AQMOS: AIR QUALITY MODEL OUTPUT STATISTICS FROM CMAQ MODEL FORECASTS

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1. INTRODUCTION

Air quality forecasters routinely use numerical air quality models for forecast guidance when issuing local ozone and $PM_{2.5}$ forecasts. Modeling systems used by forecasters include the operational National Oceanic and Atmospheric Administration (NOAA) National Air Quality Forecast Capability (NAQFC) (Otte et al., 2005), as well as the experimental U.S. Department of Agriculture (USDA) Forest Service BlueSky Gateway modeling system (Craig et al., 2007), which are both based on the Community Multiscale Air Quality (CMAQ) model (Byun and Schere, 2006). These modeling systems provide useful regional information, but they are still evolving and their site-specific forecasts could be improved.

Numerous studies have demonstrated the benefit of adjusting site-specific air quality model predictions using observational data to reduce systematic model error (bias) in surface ozone predictions (McKeen et al., 2005; Wilczak et al., 2006; Delle Monache et al., 2008; Kang et al., 2008), surface $PM_{2.5}$ predictions (Kang et al., 2010a), or both (Hogrefe et al., 2006; Djalalova et al., 2010; Kang et al., 2010b). Bias-adjustment strategies range from the relatively simple mean bias and multiplicative ratio adjustments used by McKeen et al. (2005) to the more complex Kalman Filter (Kalman, 1960) scheme developed by Delle Monache et al. (2006) and applied to NAQFC forecasts retrospectively by Kang et al. (2008, 2010a) and recently in real-time by Kang et al., (2010b). Most bias-adjustment approaches, regardless of complexity, have been shown to improve air quality model forecasts.

Air Quality Model Output Statistics (AQMOS) was developed to provide additional value to forecasters by adjusting the available model predictions with recent observations of ozone and $PM_{2.5}$ in real-time. AQMOS is a web-based software tool supported by a back-end database that performs bias-adjustments by computing daily regression equations between recent historical air quality model predictions and observations. Specific regression equations are determined for each city, pollutant, and model in the AQMOS system. Each day's equations are applied to the current model predictions for over 300 forecast cities in the AIRNow program (www.airnow.gov). Raw and adjusted model predictions are made available in real-time through an intuitive web interface (http://aqmos.sonomatech.com).

2. AQMOS METHODOLOGY

2.1 Database

AQMOS is built upon a Microsoft SQL Server database that stores historical, city-specific observations and model predictions; performs regression and bias-adjustment calculations; and delivers data to the end-user via the AQMOS web interface. AQMOS is fully automated and is dynamically updated as data from new model runs are delivered to the system. Forecast cities in AQMOS are equivalent to those in the AIRNow program, and are updated automatically as new forecast cities are added to AIRNow. The AQMOS database is designed to easily accommodate additional parameters and models as new data become available in the future.

2.2 Website

The AQMOS website (**Figure 1**) provides real-time access to same-day and next-day model predictions to end users in a convenient tabular format, with raw and bias-adjusted model predictions for a given city, model, and parameter presented side-by-side and color coded by Air Quality Index (AQI) category for easy comparison. Users can filter predictions by model, city, state, and parameter, and access graphic displays of the raw model predictions. Users can also access historical predictions back to April 1, 2009.

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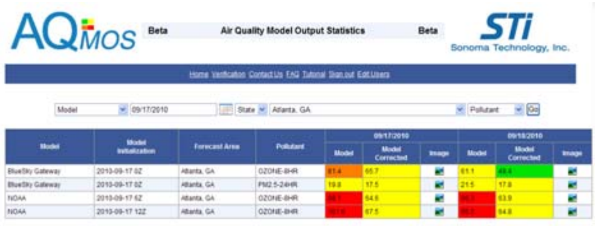

Fig. 1. Screenshot of the AQMOS web interface.

The AQMOS website also provides a model evaluation tool so users can view raw and bias-adjusted model forecasts against observations for any AIRNow forecast city during any 30-day period. This tool allows users to quickly evaluate recent or historical performance of raw and bias-corrected model predictions for any forecast city of interest. The comparative plot shown in **Figure 2** demonstrates the benefit of using a bias-adjusted model forecast when the raw model results contain a consistent bias. It is important to recognize, however, that a model's bias characteristics will likely differ across forecast cities, and can be dependent upon prevailing meteorological and air quality conditions.

Fig. 2. AQMOS model evaluation plot showing peak 8-hr average ozone concentrations from observations, the raw NAQFC forecast, and the AQMOS bias-adjusted NAQFC forecast for August 25 to September 24, 2010, at Atlanta, Georgia.

The AQMOS website also features a Frequently Asked Questions section and tutorial video that describes the AQMOS system, explains its bias-adjustment procedure, and demonstrates the use of the AQMOS website.

2.3 Data Sources

AQMOS currently ingests and stores peak daily 8-hr average ozone and 24-hr average $PM_{2.5}$ observations from AIRNow, as well as current-day and next-day forecasts from two model prediction systems. Observations are obtained from the AIRNow Gateway system (http://www.airnowgateway.org). Operational model predictions are obtained twice daily (0600 and 1200 UTC) from the NAQFC system, which is based on CMAQ simulations at 12-km resolution. Experimental model predictions are obtained once daily (0000 UTC) from the BlueSky Gateway modeling system, which is based on CMAQ simulations at 36-km resolution.

AQMOS receives air quality observations and model predictions for over 300 forecast cities in the AIRNow system. AQMOS stores the maximum observed values within each forecast area, as computed by AIRNow Gateway. The air quality monitors used to determine these peak values are the verification sites set up by AIRNow stakeholders through AIRNow-Tech.

AIRNow stakeholders use the AIRNow-Tech GeoEditor tool to associate forecast cities with ZIP Code areas. Modeled concentrations from the NAQFC and BlueSky Gateway are extracted at the geographic centroid of all ZIP Codes associated with a forecast city, and the maximum modeled concentration for each forecast city is stored by AQMOS.

2.4 Regression Calculation and Bias-Adjustment

The AQMOS bias-adjustment procedure uses a linear regression approach to adjust model results and account for systematic model bias. Each day, AQMOS queries from its database up to six months of historical observations and model predictions to compute a regression equation for each forecast city, parameter, model, and forecast period. AQMOS regressions are season-specific, so the six months of data may span two different calendar years. AQMOS defines two seasons, a warm season (April through October) and a cool season (November through March). AQMOS regressions are also specific to the model run being considered. The regression equations are then applied to the current raw model predictions to generate bias-adjusted model predictions. Separate regressions are computed for current-day and next-day forecasts, and for each model run cycle.

Figure 3 illustrates a regression developed from NAQFC 8-hr ozone data for Dallas, Texas. In this example, the NAQFC ozone predictions are generally higher than the observed concentrations. AQMOS would therefore adjust model predictions downward. If the average model bias is zero, then

AQMOS applies no adjustment to the model prediction.

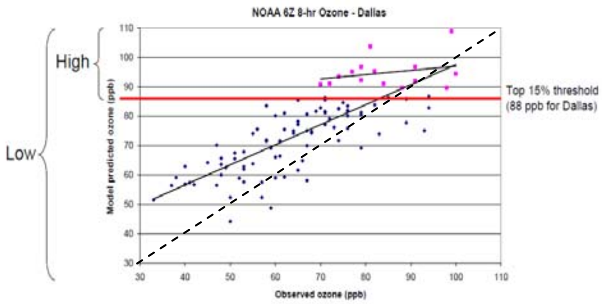

Fig. 3. Scatter plot of observed (x-axis) and NAQFC-predicted (y-axis) peak 8-hr ozone concentrations at Dallas, Texas, with one-to-one (dashed) and linear regression (solid) lines plotted. Model-observation pairs with observed data above (pink squares) and below (blue diamonds) the 88-ppb threshold are shown.

Model biases often differ between low and high pollution days. To better capture model performance on high pollution days (which are of greatest concern to air quality forecasters), AQMOS calculates the regression in one of two ways, depending on whether the model prediction for a forecast city is above or below a threshold value defined by the 85th percentile of observed pollutant concentrations. If the prediction is above the threshold value, AQMOS calculates the regression using only historical data from days when the model previously predicted above the threshold concentration. If the prediction is below the threshold concentration, or if there is an insufficient number of days above the threshold concentration, AQMOS calculates the regression using all historical model and observed data for the current season.

3. AQMOS PERFORMANCE

To assess the benefit of the AQMOS model bias-adjustment, AQMOS bias-adjusted NAQFC and BlueSky Gateway forecasts were evaluated against raw model forecasts at all forecast cities in the AIRNow program for April through October, 2009. For this evaluation, the “AQMOS improvement” statistic is defined as the difference between mean absolute errors of the raw model and the AQMOS bias-adjusted model predictions during the evaluation period. A positive AQMOS improvement indicates that the bias-adjusted prediction improved upon the raw model prediction, whereas a negative AQMOS improvement indicates that the bias-adjusted prediction was worse than the raw model prediction.

The AQMOS improvement at all AIRNow cities for next-day peak 8-hr ozone forecasts from the 0600 UTC NAQFC model run are shown in **Figure 4**. The AQMOS bias-adjustment improved upon raw NAQFC forecast for 95% of the forecast cities evaluated. The AQMOS bias-adjustment improved upon the raw NAQFC forecasts by at least 4 ppb at most cities in California, as well as the northeastern and southeastern U.S. AQMOS improvements were positive, but less than 4 ppb for most cities in the upper Midwest. The AQMOS bias-adjusted NAQFC forecasts were worse than the raw forecasts in the Salt Lake City area, and in the Imperial Valley region of California. **Table 1** shows the five cities with the best and worst AQMOS improvement statistic for NAQFC ozone forecasts.

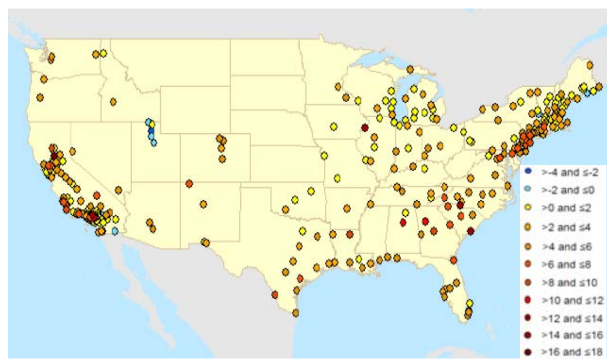

Fig. 4. AQMOS improvement (ppb) at AIRNow forecast cities for NAQFC next-day peak 8-hr ozone forecasts from April through October, 2009.

City	AQMOS improvement, 6Z NOAA Ozone model (ppb)
Yuba City/Marysville, CA	17.3
York/Chester/Lancaster, PA	15.0
Charleston, SC	13.5
Rock Island-Moline, IL	13.4
East San Gabriel, CA	12.4
. . .	. . .
Banning, CA	-0.8
Imperial Valley, CA	-0.9
Provo, UT	-1.2
Washakie Reservation, UT	-1.7
Ogden, UT	-3.1

Table 1. AQMOS improvement (ppb) for the top and bottom five cities for NAQFC next-day peak 8-hr ozone forecasts from April through October, 2009.

The AQMOS improvement statistics for next day 24-hr average $PM_{2.5}$ forecasts from the 0000 UTC BlueSky Gateway model are shown in **Figure 5**. As with the NAQFC ozone forecasts, the AQMOS bias-adjustment improved upon raw BlueSky Gateway $PM_{2.5}$ forecasts for 95% of the forecast cities evaluated. The AQMOS bias-adjusted BlueSky Gateway forecasts improved upon the raw model forecasts by up to 2 $\mu g/m^3$ at most cities. AQMOS improvements exceeded 4 $\mu g/m^3$ at several cities in southern California, the Salt Lake City area, and the Northeastern U.S. The AQMOS bias-adjusted BlueSky Gateway forecasts were less accurate than the raw model forecasts in California's Sacramento Valley.

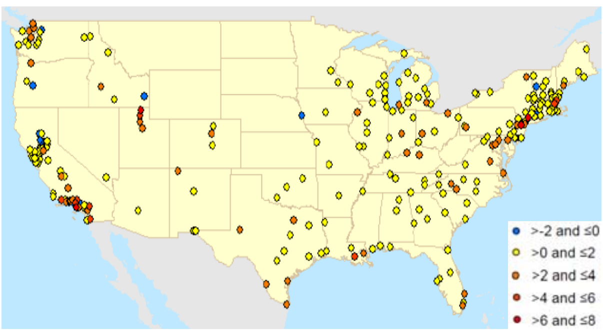

Fig. 5. AQMOS improvement ($\mu g/m^3$) at AIRNow forecast cities for BlueSky Gateway next-day 24-hr average $PM_{2.5}$ forecasts from April through October, 2009.

The AQMOS improvements shown in Figure 4 and Figure 5 are calculated for all days of the evaluation period, regardless of AQI category. Model performance on critical air quality days when either the observed or predicted AQI is Unhealthy for Sensitive Groups (USG) or worse is of particular interest to air quality forecasters because forecasts of poor air quality conditions can trigger public air quality alerts and warnings.

The percentage of critical air quality days on which the AQMOS bias-adjustment improved upon model forecasts in six major U.S. cities is presented in **Table 2**. Overall, The AQMOS bias-adjustment improved upon the raw model predictions on at least 50% of critical air quality days. The bias-adjustment improved upon BlueSky Gateway $PM_{2.5}$ forecasts on all critical air quality days in Philadelphia, Sacramento, and St. Louis; however, this was based on a limited number of critical air quality days during the evaluation period. Note that the AQMOS bias-adjusted forecasts improved upon BlueSky Gateway $PM_{2.5}$ predictions for critical air quality days in Sacramento, but were less accurate than BlueSky Gateway predictions when all days were considered.

City	NOAA 6Z Ozone	NOAA 12Z Ozone	BlueSky 0Z $PM_{2.5}$
Atlanta	92%	90%	33%
Houston	50%	50%	67%
Philadelphia	82%	67%	100%
Sacramento	76%	80%	100%
St. Louis	63%	75%	100%
Salt Lake City	60%	38%	----

Table 2. Percentage of days on which AQMOS bias-adjusted NAQFC and BlueSky Gateway forecasts improved upon raw model forecasts on days for which either observed or model-predicted air quality was USG or higher during the April 1 to October 31, 2009, evaluation period. Green, orange, and blue cells indicate AQMOS improvement on at least 75%, 50-75%, and fewer than 50% of days, respectively.

4. CONCLUSION

The AQMOS system was developed to provide additional value to air quality forecasters by adjusting the available model predictions with recent observations of ozone and $PM_{2.5}$, and by making raw and bias-adjusted model predictions easily accessible in real-time through an intuitive web-based data display system. AQMOS uses a linear regression approach to calculate bias-adjusted model forecasts. This bias-adjustment improved model predictions of peak 8-hr average ozone and average 24-hr $PM_{2.5}$ for most forecast cities during the summer 2009 evaluation period. On critical air quality days when observed or predicted AQI was USG or greater, the AQMOS bias-adjustment improved upon raw model results at least 50% of the time in the six U.S. cities evaluated.

AQMOS is currently available to air quality agencies. Like other statistical forecast guidance, AQMOS is a tool that should be used in conjunction with other tools and guidance in the air quality forecasting process. User accounts can be requested through the AQMOS website at http://aqmos.sonomatech.com.

6. ACKNOWLEDGMENTS

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