1. INTRODUCTION

1.1. Motivation

The performance of quantitative precipitation forecasts (QPF) from numerical weather prediction (NWP) models has improved steadily in the decades since their widespread use began. However, NWP model QPF continues to lag in skill during the first several hours after model initialization, due largely to the “spin-up” problem of having to produce dynamically consistent vertical motion fields. Consequently, numerous authors (e.g., Doswell et al. 1986) have suggested that extrapolation-based nowcasting techniques have significant value relative to the counterpart NWP output. In addition, NWP models continue to exhibit difficulties in properly handling mesoscale precipitation features such as mesoscale convective systems (MCS’s). In response, numerous efforts have been undertaken to develop objective nowcasting techniques to improve forecaster QPF skill.

1.2. Nowcasting Studies at the Office of Research and Applications (ORA)

At the National Oceanic and Atmospheric Administration (NOAA) National Environmental Satellite, Data, and Information Service (NESDIS) Office of Research and Applications (ORA), significant research has been performed into the behavior of organized convective systems (e.g., Shi and Scofield 1987; Juying and Scofield 1989), and this work has in turn been applied by analysts at the NESDIS Satellite Analysis Branch (SAB) in producing satellite-derived nowcasts of rainfall. These nowcasts complemented estimates of rainfall produced by SAB analysts.

To provide guidance to SAB analysts and improve productivity, work has been performed at ORA to produce automated versions of the algorithms used at SAB for rainfall analysis and nowcasting. Since the automated estimates of rainfall form the basis for the nowcasts, the operational Hydro-Estimator (HE) algorithm will be briefly described before focusing on the nowcasting algorithm.

1.3. The Hydro-Estimator (HE)

The HE is a descendant of the Auto-Estimator (AE) algorithm developed by Vicente et al. (1998) to partially automate the SAB manual rainfall estimation technique (Scofield 1987). The HE was developed to correct for a number of weaknesses of the AE, including overestimation of the spatial coverage of rainfall due to incorrectly identifying cold cirrus clouds as raining (Scofield and Kuligowski 2003).

The HE begins by determining whether a pixel of interest is warmer or colder than its surroundings using the variable $Z = \frac{T - \mu_T}{\sigma_T}$ where $T$ is the pixel brightness temperature, $\mu_T$ is the mean value of $T$ in the surrounding cloud and $\sigma_T$ is the standard deviation of $T$ in the same region. Pixels with a positive value of $Z$ are colder than their surroundings and are assigned nonzero rainfall rates, based on the assumption that these clouds are above updrafts and thus are active. All other pixels are assumed not to be producing rainfall.

Once raining pixels have been identified, rainfall rate is based on a number of factors, including $T$ (higher rain rates for lower values of $T$, based on an exponential curve fit), NWP model precipitable water PW (higher rain rates for higher values of PW), and $Z$ (higher rain rates for higher values of $Z$). In addition, the value of $T$ is itself adjusted downward in regions where the NWP-derived convective equilibrium temperature is above 213 K—that is, in regions where $T$ values significantly below 213 K would not be expected from thermodynamic considerations. Such
regions can still contain strong updrafts and heavy rainfall, but will not exhibit the very cold cloud signatures typically associated with such rainfall.

Adjustments to these rain rate estimates are then made based on NWP-derived mean surface-to-700 hPa relative humidity (reduction of rainfall rates in dry regions), and on updrafts or downdrafts induced by topography (enhancement in regions where the horizontal wind incident on surface topography produces upward vertical motion; reduction in regions where downward motion results). This algorithm has shown some skill at fine-scale rainfall estimation (Scofield and Kuligowski 2003) and has significantly contributed to productivity gains among SAB forecasters (C. Kadin, SAB, personal communication).

1.4. The Hydro-Nowcaster (HN)

In addition to providing automated objective guidance for rainfall estimation, efforts are being made to provide companion guidance for 0-3 h nowcasts of rainfall. The HN algorithm focuses on two primary components of nowcasting of rainfall: motion of rain cells, and growth or decay of these cells.

The initial step in determining motion is to identify cloud clusters bounded by isotherms of brightness temperature. Two consecutive (typically 15 minutes apart) images are then compared to diagnose cluster motion. The 100x100-pixel regions centered on the cluster in the two images are shifted relative to one another until the Pearson correlation coefficient between the two is maximized, and this shift is assumed to be the cluster motion vector. These motion vectors are then used first to match clusters in consecutive images, and then to extrapolate the position of each cluster forward 3 hours in time.

The growth or decay of cells with time is based on the three characteristics of each cell:

- Change in size of the cloud cluster from one image to the next (an increase in size is associated with strengthening);
- Change in temperature of the coldest pixel in the cluster (a decrease in temperature is associated with strengthening);
- Change in average temperature of the cluster (a decrease in temperature is associated with strengthening).

The growth/decay factor is linearly reduced to zero over the 3-h nowcast period to avoid physically unreasonable results.

2. EXAMPLES OF INITIAL RESULTS

2.1. A mid-Atlantic Cold Front

On 4-5 September 2003, an active cold front passed through the mid-Atlantic region of the United States, triggering a SW-to-NE oriented line of rainfall with embedded convective cores. Figure 1 depicts an example of the 1- and 3-h nowcasts from the HN compared to the corresponding rainfall accumulations from the HE satellite estimates and the Stage IV radar/rain gauge products, the latter of which are taken to be “ground truth” in this case. The HN captures the essential spatial patterns as depicted in the analysis products; however, the HN does underestimate the spatial coverage of the light rain but overestimates the magnitude of the heaviest rain in North Carolina, especially for the 3-h nowcast.

![Figure 1. Comparison of the HN (nowcast), HE (satellite estimate), and Stage IV (radar/rain gauge field) for the 1-h (top) and 3-h (bottom) nowcasts beginning at 2100 UTC 4 September 2003 over the mid-Atlantic region of the U.S.](image-url)

Careful examination of this figure indicates that a significant amount of the error in these nowcasts is related to errors in the HE, such as the overestimation of rainfall in North Carolina.
2.2. Landfall of Hurricane Isabel

A second sample case is that of Hurricane Isabel, which made landfall in the mid-Atlantic region of the United States on 18 September 2003 as a Category 2 hurricane with 85-kt sustained winds. Figure 2 is an example of the 1-h and 3-h nowcasts for the post-landfall rainfall compared to the corresponding HE estimates and Stage IV rainfall accumulations. Although the Hydro-Nowcaster correctly predicts the magnitude of the heaviest rainfall, the spatial distribution of that rainfall is considerably in error. This is apparently because of the underlying assumption of linear cell motion in the HN, whereas in landfalling tropical systems the motion is cyclonic.

![Figure 2. Comparison of the HN (nowcast), HE (satellite estimate), and Stage IV (radar/rain gauge field) for the 1-h (top) and 3-h (bottom) nowcasts beginning at 2100 UTC 18 September 2003 over the mid-Atlantic region of the U.S.](image)

3. CURRENT AND PLANNED WORK

As shown in Fig. 1, the performance of the HN is significantly influenced by the performance of the HE rain rates upon which it is based. Consequently, the improvement has started with a recalibration of the HE to transition from the largely empirical relationships contained therein to relationships based on statistical analysis of the data from the recalibration period.

A second component of improving the HN is to modify the technique for strengthening or weakening cells with time. At present these relationships are also empirical (in part based upon techniques developed by operational forecasters) but are in the process of being objectively calibrated using multiple linear regression relationships on the test data. Results of this recalibration are not available as of the time of writing of this extended abstract.

An area for future improvement is the development of schemes to identify cyclonic or otherwise nonlinear motions and to apply appropriate extrapolation vectors that change with time and avoid creating misplaced rainfall such as that depicted in Fig. 2. Finally, efforts will be made to automate some of the empirical techniques described in Shi and Scofield (1987) and Xie and Scofield (1989) and incorporate them into the HN.

4. REFERENCES


Vicente, G. A., R. A. Scofield, and W. P. Menzel, 1998:


5. ACKNOWLEDGMENTS

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6. DISCLAIMER

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