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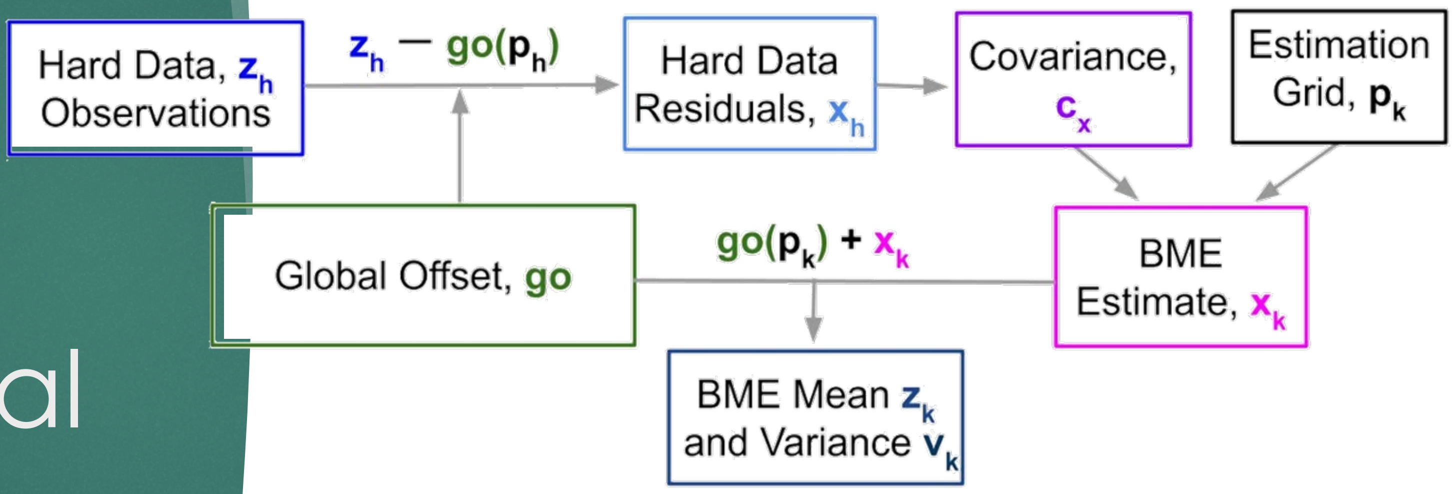
Combining station observations and bias corrected models to estimate ozone across the globe

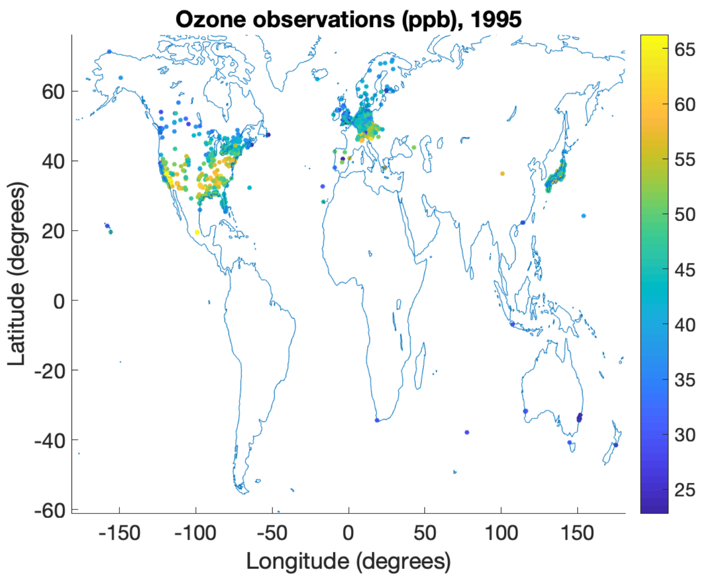
Goal: Model ozone annual at fine resolution and improve on our GBD 2019 product's ability to correct away from observations

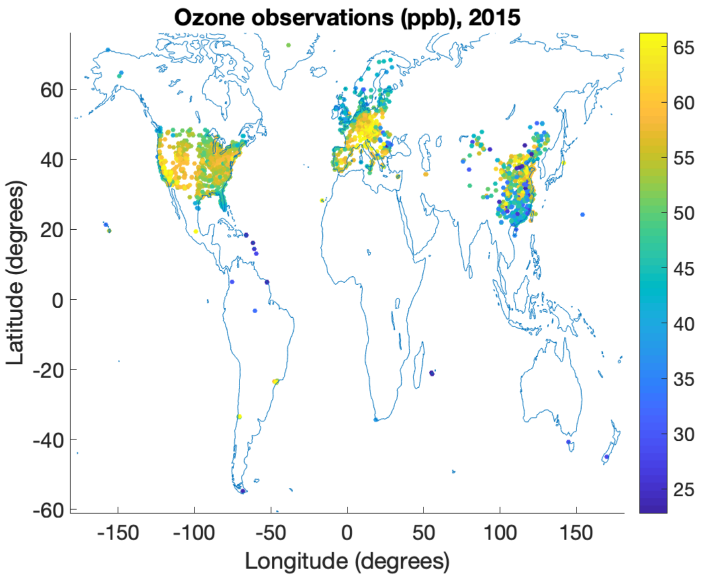
1) Observations (Hard Data)
2) Model Fusion
3) RAMP Model Correction (Global Offset)
4) BME Data Fusion



Ozone Observation Stations- Hard Data

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

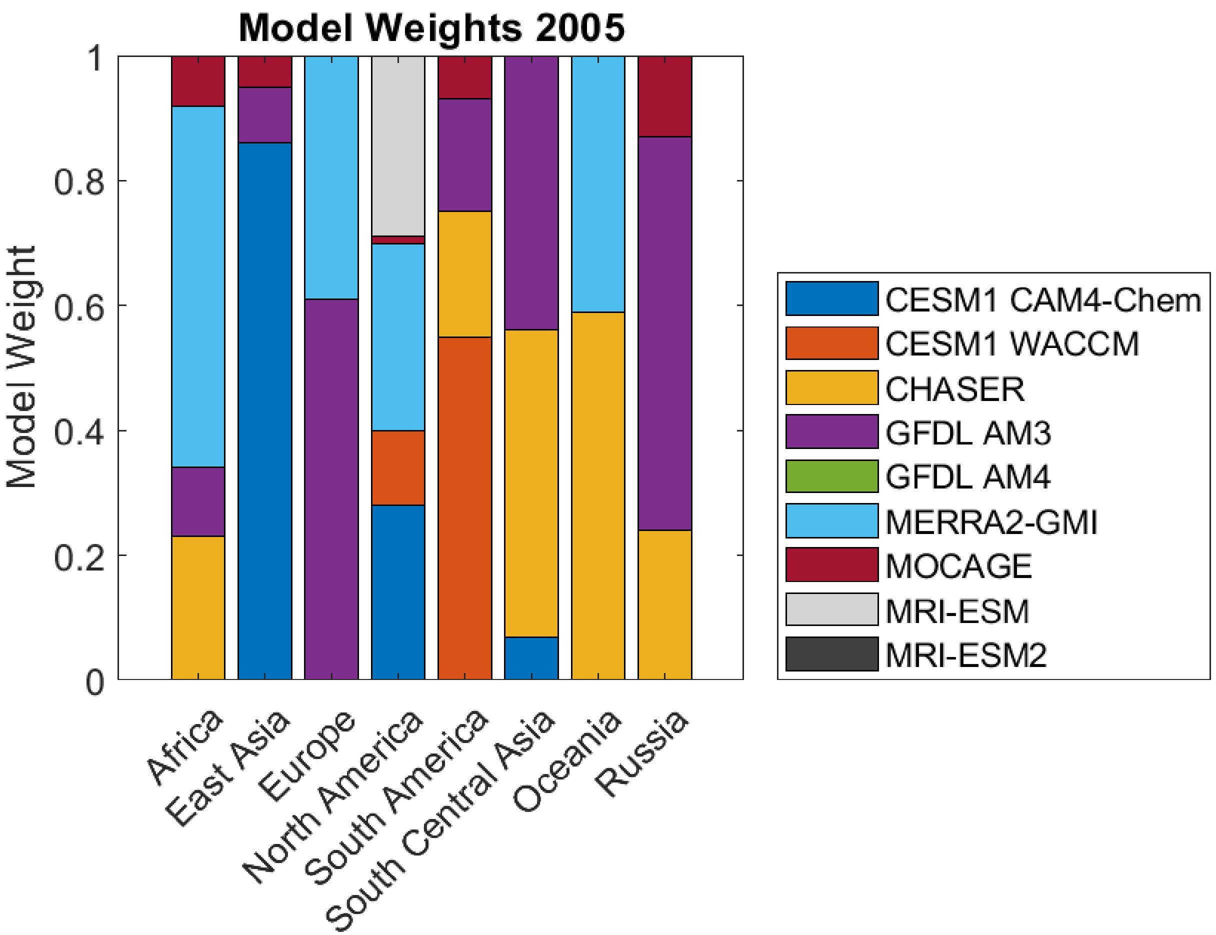


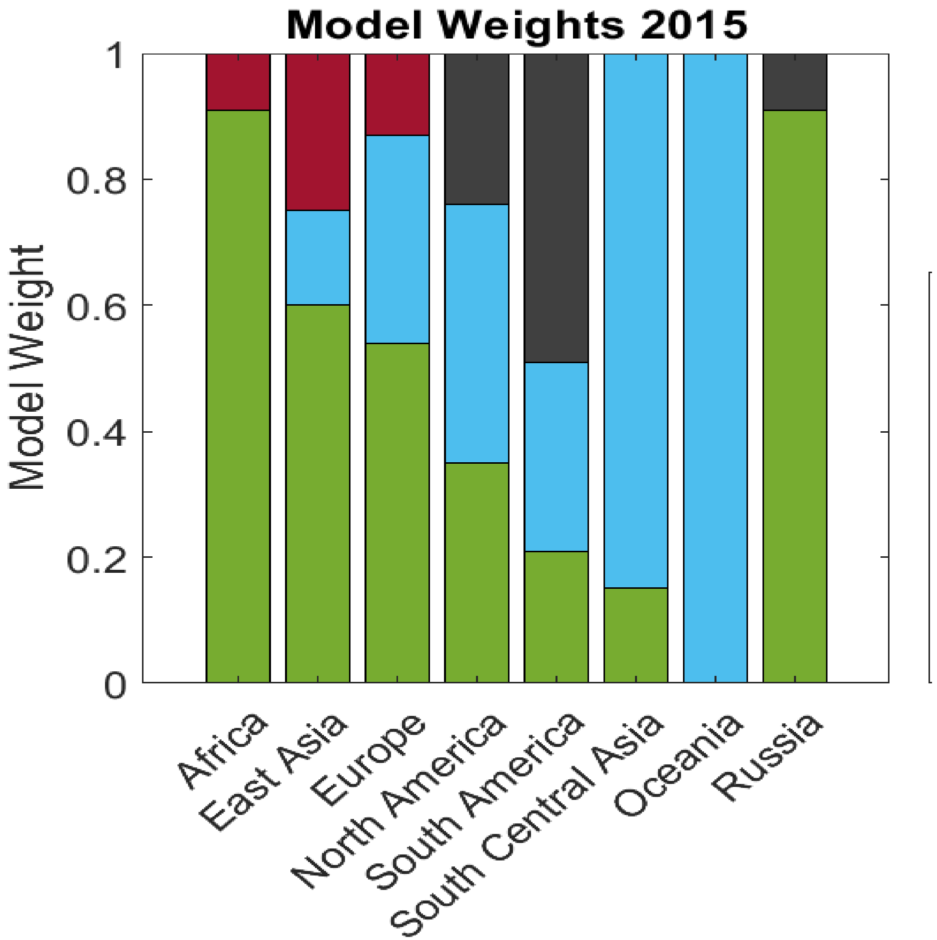


M3 Model Fusion – Kai-Lan Chang

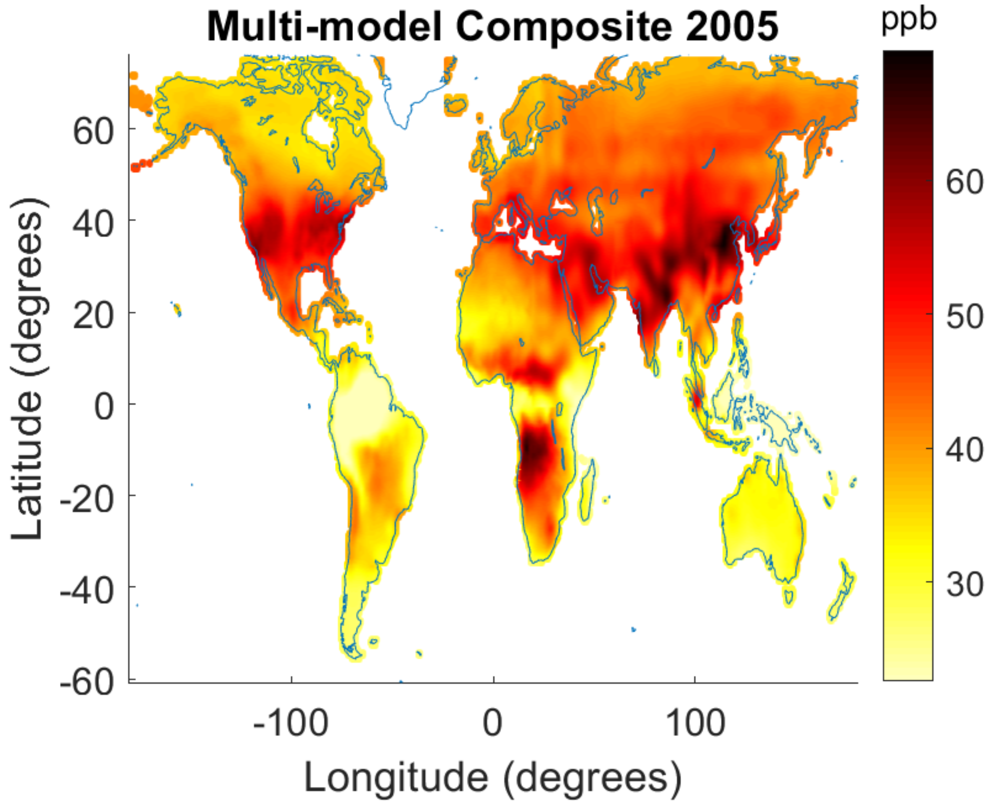
- 8 Models: CHASER (1990-2010), MOCAGE (1988-2016), MRI-ESM (1988-2017), NASA MERRA2-GM I(1988-2017), NCAR CESM-Chem (1988-2010), NCAR WACCM (1988-2010), GFDL AM3 (1988-2014), and GFDL AM4 (2010-2016)
- Models were weighted in each region and year to minimize the difference between the bias-corrected multi-model composite and interpolated observations (Chang et al. 2019)

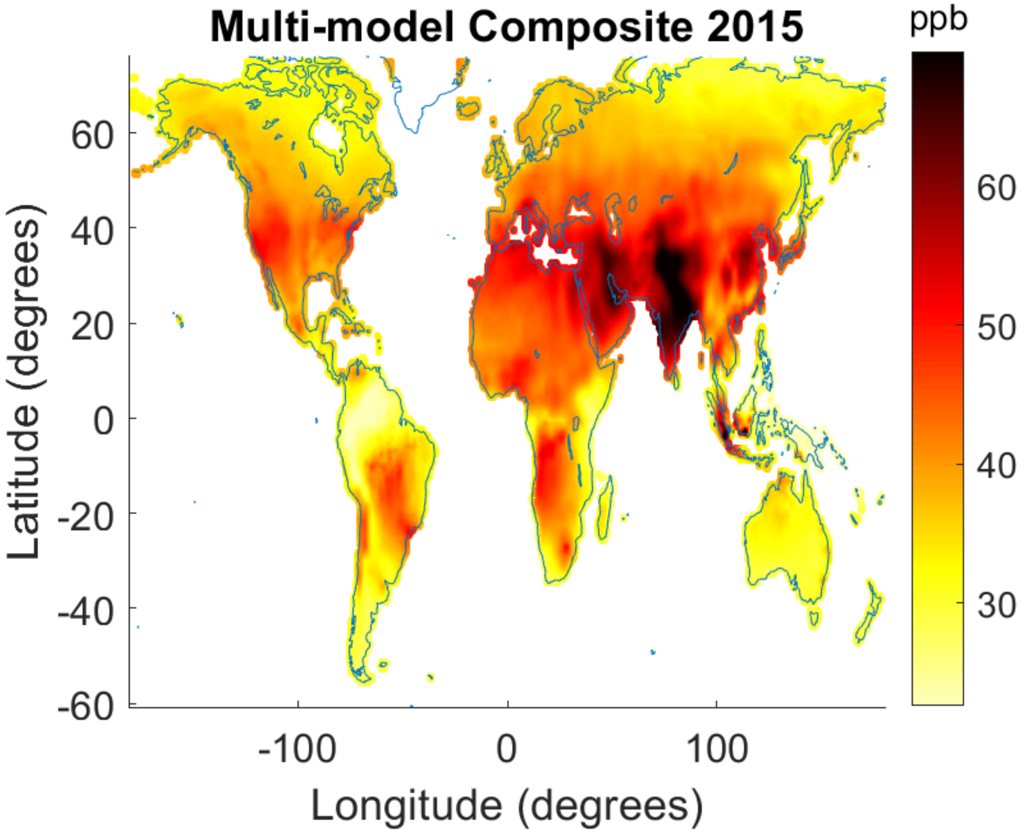
Up to 8 Models -> 1 Model Composite for each year





M3 Model Fusion – Kai-Lan Chang



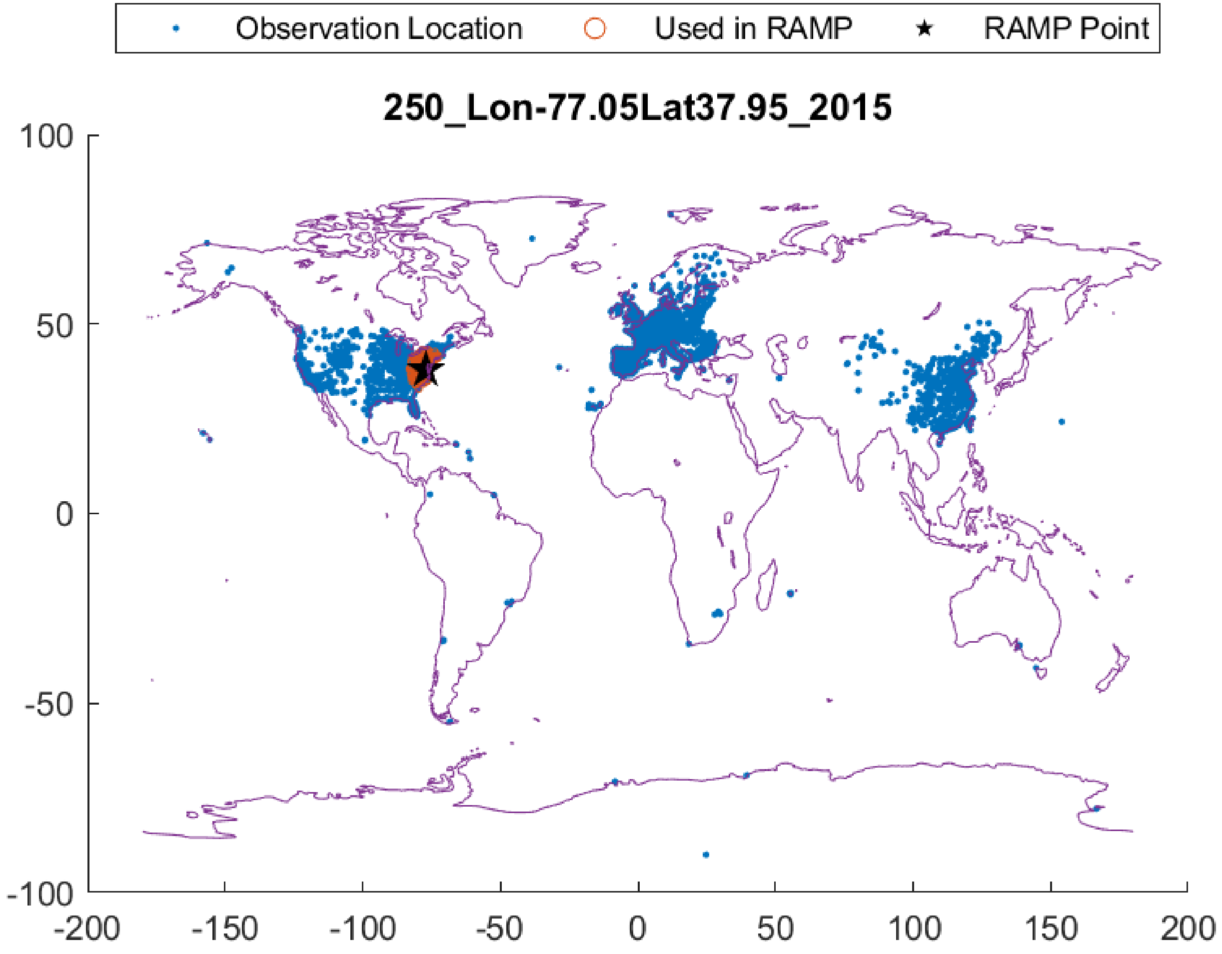


Regionalized Air Quality Model Performance (RAMP) Correction

- 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

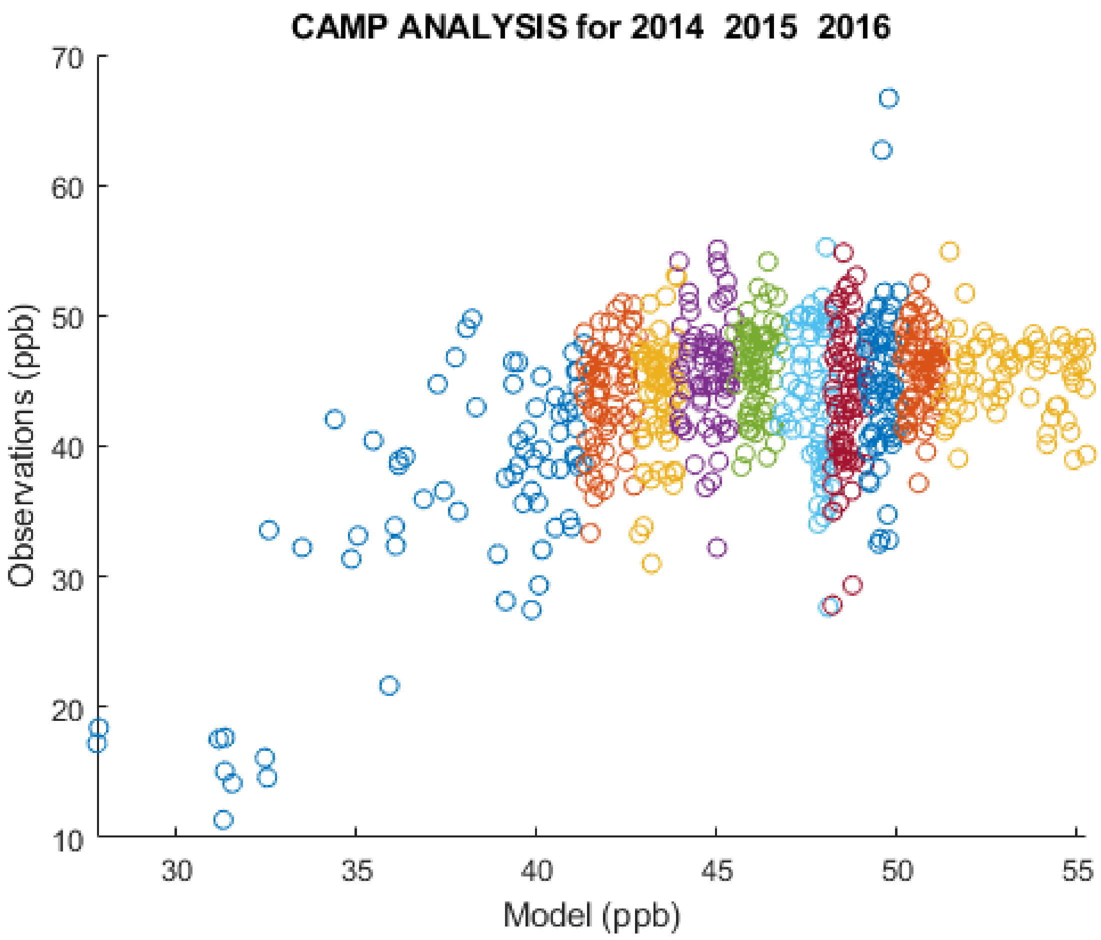
RAMP Correction

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



RAMP Correction

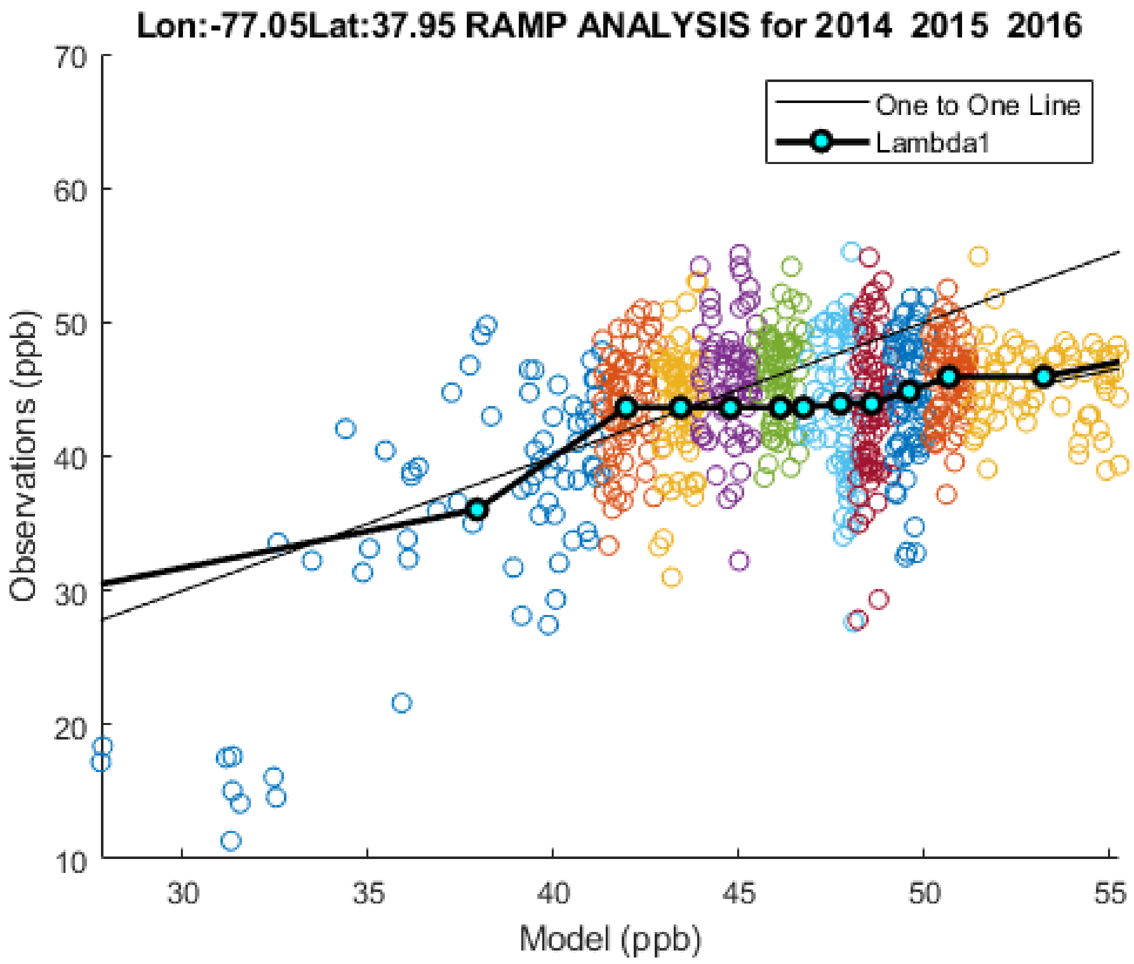
2) Match each observation with the model estimation at that space-time location



RAMP Correction

3) Sort each paired value into 10 equally sized bins (colors) and calculate λ1=mean

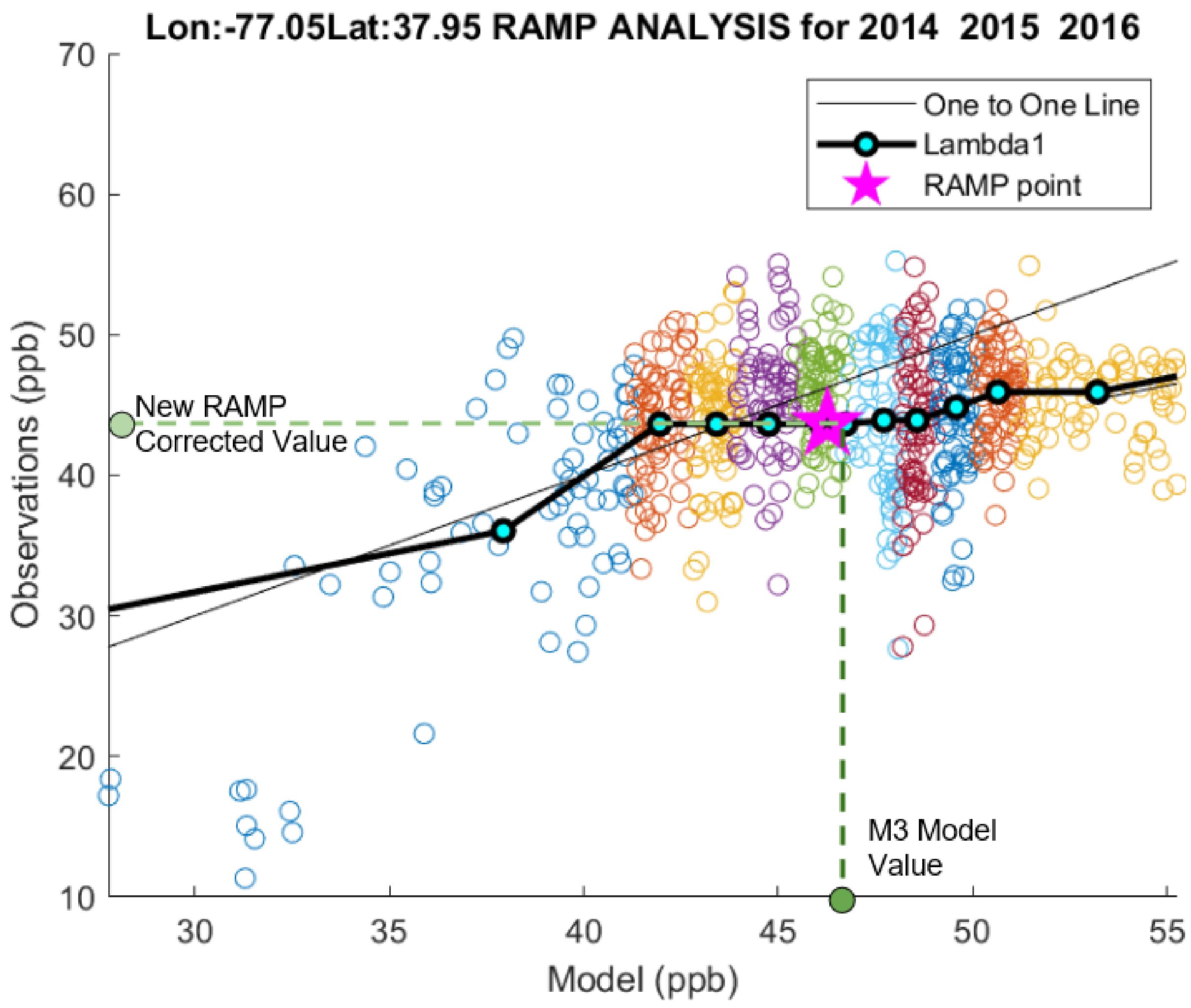
$$\lambda_1(\tilde{x}_i) = \frac{1}{n(\tilde{x}_i)} \sum_{j=1}^{n(\tilde{x}_i)} \hat{x}_j$$



RAMP Correction

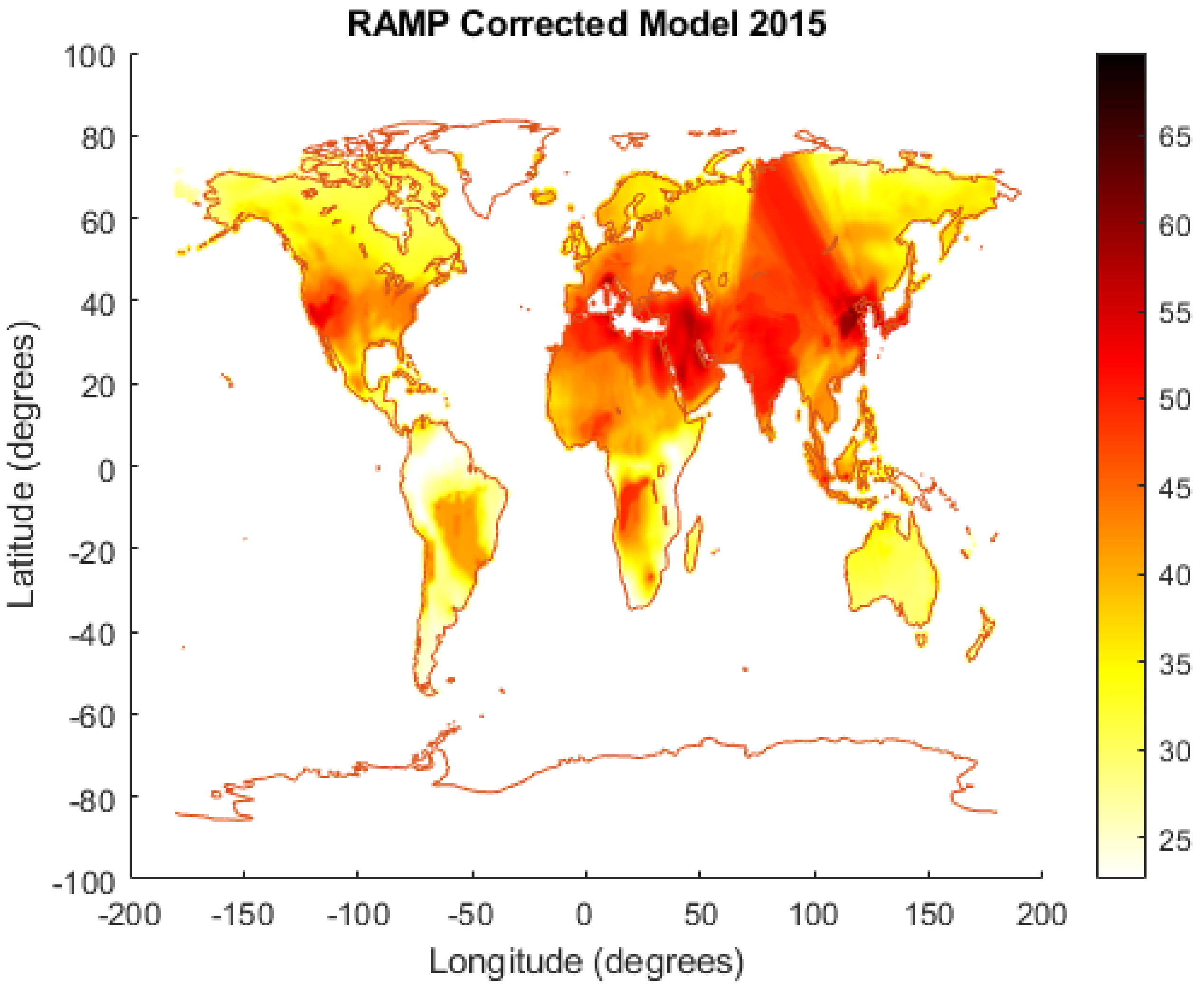
4) Interpolate between λs, restricting slope to >0 , to find the new RAMP corrected model value at this spacetime location.

Repeat for every M3 Model Point



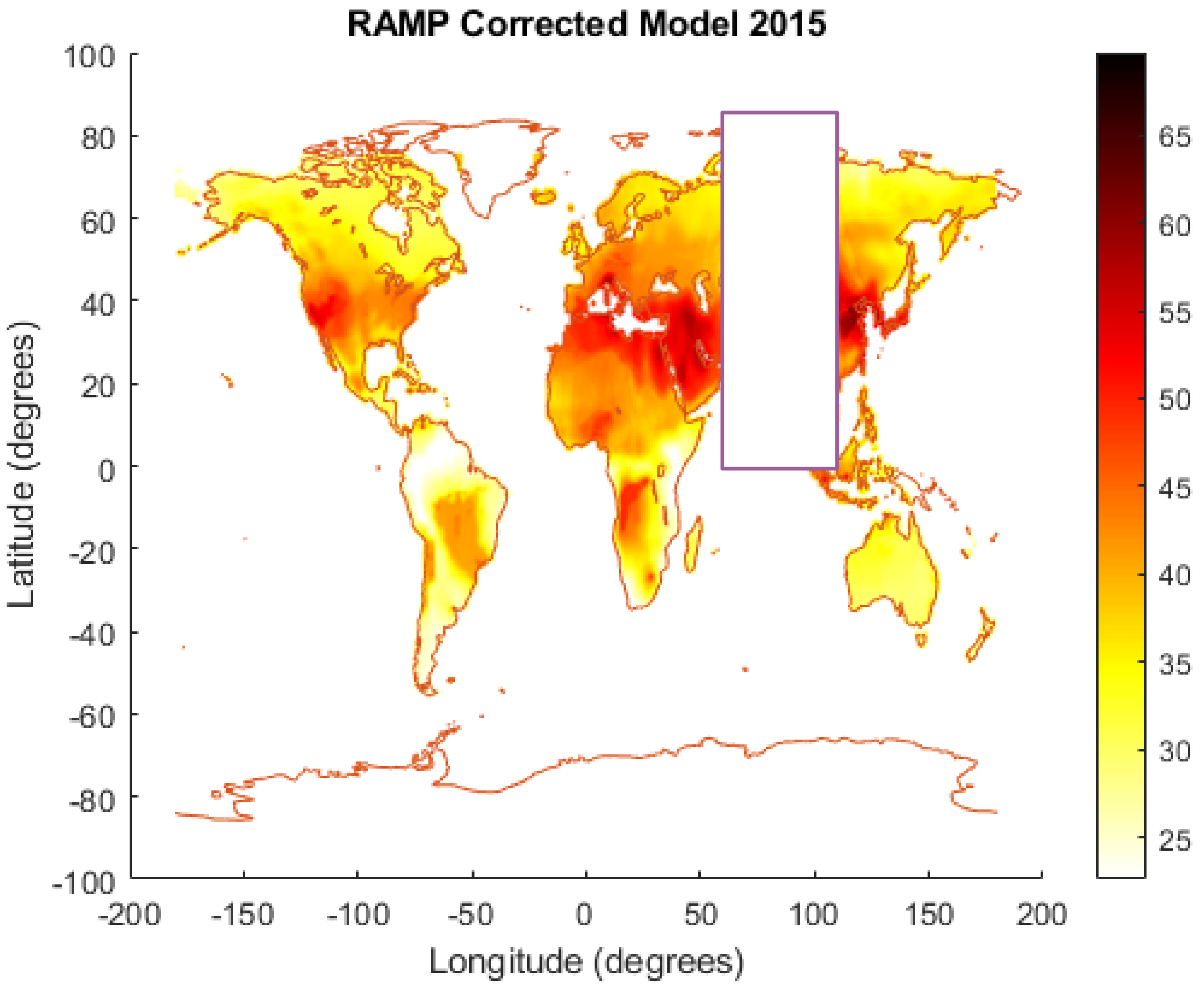
RAMP Output

RAMP Corrected M3 Multi model Composite



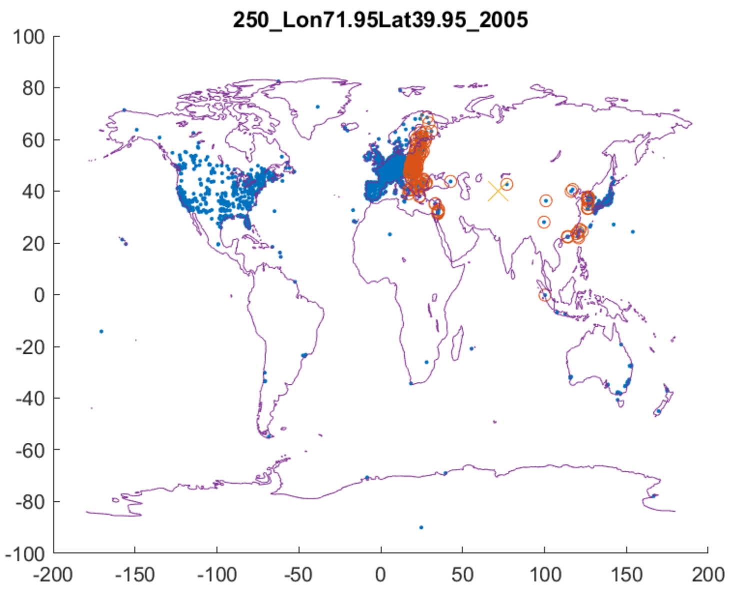
RAMP Output

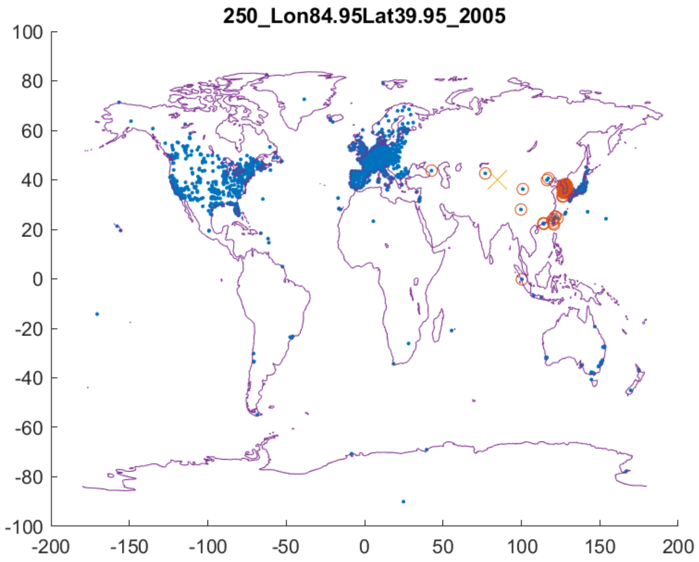
The Good



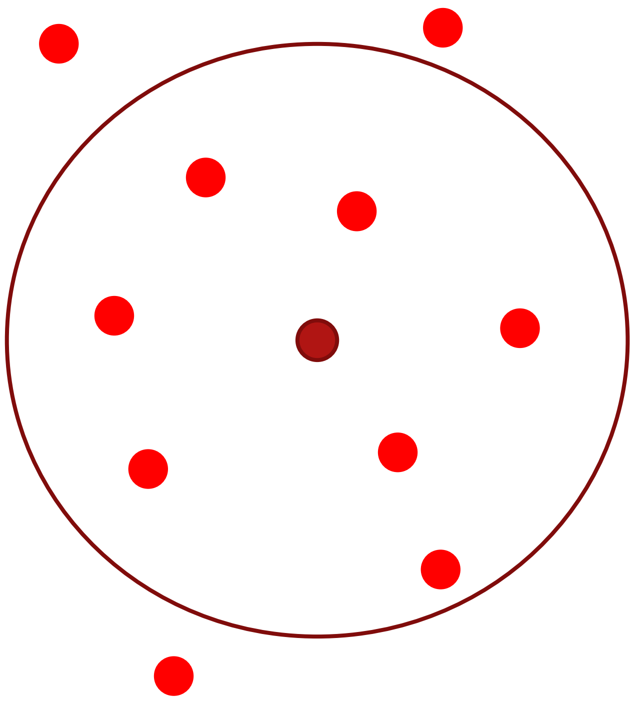
RAMP Output

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

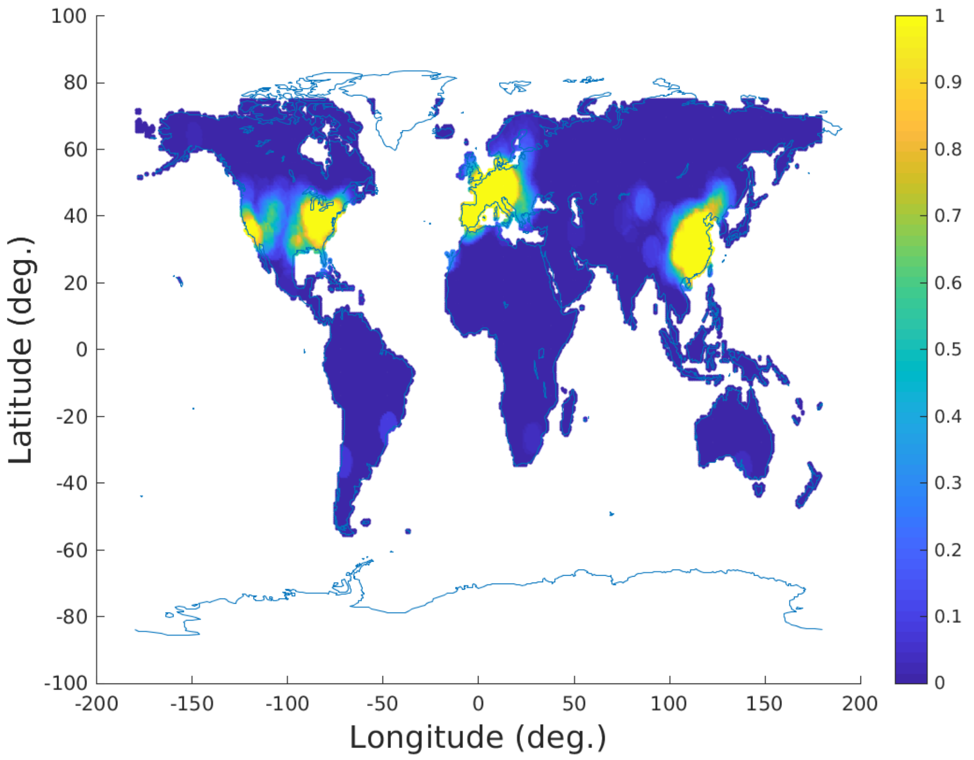
Corrected Model Value = (Nr/N)*RAMP value + (1-Nr/N)*M3Value.

In this case: (7/10)*RAMP value + (3/10)*M3Value

RAMP Output

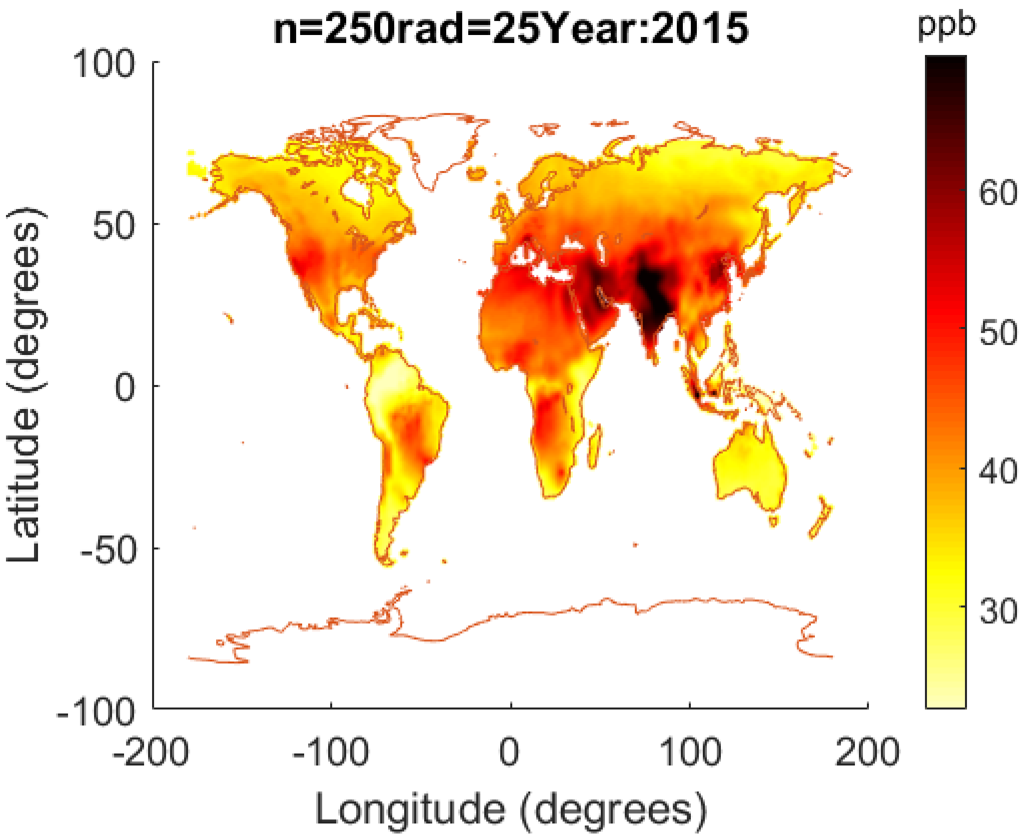
Solution: Weigh RAMP by proximity to points used to create a smooth transition, using M3 when far away from RAMP points

Alpha=1

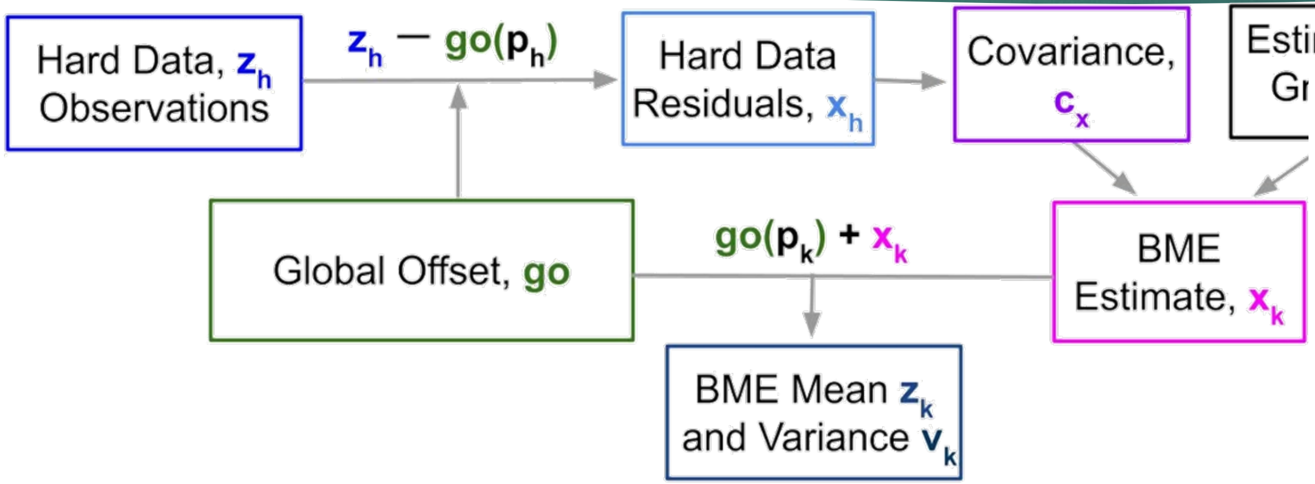


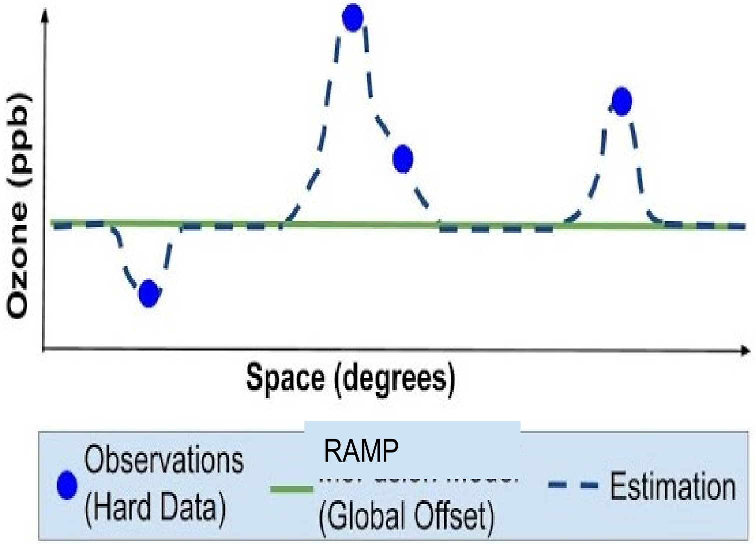
Weighted RAMP

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



BME Data Fusion

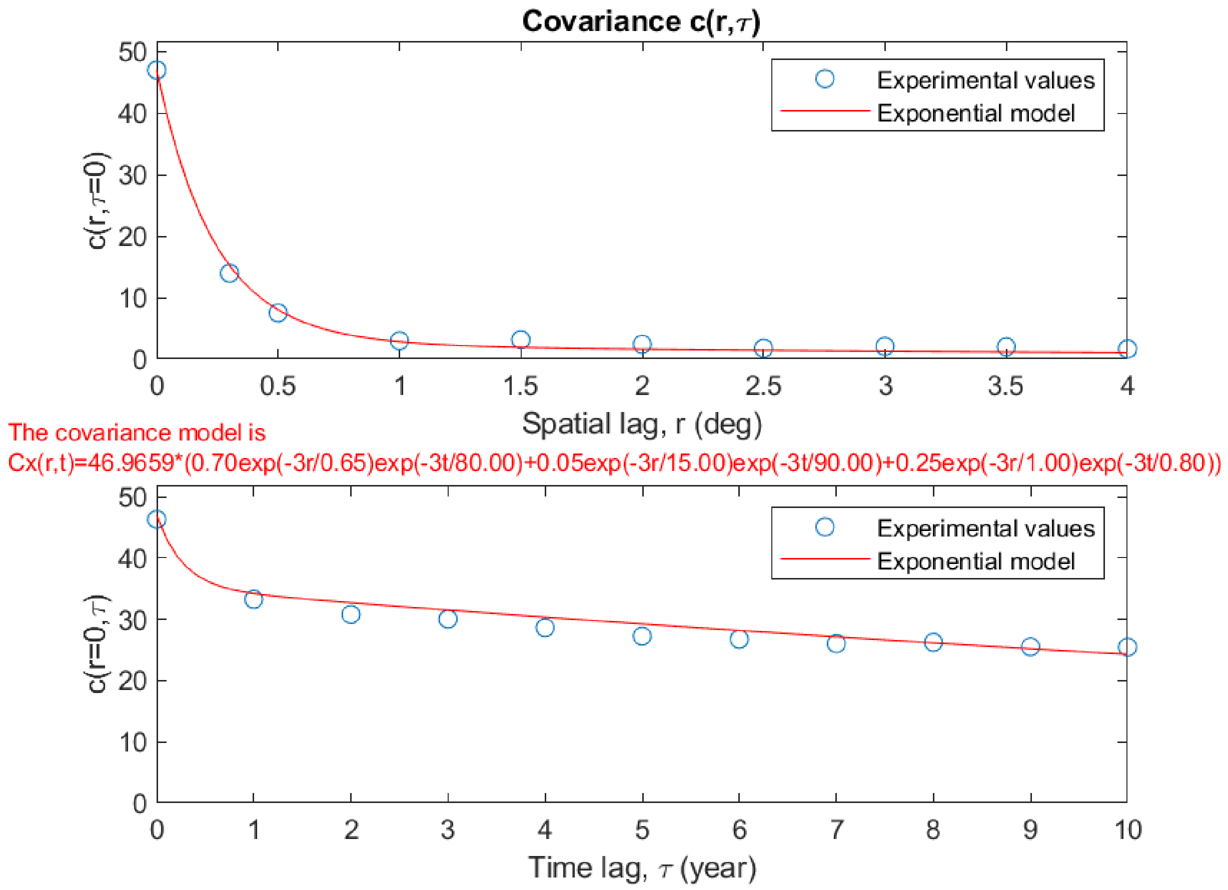




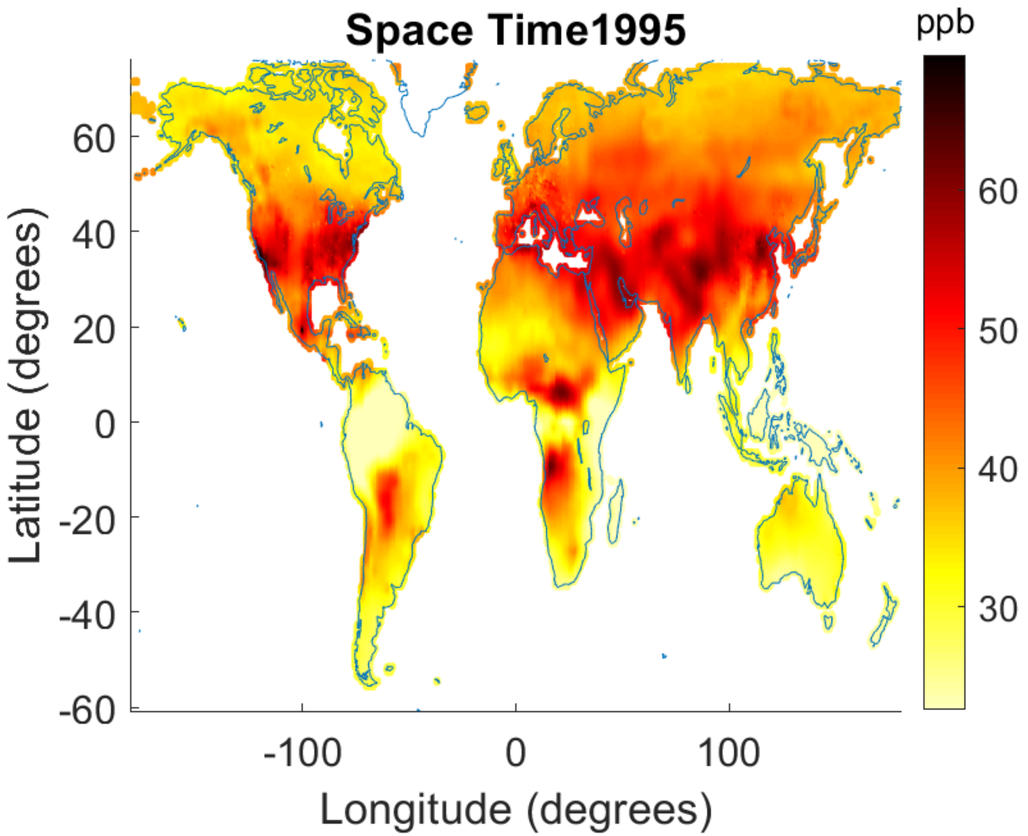
- Hard Data: Station Observations
- Global Offset: RAMP Corrected M3 Model
- Estimation Grid: Chosen by modeler

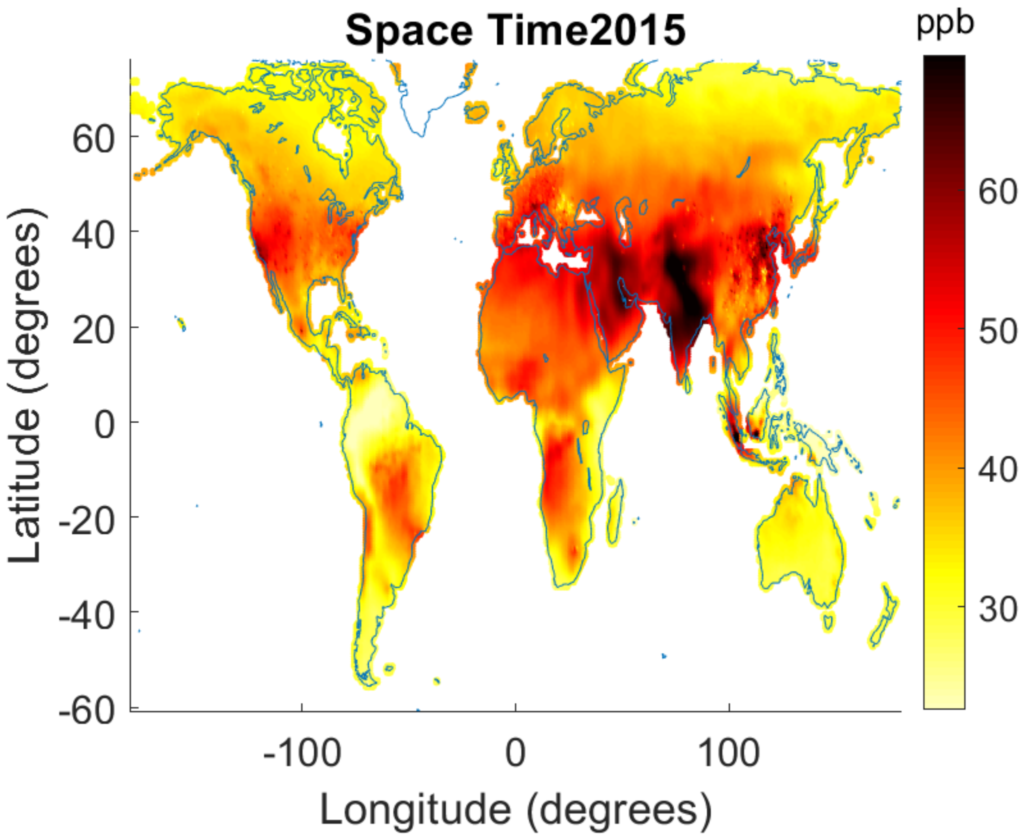
Covariance

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



Final RAMP Corrected BME Estimate



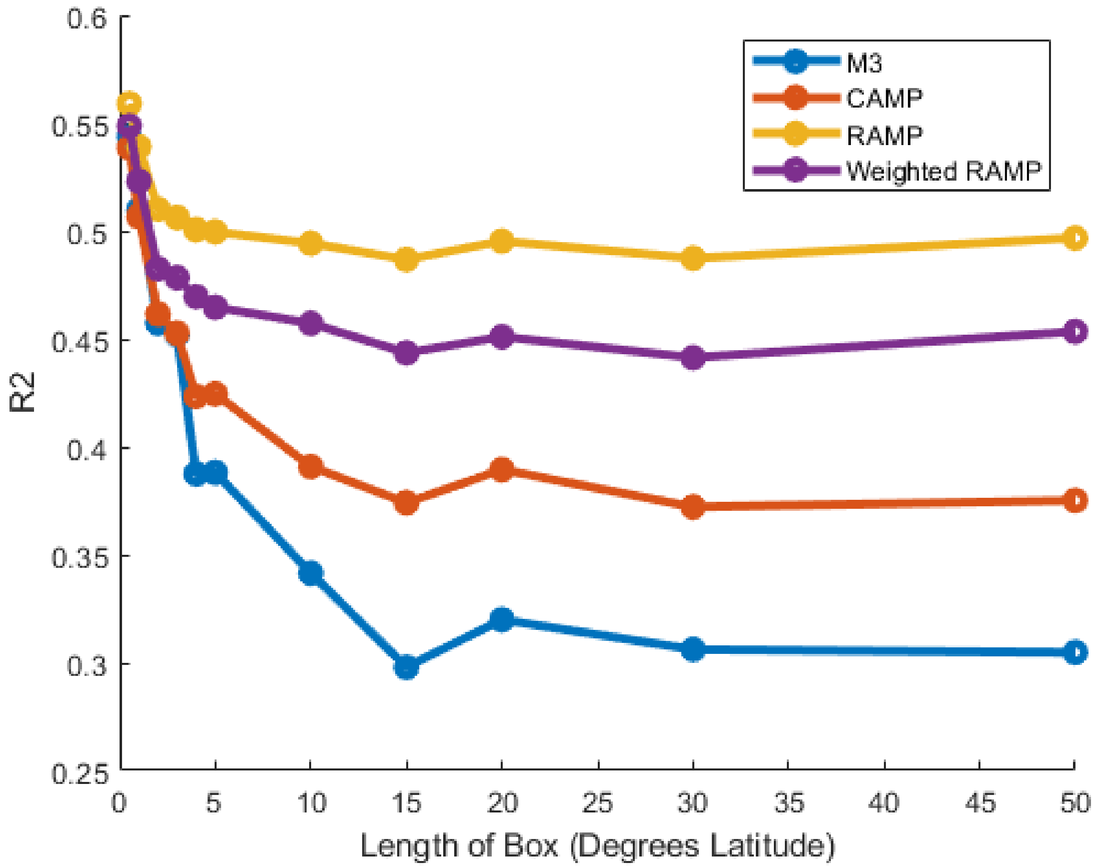


Was it Worth It? R^2 says yes

Leave One Out X-Validation

Scenario	MSE (ppb2)	R2
Simple Model Mean	189.23	0.28
M3 Fusion	61.14	0.30
BME w/M3 as offset	15.94	0.81
BME w/RAMP as offset	14.5	0.83
BME w/weighted RAMP as offset	14.5	0.83

Checkerboard X-Validation



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

M3 Model Fusion – Kai-Lan Chang

- Let sg be the grid cell at resolution 0.5° × 0.5°, ŷ(sg) be the interpolated observations, {ηk(sg); k = 1, . . . , n} be the model output registered onto the same grid from the n models available in a given year. ar is a constant that allows adjustment to the overall (regional) underestimation or overestimation and βrk is an optimal weight for the k-th model in region r.

$$\underset{\{\alpha_r,\beta_{rk};\,k=1,..,n\}}{minimize} \sum_{s_g \in Region\, r} \left(\hat{y}(s_g) - \alpha_r - \sum_{k=1}^{n} \beta_{rk}\eta_k(s_g) \right)^2,$$

$$subject\ to \sum_{k=1}^{n} \beta_{rk} = 1\ \ and\ \beta_{rk} \geq 0$$

Advanced Weighting Formula

- wM3=(1-nr/N)*alpha, alpha between 0 and 1, alpha is the most M3 can count an alpha <1 makes RAMP have a floor of 1-alpha
- wRAMP=1-wM3