IMPLEMENTATION OF REAL-TIME BIAS-ADJUSTED O_3 AND $PM_{2.5}$ AIR QUALITY FORECASTS AND THEIR PERFORMANCE EVALUATIONS DURING 2008 OVER THE CONTINENTAL UNITED STATES

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Ozone (O_3) and fine particulate matter ($PM_{2.5}$; particles with aerodynamic diameters less than 2.5 μm) air pollution is of concern due to their adverse effect on human and ecosystem health. Ambient levels of O_3 and $PM_{2.5}$ are the two primary components used in the calculation of the Air Quality Index (AQI), a standardized indicator of air quality degradation at a given location. The National Oceanic and Atmospheric Administration (NOAA), in partnership with the United States Environmental Protection Agency (EPA), is operationally implementing an Air Quality Forecast (AQF) system. This program, which couples NOAA's North American Mesoscale (NAM) weather prediction model with EPA's Community Multiscale Air Quality (CMAQ) model, has provided forecasts of ozone (O_3) mixing ratios since 2004. Developmental $PM_{2.5}$ forecasts were initiated in 2005 (Mathur et al., 2008). The modeling domain for both the operational and developmental predictions currently covers the continental U.S. (CONUS).

Bias-adjustment techniques have been used to correct systematic biases in surface O_3 predictions (Delle Monache et al., 2006; Wilczak et al., 2006; and Kang et al., 2008), and more recently have also been extended for $PM_{2.5}$ forecasts (Kang et al., 2009). Among these techniques, Kalman Filter (KF) predictor forecast method has shown the most improvement in forecast skill. To test the applicability of the methods in an operational real-time setting, during 2008 the KF bias-adjustment technique (Kang et al., 2008 and Kang et al., 2009) was implemented in near real-time along with the NAM/CMAQ AQF system to provide daily bias-adjusted O_3 and $PM_{2.5}$ forecasts at all the locations where observations from EPA's AIRNOW network were available within the CONUS domain. The bias-adjusted O_3 forecasts were performed from the beginning of April to the middle of September covering the entire O_3 season, and the $PM_{2.5}$ bias-adjusted forecasts were conducted through the whole year. In this paper, the preliminary

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performance evaluations of the KF bias-adjusted O_3 and $PM_{2.5}$ forecasts are presented. To facilitate performance evaluations for $PM_{2.5}$, the study period is divided into cold season (from January to April 20th and from September to December) and warm season (from April 21st to August 31st).

Implementation of the KF bias-adjustment method

The KF predictor bias-adjustment algorithm is described in detail by Delle Monache et al. (2006). The adaptation and implementation of the technique in our applications is presented in Kang et al., (2008). Also in our previous study (Kang et al., 2008), the error ratio, a key parameter in the KF approach which determines the relative weighting of observed and forecast values, was investigated extensively with O_3 forecasts at over 1000 monitoring locations. Even though the optimal error ratios inherent in the KF algorithm implementation were found to vary across space, the impact of using the optimal values on the resultant bias-adjusted predictions was insignificant when compared with using a reasonable single fixed value of this parameter for all the locations within the modeling domain. In this study, the same single fixed error ratio value of 0.06 was used to all the locations for the real-time bias-adjusted O_3 and $PM_{2.5}$ forecasts.

The KF bias-adjustment technique was implemented for O_3 and $PM_{2.5}$ forecasts separately. First, the KF was initialized with the initial estimates of KF parameters as outlined in Kang et al. (2008) and with two days of hourly observations and raw model predictions. It then generated the third day's bias-adjusted forecasts by combining with the third day's raw model forecasts with the updated KF parameters. All the updated KF parameters for each hour and at each site were saved into a file for use in the next KF run. The KF runs then continued by reading the previous day's KF parameters and two preceding days' observations and raw model predictions to continuously generate the next day's bias-adjusted forecasts through combining with the next day's raw model forecasts. The KF simulations run daily when the preceding day's observations and the raw model forecasts for next day (issued on current day) were available. In our implementation, if two consecutive days' data were missing at a site, the method would automatically drop this site from future bias-adjustment forecasts; however, if a new site with two consecutive days' data appeared in the observation data set, the KF would initialize the site with initial values of KF parameters and generate bias-adjusted forecasts further on. This implementation is very adaptable to the variable nature of monitoring stations which report hourly observations to the AIRNOW network and can be easily combined with AQF system to perform real-time bias-adjusted forecasts. The bias-adjusted forecasts were initialized on January 4 and April 3 for $PM_{2.5}$ and O_3 forecasts, respectively, and the programs were run daily on a Linux system; it took less than 10 minutes of computation to create a bias adjusted forecast.

Performance Evaluations

Table 1 presents a summary of domain (Dom) and sub-regional mean discrete statistics for the raw model and the KF forecast daily maximum 8-h O_3 mixing ratios during the study period. Table 2 presents similar model performance statistics for daily mean PM2.5 concentrations for warm and cold seasons; in each cell, the value on the left of slash (/) is for warm season and the value on the right of the slash is for the cool season; the values in the rows with white background marked with "–mod" represent

Table 1. Regional summary of discrete statistics for raw model and KF bias-adjusted daily maximum 8-hr O_3 forecasts during 2008 summer season

TYPE	RMSE (ppb)	NME (%)	MB (ppb)	NMB (%)	r
Dom-mod	12.5	20.1	3.2	6.8	0.65
Dom-kf	9.1	14.5	0.6	1.3	0.81
NE-mod	10.6	16.9	2.7	5.6	0.70
NE-kf	8.9	13.8	0.7	1.4	0.78
SE-mod	12.2	20.1	5.8	12.2	0.70
SE-kf	9.1	14.7	0.5	1.1	0.80
UM-mod	10.4	17.5	2.5	5.4	0.59
UM-kf	8.5	13.7	0.7	1.5	0.72
LM-mod	13.6	27.0	7.0	16.9	0.64
LM-kf	9.8	17.7	0.8	1.9	0.77
RM-mod	11.4	16.4	2.7	5.1	0.50
RM-kf	8.9	12.8	0.7	1.3	0.70
PC-mod	16.0	21.9	-3.2	-5.9	0.60
PC-kf	10.5	14.5	0.2	0.3	0.84

Table 2. Regional summary of discrete statistics for raw model and KF bias-adjusted daily mean $PM_{2.5}$ forecasts during 2008 warm/cold season

TYPE	RMSE (ug/m3)	NME (%)	MB (ug/m3)	NMB (%)	r
Dom-mod	9.6/10.5	47.5/70.5	-2.3/4.5	-19.6/45.1	0.33/0.53
Dom-kf	6.6/6.4	32.9/42.5	-0.1/1.7	-0.4/16.5	0.71/0.68
NE-mod	7.5/12.3	39.5/76.1	-2.4/6.6	-17.8/59.9	0.56/0.63
NE-kf	5.5/7.3	29.1/44.7	-0.4/2.4	-2.7/22.1	0.76/0.72
SE-mod	7.8/9.1	41.5/62.1	-3.9/4.6	-27.5/43.8	0.40/0.47
SE-kf	5.3/5.4	27.1/37.2	-0.4/1.3	-2.7/12.8	0.63/0.58
UM-mod	6.0/10.7	36.6/68.3	-0.7/6.5	-6.0/57.4	0.58/0.62
UM-kf	5.0/6.1	30.7/37.3	-0.2/1.7	-1.7/15.2	0.69/0.73
LM-mod	8.7/9.4	52.4/67.7	-4.0/3.6	-32.9/36.8	0.17/0.32
LM-kf	5.8/5.9	34.9/42.5	-0.2/1.2	-1.5/12.2	0.37/0.49
RM-mod	6.4/9.3	50.5/75.7	-1.5/3.5	-17.2/43.1	0.18/0.37
RM-kf	4.6/5.6	33.5/44.4	0.0/1.3	0.2/16.2	0.57/0.62
PC-mod	15.3/10.2	57.9/60.2	-3.4/1.8	-30.6/15.8	0.23/0.53
PC-kf	10.5/7.0	39.0/40.9	0.2/1.2	1.9/10.4	0.73/0.72

statistics associated with raw model forecasts, while those in the rows with shaded background and with the extension "–kf" represent the statistics associated with the KF bias-adjusted forecasts. As seen in Table 1, for daily maximum 8-h O_3 forecasts, the Root Mean Square Error (RMSE) values associated with raw model forecasts ranged from 10.4 to 16.0 ppb. The application of the KF bias-adjustment, reduced the RMSE to

8.5 -10.5 ppb; on average, this corresponds to more than 25% reduction. Similar reduction was reflected by Normalized Mean Bias (NMB). More remarkable forecast improvement by the KF forecasts over raw model is reflected by the Mean Bias (MB) and Normalized Mean Bias (NMB); the MB values were reduced from several ppb to less than 1 ppb for all the regions, and NMB from as high as 17% to less than 2%. The correlation coefficients (r) also increased systematically from 0.5-0.7 for the raw model to 0.7 - 0.84 in the KF forecasts. Similar forecast skill improvement in $PM_{2.5}$ forecasts by the KF forecasts over raw model is shown in Table 2, though compared to O_3 forecasts, the overall statistics for $PM_{2.5}$ forecasts still need to be improved due to the difficulty in simulating the complexity of $PM_{2.5}$ formation and distribution by the raw model.

It is important for an air quality forecast product to be able to accurately predict exceedance and non-exceedance events (categorical predictions). Categorical evaluations for the raw model and KF bias-adjusted forecasts for daily maximum O_3 and daily mean $PM_{2.5}$ concentrations have shown that the KF bias-adjusted forecasts were able to significantly reduce False Alarm Ratio (FAR) values and increase Hit rate (H) values for both daily maximum 8-h O_3 forecasts and daily mean $PM_{2.5}$ forecasts.

Summary

The near real-time KF bias-adjustment technique was applied to NAM-CMAQ O_3 and $PM_{2.5}$ air quality forecasts over the continental United States. These bias-adjustment forecasts were implemented to run daily for improving next-day forecasts. The bias-adjustment post-processing adds minimal computational burden; on a daily-basis, it required less than 10 minutes of CPU on a single processor Linux machine. Hourly O_3 and $PM_{2.5}$ bias-adjusted forecasts were provided at all the locations where the observations were available from the AIRNOW network. The performance evaluation of the bias-adjusted forecasts for both O_3 and $PM_{2.5}$ has shown significant improvement over the raw model forecasts for a variety of performance evaluation statistical measures. Specifically, errors and biases were systematically reduced, the correlation coefficients were increased, false alarm ratios went down, and hit rates went up. The robustness of this technique was also manifested through time and space and over all the concentration bins; the forecast skills were improved at all the locations within the domain during all the seasons.

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