P1.28 CHALLENGES IN COMPARING REALISTIC, HIGH-RESOLUTION SPATIAL FIELDS FROM CONVECTIVE-SCALE GRIDS

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1. INTRODUCTION

An outstanding problem in storm-scale numerical prediction is the determination of useful methods to compare high resolution spatial fields, such as comparing forecast and observations or multiple analyses resulting from an ensemble system. Recent development of meaningful, objective methods for comparing gridded, high-resolution forecasts that contain realistic detail to observations has focused primarily on ways of evaluating the "realism" of forecasts, following suggestions made by Anthes (1983). One such general method involves the comparison of measures related to the structure of detailed fields, such as Fourier power spectra (e.g., Skamarock 2004; Harris et al. 2001; Zepeda-Arce et al. 2000). Another potentially useful suggestion involves the comparison of characteristics of specific meteorological phenomena, often called the "object-oriented" approach (e.g. Ebert and McBride 2000; Nachamkin 2004; Case et al. 2004). Examination of the spatial distribution of errors along with their significance has also been considered (Elmore et al. 2005).

In this poster, several objective techniques will be applied to high-resolution, detailed meteorological fields. Two types of ensemble model forecasts/analyses were generated using data from the 8-9 May 2003 central plains tornado outbreak. First is an ensemble Kalman filter analysis and forecast using a 25 member ensemble covering the central plains. Six-hour, high resolution (2km horizontal resolution) forecasts are employed to explicitly predict the convective evolution. The high resolution runs are generated from an EnKF data assimilation of surface data using the MM5 model at 30 km resolution. Predicted and observed radar reflectivities and will be compared.

A second perspective analyzes the details of one individual storm. High resolution Doppler and reflectivity data from the NSSL KOUN data are used to create an EnKF analysis of the 8 May 2003 Oklahoma City (Moore) tornadic storm. An ensemble of 49 cloud model forecasts at 500m grid spacing are compared to a "verification" run. This verification array is obtained from a 1 km grid spacing run of the same cloud model, interpolated to 500 m (Fig. 1). This comparison will allow us to test a variety of procedures for comparing gridded forecasts and verification analyses at cloud-resolving grid spacings.

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2. OBJECT-ORIENTED VERIFICATION FRAMEWORK

In general, the framework for object-oriented verification consists of three basic steps: object identification, characterization, and comparison. To complete the first step in this process, specific meteorological phenomena must be located and identified using weather-related information. The object-identification process could be performed manually (e.g., Smith and Mullen 1993), although such a process would usually involve considerable time and labor. Automated procedures for identifying meteorological objects are necessary in order to perform long-term verification studies and obtain comprehensive information on forecast performance. Criteria for object identification must be established and documented so that results can be duplicated by other researchers. Such criteria will vary depending upon the phenomena of interest. Results will also be sensitive to the spatial and temporal scales that the meteorological data can resolve, data analysis techniques, etc. Routines for identifying objects should not be a function of both the observed and predicted fields, otherwise different objects will be defined for different forecast systems, making comparative verification infeasible. Examples of automated object-identification procedures that have been established in previous work include agglomerative cluster analysis methods (Lakshmanan et al. 2003; Peak and Tag 1994), as well as thresholding-type methods of identifying sea breeze fronts (Case et al 2004), Mistral wind storms (Nachamkin 2004), and contiguous rain areas (Ebert and McBride 2000). In this work, the meteorological phenomena of interest are supercell thunderstorms. An automated procedure for identifying precipitating weather systems was developed by Baldwin and Lakshmivarahan (2003). This automated procedure identifies rainfall systems as connected regions of precipitation through the use of image processing routines (Klette and Zamperoni 1996). The definition of connected regions is relaxed to allow systems that are situated very close together to be grouped as a single precipitation system. This procedure was used as the basis of an automated rainfall system classification procedure (Baldwin et al. 2005).

Once objects have been identified within the forecast and observed meteorological data, the characteristics of those objects must be extracted in order to provide a useful description of each object. Meteorological phenomena can be described by statistical characteristics, properties, or *attributes*. Ideally, one would select a set of attributes that can describe the most important and discriminating aspects of an event in a concise fashion. For example, the i^{th} forecast event could be described by an *attribute vector* of *m* dimension $\mathbf{f_i} = (\alpha_i, \beta_i, \ldots, x_i, y_i)^T$ where x_i, y_i are the attributes associated with the spatial location of this event (perhaps latitude and longitude), and α_i, β_i,..., are attributes that could be associated with the size, intensity, orientation, continuity, intermittancy, etc., of the event. Of course, observed events must be described with the same set of attributes, for example, the vector describing the j^{th} observed event would contain $\mathbf{o_j} = (\alpha_j, \beta_j, \ldots, x_j, y_j)^T$.

In order to measure the accuracy of the forecast and quantify the agreement between forecast and observed events, the similarity between these vectors can be measured. There are numerous possible choices of similarity/dissimilarity measures, for example, the correlation coefficient between $\mathbf{f_i}$ and $\mathbf{o_j}$ is an example of a *similarity* measure, since the higher the correlation coefficient is, the more similar $\mathbf{f_i}$ and $\mathbf{o_j}$ are. Once the similarity measure has been chosen, overall summary verification scores or accuracy measures could then be obtained. This approach to verifying events would be analogous to the "measures-oriented" approach to verification (Brooks and Doswell 1996). A more comprehensive analysis of the verification information could also be obtained by examination of the joint distribution of forecast and observed events, dubbed the "distributions-oriented" approach by Brooks and Doswell (1996). This could be considered an extension to the verification framework outlined by Murphy and Winkler (1987).

The current status and results from this ongoing research will be presented at the conference.

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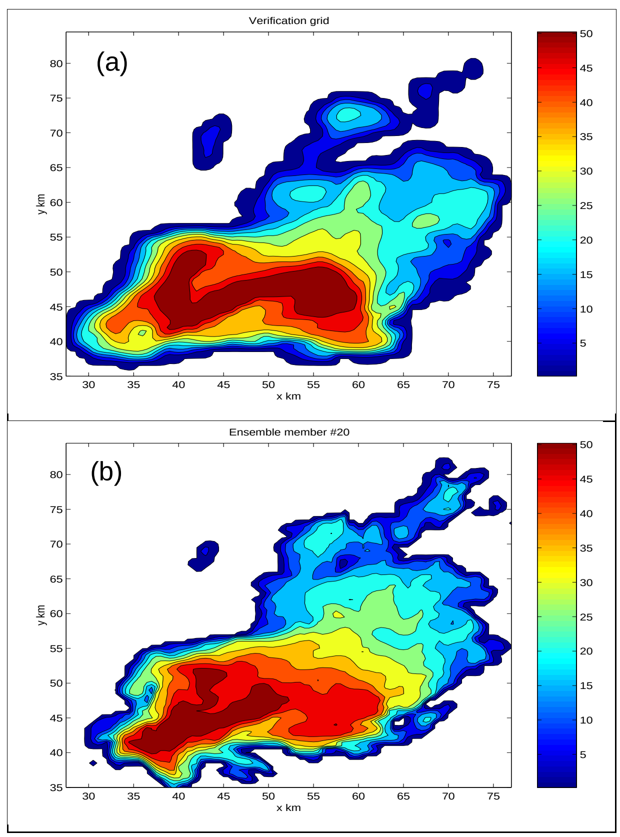

Figure 1: Verification grid (a) and a sample member #20 (b) of the 49 member cloud model ensemble. 10 min forecast of reflectivity (dbZ) 1km above ground, valid 2220 8 May 2003.