Multiscale Meteorological Modeling for Air Quality Modeling Applications

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Model Development and Diagnostic Testing

Environmental Issue

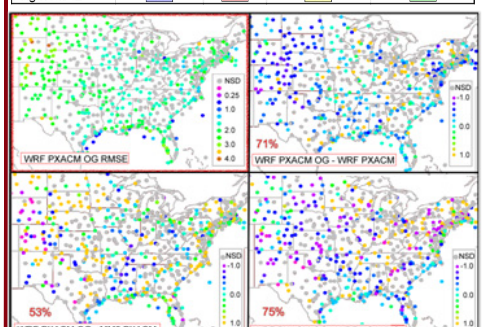
Air quality models require accurate representations of air flow and dispersion, cloud properties, radiative fluxes, temperature and humidity fields, boundary layer evolution and vertical mixing, and surface fluxes of both meteorological (heat, moisture, and momentum) and chemical species (dry deposition and evasion). Thus, meteorological models are key components of air quality modeling systems. However, the conditions under which the most severe air pollution episodes occur—subsidence inversions with light winds and clear skies—are not the prime foci of numerical weather model research and development. Hence, our efforts in meteorological model development and assessment do not duplicate model research programs but contribute to needed improvements in meteorological modeling systems for use in air quality modeling applications.

Research Objectives

The overarching objective of our improvements to meteorological modeling is to support air quality modeling by providing meteorology that is as accurate as possible. This top-tier objective has several specific research components, two of which are listed below.

- Challenge our established model run protocols as the state of science advances. This includes an examination of new models, physics options, and assimilation/nudging strategies to help reduce uncertainty of the meteorology.
- Contribute to the state-of-science of these models by developing improved physics, especially those that target retrospective simulations that are most often used in air quality applications.

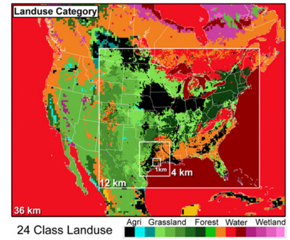
Best / Worst	WRF PXACM	MM5 PXACM	WRF NOAHYSU	WRF PXACM OG
2-m Temperature				
January RMSE	2.87	2.41	2.31	2.36
August RMSE	2.03	1.97	2.23	1.98
2-m Mixing Ratio				
January RMSE	1.00	0.90	0.86	0.97
August RMSE	1.90	1.88	2.16	1.83
10-m Wind Speed				
January RMSE	1.65	1.64	1.87	1.61
August RMSE	1.39	1.43	1.51	1.39
10-m Wind Dir				
January MAE	21	23	22	20
August MAE	30	32	31	29



Modeling Approach

Models: Two main models are being utilized to produce gridded meteorology over the United States for air quality applications. **MM5** (Grell et al., 1995) is a limited-area, nonhydrostatic, terrain-following sigma-coordinate model designed to simulate mesoscale atmospheric circulation on multiple scales. **WRF** (Skamarock et al., 2005) is the result of a multi-agency effort to develop the next-generation mesoscale model that is also nonhydrostatic, but designed to conserve mass and work well on a broader spectrum of applications that ranges from the global scale to large eddy simulations.

Model Configuration: Model domains for typical multiscale applications are shown on the right. The eastern US 12-km resolution grid is used for the MM5-to-WRF transition research and is the focus of the results presented here. Sensitivity experiments, various combinations of model physics options, data assimilation techniques, and sources of observed data have been examined. These factors have been used to determine the best configurations for air quality applications.

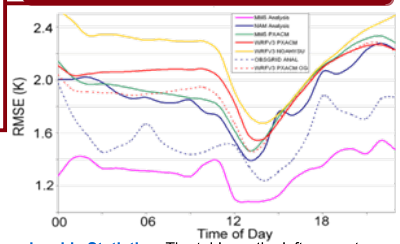


24 Class Landuse

RUN ID	LSM	PBL	Surface-layer	FDDA Analyses
WRF PXACM	PX	ACM2	Pleim	NAM 12km
WRF PXACM OG	PX	ACM2	Pleim	OBSGRID
MM5 PXACM	PX	ACM2	Pleim	RAWINDS
WRF NOAHYSU	NOAH	YSU	Monin-Obukhov	NAM 12km

LSM and PBL Physics: In-house development efforts have focused mainly on new LSM and PBL models. The above table lists the land-surface, PBL, and surface-layer configurations used to measure the performance of the Pleim-Xiu land-surface model (PX), Asymmetric Convective Model version 2 (ACM2) and the Pleim surface layer (Pleim) implementation in WRF. The table also shows the analyses used for the 3-D grid nudging and soil moisture and temperature nudging. Note that NAM 12km is the unmodified analyses from the National forecast model; OBSGRID and RAWINDS are re-analysis tools that are designed to lower the error of the NAM 12km analyses.

Results and Discussion



Domain-wide Statistics: The table on the left presents a summary of the error (RMSE) for January and August for each model configuration. The figure above shows the RMSE as a function of time of day for August.

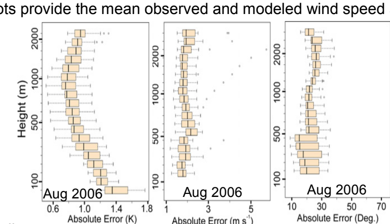
- The WRF PXACM OG has less overall error, considering all variables and both months, than the other simulations.
- The RMSE of the WRF PXACM simulation is reduced (WRF PXACM OG) when the OBSGRID analysis is used rather than the NAM analysis.

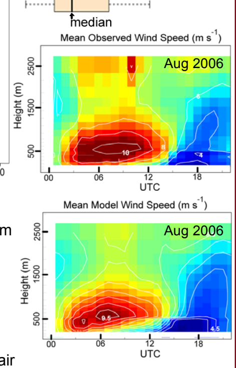
Spatial Statistics: The figures to the left present RMSE of 2-m temperature (top left) for the WRF PXACM OG simulation for August and the difference of RMSE with the other simulations being compared as indicated by the labels. Sites that are identified with a gray dot indicate no statistical difference (NSD) with the observations. The percentage indicated in each difference figure is the percentage of sites where the WRF PXACM OG has lower error.

- WRF PXACM OG has RMSE generally less than 2.0 K and at many sites there is no statistical difference from the observations.
- OBSGRID decreases 2-m temperature error at 71% of sites.
- WRF PXACM OG has lower overall error than MM5 PXACM (53%) and WRF NOAHYSU (75%).

Profile Statistics: Below are the box plot distributions of absolute error as a function of model vertical level for temperature (K), wind speed (m s^{-1}) and wind direction (degrees).

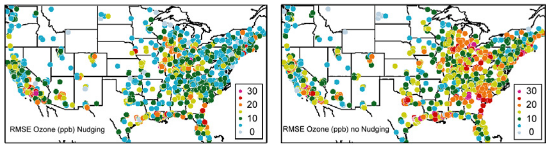
- Temperature is simulated with low error throughout the PBL. This error is close to the 2-m temperature error near the surface (~1.5 K), but much lower in the middle part of the PBL.
- Wind speed errors are between 1.0 and 2.0 m s^{-1} throughout the PBL, and wind direction errors are between 15 and 30 degrees, which is generally the same as at 10 m. Other plots provide the mean observed and modeled wind speed as a function of time of day.





Impact of Nudging on Ozone Estimates: The two figures below provide RMSE of 1-h ozone from CMAQ for a case (July 2001) that uses meteorology with and without nudging, and they demonstrate two important points:

- RMSE of the ozone predictions decrease significantly when FDDA is utilized (Otte, 2008).
- Improved meteorology leads to more accurate air quality simulations.



Conclusions

The transition from MM5 to WRF, which includes the implementation of the PX LSM, ACM2 PBL, and the Pleim surface-layer scheme, provides improved meteorology in terms of near surface error statistics. Although not shown in detail here, this improvement is generally maintained across variables and seasons. Also, our nudging strategies have proved to not only decrease the uncertainty of the meteorology, but also translate to more accurate air quality simulations.

Future Directions

- A large number of observations, mostly non-standard upper air observations will be added to the OBSGRID analyses used for nudging.
- The National Land Cover Dataset (NLCD) that provides higher resolution, more accurate, and more up-to-date land information, will be incorporated into the PX LSM and CMAQ's dry deposition model.
- Advanced data assimilation techniques, such as 3-d variational analysis, are being evaluated.
- Satellite data products from GOES, such as solar insolation, surface albedo, and skin temperature are being tested for use in WRF to improve representation of cloud and surface effects.

Impact

It has been shown that relatively small changes in meteorology model simulations can have large impacts on air quality model results. Reduction of errors and biases in key meteorological parameters leads to improved air quality model simulations for both assessment and emission reduction scenarios. Recognizing that the meteorological requirements for air quality application are different from the needs of the numerical weather prediction community, our efforts in meteorological model development and assessment are critically important for improved air quality modeling systems. Our work has established this group as a leader in the field of meteorological modeling for air quality applications.

Collaborators

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