Mapping yearly global surface ozone through Regionalized Air Quality Model Performance corrections and Bayesian Maximum Entropy data fusion of observations and model output for 1990-2017

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Combining station observations and bias corrected models to estimate ozone across the globe

Goal: Model ozone annual at fine resolution and improve on our GBD 2019 product’s ability to correct away from observations
1) Observations (Hard Data)
2) Model Fusion
3) RAMP Model Correction (Global Offset)
4) BME Data Fusion
Ozone Observation Stations - Hard Data

- Tropospheric Ozone Assessment Report (TOAR)
  - 1990-2017
- China National Environmental Monitoring Center (CNEMC)
  - 2013-2017

Models were weighted in each region and year to minimize the difference between the bias-corrected multi-model composite and interpolated observations (Chang et al. 2019)
Up to 8 Models -> 1 Model Composite for each year
M3 Model Fusion – Kai-Lan Chang

Multi-model Composite 2005

Multi-model Composite 2015
Regionalized Air Quality Model Performance (RAMP) Correction

- Further correct the M3 Multimodel Composite
- More local, non-homogenous, non-linear, non-homoscedastic correction
- Corrects each model point individually, based on the trends in the M3 Model
RAMP Correction

1) Select the 250 closest observations to each model point in a given year, as well as the years before and after.
RAMP Correction

2) Match each observation with the model estimation at that space-time location
RAMP Correction

3) Sort each paired value into 10 equally sized bins (colors) and calculate $\lambda_1 = \text{mean}$

$$\lambda_1(x_i) = \frac{1}{n(x_i)} \sum_{j=1}^{n(x_i)} x_j$$
RAMP Correction

4) Interpolate between $\lambda$s, restricting slope to $>0$, to find the new RAMP corrected model value at this spacetime location.

Repeat for every M3 Model Point
RAMP Output

RAMP Corrected M3 Multi model Composite
RAMP Output

The Good
RAMP Output

Issue: Streak where the RAMP points used for correction change
RAMP Weight

- = Model Point
- = n closest ozone observations (n=250)
○ = Radius r centered on estimation point

Look at the N closest observations to the estimation point

Let N be the number of closest observation points to a specific Grid Cell

Let Nr be the number of the N closest points within radius r

Corrected Model Value = (Nr/N)*RAMP value + (1-Nr/N)*M3 Value.

In this case: (7/10)*RAMP value + (3/10)*M3 Value
RAMP Output

Solution: Weigh RAMP by proximity to points used to create a smooth transition, using M3 when far away from RAMP points
Weighted RAMP

This is our final product to use as a global offset (default)
BME Data Fusion

- Hard Data: Station Observations
- Global Offset: RAMP Corrected M3 Model
- Estimation Grid: Chosen by modeler
Covariance

- Influence nearby observations have on BME estimate
- Decays over space and time

The covariance model is:

$$C(r, \tau) = 46.9659 \times (0.70 \exp(-3r/0.65)\exp(-3\tau/80.00) + 0.05\exp(-3r/15.00)\exp(-3\tau/90.00) + 0.25\exp(-3r/10.00)\exp(-3\tau/80.00))$$
Final RAMP Corrected BME Estimate

Space Time 1995

Space Time 2015
Was it Worth It? $R^2$ says yes

### Leave One Out X-Validation

<table>
<thead>
<tr>
<th>Scenario</th>
<th>MSE (ppb2)</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Model Mean</td>
<td>189.23</td>
<td>0.28</td>
</tr>
<tr>
<td>M3 Fusion</td>
<td>61.14</td>
<td>0.30</td>
</tr>
<tr>
<td>BME w/M3 as offset</td>
<td>15.94</td>
<td>0.81</td>
</tr>
<tr>
<td>BME w/RAMP as offset</td>
<td>14.5</td>
<td>0.83</td>
</tr>
<tr>
<td>BME w/weighted RAMP as offset</td>
<td>14.5</td>
<td>0.83</td>
</tr>
</tbody>
</table>

### Checkerboard X-Validation

![Graph showing R2 values over length of box (degrees latitude)]
Conclusions

- BME data fusion vastly improves estimation over pure model approaches.
- RAMP Correction of M3 Model gives better results by correcting locally, but at a global scale with large gaps in observations has “streaks” where the observations being used rapidly change.
- Weighing RAMP by distance from observations preserves much of the correction and avoids such streaks, but at a slight loss of R2.
- The advantage of RAMP is seen in the checkboard cross validation, where BME must rely on the global offset to estimate points far away from observations.
FUN EXTRAS
Let $sg$ be the grid cell at resolution $0.5^\circ \times 0.5^\circ$, $\hat{y}(sg)$ be the interpolated observations, $\{\eta_k(sg); k = 1, \ldots, n\}$ be the model output registered onto the same grid from the $n$ models available in a given year. $\alpha_r$ is a constant that allows adjustment to the overall (regional) underestimation or overestimation and $\beta_{rk}$ is an optimal weight for the $k$-th model in region $r$.

$$\begin{align*}
\text{minimize} & \quad \{\alpha_r, \beta_{rk}; k = 1, \ldots, n\} \\
& \quad \sum_{s_g \in \text{Region } r} \left( \hat{y}(s_g) - \alpha_r - \sum_{k=1}^{n} \beta_{rk} \eta_k(s_g) \right)^2, \\
\text{subject to} & \quad \sum_{k=1}^{n} \beta_{rk} = 1 \text{ and } \beta_{rk} \geq 0
\end{align*}$$
Advanced Weighting Formula

- \( w_{M3} = (1 - \frac{nr}{N}) \cdot \alpha \), where \( \alpha \) is between 0 and 1, \( \alpha \) is the most \( M3 \) can count an \( \alpha < 1 \) makes \( RAMP \) have a floor of \( 1 - \alpha \)

- \( w_{RAMP} = 1 - w_{M3} \)