

Brian J. Etherton*
University of North Carolina at Charlotte, Charlotte, NC

Leesa Brieger
Renaissance Computing Institute (RENCI), Chapel Hill, NC

1. INTRODUCTION

The numerical prediction of convective precipitation depends, to a great deal, on the physics of a forecast model. Additionally, initial conditions play a role in where convection will develop. Given the uncertainty inherent in prediction of precipitation, an ensemble approach is warranted.

Many regional ensemble forecast systems have been developed (Tracton *et al.*, 1998, Jones *et al.*, 2007; Eckel and Mass, 2005; Liu *et al.*, 2007, Xue *et al.*, 2007, Arnott *et al.*, 2007). The focus of our work is the use of an ensemble of convection resolving models to predict precipitation at a 4km resolution.

Mesoscale processes are, in part, influenced by synoptic circulations and by the physical processes such as air/surface fluxes, micro-physical processes within clouds, and boundary layer mixing. To accommodate the broad factors that control mesoscale weather forecasts, we constructed a 16-member ensemble of Weather Research and Forecasting (WRF, Michalakes *et al.*, 1998) model simulations was used for QPF for the Carolinas during the spring (May and June) of 2007. Ensemble members were split by: initialization time (00Z or 06Z), to account for uncertainty in the synoptic conditions, by PBL scheme (YSU or MYJ) to account for uncertainties in boundary layer moisture, by soil physics (Noah or MM5) to account for uncertainty in the air/surface exchanges of heat and moisture, and by moist physics (Lin or WSM) to account for uncertainty in precipitation processes.

2. ENSEMBLE CONSTRUCTION

The focus of the experiment was the prediction of precipitation at 4km resolution in an area centered over the Carolinas. Our ensemble consisted of 16 forecasts from the WRF model. We constructed a 16-member ensemble, each member having an outer (12-km) and inner (4-km) nest. We evaluated forecasts only on the inner domain. See Figure 1 for the area covered by our inner domain.

The 16 ensemble members were produced by having each member uses one of 2 options for four different parameters: initialization time, PBL scheme, moist physics, and soil physics. Table 1 shows the 16 different combinations used for each of the ensemble members.

* *Corresponding Author Address:* University of North Carolina at Charlotte, Department of Earth Sciences, Charlotte, NC 28223-0001; email: betherto@uncc.edu

FIGURE 1

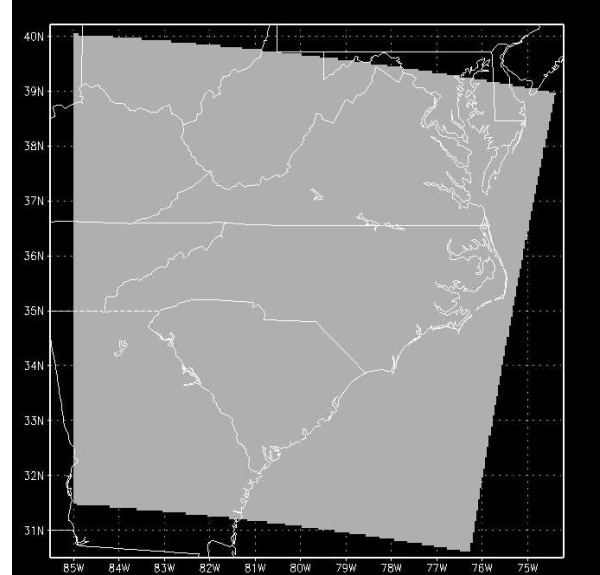


Figure 1. The inner domain for the WRF ensemble. The resolution of this domain is 4km.

TABLE 1

	INITIAL TIME	PBL SCHEME	MOIST PHYSICS	SOIL SCHEME
1	00Z	YSU	LIN	NOAH
2	00Z	MYJ	LIN	NOAH
3	00Z	YSU	WSM	NOAH
4	00Z	MYJ	WSM	NOAH
5	00Z	YSU	LIN	MM5
6	00Z	MYJ	LIN	MM5
7	00Z	YSU	WSM	MM5
8	00Z	MYJ	WSM	MM5
9	06Z	YSU	LIN	NOAH
10	06Z	MYJ	LIN	NOAH
11	06Z	YSU	WSM	NOAH
12	06Z	MYJ	WSM	NOAH
13	06Z	YSU	LIN	MM5
14	06Z	MYJ	LIN	MM5
15	06Z	YSU	WSM	MM5
16	06Z	MYJ	WSM	MM5

Table 1 – the construction of the 16 different WRF ensemble members.

The 16 ensemble members were run for 32 different days, at considerable computational expense (nearly 175,000 CPU hours). We thank the Open Science Grid (OSG) for donation of these computing resources to this study.

3. RESULTS

The results presented are from 16-member ensemble output from May 3rd, 2007 to May 23rd, 2007. This represents the data available at press time. In the presentation, an assessment of ensemble forecasts through mid-June will be presented.

(a) Ensemble Mean Forecasts

As a first measure of the skill of the ensemble to predict precipitation, simple equal weighting ensemble mean forecasts of precipitation were compared to stage 4 precipitation data. The comparison area was the domain of the inner nest of our ensemble members – shown in figure 1. Note that comparisons are for only the inner nest (4 km resolution) forecasts. For the comparisons, we only count those gridpoints where either the ensemble mean forecast or the stage-4 precipitation data totaled 0.01". Those gridboxes for which both the ensemble mean and the stage-4 data were zero were not included in the averaging.

When evaluating the ensemble mean forecasts, we bin members by initialization time, by boundary layer scheme, by moist physics scheme, and by land surface scheme. In essence, our 16-member ensemble is split into two 8-member ensembles using four different criteria. This leads to 8 00Z members and 8 06Z members, 8 YSU members and 8 MYJ members, and so on.

i. Precipitation in 3-hour increments

Evaluation of the ensemble mean precipitation forecasts shows that for the full 16-member ensemble as well as every 8-member sub-ensemble, there is an over prediction of precipitation. All members have a 'wet-bias'. There are, however, patterns to the biases. Results are shown in figure 2.

FIGURE 2

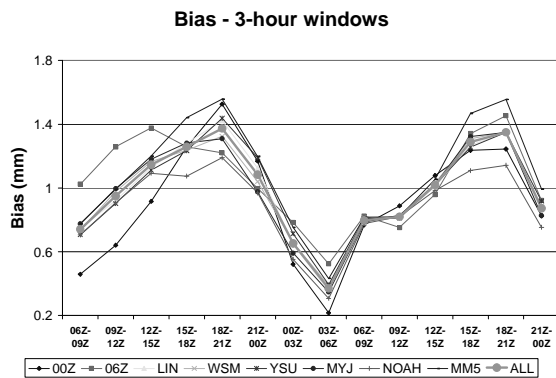


Figure 2. Bias in ensemble mean forecasts as compared to Stage-4 Precipitation Data. In addition to the mean of the full 16-member ensemble, ensemble members are stratified

by initialization time, boundary layer scheme, moist physics scheme, and land surface scheme. Values in millimeters.

In the first few hours of the forecast, the 00Z initialized members have a less pronounced bias, whereas the 06Z initialized members have a larger wet bias. The MM5 soil scheme members have a larger wet bias than the Noah soil scheme members – and most pronounced in the daytime hours. The Lin moist physics and MYJ boundary layer members produce a little more precipitation than their WSM and YSU counterparts.

ii. Precipitation for the entire forecast

In addition to calculating the bias, the mean squared error is also used to evaluate model skill. Results are shown in figure 3.

FIGURE 3

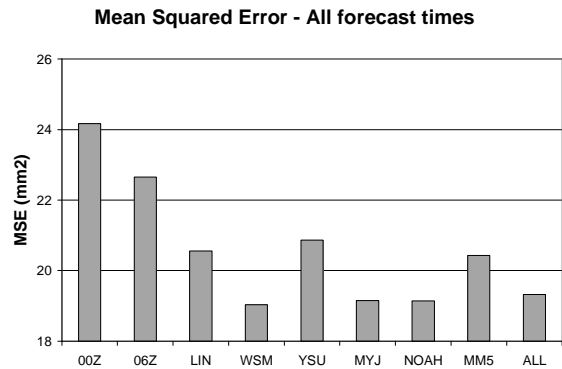


Figure 3. Mean squared error of all ensemble-mean forecasts at all forecast times. Values in millimeters squared.

If no bias correction is applied, the most accurate ensemble mean forecasts are from the 8-member ensemble using WSM for moist physics. Those using the MYJ boundary layer and those using the NOAH land surface scheme also fare slightly better than the mean forecasts from the full 16-member ensemble.

In contrast to varying the physics options, varying the initial conditions has a negative impact on ensemble mean forecasts. The mean of the 8 00Z members and the mean of the 8 06Z members has a greater mean squared error than the full 16-member ensemble.

(b) Probabilistic Forecasts

Probabilistic forecasts of precipitation were made by summing the number of forecasts for which precipitation forecasts exceeded a given amount. These forecasts were compared to the event occurring in the stage-4 precipitation data. Only gridpoints where either the precipitation value was at or above the threshold amount and the probabilistic

forecast was greater than zero were included. Gridpoints where there were neither predictions of more than 0% nor verified values of the threshold value were not included in the summary statistics.

i. Probability of 0.10" of precipitation in 3-hours

Figure 4 shows the average difference between the ensemble mean forecast (between 1/16 and 1) and the verified value (0 or 1) for the prediction of 0.10" of precipitation in a 3-hour period. Notice that the greatest number of forecasts occurs during the afternoon hours – consistent with the diurnal pattern of convection.

In addition to having a high bias in total amount of precipitation, the ensemble mean forecasts also have a high bias in the area coverage of precipitation – all forecast biases are positive. The patterns of bias are also consistent with the bias in total precipitation. The 06Z initialized members, which had a greater wet bias in total amount, also have a greater high bias in the predicted area of 0.10" or greater precipitation.

FIGURE 4

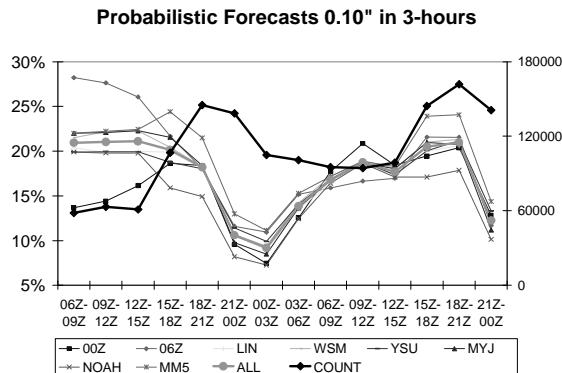


Figure 4. Mean squared error of all ensemble-mean forecasts at all forecast times. Values in millimeters squared.

ii. Probability of 1.00" of precipitation in 3-hours

Figure 5 shows the average difference between the ensemble mean forecast (between 1/16 and 1) and the verified value (0 or 1) for the prediction of 1.00" of precipitation in a 3-hour period. Notice that the number of forecasts is about 1/10th the number of 0.10" precipitation in 3-hours forecasts. Clearly, 1.00" of precipitation in a 3-hour period is a more rare occurrence than 0.10" of precipitation in 3-hours.

Again, the ensemble mean forecasts have a high bias in the area coverage of precipitation – all forecast biases are positive. The patterns of bias are also consistent with the bias in total precipitation. The 06Z initialized members, which had a greater wet bias in total amount, also have a greater high bias in the predicted area of 1.00" or greater precipitation. In

contrast to the prediction of total precipitation amount, or of area coverage of 0.10" in a 3-hour period, it was the full 16-member ensemble that gave the most accurate predictions of area coverage of 1.00" of precipitation in 3-hours – none of the 8-member 'sub-ensembles' fared better.

FIGURE 5

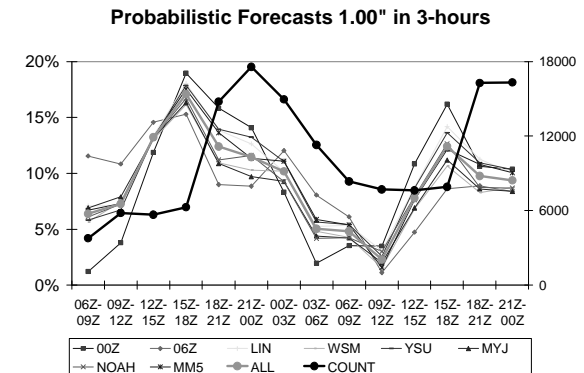


Figure 5. Mean squared error of all ensemble-mean forecasts at all forecast times. Values in millimeters squared.

4. CONCLUSIONS

A 16-member ensemble can provide useful guidance for the prediction of precipitation on small scales. Results give insights on how to best construct an ensemble for precipitation prediction. For instance, the mean of the 8 00Z members and the mean of the 8 06Z members both have a greater mean squared error than the full 16-member ensemble. The inference is that if one is going to construct an ensemble for high resolution QPF, the worst path to take is to have all members use the same initial conditions.

Improvement of the prediction where the precipitation will fall also impact the design of ensembles. For prediction of very high amounts of precipitation (1inch in a 3 hour period), the most accurate forecasts came from the full 16-member ensemble, though 8-member ensembles all using WSM moist physics (but varying initial conditions, land-surface scheme, and PBL-scheme) were nearly as accurate.

5. REFERENCES

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