

Raymond W. Arritt, Christopher J. Anderson and William A. Gallus, Jr.
Iowa State University, Ames, Iowa

1. INTRODUCTION

The past decade has seen increasing interest in ensemble methods for operational numerical weather prediction. Ensemble forecasting is motivated by the recognition that numerical predictions always contain uncertainties, so that it is desirable to use a range of plausible realizations when performing forecasts. Early implementations of ensemble methods focused mainly on uncertainties in the initial conditions. Recent studies have extended the ensemble approach to account for uncertainties in the model itself. These studies have shown the value in using ensembles constructed from realizations using either different models (e.g., Atger 1999) or different parameterization schemes in a given model (e.g., Stensrud et al. 1999, 2000).

Here we describe an approach to construct ensemble simulations that partially account for uncertainties in model formulation, using a workstation version of the NCEP Eta forecast model. This method constructs ensembles by performing simulations using different values of closure constants within parameterization schemes. This is a work in progress so that the present paper is intended as a description of the general approach along with plans for future development.

2. CONSTRUCTION OF ENSEMBLES

The version of the Eta model used in our study contains two options for the parameterization of deep convection. One is the Betts-Miller-Janjic (hereafter BMJ) scheme, which is a version of the scheme developed by Betts and Miller (1986) with revisions by Janjic (1994). This is the parameterization currently used in the operational Eta model at NCEP. The other option is the Kain and Fritsch (1990; hereafter KF) deep convection scheme. Comparisons of the BMJ and KF schemes have been given in previous studies (e.g., Stensrud et al. 2000).

At the present stage of development we have constructed ensembles by altering two parameters in the KF scheme. One parameter is the time scale for release of available buoyant energy, denoted τ . In the KF scheme this parameter controls the rate of adjustment of the resolvable-scale profile by deep convection. For a prognostic variable ϕ , the rate of adjustment is given by

$$\left. \frac{\partial \phi}{\partial t} \right|_{conv} = \frac{\phi_{adj} - \phi_0}{\tau} \quad (1)$$

where ϕ_0 and ϕ_{adj} are grid-point values before and after adjustment by deep convection, respectively. The second parameter varied in our study represents an enhancement to parcel buoyancy that depends on resolvable-scale vertical velocity, w . This enhancement T' is specified as

$$T' = aw^{1/3} \quad (2)$$

Convection is allowed to initiate (i.e., potential buoyant energy becomes available) if $T_p + T' + T'_{RH}$ at the lifting condensation level exceeds the environmental temperature, where T_p is the temperature of the rising parcel and T'_{RH} is a buoyancy adjustment that depends on relative humidity. In the standard version of the KF scheme the parameters discussed above take on the values $\tau = 1800$ s and $a = 4.64 \text{ K cm}^{-1/3} \text{ s}^{1/3}$.

We constructed ensembles by using three values for τ (1800, 3600, and 5400 s) and three values for a (0, 5, and $10 \text{ K cm}^{-1/3} \text{ s}^{1/3}$). The resulting 3x3 matrix of simulations has two possible uses. First, it allows us not only to test the sensitivity of model results to variations of each parameter, but to examine how the parameters *interact* with one another. This differs from the usual type of sensitivity study in which only one parameter is varied at a time. Second, the simulations can be used as a 9-member ensemble which may have added value compared to the control run.

3. RESULTS

Here we show an example precipitation prediction using the multidimensional ensemble approach. Our test case is 11 April 2001 in which lines of convection moved through the northern Great Plains and produced tornadic thunderstorms over Iowa. The Eta model was configured with a horizontal grid containing 199x121 points at a spacing of 32 km and 38 levels.

Predicted ensemble-mean precipitation is given in Figure 1. We find that member-to-member variations do not follow any strict pattern, implying that we have a true ensemble rather than a simple linear scaling of the reference forecast. Also, results from all members are physically plausible in that they show reasonable correspondence with observed precipitation (e.g., precipitation is not totally suppressed, or amplified to unrealistic values). In fact the ensemble spread, shown here as the standard deviation of predicted precipitation (Figure 2), is rather small. Member-to-member variations in precipitation are within about 10-20% of the ensemble mean. The small spread is reflected in the coefficient of variation (ratio of the ensemble standard deviation to the ensemble mean; Figure 3) which generally ranges 0.04-0.14.

4. SUMMARY AND DISCUSSION

We have described an approach for creating ensembles of short term forecasts using variations in a multidimensional parameter space, and have implemented the approach in a workstation version of the NCEP Eta model. Although results are encouraging in that we do not obtain a simple linear scaling, ensemble spread in the test case is rather small. The small spread may result from the parameters chosen to create the ensemble, or it may be influenced by the test case we used.

Examination of the KF scheme suggests possible reasons for the small spread in our ensemble. First, the KF scheme limits τ to the advective time scale; i.e., $\tau \leq \Delta x/U$ (where U is mean wind speed). As an example, for our grid spacing of 32 km, τ is limited to 3200 s if $U = 10 \text{ m s}^{-1}$, so that our values of $\tau = 3600 \text{ s}$ or 5400 s would not be reached. Second, once the buoyancy enhancement T' attains such a large value that convective inhibition is effectively irrelevant, further increases produce no change. Thus beyond some limit, larger values of a in equation (2) do not increase spread.

As a more thorough test we plan to run ensembles in a "quasi-operational" mode in which the ensemble is executed on a day-to-day basis though not necessarily in time for forecast use. We also will test implementations in which other closure parameters are varied in the KF scheme, as well as ensembles based on variations in the BMJ scheme or the explicit part of the moist physics parameterization. Updated results will be made available on our World Wide Web site, <http://www.mesoscale.iastate.edu>.

Acknowledgments. This research was sponsored by NSF grants ATM-9908932 and ATM-9911417, and by Iowa Agriculture and Home Economics Experiment Station project 3803, supported by Hatch Act and State of Iowa funds.

References

- Atger, F., 1999: The skill of ensemble prediction systems. *Mon. Wea. Rev.* 127, 1941-1953.
- Betts, A. K. and M. J. Miller, 1986: A new convective adjustment scheme. Part I: Observational and theoretical basis. *Quart. J. Roy. Meteor. Soc.* 112, 677-692.
- Janjic, Z. I., 1994: The step-mountain eta coordinate model: Further developments of the convection, viscous sublayer, and turbulence closure schemes. *Mon. Wea. Rev.* 122, 927-945.
- Kain, J. S., and J. M. Fritsch, 1990: A one-dimensional entraining/detraining plume model and its application in convective parameterization. *J. Atmos. Sci.* 47, 2784-2802.
- Stensrud, D.J., H.E. Brooks, J. Du, M.S. Tracton and E. Rogers, 1999: Using ensembles for short-range forecasting. *Mon. Wea. Rev.* 127, 433-446.
- Stensrud, D.J., J.-W. Bao and T.T. Warner, 2000: Using initial condition and model physics perturbations in short-range ensemble simulations of mesoscale convective systems. *Mon. Wea. Rev.* 128, 2077-2107.

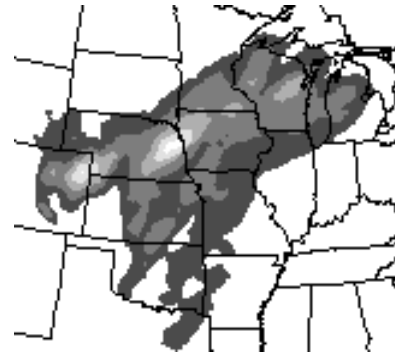


Figure 1: Ensemble mean 12-hour precipitation valid 18 UTC 11 April 2001. Shading interval is 10 mm.

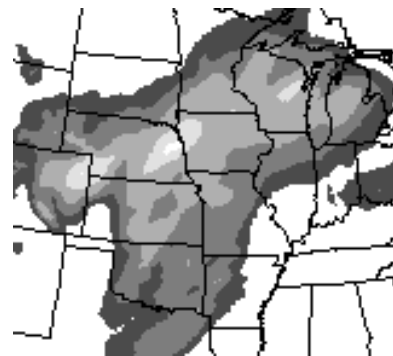


Figure 2: Standard deviation of ensemble precipitation corresponding to Figure 1. Shading interval is 0.5 mm.

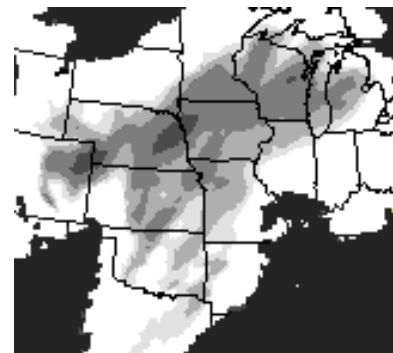


Figure 3: Coefficient of variation (ratio of standard deviation to mean) for ensemble precipitation corresponding to Figure 1. Shading ranges from 0.14 to 0.04 at intervals of 0.02. Note darker colors indicate lower values. Areas with zero mean (for which the coefficient of variation is undefined) are masked out.