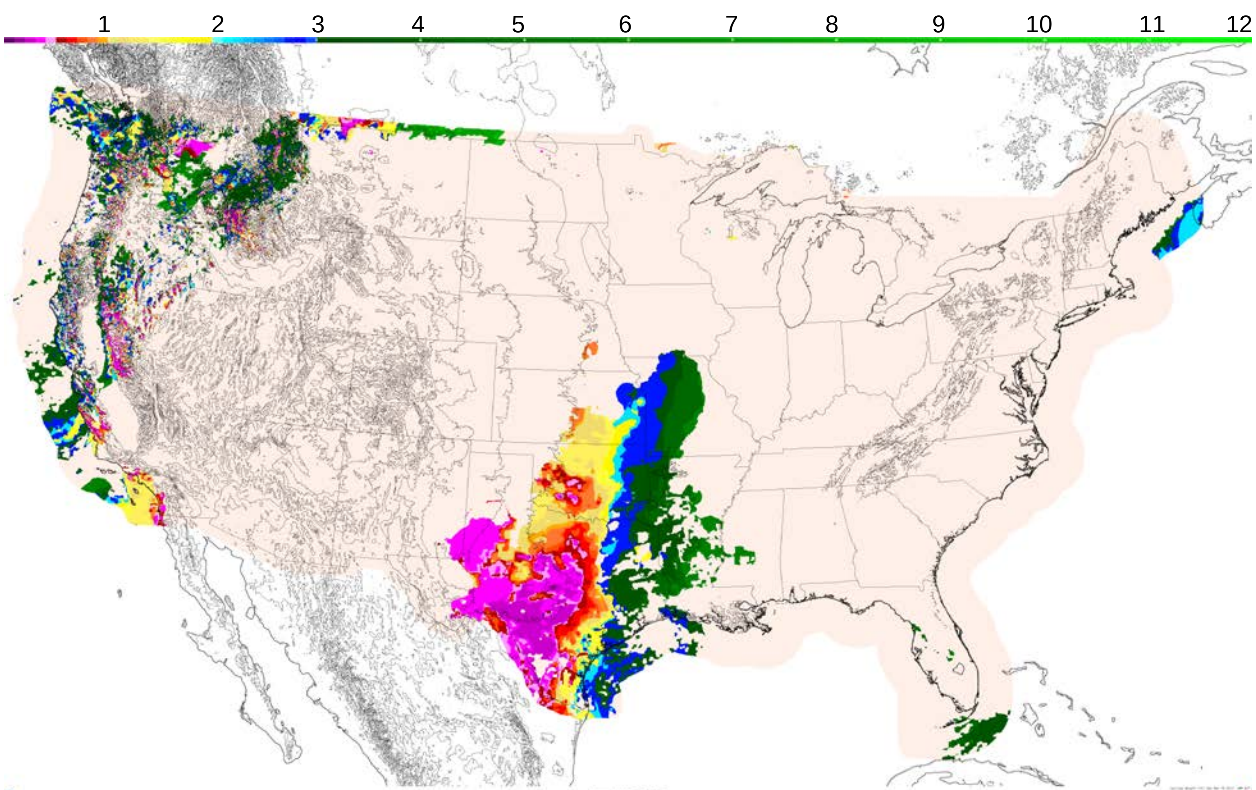


Figure 12. Eight-hour forecast from March 5, 2017, 0100 UTC of overcast when a ceiling height was forecast.

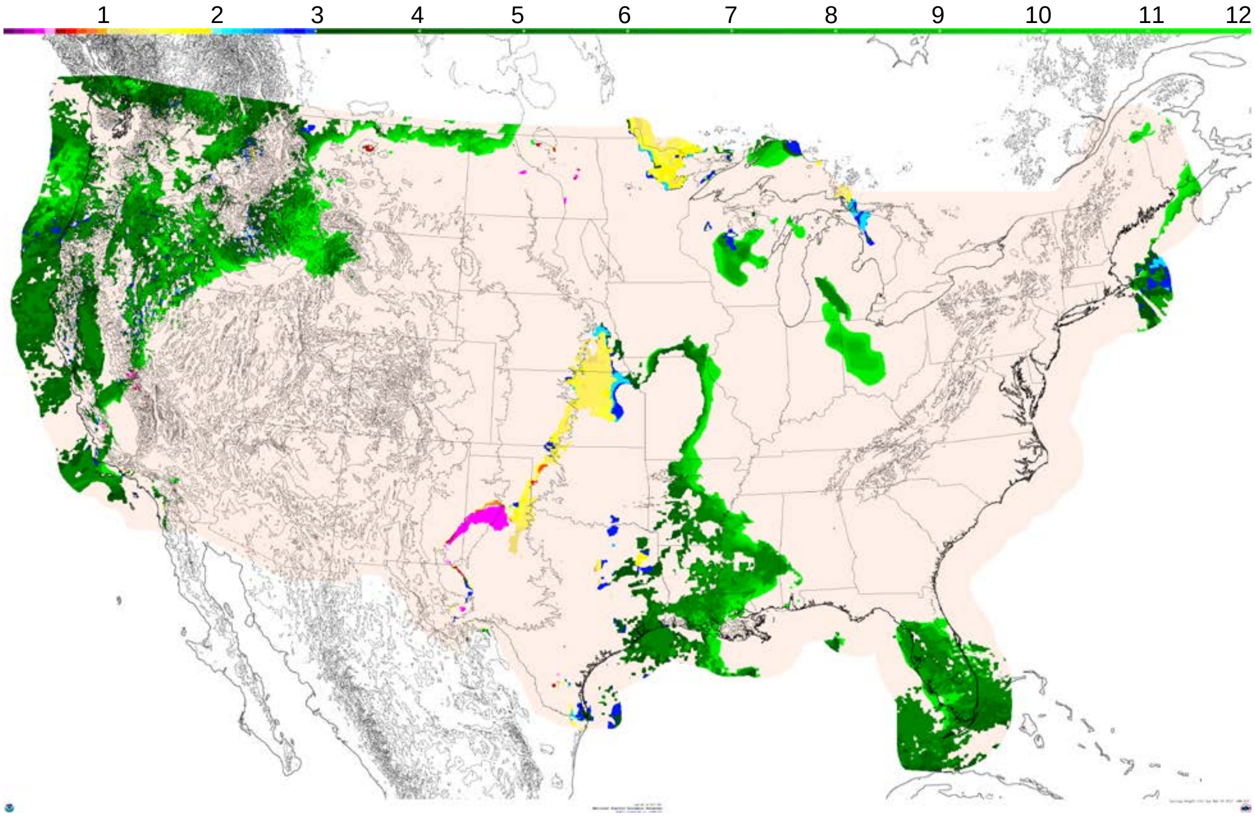


Figure 13. Eight-hour forecast from March 5, 2017, 0100 UTC of broken when a ceiling height was forecast.