

NO_x Chemical Sinks in the Upper Troposphere

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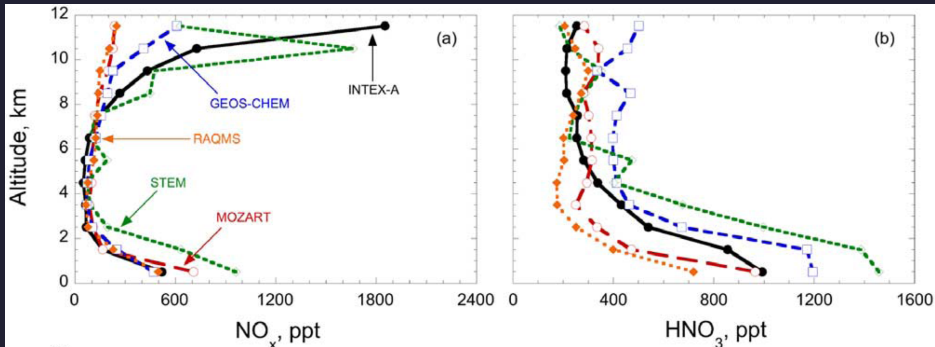
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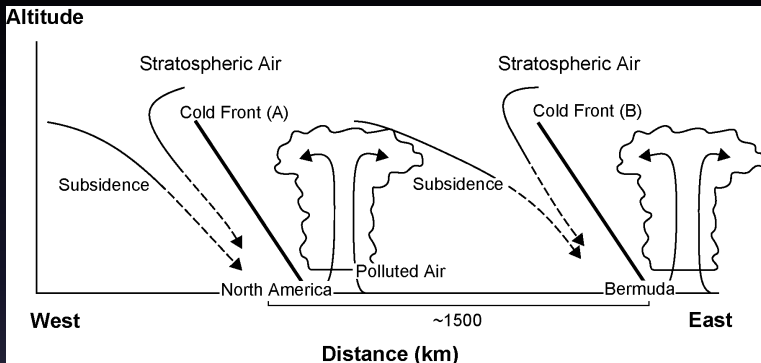
Aircraft analysis shows NO_x low-bias

Simulated NO_x vertical profiles from Singh 2007



- most models under-predict tropospheric NO_x
- STEM model uses out-dated emission inventory

Processes in the upper troposphere



Source: Prados et al., 2000

Sources

- Convection
- Lightning
- Aircraft

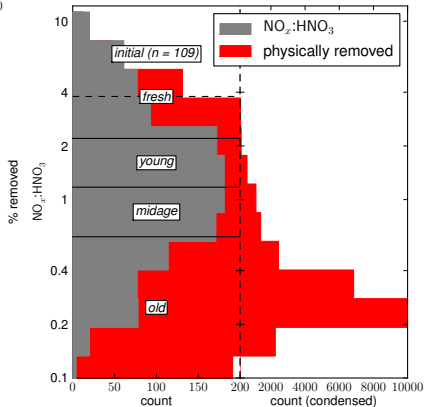
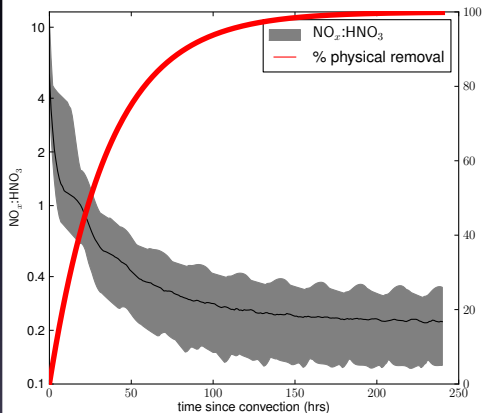
Sinks

- Chemistry
- Subsidence
- Rain, snow, ice

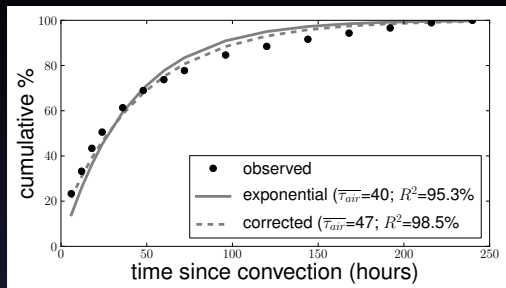
3D Models

- Simulate all
- Many uncertainty terms

NO_x Processing in the upper troposphere



Stochastic model of air parcel removal



Sample Bias

INTEX-NA observations have 21.4% near convection, but observed convection covers only 12.5% of sampling domain. Stochastic model adjusted to correct for this bias.

Simple Model

$$p(t) = \exp\left(\frac{-t}{\tau}\right) \quad (1)$$

Bias-Corrected

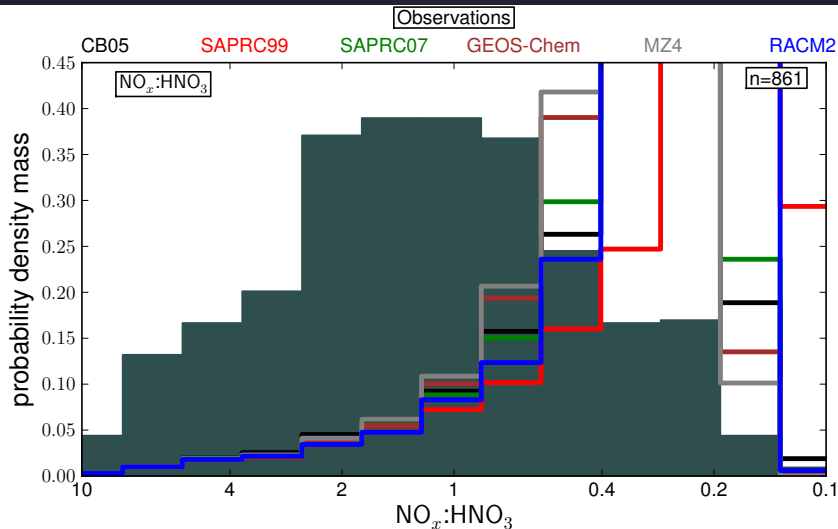
$$p(t) = \begin{cases} \exp\left(\frac{-t}{\kappa}\right) & \text{if } t \leq 6 \\ \frac{\kappa}{\tau} \exp\left(\frac{-t}{\tau}\right) & \text{if } t > 6 \end{cases} \quad (2)$$

$$\text{where } \kappa = \frac{-6}{\log\left(2 \exp\left(\frac{-6}{\tau}\right) - 1\right)} \text{ and } \tau \geq 9$$

τ is the average time an air parcel is in the upper troposphere

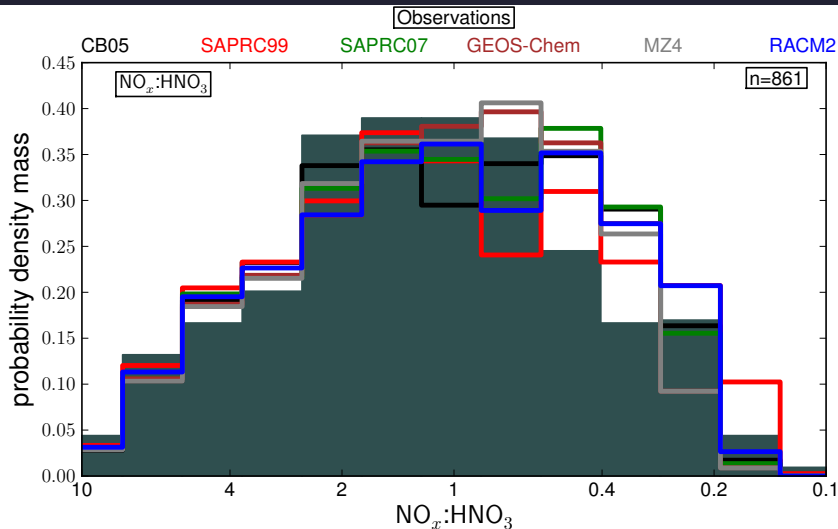
Simulation results for $\text{NO}_x:\text{HNO}_3$

IGNORING stochastic removal

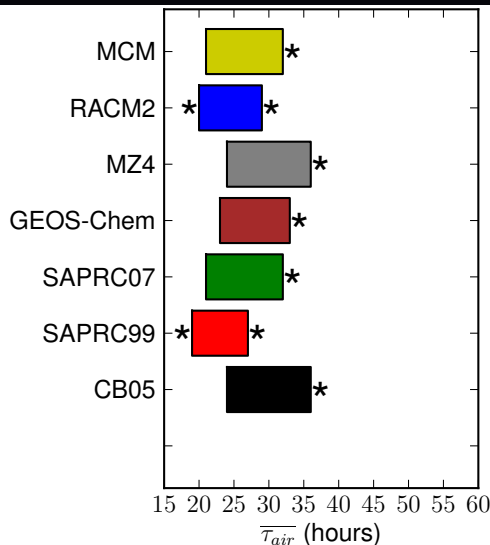


Simulation results for $\text{NO}_x:\text{HNO}_3$

INCLUDING stochastic removal



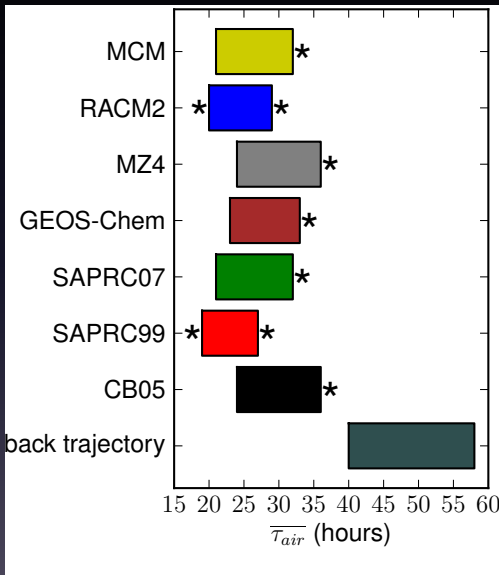
High Empirical Physical Sinks



Best fit τ

Given a chemical oxidation rate, the average air parcel lifetime would have to be τ to reproduce observed $\text{NO}_x:\text{HNO}_3$

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Back Trajectory τ

Given observed air parcel ages, the average air parcel lifetime is τ

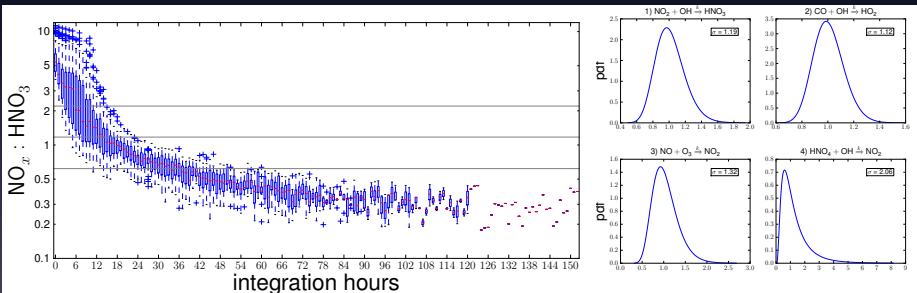
Using met τ with modeled chemical sinks causes 30% low-bias for NO_2

Can known uncertainty explain bias?

- 323 independent variables
 - Initial conditions come from experimental techniques
 - JPL and IUPAC cite experimental and systematic uncertainty for all reactions

Can known uncertainty explain bias?

- 323 independent variables
 - Initial conditions come from experimental techniques
 - JPL and IUPAC cite experimental and systematic uncertainty for all reactions
- Pre-screen influential variables
 - slow NO_x to HNO_3 conversion
 - characterized uncertainty



Cost functions for optimization

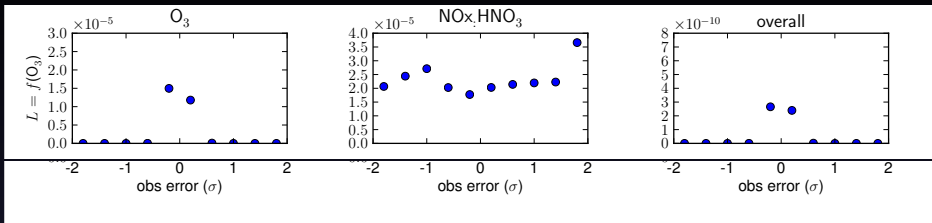
- Problem: do not have paired observations and model outputs
- Solution: Use Mann Whitney Wilcoxon U statistic (used for distribution comparison in original paper)
- U is normally distributed
 - mean: $\frac{n_1 n_2}{2}$
 - sigma: $\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}$
- Calculate the likelihood (L) of U from predictions (Y) given observations (O) of species (s)

$$L(Y_s | O_s) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \left[\frac{O - Y}{\sigma}\right]^2\right) \quad (3)$$

- Combine likelihoods as the product of individuals

$$L = L(Y_{O_3} | O_{O_3}) \times L(Y_{NO_x:HNO_3} | O_{NO_x:HNO_3}) \quad (4)$$

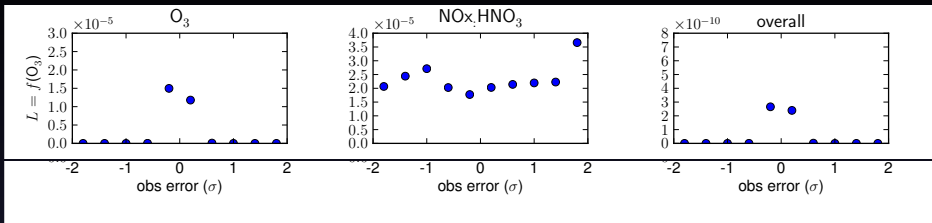
Observational Uncertainty Evaluation Results



For example, with ozone the model reproduces:

- adjusted ozone observation best near reported value
- NO_x:HNO₃ somewhat better at a lower (or very high) value
- overall, best estimate of ozone is near reported value

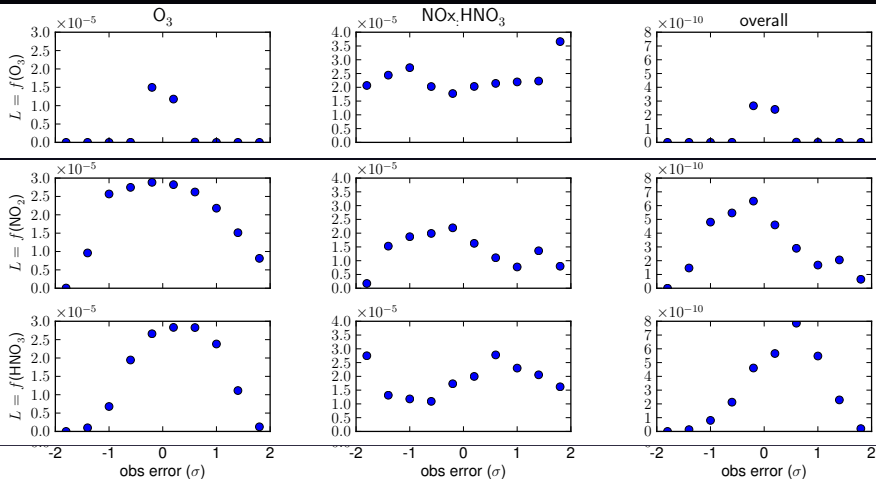
Observational Uncertainty Evaluation Results



For example, with ozone the model reproduces:

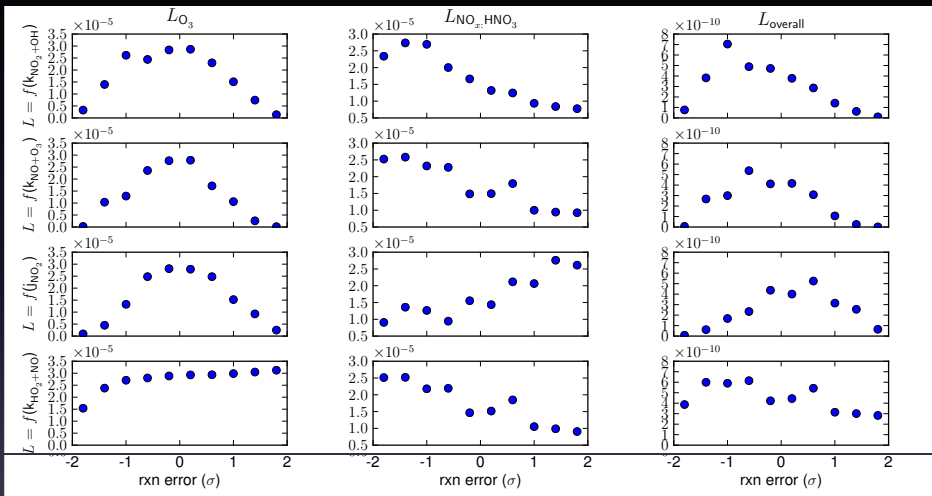
- adjusted ozone observation best near reported value
- $NO_x:HNO_3$ somewhat better at a lower (or very high) value
- overall, best estimate of ozone is near reported value
- What about other species?

Observational Uncertainty Evaluation Results



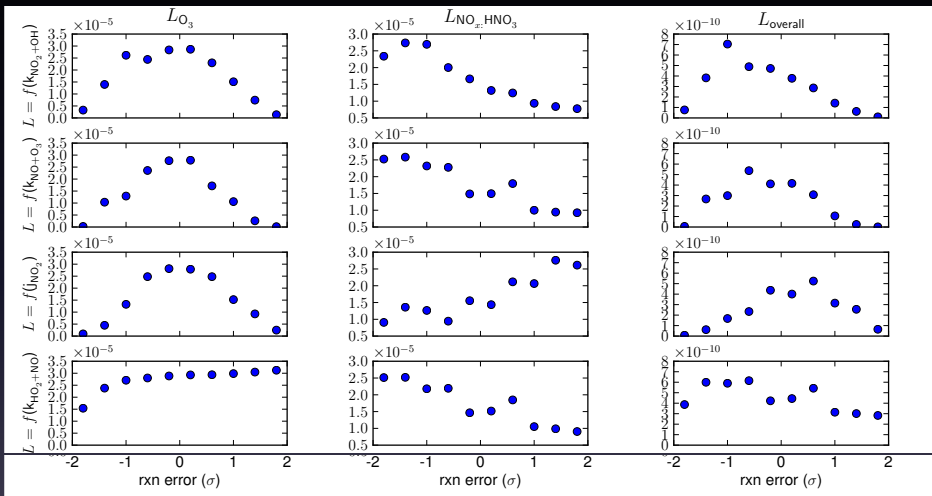
- NO_2 performs best at a slightly lower value
- HNO_3 performs best at a slightly higher value

Reaction Uncertainty Evaluation Results



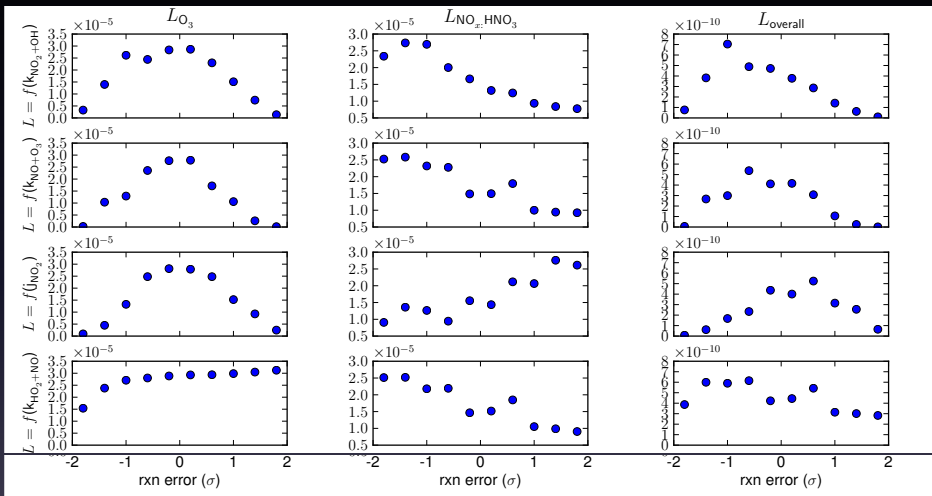
● $k_{\text{NO}_2+\text{OH}} \rightarrow \text{HNO}_3$ best at lower value (Mollner et al., 2010)

Reaction Uncertainty Evaluation Results



- $k_{NO_2+OH \rightarrow HNO_3}$ best at lower value (Mollner et al., 2010)
- $k_{NO+O_3 \rightarrow NO_2+O_2}$ best at lower value

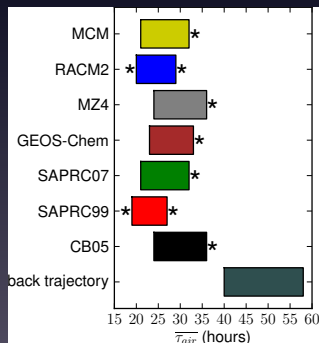
Reaction Uncertainty Evaluation Results



- $k_{NO_2+OH \rightarrow HNO_3}$ best at lower value (Mollner et al., 2010)
- $k_{NO+O_3 \rightarrow NO_2+O_2}$ best at lower value
- $k_{NO+HO_2 \rightarrow NO_2+HO}$ has a broad range of acceptable values

Ranking influential variables

Parameter	%Error	τ hrs
NO_2	(-5,-22%)	(+0,+4.8)
$\text{HO}_2 + \text{NO} \longrightarrow \text{NO}_2$	(-7,-16%)	(+0,+2)
HNO_3	(+4,+12%)	+0
$\text{NO}_2 + \text{OH} \longrightarrow \text{HNO}_3$	-10%	+0
$\text{NO} + \text{O}_3 \longrightarrow \text{NO}_2$	-10%	+0
$\text{NO}_2 \longrightarrow \text{NO} + \text{O}$	+7%	+0



Summary and Conclusions

- Evaluation:
 - ① Ensure proper understanding of the upper troposphere
 - ② Accurately attribute and apportion radiative forcing of UT O₃
- Completed a thorough uncertainty analysis for the model evaluation framework and application in Henderson et al., 2010 ACPD
- Excluded many variables due to confounding influence on key species
- Identified observations and reactions that have the potential to improve model evaluation and lengthen inferred air parcel lifetime
 - [NO₂]
 - $k_{\text{HO}_2+\text{NO}} \longrightarrow \text{NO}_2+\text{HO}$

Next steps

- Use Bayes Theorem to constrain uncertainty of key reactions
 - posterior: updated using likelihood function
 - prior: JPL reported uncertainty

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