A Clearer View of Tomorrow's Haze
Improvements in Air Quality Forecasting

A look at current approaches to air quality forecasting, as well as capabilities of air quality forecasting systems, enabling technologies, and future directions.

By Yongtao Hu, M. Talat Odman, Pius Lee, Daniel Tong, Scott Spak, and Armistead G. Russell

Yongtao Hu is a senior research scientist, **M. Talat Odman** is a principal research engineer, and **Armistead (Ted) G. Russell** is the Howard T. Tellepsen Chair and Regents' Professor, all with the School of Civil and Environmental Engineering at Georgia Institute of Technology; **Pius Lee** is the leader of the National Air Quality Forecasting Capability Project; **Daniel Tong** is an emission expert with Air Resources Laboratory at NOAA; and **Scott Spak** is an assistant professor of Urban and Regional Planning and Civil and Environmental Engineering, at the University of Iowa. E-mail: Armistead G. Russell, ted.russell@gatech.edu.

While most of us are quite used to seeing, and relying upon, detailed weather forecasts many days in advance, people who are sensitive to air pollution (e.g., asthmatics) and air quality managers likewise plan their activities depending on air quality forecasts. As with weather forecasts, the accuracy of air quality forecasts is important, as is how far in advance they can be supplied. If you are sensitive to air pollution, you may not want to plan an activity that will be curtailed (perhaps catastrophically so) due to unexpectedly poor air quality. Further, air quality managers rely on forecasts to potentially

The clearer picture satellite data provide makes it much more feasible to accurately forecast future air quality.

reduce emissions (e.g., "Spare the Air" alerts, http://sparetheair.org/) or alert the public to potentially harmful air quality, but they do not want to take potentially costly actions unnecessarily.

In response to the increasing demand, air quality forecasts are available, both from local agencies as well as nationally in many countries, and their accuracy and abilities are improving. Most recent forecasting systems have concentrated on forecasting either ozone (O_3) or particulate matter (PM, including $PM_{2.5}$, which is PM whose particles are less than 2.5 µm in diameter), criteria pollutants of widespread concern, though air quality forecasting systems have been developed for other pollutants. Advancing technologies are allowing forecasters to provide more accurate estimates of air quality days in advance. Of particular interest is the integrated use of advanced air quality models and satellite observations to provide air quality information and forecasts where the lack of ground-based observations hindered past efforts. The much clearer picture that satellite data provide about pollution (both pollutant concentrations and emissions) "right now" makes it much more feasible to accurately forecast future air quality.

Air Quality Forecasts

Probably the most widely known and utilized forecasts are those given by AIRNow (http://www.airnow.gov). AIRNow reports local forecasts made in about 300 U.S. cities. How the individual city AIRNow forecasts are done, and who does them, can differ, relying on trained forecasters with local expertise who can use a wide variety of methods, as described below. One of the primary pieces of information available to the local experts is the NOAA National Air Quality Forecasting Capability (NAQFC) forecasts for the continental United States,[1] which can be supplemented by other forecast methods and expert assessment. NAQFC forecasts are derived from an air quality modeling system similar to those used to develop state implementation plans,

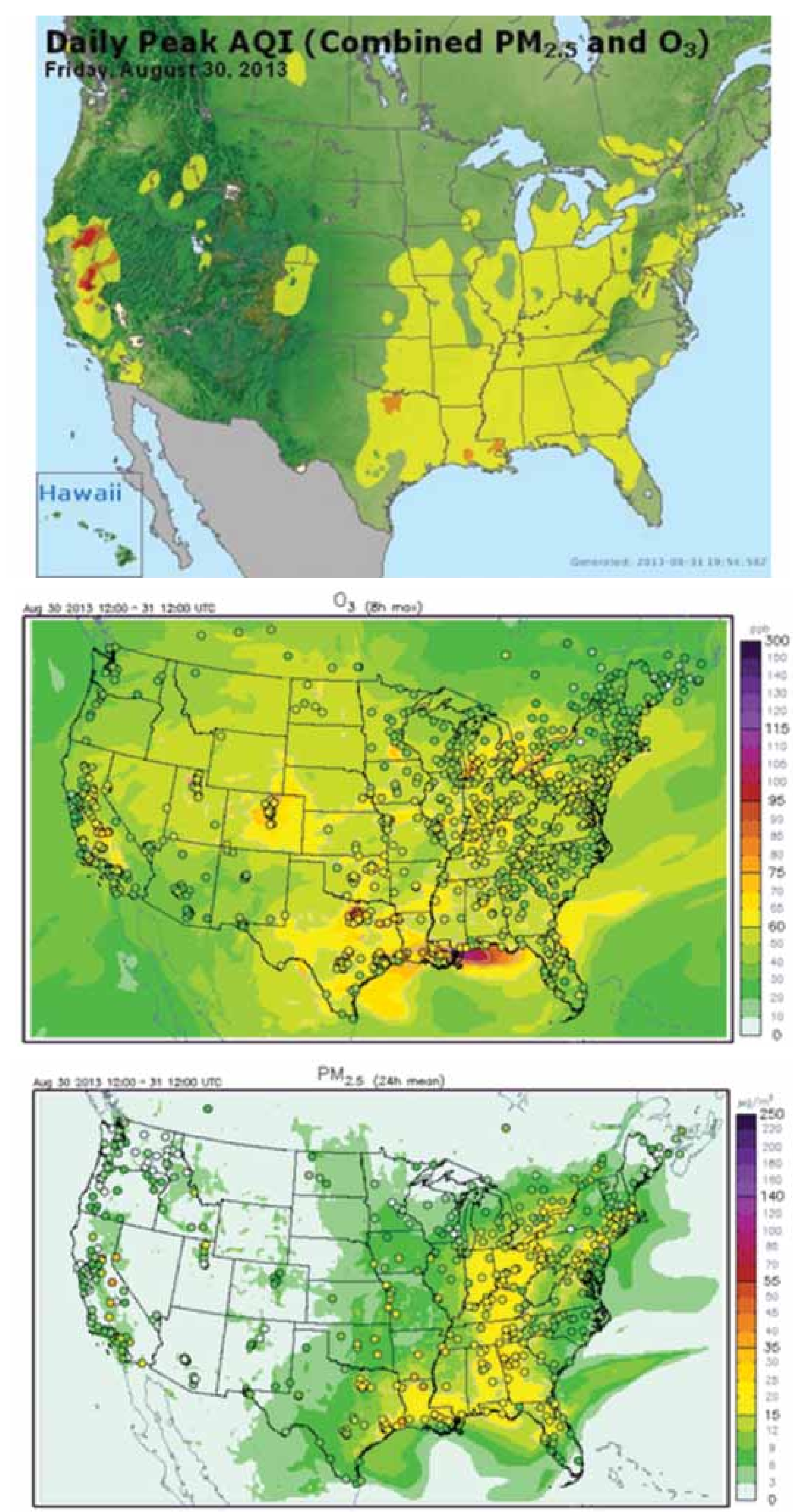

Figure 1. NAQFC and AIRNow Forecasts for August 30, 2013. (a) AIRNow AQI; (b) NAQFC O_3; and (c) NAQFC PM.
Forecast O_3 and PM concentrations are converted to the color scale associated with the health-informative AQI: (0–50 green; 51–100 yellow; 101–150 orange; and 151-200 red). The color-coded circles in the NAQFC forecast maps show the corresponding monitored values inserted afterward for evaluation purposes.

except that they are operated in a forecast mode (see Figure 1). As discussed below, the NAQFC, like many advanced systems, is benefiting from improving computational resources and greater and more rapid data availability, particularly from space.

Methods

Air quality forecasting can be based on empirical/statistical or air quality model-based (or simply "model-based") methods, or combinations of more than one method (ensembles). Empirical methods are based upon finding relationships (typically historical) between air quality and other factors relevant to the forecast location. Model-based methods use meteorological and air quality models.

Empirical

Empirical (or statistical) models are based upon past trends. They range in complexity from persistence to multivariate methods (including cluster analysis, classification and regression tree, regression and neural networks).[2] Persistence simply says that the tomorrow's air quality is the same as today's. Regression analysis is based on deriving an equation relating tomorrow's O_3 or PM to the current concentration, as well as other variables, such as forecast meteorology.[3] One of their main advantages is, once constructed, they are readily applied with low computational expense.

Model-Based

Air quality models are taking a growing role in air quality forecasting. Like their meteorological model cousins, their capabilities are growing as they become more comprehensive with greater fidelity to atmospheric processes, and as the rapid increase in computational resources enables them to improve their resolution and their ability to forecast further in to the future. Air quality model-based systems generally use forecast meteorology and historic emission estimates to provide forecasts. Such systems are based on dispersion models (like AERMOD[4]) for local forecasts of primary pollutants (e.g., soot from fires) and chemical transport models (CTMs) such as the Community Multiscale Air Quality (CMAQ) model[5] for regional forecasts of chemically-reacting pollutants such as O_3 and PM.

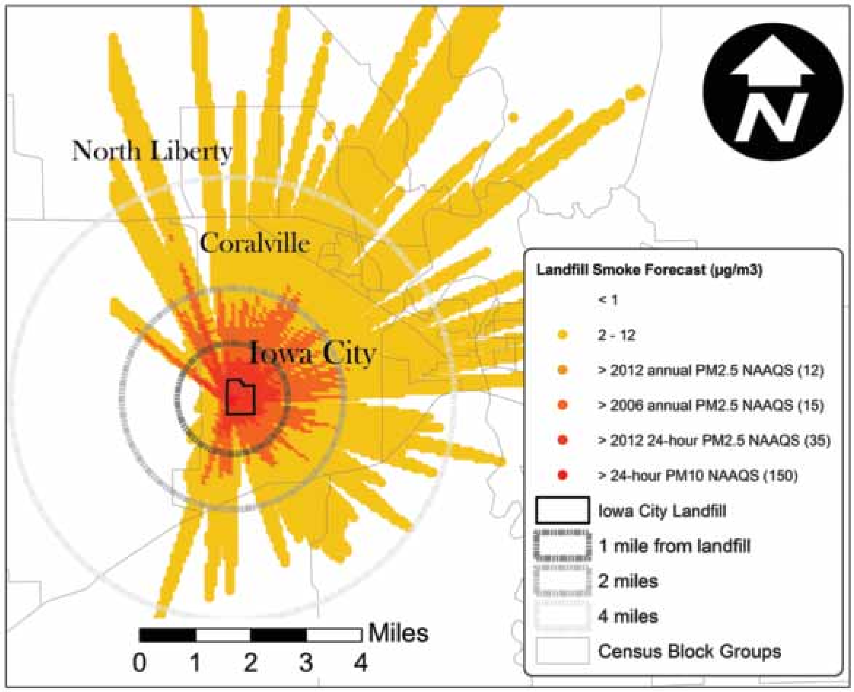

Figure 2. Iowa City Landfill Fire Air Quality Forecasting System.
The system is based on AERMOD, improvised to predict local impacts of the 2012 Iowa City Landfill fire at 100 m resolution over the Iowa City/Coralville metropolitan area. Plume color-coded by NAAQS for particulates exceeded due to the fire during the two-week event: none (yellow), annual $PM_{2.5}$ (orange), 24-hr $PM_{2.5}$ (red), and 24-hr PM_{10} (dark red). Grey concentric circles indicate 1-, 2-, and 4-mile buffers from the fire.

The NOAA NAQFC provides what is probably the most widely utilized CTM-based forecast in the United States. This system takes advantage of using the U.S. National Weather Service meteorological predictions[6] as input to CMAQ. Europe employs the European Centre for Medium-Range Weather Forecasts (ECMWF) weather forecasting model to drive their Copernicus forecasting system, using a global model to provide boundary conditions to regional models.[7] Other air quality model-based forecasting systems include the "Hi-Res" system (using CMAQ down to a 4-km horizontal resolution over the Southeast United States),[8] Airpact (4-km resolution for the Northwest United States; http://lar.wsu.edu/airpact), and the BAMS MAQSIP-RT system.[9] While these forecasting systems largely began by providing O_3 forecasts, there is a growing trend toward providing $PM_{2.5}$ forecasts as well.

A major advantage of model-based systems is that they provide predicted air quality over the complete domain and map out where pollutant hotspots will likely occur. This is important when conducting field experiments to plan when and where to sample (e.g., when planning aircraft sampling to capture plumes from cities and major sources).[10,11] Model-based forecasts are also used for cases where there are insufficient historical data to develop an accurate empirical system (e.g., when forecasting the impacts of fires, either planned or unplanned.)[12] Such forecasting systems can be developed rapidly in response to emergency situations. In 2012, when the Iowa City landfill caught fire with the liner of 1.5 millions shredded tires generating a thick toxic plume that raised immediate health concerns, a forecasting system was rapidly applied to forecast the plume impacts (see Figure 2), using AERMOD dispersion modeling driven by a weather forecast model and assimilated MODIS cloud properties.

Ensemble

Most of us are quite used to seeing forecasts of hurricane paths where different tracks calculated by different models are shown. The calculated tracks diverge with time, providing an "ensemble" estimate of the path, with a range of possibilities, plus a best estimate. The ensemble is not just a regular average because modelers know from experience some models do better than others. The same is done in air quality forecasting (and for weather forecasts as well). Results from multiple models are combined, with increased weight given to approaches that are found to be most accurate for that type of event (i.e., one method might be better for high pollutant days, another for low pollutant days). For example, the GSFC/PSU-ERM (Ensemble Research Model) uses forecast parameters that are sampled, combined and "trained" by using observations in near-real time.[11] The ECMWF-Copernicus system uses an ensemble of seven regional CTMs.[7]

Expert

Any one, or more, of the methods discussed above can be used to inform one or more experts that then provide a forecast based on the information provided, but adding human interpretation (often based upon years of involvement and knowledge of pollutant dynamics in a specific location, as well as knowledge of the strengths and weakness of other forecasting methods). As an example, the PM and O_3 forecasts developed for cities in Georgia by the Georgia Environmental Protection Division (EPD) use an expert panel approach. This effort began in 1996 for the Atlanta Olympics, and involved a model-based system and empirical methods to inform an expert team that links together on a daily basis to develop a final forecast by consensus.[8]

Forecast System Performance

The utility of air quality forecasts is highly dependent upon their accuracy. For the typical systems designed to provide routine O_3, and more recently $PM_{2.5}$, forecasts, the results are solid, showing that while there are still improvements to be made, reasonably accurate information can be provided to air quality planners and the public. The Hi-Res system[7] provides both PM and O_3 forecasts,

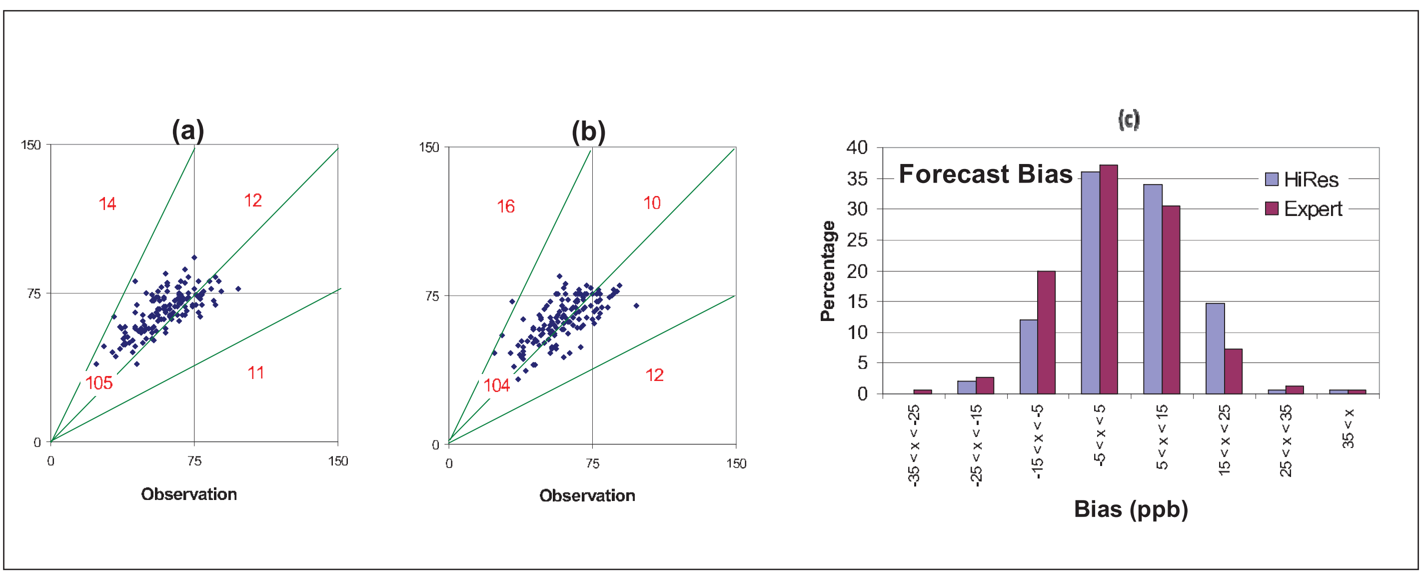

Figure 3. Performance of Model and Expert Consensus Approaches.
(a) HiRes modeled daily maximum 8-hr O_3 forecasts for the 2010 summer season compared to the (b) EPD expert analysis consensus. The (c) forecast bias frequency plots for the HiRes and expert systems show similar distributions. The mean normalized bias (MNB) and mean normalized error (MNE) for the model forecast were 14% and 18%, respectively, compared to 9% and 17% for the consensus. Modeling guidelines suggest that having an MNB and MNE of 20% and 35% are sufficient when simulating past periods, showing the forecasts now meet guidelines for conducting historic simulations.

and is a primary component of the Georgia EPD expert-analysis based forecast. The performance of the Hi-Res O_3 forecast and the expert team consensus are close (see Figure 3).

Looking Forward

While forecasting systems already provide credible forecasts days in advance, their ability to make accurate extended range forecasts is being enhanced by the NASA Air Quality Applied Sciences Team (AQAST) addressing current weaknesses. One key to making an accurate forecast, be it for tomorrow or three days from now, is having an accurate representation of today's air quality, not only locally, but wherever the air masses come from. However, it is unlikely that there are monitors at those locations (most air masses come from layers well above the surface where monitors don't exist at all). AQAST teams have demonstrated the use of satellite data to provide better spatial and temporal information to improve forecast accuracy. The ECMWF system uses satellite observations in the global model.

Another step forward addresses a second weakness: current model-based forecast systems use historic emissions inventories that are not fully up to date nor capture shorter term emission trends. Using ground- and satellite-based measurements, it is possible to dynamically update emission inventories using chemical data assimilation.[13] This can be particularly important for sources that can vary dramatically, such as biogenic emissions, biomass burning (e.g., wildfires, prescribed burns and home heating), and dust.

Forecast energy demand can also be used to forecast related emissions,[14] which can be particularly important when peaking units, that have higher emissions, are used on hot summer days. The ability to forecast how specific sources (say, cars or a specific facility) will impact O_3 and PM nationally is being explored to help target controls. Improving forecast accuracy and increased forecast system capabilities will become even more important if air quality standards are tightened as more areas will seek to use this information to more effectively improve air quality. **em**

AKNOWLEDGMENT

The research described in this article was made possible, in part, by funding from the U.S. National Aeronautics and Space Administration and the Georgia Department of Natural Resources. Any opinions expressed are those of the authors and not the funding agencies.

References

1. Lee, P.; Byun, D.; Stein, A.; Tang, Y.-H.; Lin, H.-M.; Huang, H.-C.; Lu, S.; Tsidulko, M.; McQueen, J.; Tong, D.; Yu, S.; Chai, T.; Kim, D.; Stajner, I.; Davidson, P. Effect of Temporal Averaging of Vertical Eddy Diffusivity on the Forecast Quality of Surface Ozone Concentration of the National Air Quality Forecast. In *Air Pollution Modeling and Its Application XX*; D.G. Steyn; S.T. Rao, Eds.; Springer, Netherlands, 2010; pp. 295-302.
2. *Guidelines for Developing an Air Quality (Ozone and $PM_{2.5}$) Forecasting Program*; U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, 2003.
3. Hadjiiski, L.; Hopke, P.K. Application of Artificial Neural Networks to Modeling and Prediction of Ambient Ozone Concentrations; *J. Air Waste Manage. Assoc.* **1995**, *50* (5), 894-901.
4. *AERMOD: Description of Model Formulation*; A-454/R-03-004; U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, 2004.
5. Byun, D.W.; Lee, D.-G.; Kim, H.-C.; Kim, S.; Ngan, F.; Czader, B.; Rappenglueck, B.; Kondragunta, S.; Pierce, B. Efficacy of Incremental Reduction of Input Uncertainties to Improve Air Quality Prediction. In *Air Pollution Modeling and Its Application XXI*; D.G. Steyn; S.T. Castelli, Eds.; Springer, Netherlands, 2012; pp. 341-346; doi: 10.1007/978-94-007-1359-8_64.
6. Stajner, I.; Davidson, P.; Byun, D.; McQueen, J.; Draxler, R.; Dickerson, P.; Meagher, J. U.S. National Air Quality Forecast Capability: Expanding Coverage to Include Particulate Matter. In *Air Pollution Modeling and Its Application XXI*; D.G. Steyn; S.T. Castelli, Eds.; Springer, Netherlands, 2012; pp. 379-384; doi: 10.1007/978-94-007-1359-8_64.
7. Flemming, J.; Peuch, V.-H.; Engelen, R.; Kaiser, J.W. A European Global-to-Regional Air Pollution Forecasting System that Combines Modeling with Satellite Observations; *EM*, November 2013, pp. 6-10.
8. Odman, M.T.; Hu, Y.; Russell, A.G.; Chang, M.E. Forecasting Ozone and $PM_{2.5}$ in Southeastern U.S. In *Air Pollution Modeling and its Application XVIII*; C. Borrego; E. Renner, Eds.; Elsevier, Amsterdam, 2007; pp. 220-229.
9. McHenry, J.N.; Ryan, W.F.; Seaman, N.L.; Coats Jr., C.J.; Pudykeiwicz, J.; Arunachalam, S.; Vukovich, J.M. A Real-Time Eulerian Photochemical Model Forecast System: Overview and Initial Ozone Forecast Performance in the N.E. U.S. Corridor; *Bull. Amer. Meteor. Soc.* **2004**, *85* (4), 525-548.
10. McKeen, S., et al. An Evaluation of Real-Time Air Quality Forecasts and Their Urban Emissions Over Eastern Texas during the Summer of 2006 Second Texas Air Quality Study Field Study; *J. Geophys. Res.-Atmos.* **2009**, *114* (D00F11); doi:10.1029/2008JD011697.
11. Garner, G.G.; Thompson, A.M.; Lee, P.; Martins, D.K. Evaluation of Numerical Air Quality Performance in Forecasting Near-Surface Ozone during the 2011 DISCOVER-AQ Campaign; *J. Atmos. Chem.* **2013** (published online); doi: 10.1007/s10874-013-9251-z, 2013.
12. Odman, M.T.; Hu, Y.; Garcia-Menendez, F.; Davis, A.; Russell, A.G. Fires and Air Quality Forecasts: Past, Present, and Future; *EM*, November 2013, pp. 12-21.
13. Garner, G.G.; Thompson, A.M. Ensemble Statistical Post-Processing of the National Air Quality Forecast Capability: Enhancing Ozone Forecasts in Baltimore, Maryland; *Atmos. Environ.* **2013**, *81*, 517-522.
14. Yun, J.; Doraiswamy, P.; Hogrefe, C.; Zalewsky, E.; Hao, W.; Ku, J.Y.; Beauharnois, M.; Demerjian, K.L. Developing Real-Time Emissions Estimates for Enhanced Air Quality Forecasting; *EM*, November 2013, pp. 22-27.