16B.4

Updraft Helicity Skewness as a Parameter to Forecast Probability of Convective Mode

David E. Jahn[1,2], Israel L. Jirak[2]

[1]Cooperative Institute for Severe and High-Impact Weather Research and Operations/Univ. of Oklahoma
[2]Storm Prediction Center/National Weather Service

1. Introduction

To provide pertinent warning of imminent severe weather, it is important to forecast not only the anticipated development of severe storms but also the anticipated convective mode, such as storm cells developing as part of a line, within a cluster, or isolated. It has been shown that the anticipated type of weather hazard (e.g. significant winds and hail or tornadoes) is highly related to convection mode (Gallus et al. 2008, Smith et al. 2010). Various studies have proposed thresholds and subjective guidelines using observational data, primarily radar reflectivity, to classify storm mode (Smith et al. 2012, Thompson et al. 2012). This latter study incorporated also numerically analyzed gridded environmental parameters such as storm-relative helicity, bulk wind difference, and CAPE to differentiate environments of tornadic supercells and tornadic quasi-linear convective systems (QLCSs).

Here, updraft helicity (UH) and its statistical distribution within a simulated storm complex is investigated to differentiate storm mode of High Resolution Ensemble Forecast (HREF) convective storms. UH has been used as a proxy for identifying rotating storms in convective-allowing model (CAM) forecasts (Gallo et al. 2018, Jahn et al. 2020), but Jahn et al. (2022) provided evidence that MCSs and supercells can both exhibit a relatively similar range of mean UH values and, thus, do not necessarily differentiate storm mode. They investigated higher-order UH statistical moments (standard deviation, skewness, and kurtosis), and found that UH skewness (UHS), in particular, best differentiated among MCSs and supercells. Their study, however, is considered preliminary in that it involves a relatively small set of cases (i.e., n=120) and is expanded here to investigate UHS as a means of objectively forecasting storm mode by implementing a larger dataset, one with 722 cases. In addition, the ability to predict the probability (i.e., rather than a strictly binary determination) of storm mode is investigated here.

2. Methodology

Calculating UHS

To objectively distinguish convection in an HREF domain as either a supercell or a mesoscale convective system (MCS), a simple and straightforward grid-point-based (i.e., not an object-based) approach is employed by examining the statistical attributes of UH values within the local region of the simulated convection. A distribution of the 2-5 km AGL UH field is identified by sampling values at all surrounding points within a 40-km circular region of a point in the HREF domain for which a simulated rotating storm was identified (such that UH exceeded 99.985% of the HREF member UH climatology, a method consistent with that used in Gallo et al. 2018 and Jahn et al. 2020). Histograms in Figs. 1 and 2 give examples of UH distributions for a supercell and an MCS case, respectively. A skewness of 0.27 (1.12) for the UH distribution of the supercell (MCS) is consistent with the proposed skewness threshold in Jahn et al. (2022), that is, a value less (greater) than 1.0 indicates a higher possibility of a supercell (MCS).

Subjectively identifying storm mode

To investigate this hypothesis, that relatively low (high) UH skewness differentiates supercells (MCSs), a relatively large set of 722 study cases was formulated. To do so, an online survey was constructed to allow for subjective classification of storm mode case by case. For each case, survey participants were provided HREF reflectivity and UH plots depicting convection at a specific forecast time and position defined by a local UH maximum. An example FV3 case from the on-line survey is given in Fig. 3, which lists the six categories from which survey participants could choose to

* *Corresponding author address:* David E. Jahn, CIWRO/Univ. of OK, 120 David L. Boren Blvd., Norman, OK 73072; e-mail: djahn@ou.edu.

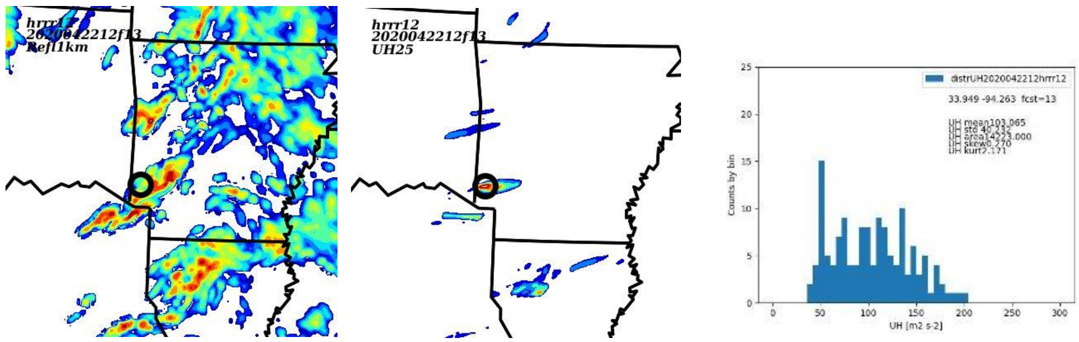

Figure 1. HREF (HRRR member) 13-hour forecast valid 4/23/20 @01 UTC for (a) 4-km reflectivity, (b) 2-5 km vertically integrated UH, and (c) distribution of UH within a 40-km radius of the circle that denotes a local UH maximum where UH > 99.985% of HREF member UH climatology.

Figure 2. Same as Fig. 1 but for an HREF (ARW member) 12-hour forecast valid 4/23/20 @00 UTC.

characterize the convective mode. In all, 11 SPC forecasters and researchers elected to participate in the survey, categorizing the storm mode of as many or as few of the cases as they wished. The survey consisted roughly of an equal representation of forecasts from the five HREF ensemble members (ARW, NSSL, HRRR, NAM, FV3).

For simplicity, survey responses for the six storm mode classifications were grouped into three categories: supercell (supercell:discrete, supercell:in cluster), MCS (QLCS:line, QLCS:hybrid, supercell:in line), and disorganized (DO). Survey results (Fig. 4) reveal that of the 2864 total responses, participants identified 60.7% of the cases as supercells and 30.7% as MCSs. Of the ensemble members, NAM forecasts were evaluated as having the lowest percentage of supercell cases, 52.2%, while FV3 forecasts were evaluated with the most, 70.8% (not shown).

Linear regression model: predicting storm mode probability based on UHS

The fact that there were 2864 survey responses indicates, on average, roughly 4 responses for each of the 722 cases. Having multiple responses for each case allows for assignment of storm mode probabilities by case. The results of each case can then be used to populate a scatter plot, with UHS as the x-coordinate and the probabilities for the three storm modes (SC, MCS, and DO) for the same case as y-coordinates.

A scatter plot representing cases associated strictly with the NSSL HREF member convective forecasts is given in Fig. 5. Cases with relatively low UHS (e.g., less than 1.0) were categorized as a supercell (blue points) by a majority of survey participants. Conversely, cases with relatively high UHS (e.g., greater than 1.0) were categorized as an MCS (yellow points) by a majority. The probability that a case was classified as disorganized (DO, green points) does not vary greatly by UHS and remains consistently below 20%.

Using linear regression, curves are fitted to the data by storm mode (SC, MCS, DO) to represent a simple model that provides probabilities of each storm mode based on UHS. A weighted linear

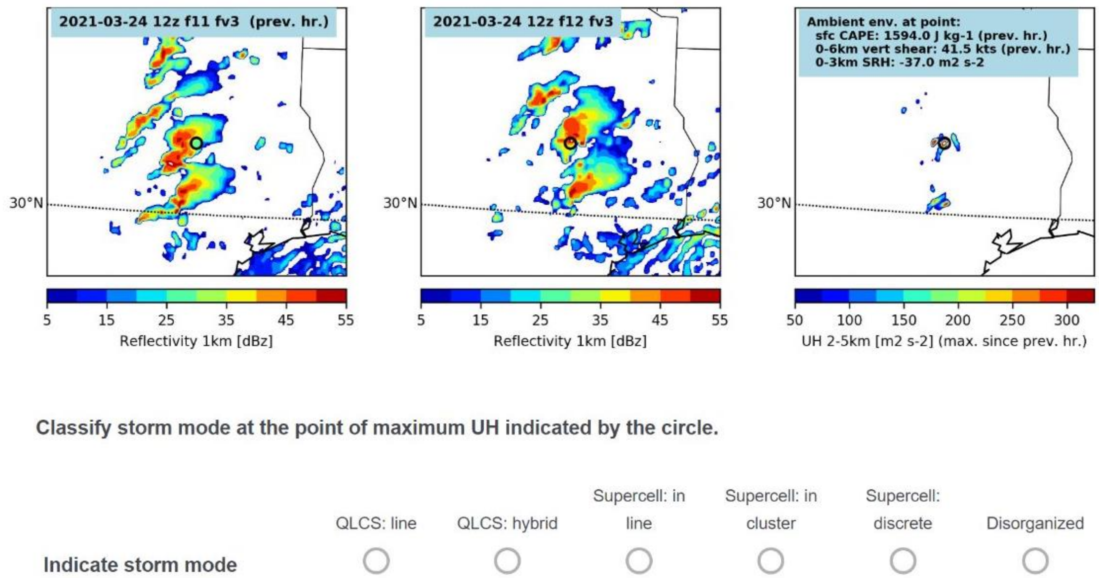

Figure 3. An example case from on-line survey for an FV3 forecast initialized 3/24/21 @12 UTC, showing 1-km reflectivity valid @23 UTC (left plot) and @00 UTC (center plot), and UH @00 UTC (right plot) along with related environmental values(CAPE, vertical shear, and storm-relative helicity, SRH). Participants selected one of six classifications (listed below plots) that categorizes the storm mode of the convective complex at the point of the UH local maximum (small black circle).

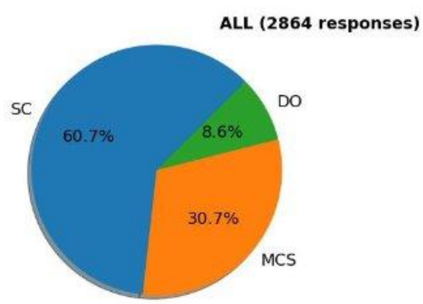

Figure 4. Subjective results of survey showing percentage by storm mode: supercell (SC, blue), MCS (orange), and disorganized (DO, green) for all cases.

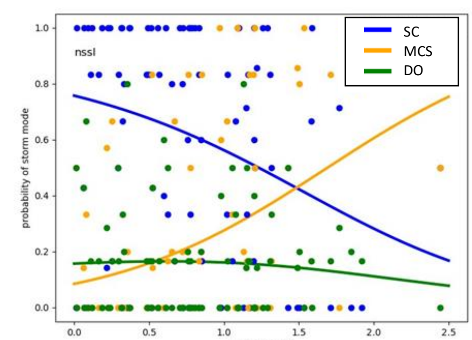

Figure 5. Scatter plot showing probability of storm mode (SC, blue; MCS, yellow; DO, green) for NSSL cases. Weighted linear regression curves represent correlation between UHS and storm mode probability.

regression method is invoked such that the sum of all storm mode probabilities equals 100% for a given UHS.

Scatter plots include only cases from the same ensemble member (not shown), and linear regression models are formulated to represent the correlation of storm mode probabilities and UHS values for each ensemble member (Fig. 6). For these scatter plots and associated regression curves, 80% of the survey data was used for a training set and 20% was saved for a test set. The trend in these plots, such that relatively low (high) UHS coincides with a relatively high probability for

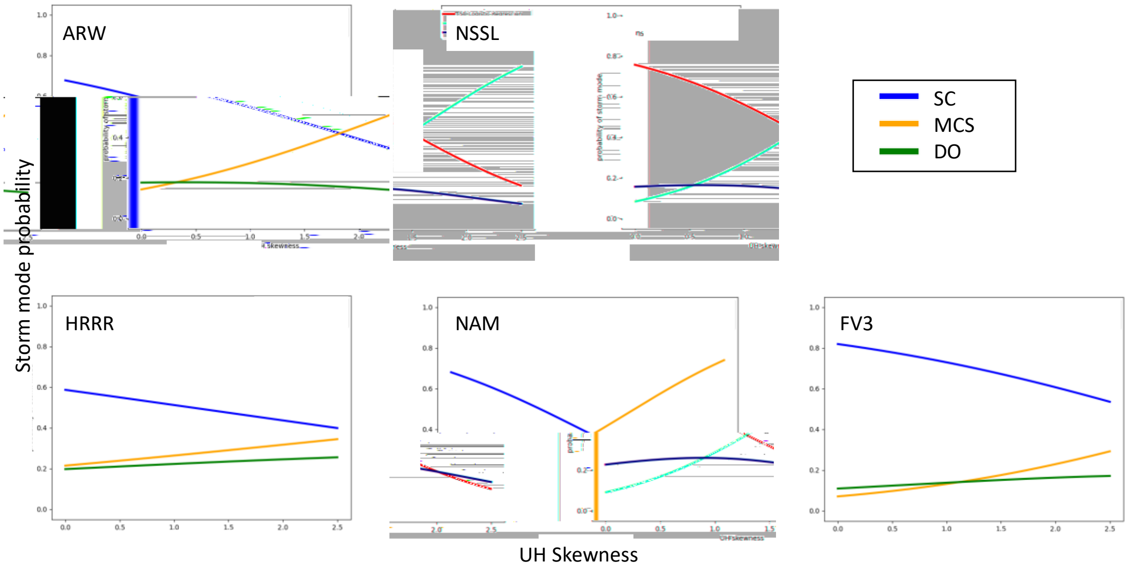

Figure 6. Linear regression model of storm mode probabilities by UHS. Storm mode indicated by color as given in the legend. Models trained separately by HREF ensemble member: ARW, NSSL, HRRR, NAM, and FV3.

the formation of supercells (MCSs), is evident in the regression models for NSSL, ARW, and NAM forecasts, but less so for the other two ensemble members. Storm mode probability is not as well differentiated by UHS for the HRRR and FV3 models, which both favor the formation of supercells over MCSs across the full range of represented UHS values.

3. Results

Figure 7 provides an example application of this UHS-based storm mode probability model. UHS values in the vicinity of the central circle range from 0.8 to 1.2, which according to the NSSL linear regression model, predicts a supercell probability between 55-65%, and an MCS probability between 20-30%. These results concur with the subjective (survey) results for which a higher percentage (43%) of survey responses classified this case as a supercell as compared to those classifying it as an MCS (14%).

To assess more broadly the performance of the five storm mode probability models (one for each HREF ensemble member) a Brier score and associated bias were calculated across a set of 124 test cases (Fig. 8a,b). The Brier score represents the average difference between

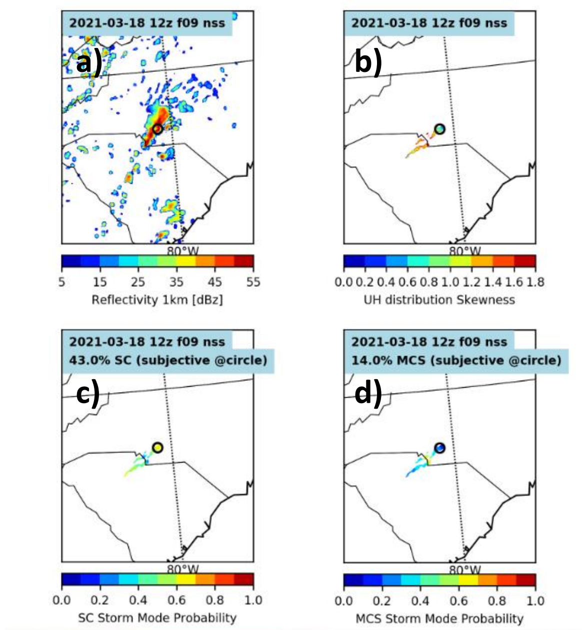

Figure 7. NSSL forecast initialized 3/18/21 @12 UTC, showing 1 km reflectivity (a) and UH (b) valid 3/19/21 @09 UTC. Linear regression model predicted probability of supercell (c) and MCS (d) represented by color bar.

objective (e.g. model predicted) and subjective (e.g. survey evaluated) storm mode probabilities. Lower Brier scores are better. The UHS approach performed nearly the same in predicting the supercells for all HREF members, except FV3, which consistently over-predicted supercells using this technique, and the NAM registered the lowest (near zero) bias. It could be argued that the UHS approach worked well in the ARW, NSSL, and NAM models for identifying MCSs given the relatively low Brier scores and very low biases.

To provide context and further evidence for the efficacy of these results, it is helpful to address the skill of these models as compared to climatology. These results were evaluated using a Brier Skill Score (BSS, Fig. 8c), for which a climatology was defined using the percentage occurrence of the three storm modes as defined by the survey for each of the ensemble members (Fig. 4). Higher BSS values are better. The ARW, NSSL, and NAM models all registered a skill higher using the UHS approach than climatology in the prediction of supercells and MCSs, with the UHS approach working best with the NAM model for supercells and NSSL model for MCSs. The FV3 model demonstrated no skill using this technique to identify convective mode, while the HRRR model registered only a slight skill using UHS for predicting supercells.

4. Summary

The efficacy of UHS to discriminate the mode of HREF simulated storms was investigated in this study. Using a relatively large (722) set of HREF forecasts of convective storms, the probabilities of storm mode (SC, MCS, and DO) were subjectively identified case by case through a survey, and UHS was calculated from the associated HREF forecast data. A linear regression model represented the relationship between UHS and storm mode probability. Storm mode models were created separately for each of the five HREF ensemble members. Results associated with ARW, NSSL, and NAM storm mode models generally concurred with the hypothesis that low (high) UHS corresponds to a higher probability of simulated supercells (MCSs). Their positive BSSs are evidence that this approach has some skill in determining storm mode with these three models. The FV3 and HRRR, however, did not show as strong of relationship between convective mode and UHS and their BSSs communicated little or no skill.

It is worth noting that the focus here is on the use of UHS alone to predict HREF storm mode. The intent, however, is not to consider UHS in lieu of other (object-based) approaches, such as the shape and eccentricity of the reflectivity field, but rather to propose UHS be considered as an additional gridded storm-attribute HREF field that could provide complementary and useful information in the diagnosis of convection mode.

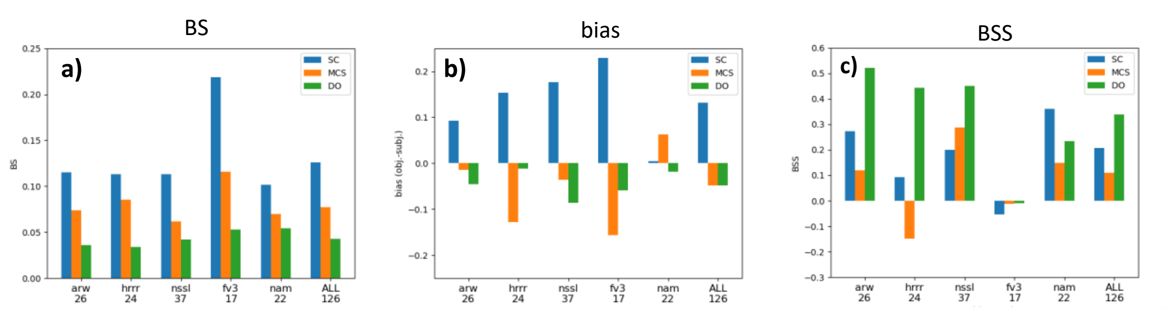

Figure 8. Based on 124 test cases, calculated Brier Score (a), bias (b), and Brier Skill Score (c). Results given separately for the UHS approach for predicting storm mode based on the five HREF ensemble forecasts: ARW, HRRR, NSSL, FV3, and NAM. The number of test cases used to evaluate each is listed along the x-axis below the associated HREF ensemble forecast name.

5. Acknowledgements

Funding provided by NOAA/Office of Oceanic and Atmospheric Research under NOAA-University of Oklahoma Cooperative Agreement #NA21OAR4320204, U.S. Dept. of Commerce. The statements, findings, conclusions, and recommendations are those of the author(s) and do not necessarily reflect the views of NOAA or the U.S. Department of Commerce.

6. References

Gallo, B. T., A. J. Clark, B. T. Smith, R. L. Thompson, I. Jirak, 2018: Blended probabilistic tornado forecasts: Combining climatological frequencies with NSSL-WRF ensemble forecasts. *Wea. Forecasting*, **33**, 443-459.

Gallus, W. A., N. A. Snook, and E. V. Johnson, 2008: Spring and summer severe weather reports over the Midwest as a function of convective mode: A preliminary study. *Wea. Forecasting*, **23**, 101–113.

Jahn, D. and I. Jirak, A. Wade, J. Milne, 2022: Storm mode and tornado potential determination using statistical moments of updraft helicity. 27th Conf. on Num. Wea. Pred, 23-27 Jan., Amer. Meteor. Soc., Houston.

Jahn, D. E., B. T. Gallo, C. Broyles, B. T. Smith, I. Jirak, J. Milne, 2020: Refining CAM-based tornado probability forecasts using storm-inflow and storm-attribute information. 26th Conf. on Numerical Weather Pred., Amer. Meteor. Soc., Boston.

Smith, B.T., R.L. Thompson, J.S. Grams, C. Broyles, and H.E. Brooks, 2012: Convective Modes for Significant Severe Thunderstorms in the Contiguous United States. Part I: Storm Classification and Climatology. *Wea. Forecasting*, **27**, 1114-1135.

Smith, B. T., R. L. Thompson, J. S. Grams, and C. Broyles, 2010: Convective modes associated with significant severe thunderstorms in the contiguous United States. 25th Conf. Severe Local Storms, Amer. Meteor. Soc., Denver.

Thompson, R.L., B.T. Smith, J.S. Grams, A.R. Dean, and C. Broyles, 2012: Convective modes for significant severe thunderstorms in the contiguous United States. Part II: Supercell and QLCS tornado environments. *Wea. Forecasting*. **27**, 1136-1154.