Object-based Verification of WRF Precipitation Forecasts

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1. Introduction

One of the downfalls of standard verification approaches is that they often do not provide results that are consistent with subjective perceptions of the quality of a forecast (Ebert 2003). While subjective verification in general cannot provide consistent and meaningful results for more than a handful of cases, it is desirable to mimic some attributes of human capability in determining the "goodness" of the forecasts. Thus, our approach objectively identifies "objects" in the forecast and observed fields that are relevant to a human observer. These objects can then be described geometrically, and relevant attributes of forecast and observed objects can be compared. These attributes include items such as location, shape, orientation, and size, depending on the user of the verification information.

Ebert and McBride (2000, hereafter EM) were among the first to explore defining and verifying rainfall using objects labeled contiguous rainfall areas (CRAs). Their method identified rainfall areas in both forecasts and observations, and it determined displacement errors and other parameters for matched regions. The accumulated statistics for errors in position could be constructed and biases, mean error, etc., computed.

Our methodology, loosely based on EM and described in Sec. 2, is used to evaluate precipitation forecasts from the Weather Research and Forecast (WRF) model (Michalakes et al. 2001). Herein we verify daily 36 h forecasts on a 4-km sub-CONUS grid covering the period May13 – July 9, 2003, roughly coincident with the Bow Echo and MCV Experiment (BAMEX, Davis et al. 2004). Human generated object-based verification of mesoscale convective systems produced by these forecasts can be found in Done et al. (2004).

We have chosen to use the NCEP Stage IV analysis as verification data. This analysis, which combines information from radar and gauge reports, is produced hourly in real-time on a 4-km CONUS grid. To compare with forecast precipitation, the Stage IV precipitation fields are interpolated to the model grid, preserving area average values of rainfall.

2. Identifying and Characterizing Rain Areas

i. Overview

Our verification approach, described in more detail by Brown et al. (2002), involves several steps. First, the data field is convolved with a disc. Convolution is tantamount to spatial smoothing. It simply replaces the

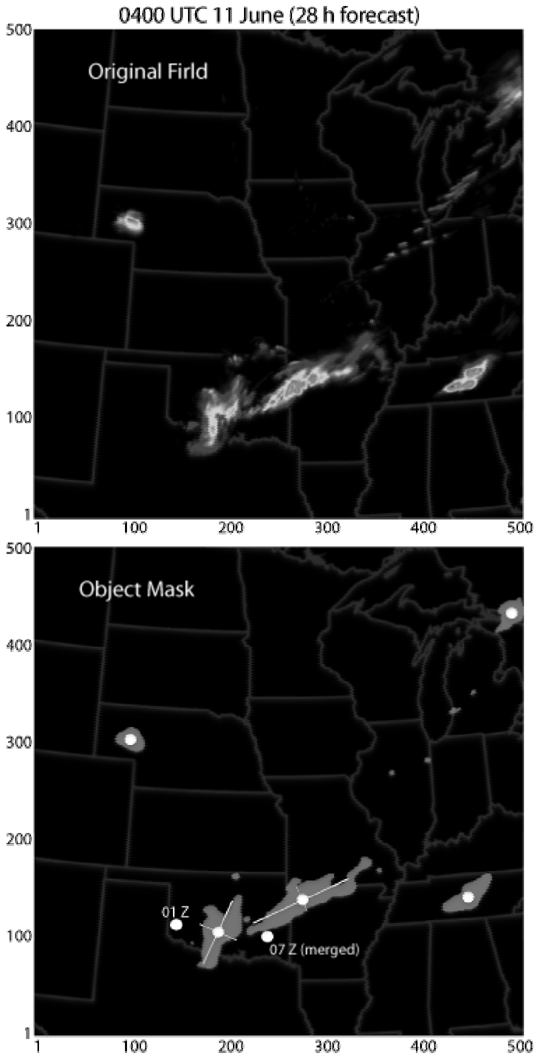

Figure 1. (a) WRF 1-hour accumulated rainfall valid 0400 UTC 11 June; (b) Convolved and thresholded field, with white dots indicating centroids of rainfall areas, and white line segments depicting axes of selected rainfall areas.

precipitation value at a point with its average over the area with a simple geometric shape (i.e. a disk) whose centroid is located at that point.

Second, the convolved field is thresholded. This allows object boundaries to be detected. Thresholding without convolving does not result in object boundaries that are similar to those a human would draw – many objects would be filled with holes of various sizes, and the boundaries would be more jagged than human-rendered outlines. Note however, that the original precipitation values are retained and their statistics within each patch can be examined.

Third, object properties are deduced. These include centroid location, area, major axis length, minor axis length orientation angle and moments of the rainfall intensity distribution. Figure 1 provides an example. The objects we consider in this study were restricted to those with attributes in accord with mesoscale convective systems. The 75^{th} percentile of hourly rainfall had to be above average (with respect to either forecast or observed averages), and the long axis of the area had to exceed 100 km. These criteria ruled out individual thunderstorms and mesoscale areas of lighter rain.

ii. Rain systems and matching

The time dimension is also a crucial component of convective system identification. Because the movement of rain areas is believed to be relatively independent of size, we use a fixed threshold of the distance separating two rain areas at an hourly interval to determine whether both are part of the same rain *system*. A rain system, defined as a collection of consecutively matched rain areas with a single data set, is the objective equivalent of an MCS.

A rain system is identified by its mean position, mean time, mean axis lengths, and duration. Matching is based on the duration of the forecast system being within a factor of two of the duration of the observed system, and the mean time being within 3 h of that observed. We consider three criteria for distance separation, D; $D < D_2$, $D < 2D_2$ and $D < 4D_2$.

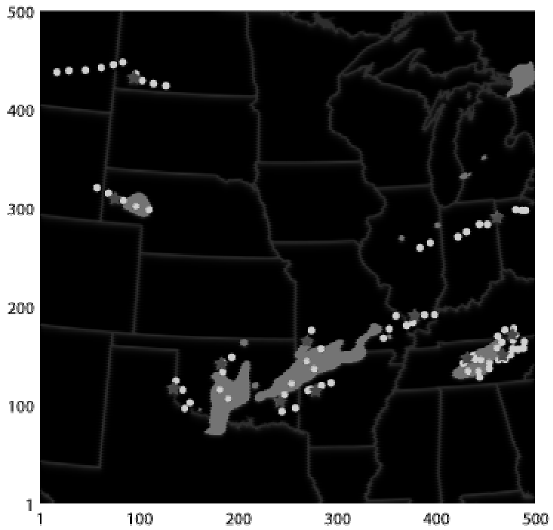

Figure 2. As in Fig. 1b, but with dots denoting all positions of rain areas from 1200 UTC 10 to 1200 UTC 11 June. Stars denote locations of rain systems.

3. Results

Before we consider matching, we examine the distribution of some rain system attributes in the forecast and observed data sets, respectively. In Fig. 3, we show distributions of two parameters, size, expressed as a cumulative size (number of systems x mean size x duration) as a function of duration. This corresponds to the total footprint of all systems. From Fig. 3a, it is apparent that WRF predicts too many long-lived rain areas and too few short-lived areas, although the integral of cumulative size over all durations is close to what is observed.

From Fig. 3b, it is clear that WRF has a positive intensity bias independent of duration. This means that the total rain production for long-lived systems exceeds what is observed.

Given a set of matched forecast and observed rain systems, we may compute statistics that describe the nature of the model errors. The spatial accuracy of WRF forecasts of rain systems can be assessed by computing the critical success index (CSI; Wilks 1995) for matching between forecasts and observations. That is, a match is a hit, a forecast rain system without an observational counterpart is a false alarm, and an observed system with no forecast counterpart is a miss. We do not attempt to estimate the successful null forecasts.

Figure 4a shows the CSI values for three criteria for minimum separation between rain systems. It is apparent that CSI increases for rain systems of greater duration. Note that the CSI values are roughly consistent with those obtained by Done et al. (2004) for manually evaluated, object-based forecasts of MCSs from the same datasets.

Timing errors can also be directly computed. Given that matching

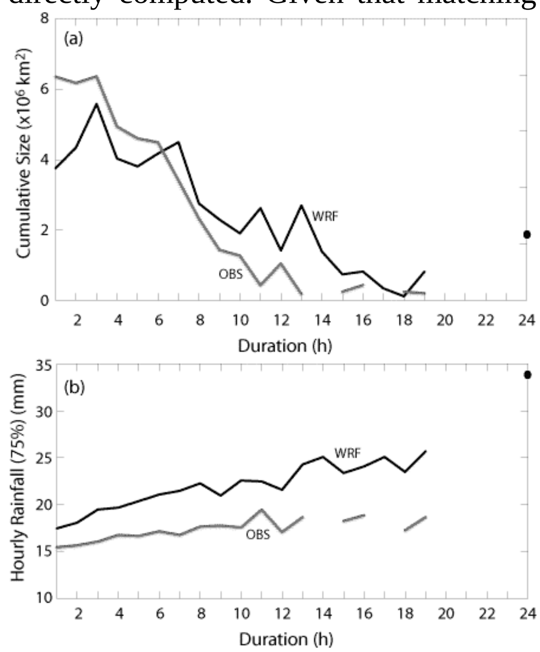

Figure 3. (a) Cumulative size (see text) versus duration; (b) value of 75^{th} percentile of rainfall distribution versus system duration.

requires the timing error to be less than three hours, these distributions are constrained. Nonetheless, there are systematic errors, most significant for shorter-lived systems. Roughly speaking, the mean time of WRF rain systems is an hour later than observed. For short-lived systems, this means that there is often a small temporal overlap between forecast and observed systems. This is consistent with the idea that short-lived systems are relatively less predictable.

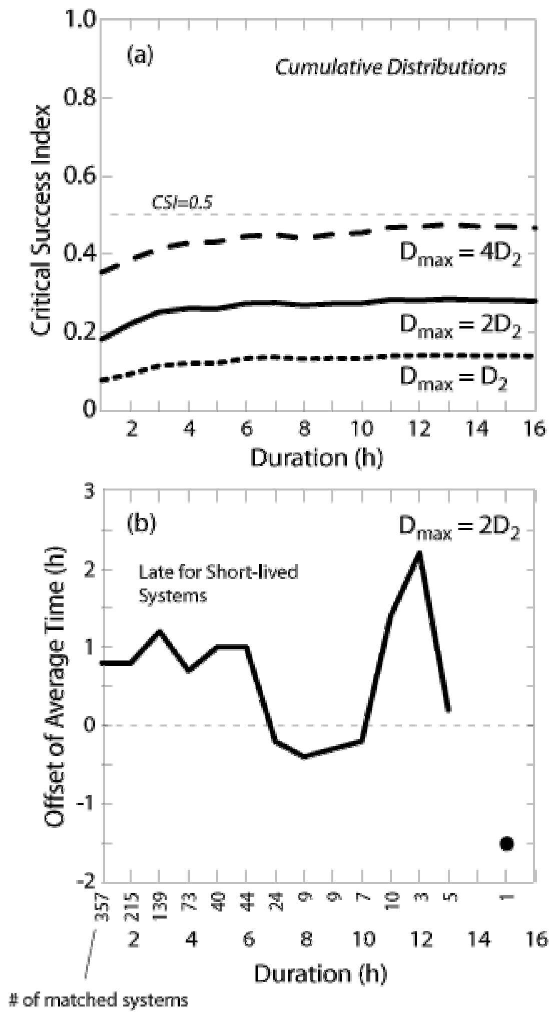

Figure 4. (a) CSI for matching forecast and observed rain areas; (b) Timing bias (h) (WRF – Obs)

4. Conclusions

We have developed an automated object-based verification technique for the evaluation of high resolution forecasts of precipitation, and, in principle, other variables. We have shown that the method produces results consistent with subjective evaluation. In particular, WRF forecasts of convective systems are shown to have positive biases in the intensity and longevity of rain systems.

5. References

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