2.2 PRELIMINARY RESULTS OF AN ENSEMBLE AIR QUALITY FORECAST SYSTEM OVER THE LOWER FRASER VALLEY, BRITISH COLUMBIA

Luca Delle Monache* and Roland B. Stull
University of British Columbia, Vancouver, British Columbia, Canada

1. INTRODUCTION

The ensemble-averaging approach is potentially a technique for improving the performance of real-time photochemical air-quality modeling. Ensemble photochemical air-quality forecasts will be tested extensively using the Community Multiscale Air Quality (CMAQ) model-system and the Emergency Weather Net (EmWxNet) and the Quality-Controlled AQ Data Set over the Lower Fraser Valley (LFV).

The main focus of this research is on improving the ability to forecast ozone concentration. The CMAQ aerosol module will become more important as improvements are made of the model-system ability to represent aerosol dynamics and chemistry. Therefore another goal is to quantify the ability of the ensemble approach to predict particulate matter (PM) concentration. The focus will be on $PM_{2.5}$ (particles with diameter equal or less than 2.5 μm) and PM_{10} (particles with diameter equal or less than 10 μm).

2. DISCUSSION

Ensemble weather forecasts have been extensively evaluated over the past decade, and have been found to provide better accuracy than any single numerical model run (Wobus and Kalnay 1995; Molteni et al. 1996; Du et al. 1997; Hamill and Colucci 1997; Toth and Kalnay 1997; Stensrud et al. 1998; Krishnamurti et al. 1999; Evans et al. 2000; Kalnay 2003). Different Numerical Weather Prediction (NWP) models usually perform better for different synoptic situations, and often their behavior cannot be anticipated. Hence, their combination into a multi-model ensemble is usually fruitful. NWP ensembles have been created with different inputs (Toth and Kalnay 1993; Molteni et al. 1996) (initial conditions ICs and/or boundary conditions BCs), different parameterizations within a single model (Stensrud et al. 1998) (physics packages, parameter values), different numerics within a single model (Thomas et al. 2002) (finite difference approximations and solvers, grid resolutions, compiler optimizations), and different models (Hou et al. 2001), trying to take into account different sources of uncertainties.

The ensemble technique can potentially yield similar benefits to air-quality (AQ) modeling, because there are similar code complexities and constraints (Delle Monache and Stull 2003). Different AQ models can be better for different air-pollution episodes, also in ways that cannot always be anticipated. For AQ, the ensemble-mean can be created similarly with different inputs (background concentrations, emissions inventories, meteorology), different parameterizations within a single model (chemistry mechanisms, rate constants, advection and dispersion packages), different numerics within a single model (finite difference approximations and solvers, grid resolutions, compiler optimizations), and different models (Delle Monache and Stull 2003). Given the nonlinear nature of photochemical reactions, the ensemble spread might be useful to account for the uncertainties associated with each component of the modeling process.

Preliminary results of an AQ ensemble forecast system will be presented. The system includes the Community Multiscale Air Quality Model (CMAQ), driven by the Fifth-Generation NCAR / Penn State Mesoscale Model (MM5), the Weather Research and Forecast model (WRF), and the Mesoscale Compressible Community Model (MC2). CMAQ is run with a resolution of 12 and 4 km. The spatial domain considered in the simulation includes the Lower Fraser Valley (LFV) of Southern British Columbia. In this region, the Emergency Weather Net (EmWxNet) meteorological data and the Quality-Controlled AQ Data Set (from

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* *Corresponding author address:* Luca Delle Monache, University of British Columbia, Dept. of Earth and Ocean Sciences, 6339 Stores Road, Vancouver, BC V6T 1N4, Canada; e-mail: lmonache@eos.ubc.ca.

Environment Canada and the Greater Vancouver Regional District) are provided each day for several locations, and include hourly time series of meteorology, ozone, and particulate matter (PM). This data set allows extensive testing, in a wide range of meteorological scenarios and air-pollution episodes.

Ideally the ensemble should be composed of state-of-the-art photochemical models that are run starting from the best possible emission scenario, as well as with the best possible meteorological fields. The meteorological fields can be indeed different for different photochemical models, since each of them is obtained differently (from different mesoscale models, and then different starting analyses, map projections, domain grids, etc.). Moreover, the different model formulations (the different advection and turbulence transport schemes and the different chemical mechanisms implemented in each model) should assure a good ensemble spread, which is desirable to define the likely bounds of possible pollutant-concentration fields. The uncertainty in each of those components should average out by the ensemble approach.

The ensemble tested in this study has some of those desirable features. For example, there are differences in the emission data of each ensemble member, partly because the hourly emission values (i.e., biogenic and mobile sources) depend on the meteorology that differs from one mesoscale model to another. These differences can take into account the uncertainty in the emissions estimate, which is often a factor of three or more, and which is the dominant limitation in the photochemical model performance (Russell and Dennis 2000). For the same reason, the different meteorological input fields from MM5, WRF and MC2 allow the ensemble to filter out some of the unpredictable components of the weather. Furthermore, different ensemble members run at different resolutions, which lead to different parcel trajectories, and this allows the ensemble to take into account the uncertainties related to the different but plausible choices of the grid location and resolution.

It would be interesting to also test the feasibility of an ensemble where each ensemble member is obtained starting from a perturbation of the emission base values. One possible approach, it's to replicate the successful experience that has already been done for weather forecasts by pertubating the ICs (Kalnay 2003). In this case each pertubated emission should belong at a subspace identified by a hyperellipsoid in a *n*-dimensional space, where *n* is the number of independent parameters needed to completely define the emission base values. This hyperellipsoid should have as its center the emission base values, and as the *n* semiaxes lengths the estimates of the uncertainties (i.e., variances) of the *n* independent parameters.

In the construction of such an ensemble the following are the main challenges that must be faced:

1) Define the *n* independent parameters that completely define the emissions values. That would possibly include total or speciated VOC, NO_x emissions values, the NO_2/NO_x ratio, or some important lumped class of aromatics as ARO2 (Jiang et al. 1997);

2) Find in the literature estimates of the different parameters uncertainties (Russell and Dennis 2000);

3) Define an optimal number of ensemble members, taking in consideration the computational burden limitation, and a minimum required benefit of the ensemble forecast.

Preliminary results with a small ensemble will be presented. This ensemble uses a single emission inventory, but is derived by two meteorological models (MC2 and MM5).

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