Quantifying and Accounting for the Effect of Inter-annual Meteorological Variability in Dynamic Evaluation Studies

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• 1990 -2010 Simulations:
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• 2002, 2005 Simulations:
  – Meteorology: Rob Gilliam, Lara Reynolds
  – Emissions: Allan Beidler, Ryan Cleary, Alison Eyth, Rob Pinder, George Pouliot, Alexis Zubrow
  – Boundary Conditions: Barron Henderson (now at Univ. of FL), Farhan Akhtar (now at US State Dept.)
Dynamic Evaluation of Air Quality Models

• **Motivation:** Air quality models are used to determine the impact of different emission reductions strategies on ambient concentration levels. Dynamic evaluation is one component of a thorough model performance evaluation.

• **Dynamic Evaluation:** Evaluating the model’s ability to predict changes in air quality given changes in emissions (or meteorology).

• **EPA’s Nitrogen Oxides State Implementation Plan Call (NO\textsubscript{x} SIP Call) provides a valuable retrospective case study.**
  
  – The rule was targeted at reducing NO\textsubscript{x} emissions from EGUs in the eastern US and was implemented in 2003 and 2004.

• **Previous studies (e.g. Gilliland et al. 2008; Godowitch et al. 2010; Napelenok et al. 2011; Zhou et al. 2013; Kang et al. 2013) have shown a tendency for CMAQ modeling to underestimate the observed ozone reductions across this period.**
Challenges in Dynamic Evaluation of Modeled Response to Emission Changes

- **Challenge:** Observed air quality changes over time are driven by both changes in emissions and meteorological variability, making it difficult to diagnose the source of model error in dynamic evaluation studies.

- Attainment demonstrations are based on observed ozone levels averaged across multiple years ($O_3$ design value) to account for meteorological variability and better isolate air quality trends due to emission changes.

- Modeling for attainment demonstrations is typically done using constant meteorology inputs. Thus for regulatory modeling applications, we are most interested in evaluating the model’s ability to capture the impact of changing emissions on air quality levels.

- **Two dynamic evaluation approaches** proposed here for address confounding effect of meteorological variability:
  - 1990 – 2010 time series of WRF-CMAQ simulations (36km grid, consistent emissions developed by Xing et al. (2013))
  - 2002, 2005 CMAQv5.0.1 simulation study with ‘cross’ simulations (12km grid, ‘02/05 NEI based emissions described in Foley et al. (2014))
Dynamic Evaluation using WRF-CMAQ simulations


**Observed 2005 - 2002 change (ppb)**

**Modeled 2005 - 2002 change (ppb)**

# sites = 262 (subset to AQS sites with data for all 21 years)

* Metric of interest: Average of ten highest daily max 8-hr average ozone (MDA8 O₃) values over June-August.
Model underestimates decrease in high summertime ozone in the NO$_x$ SIP call region from 2002 to 2005.

Data from $n=262$ sites.
Dynamic Evaluation using WRF-CMAQ simulations

- Model underestimates decrease in ozone from 2002 to 2005 but overestimates the decrease from 2001 to 2006.

Data from n = 262 sites.

Observed 2006 - 2001 change (ppb)

Modeled 2006 - 2001 change (ppb)

# sites = 262 (subset to AQS sites with data for all 21 years)
Impact of Model Bias on Dynamic Evaluation

- Model performance varies from year to year.
- Model overprediction of high summertime MDA8 ozone is greater in 2005 compared to 2002.
- The opposite is true for the bias in 2006 compared to 2001.

Bias in average of 10 highest MDA8 O3 (ppb)

Average bias across n= 262 sites.
• Modeling 3- or 5-year centered averages can stabilize the model bias → we can more confidently assess the model’s response to emission reductions, i.e. results are not as sensitive to the chosen starting/ending year.

• Multi-year model averages are also more consistent with the observed design value metric used in ozone attainment demonstrations.
Using Multi-year Model Averages in Dynamic Evaluation

- Use 21 year time series to look at all possible “base” year and “future” year projections separated by at least 3 years (n=136 pairs).

- Modeling 3- or 5-year centered averages reduces the variability in the observed and modeled trends, providing a more robust dynamic evaluation of the modeling system.

Data from n = 262 sites x 136 projection pairs = 35,632
For dynamic evaluation studies, focusing on individual pairs of years may not fully assess the model’s ability to capture emission-induced trends due to the confounding effect of meteorological variability.

Longer model simulations offer the opportunity to account for this variability by using multi-year averages.

Question remains: Why is model bias so different from year to year?

- Misspecified emission trends?
- More complex problems with modeling changes in meteorology and chemistry?

CMAQv5.0.1 simulations for 2002 and 2005 are used to separate the change in ozone due to \( \Delta \) emissions vs \( \Delta \) meteorology.
Dynamic Evaluation using CMAQv5.0.1 Simulations


**Observed** 2005 - 2002 change (ppb)

**Modeled** 2005 - 2002 change (ppb)

# AQS sites = 729
Creation of 2002/2005 “Cross” Simulations

• 4 Simulations:
  – 2 Base: Summer 2002, Summer 2005
  – 2 Cross: 2002 emissions with 2005 met
                2005 emissions with 2002 met

• Emissions for cross simulations:
  – EGU emissions (with CEM data) based
    on unit specific adjustments to account
    for met influences on electricity demand.
  – Mobile emissions: MOVES simulations using designated emission
    year and met year.
  – Nonroad, industrial point and large marine sectors use emissions
    year shifted to match the day of the week of the met year.
  – Emissions from fertilizer application, biogenic sources, NOx from
    lightning, fires, dust are tied to meteorological year
  – All other sectors have the same inventory for all scenarios except
    modified for the day-of-the-week of the met year.
Change in high ozone due to changes in **EMISSIONS** (with 2002 meteorology)

Change in high ozone due to changes in **METEOROLOGY** (with 2002 emissions)

“Interaction” term

\[
\text{Change in high ozone due to changes in high summer ozone} = \text{Change in high ozone due to changes in emissions} + \text{Change in high ozone due to changes in meteorology} + \text{Interaction term}
\]
Meteorology-Adjusted Ozone Trends

- Method developed by Cox and Chu (1996), Camalier et al. (2007) is used by EPA/OAQPS to provide met-adjusted trends in average ozone.

- We use this data to evaluate the model-predicted change in ozone due to meteorology.

http://www.epa.gov/airtrends/weather.html
Met-adjusted observed ozone values for 2002 and 2005 are only available at select AQS and CASTNet stations and are based on May – September summer averages.
Observed and Modeled 2005 – 2002 change in mean summertime ozone due to changes in meteorology.

- Predicting too large of an increase in ozone in the northeast.
- Missing the region of increasing ozone in the midwest.
Model errors in predicting change in ozone due to meteorology do not fully explain why model predictions underestimate the observed ozone reduction across these years.

Next Steps: Quantile regression statistical model can be used to estimate met-adjusted observed ozone trends for different percentiles (e.g. 90th percentile rather than mean $O_3$) to better evaluate the model predicted change in ozone due to meteorology.
Summary

- Dynamic evaluation studies that focus on individual pairs of years may not fully assess the model’s ability to capture emission-induced trends due to the confounding effect of meteorological variability.

- Longer model simulations offer the opportunity to account for this variability by using multi-year averages.

- Model sensitivity simulations can be used to isolate the effects of emission changes on pollutant concentrations from the effects of meteorological changes.

- Better diagnosing prediction errors identified in a dynamic evaluation study depends on improving how we use observed data to evaluate model predicted changes in air quality.