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Development of an automated approach for identifying convective storm type using reflectivity-derived and near-storm environment data

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ABSTRACT

Extending storm classification into a separation of convective storm types has applications to nowcasting, severe weather warning and quantitative precipitation estimation and forecasting. This work presents an exploration of an automated classification scheme that uses a combination of radar reflectivity products and near-storm environmental parameters derived from Rapid Update Cycle (RUC) model analyses to assign one of eight classes to each storm observed. An assessment is made of the classification accuracy, and it is found that the scheme that uses the combination of radar and model data outperforms the scheme that uses only radar products. This is particularly notable in the identification of storms that have rotation, and therefore improves the assessment of those storms' potential longevity and severe weather threat.

1. Introduction

Research into the classification of convective storms is motivated by the need to understand physical processes in severe weather environments, to improve quantitative precipitation estimates from radar, and nowcasting or short-range forecasting applications. Regardless of the application, there are a broad range of choices to be made in terms of object detection in the observed fields and the selection of near storm environmental variables when creating a classification process. This paper attempts to show the benefits of combining radar observations with Near-Storm Environment (NSE) information in order to produce a more accurate method of classification of storm types.

Recently, Lakshmanan et al. (2008, 2010) described a convective storm-type classification competition that used a broad dataset of storms classified using radar parameters extracted using the Warning Decision Support System — Integrated Information (WDSS-II: Lakshmanan et al., 2007). Storms were classified into four categories: supercell, linear, pulse, and unorganized. That competition used a large dataset of storms (Guillot et al., 2008) and an example of one of the successful storm discrimination schemes is assessed in Gagne et al. (2009). A number of classification methods, including decision trees, were tested and the main finding was that the choice of classification system is not critical when using just radar parameters and a limited number of general storm types. The work described here extends this concept to discover whether or not radar-based convective storm classification can be improved by the inclusion of mesoscale model data.

Storm identification and classification has been ongoing for decades as observational meteorology has been the crux for understanding atmospheric phenomena for the primary purpose of modeling future states of the atmosphere. An early study of classification of squall lines or Mesoscale Convective Systems (MCS) from Bluestein and Jain (1985) utilized radar reflectivity data combined with satellite observations of cloud extent. The observed classes of squall lines were then compared against representative soundings derived from National Weather Service (NWS) synoptic observations and rawinsonde data. The goal of this study was

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simple; to understand the physical differences between the squall line types. Fields such as Convective INhibition (CIN), Convective Available Potential Energy (CAPE), relative Helicity (H), the Bulk Richardson Number (BRN), boundary layer moisture, and squall line orientation compared with shear were used to distinguish the line types. Parker and Johnson (2000, 2004) extended the earlier work from Bluestein and Jain (1985) to break down the squall lines into MCS archetypes. Three main archetypes were introduced including the trailing stratiform, leading stratiform, and parallel stratiform MCS (Parker and Johnson, 2000). The motivation for this study was, again, to understand the physical environment of the MCS archetypes. The advances in modeling for this study allowed the authors to produce high resolution simulations and NSE parameters of the MCSs.

Although MCSs are responsible for a large portion of the significant damage by storms, numerous studies comparing radar and satellite observations to observed or numerically-derived NSE have focused on supercells. Primarily, research has focused on being able to predict not only general supercell formation given observations and modeled environments, but to determine what type of supercell to expect. One such study utilizing near-storm environment parameters in the case of supercells comes from Rasmussen and Blanchard (1998). That paper served as a baseline for supercell climatology and was based on over 6000 near-storm soundings. In addition to the parameters examined from Bluestein and Jain (1985), additional low-level thermodynamic parameters were examined as derived from the National Center for Atmospheric Research (NCAR) Mesoscale Model, version 5 (MM5). Parameters such as Storm-Relative Helicity (SRH), the Energy-Helicity Index (EHI) and the Vorticity Generation Parameter (VGP) were included in this study. In the Rasmussen and Blanchard (1998) study, it was found that although VGP and EHI were good discriminators between supercell types, especially the ordinary (non supercell) storm versus supercell instance, the false alarm rate is high when looking at these variables alone. Additionally, the BRN, CAPE, and CIN were shown not to be good discriminators of storm type in this study. Overall, the database of storms used, combined with the variables studied in that research, provided a practical outline for the need for multi-variable cell classification in some type of automated decision model.

When examining precipitation systems with radar, many different types of objects may be identified. The simplest distinction between types of precipitation objects is the separation of convective from stratiform precipitation areas. Such automated classification procedures have been developed and employed by hydrometeorological users (e.g. Biggerstaff and Listemaa, 2000). In applications such as this, the primary motivation for identifying cells as convective or stratiform has been to improve estimates of rainfall rate from radar. Baldwin et al. (2005) attempted to automate the process of classification using radar rain estimates combined with rain gauges using shape and structure characteristics. The Baldwin et al. (2005) methodology relies on a hierarchical framework of classes of rainfall. The first stage in the classification separates convective and stratiform rainfall class. Inherently, the convective storm class generally produces higher rainfall totals than the non-convective, or stratiform, type. The second stage of the classification procedure is to separate the linear types of storms from those that appear cellular in nature, using an arbitrary 3 to 1 rectangular fit to delineate linear systems from cellular systems. The work of Baldwin et al. (2005) clustered precipitation objects in a training data set of Stage 4 one-hour precipitation accumulation fields (the processed precipitation product used by River Forecast Centers in the US for hydrologic forecasting) and then assigned classes based on the intensity and shape of the rain region area. The Stage 4 data smoothes the rainfall fields to a 4-km resolution, and incorporates gauge data, but it is not suitable for a real time application. Both Biggerstaff and Listemaa (2000) and Baldwin et al. (2005) provided a framework for improving Quantitative Precipitation Forecasts in some way and can give insight into mesoscale processes, but the process of identifying specific types of convective cells remains unexplored.

Currently, there are a few methods that use US radar data for the identification and classification of storms. One such method devised by Stalker and Knupp (2002) utilizes multiple Doppler radars in order to achieve an estimate of vertical (updraft) velocity within convective cores of multicellular storms. This method relates the updraft strength with corresponding storm-top heights observed by radar in order to identify the stage and subsequent growth, decay, and merging of convective elements within a cluster of cells. An additional study by MacKeen et al. (1999) attempted to forecast storm longevity using radar reflectivity-derived quantities by examining growth and decay, which is an important aspect of nowcasting. The overarching conclusion of the study indicated that reflectivity-derived fields alone cannot be used to assess the potential of storm longevity.

These previous studies are used to inform the one reported here. In particular, some of the storm-type classifications follow previously published ones, and the selection of NSE parameters to use in the discrimination is informed by studies that have shown the value of these parameters. The benefits of including NSE variables along with radar-derived quantities will be illustrated. It should be noted that using model products means that there are a vast number of possible parameters that could be extracted and used, and the initial choice of which to extract, while necessary in practical terms, may overlook parameters that could warrant further examination. Overall, the goal of the research presented herein is to demonstrate a potential automated approach to classify convective echoes from radar imagery by using a combination of radar-derived variables from the WDSS-II system and NSE data produced by a relatively high resolution numerical model. This paper examines how critical it is to incorporate NSE data into the classification scheme and provides a framework for an automated convective storm-cell classification algorithm, which includes linear convective systems, supercells, pulse thunderstorms and non-severe/severe discrimination.

The identification and classification of storm cells in this framework are primarily aimed at adjusting life-cycle parameters in a nowcasting (0–2 hour forecast of reflectivity) framework. The underlying idea is that classifying a convective system and retaining information from prior time steps can lead to an understanding of growth, decay, and morphology of a particular storm. In particular this work is aimed at providing input parameters to constrain convective storm