6R.2 **DETERMINING KEY PREDICTORS FOR NCAR'S CONVECTIVE AUTO-NOWCAST SYSTEM USING CLIMATOLOGICAL ANALYSES**

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1. INTRODUCTION

The National Center for Atmosphere Research (NCAR) Auto-Nowcast (ANC) system is an expert system which utilizes fuzzy logic (McNeill and Freiberger 1993) to produce short-term (0-1 hr) nowcasts of thunderstorm initiation, growth, and decay. A full description of the ANC system can be found in Mueller et al. (2003) and therefore only a brief overview will be provided in this paper. The ANC system ingests various data sets; including single or multiple WSR-88D radar, satellite, surface, sounding, and numerical model data. Algorithms utilize these data sets to produce predictor fields that can be transformed into interest fields by applying membership functions to them. The resulting interest fields are weighted and then summed to give the final forecast interest field. The ANC system produces both initiation and growth/decay interest fields, however, for this paper only the initiation interest fields are considered since the focus will be on discriminating predictor field signals observed in storm initiation areas from no storm initiation areas.

The goal of this paper is to show that predictor fields have different attributes for storm initiation areas compared to no storm initiation areas and furthermore, the attributes for some of the fields show further differences based on the type of convective events that are observed. These analyses should assist with setting up the forecast logic (i.e. determining which fields are included and defining the associated membership functions and weights). They also suggest that for optimal results, different forecast logic should be used based on the expected type of convective forcing.

A description of how the forecast logic is currently setup is provided in Sect. 2. Climatological analyses of storm initiation and no initiation areas are provided in Sect. 3 for four model-based predictor fields. In Sect. 4 some examples of how the results are modified when different types of convective forcing are considered are presented and a summary is included in Sect. 5.

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2. CURRENT METHODS

Currently the forecast logic is setup using physically based reasoning based on previous research results to define the various membership functions and their associated weights. Once the initial set of rules are developed, the logic is generally tested on several representative cases from the area where the system is being deployed, if available. The membership functions and weights are then usually adjusted slightly to attain optimal results for the chosen cases. Depending on the cases chosen for the initial testing, oftentimes further minor adjustments are required after running operationally. It has been observed that when using this method the logic tends to work better in certain types of convective scenarios than others. The effects that different types of convective forcing have on the forecast logic will be explored further in Sect. 4.

3. CLIMATOLOGICAL ANALYSES OF STORM INITIATON LOCATIONS

In order to gain a better understanding of the differences in the predictor field attributes for storm initiation areas compared to no storm initiation areas, an analysis which provides histograms of the predictor fields for these two situations have been produced. In this study, the TITAN (Thunderstorm Identification, Tracking, Analysis, and Nowcasting; Dixon and Weiner, 1993) software was used to identify storm initiation locations in the ANC system's IL/IN installation domain from 25 May 2004 through 31 July 2004. The initiation locations were mapped to a Cartesian grid and then expanded spatially by 40 km. This gridded initiation location data was then matched to numerous numerical model (RUC, Rapid Update Cycle; Benjamin, et al., 2004) based predictor fields that would have been available at the forecast generation time. Histograms were then produced for the various predictor fields for the storm initiation and no storm initiation areas. Lastly, the histograms were converted to cumulative probability distributions and will be discussed below.

The first predictor field that was examined was the RUC 875 – 725 mb mean Relative Humidity (RH). The resulting cumulative probability distributions

(Fig. 1) shows that storms were much more likely to initiate when the mean RH is higher, with over 80% of the storm initiation areas having mean RH values greater than 60% whereas only about 45% of the non-initiation areas had RH values above that value. This would suggest that for mean RH values less than 60% the membership function should have negative interest with positive interest for higher mean RH values. Since there are significant differences between these two distributions, it suggests that this predictor field should be given a relatively high weight in the forecast logic.

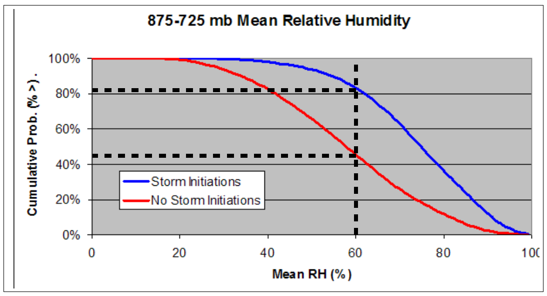

Figure 1. Cumulative probability distribution plots for the RUC 875-725 mean RH predictor field for storm initiation areas (blue) and no storm initiation areas (red).

The frontal likelihood predictor is a field which tries to identify frontal areas based on vorticity, convergence, and gradients in Theta E in the low-level RUC data. The resulting cumulative probability distributions (Fig. 2) look quite similar suggesting that this may not be overly useful in identifying initiation regions and if used, should be given a relatively small weight.

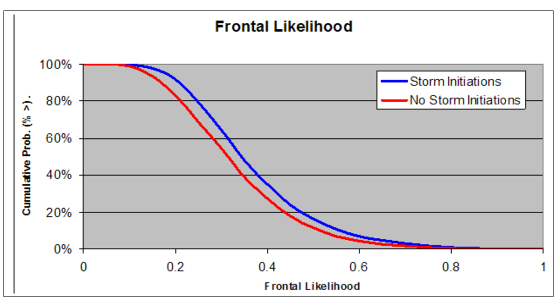

Figure 2. Same as Fig. 1 except for the frontal likelihood predictor field.

The cumulative probability distributions for the Convective Available Potential Energy (CAPE) predictor field, which is calculated from the RUC data, is provided in Fig. 3. This predictor field uses the maximum CAPE value found in the column between 900 and 700 mb. Figure 3 shows that higher CAPE values are more conducive to storm initiation than areas where there is little or no CAPE. This suggests that the membership function should have negative interest for very low CAPE values and then turn positive for values greater than about 100 J/kg. The differences between the two distributions suggest that this predictor field should be given a relatively high weight in the forecast logic.

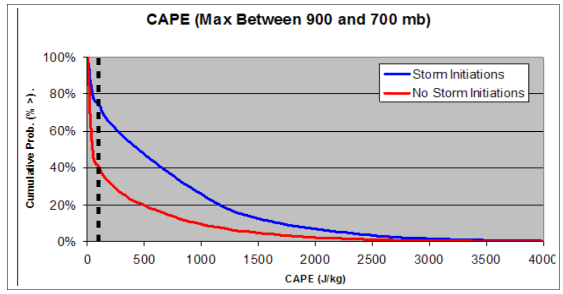

Figure 3. Same as Fig. 1 except for the maximum RUC CAPE between 900 and 700 mb predictor field.

The last predictor field that will be discussed here is the RUC 1000 mb Theta E. The cumulative probability distributions (Fig. 4) show that there are some distinct difference between the storm initiation and no initiation areas. This field is not currently being used in the ANC forecast logic, but these results suggest that it may be a good candidate for inclusion with values less than about 330 K given a negative interest and values above 350 K given a large positive interest.

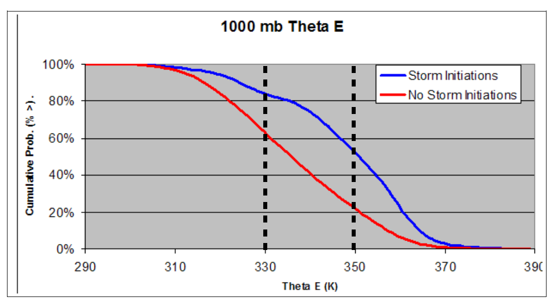

Figure 4. Same as Fig. 1 except for the RUC 1000 mb Theta E predictor field.

While the individual predictor fields shown here do show differences between the storm initiation areas and no initiation areas, it is also clear that what is really crucial for effective initiation forecasts is the combination of the various predictor fields. No one individual predictor field can readily be used as a predictor of storm initiation. This fact makes the use of a fuzzy-logic based approach to convective initiation nowcasting an especially attractive one.

4. EFFECTS OF DIFFERENT TYPES OF CONVECTIVE FORCING

The effect that different types of convective forcing have on the above described analyses has also been explored. The time period for the previous analyses has been broken down into periods when there was large scale frontal forcing and periods when there was not large scale frontal forcing. The resulting effects on the cumulative probability distributions for four of the predictor fields will be presented.

The cumulative probability distributions for the mean RH predictor field separated out based on whether there was frontal forcing or not are provided in Fig. 5. It can be seen that for the non-frontally forced times, the mean RH field shows more discrimination between storm initiation areas and no initiation areas than for the frontally forced days. This suggests that the membership functions for these two different types of days could be slightly different and it also suggests that the weighting factor could be larger for this predictor field on the non-frontally forced days.

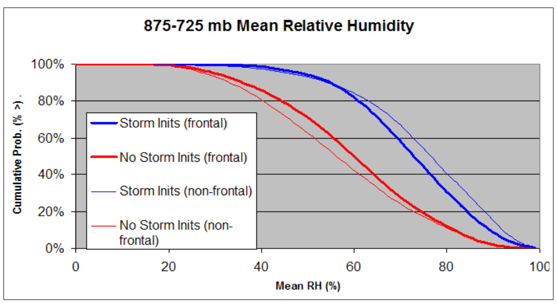

Figure 5. Cumulative probability distribution plots for the RUC 875-725 mean RH predictor field for storm initiation areas (blue) and no storm initiation areas (red). The thick lines represent time periods when there was large scale frontal forcing present and the thin lines represent time periods when there was not any frontal forcing.

The cumulative probability distribution for the frontal likelihood predictor field separated out based on the presence of frontal forcing or not is provided if Fig. 6. As one would expect the distribution shows very little difference on the non-frontally forced days compared to the frontally forced days. This suggests that the frontal likelihoods field should not be used on non-frontally forced days. The frontally forced days also do not show really large difference between the storm initiation and no initiation areas. The main reasons for this is that oftentimes a number of the initiations occur out ahead of the areas that have higher frontal likelihood values and also the higher frontal likelihood field values oftentimes cover large areas and the storm initiations occur in only a limited area.

The cumulative probability distributions for the CAPE predictor field separated out based on the presence of frontal forcing or not is provided in Fig. 7. The distributions for the frontally forced and non-frontally forced days have a similar shape, but the CAPE values are shifted to lower values for the non-frontally forced days. This suggests that the CAPE field should be given the same general weight in the forecast logic for both frontal and non-frontal days, but the membership function should be shifted to lower values for the non-frontally forced days.

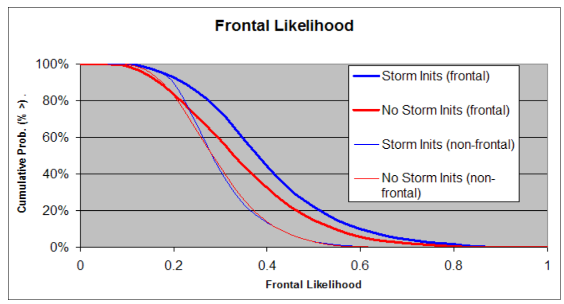

Figure 6. Same as Fig. 5 except for frontal likelihood predictor field.

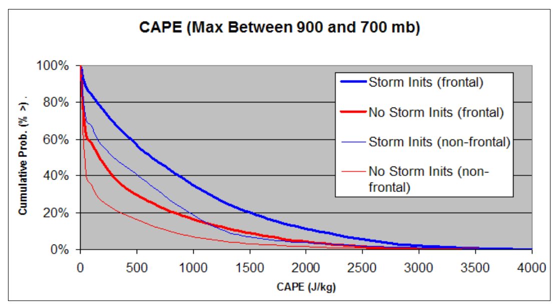

Figure 7. Same as Fig. 5 except for the maximum RUC CAPE between 900 and 700 mb predictor field.

The cumulative probability distribution for the 1000 mb Theta E predictor field separated out based on the presence of frontal forcing or not is provided in Fig. 8. The distributions for the frontally forced and non-frontally forced days are very similar. This suggests that this predictor field may not need to be adjusted for different types of convective forcing.

This initial approach to separating out different types of convective events was a simply one whose goal was to show that by looking at different types of events, some differences in the attributes of the predictor fields can be realized. Clearly, a more sophisticated approach which includes more detailed classes of convective forcing should be undertaken to realize the full effectiveness of this methodology.

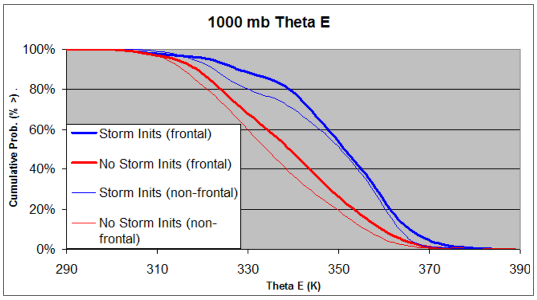

Figure 8. Same as Fig. 5 except for the RUC 1000 mb Theta E predictor field.

5. SUMMERY

A method for using climatological analyses to help define membership functions and weights for the NCAR ANC system has been presented. The method has advantages over the currently used methods in that much more data is used and therefore the dependence on the choices for the tuning cases is minimized. The differences between the distributions for the storm initiation and no storm initiation areas can be used to better define the membership functions and also give an indication of the relative weight that should be given to the respective fields in the forecast logic. The results show that some fields currently used in the forecast logic are good choices, but some of the membership functions may be better defined and their weights in the forecast logic could be more optimally set. The results also show that some fields that are not currently used in the forecast logic may be good additions, especially the 1000 mb Theta E field.

It has also been shown that the attributes of some of the predictor fields show differences for frontal vs non-frontal forcing events. This suggests that an improved set of forecast logic should be achievable if these differences are accounted for in the system. Similar analyses need to be completed on other fields, including both currently used fields and also fields that are not being used at this time. The results of these analyses need to be tested on independent data.

Acknowledgments:

The National Center for Atmospheric Research is sponsored by the National Science Foundation. This study is supported by the FAA Aviation Weather Research Program through an Interagency Agreement.

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